To the Graduate Council:

I am submitting herewith a dissertation written by Todd Arron Koetje entitled "Approaches to the Investigation of Intrasite Spatial Patterning in Three Dimensions." I have examined the final copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Anthropology.

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APPROACHES TO THE INVESTIGATION OF INTRASITE SPATIAL PATTERNING IN THREE DIMENSIONS

A Dissertation

Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Todd Arron Koetje

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For Edward and Arlene Koetje

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ABSTRACT

Until very recently virtually all spatial analyses in archaeology have been restricted to sites or levels that are amenable to the consideration of spatial patterning in the two horizontal dimensions. This was accomplished either through pre-screening of sites, or investigating vertical variation and defining limits to what would be considered appropriate for two dimensional research. The utility of the K-means technique and the necessary modifications to it for the study of three dimensional spatial structures is examined here through analysis of simulated archaeological levels. Results from these experiments were abstracted and applied to the analysis of two different sites from the Southwestern French Paleolithic: the Magdalenian site of Le Flageolet II and the Grotte XVI, a multicomponent site.
Results of these analyses contribute to our understanding of the range of variation inherent in spatial patterning with archaeological sites, indicate that the techniques are useful, and suggest that similar sites not usually deemed amenable to the more limited two dimensional methods can no longer be ignored.

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CHAPTER I

GENERAL INTRODUCTION

I.1 Introduction

This dissertation represents attempts to investigate methods of spatial analysis that might be useful in considering spatial patterning in both the horizontal and vertical dimensions. My main concern here is to develop and place in a relevant archaeological context such methods. Virtually all previous archaeological spatial analyses have focused on sites or levels from within sites that are amenable to consideration in two horizontal dimensions alone. Such vertical variation as existed was nearly always collapsed onto a single horizontal plane. In those few cases where vertical variation was explicitly considered, the context was usually that of justifying the use of a two dimensional approach in questionable situations. There are many sites, however, where consideration of material patterning in only two dimensions is obviously unwarranted and certainly unprofitable. These have generally been excluded from analysis altogether. If any part of Archaeology can be said to suffer from a "Pompeii Premise" (Binford 1981), it is intrasite spatial analysis. Here, (in Chapter II) I wish to examine exactly this type of situation more

closely and show that there are useful ways of thinking about and characterizing the patterning of objects in sites using their full three dimensional provenience. To do this means that some of our more cherished and explicit attitudes about behavioral reconstruction as a necessary goal of intrasite spatial analysis be abandoned or heavily modified.

There are four main aspects to this investigation. First, a brief history of spatial analysis in archaeology and its main concerns, methods, and their recent advances is outlined. This is an important step in understanding the course of spatial analysis in archaeology, and why this study is a significant step beyond previous approaches. Next, a model of archaeological deposition as it may occur in three dimensions is developed, and its main axes of variation and their implications for the eventual analyses delimited. Third, a series of simulated archaeological layers are examined through the use of new modifications to the K-means clustering technique. This part of my investigation is specifically designed to allow estimation of errors in recovering meaningful layers given a wide range of site characteristics that may then be applied to the "real" site analyses. This section also includes a detailed discussion of the assumptions built into these methods, and their general characteristics. Fourth, two analyses

are performed using archaeological data from the French Paleolithic. The first, on couche IX from the Magdalenian site of Le Flageolet II (Dordogne, France), and the second on the Grotte XVI, a Middle and Upper paleolithic site from the same area that is currently under excavation. These analyses are then compared and more detailed characterizations of the main methods involved are presented.

Each of the site analyses has distinct goals. The Le Flageolet II analysis is oriented towards exploring appropriate methods when a rather thick, dense deposit from a single culture, and perhaps cultural phase is being considered. Couche IX from this site and its materials are examined from several perspectives, with an eye towards legitimately characterizing their spatial patterning in an objective, repeatable and useful manner. This type of site is particularly intractable to the more typical methods of spatial analysis because it is difficult to justify collapsing their extensive vertical variation onto a horizontal plane, and has generally been completely excluded from analysis or consideration. Such deposits are not uncommon however, in the European Upper Paleolithic. In contrast, analysis of a restricted portion of the Grotte XVI materials, is focused on the utility of similar methods in examining stratigraphic discontinuities and providing guidance for future

excavations given a comparatively sparse, multicomponent material distribution spanning some 40,000 plus years.

I.2 Theoretical Development of Spatial Analysis

Initially concerned with characterizations of global site patterning (Clark and Evans 1954, Dacey 1973, Hodder and Orton 1976), Archaeological spatial analysis has developed into a broad concern with the patterning of artifactual materials at many levels. Clarke wrote one of the most influential early essays on the theoretical basis of spatial analysis in archaeology (1977). He noted the generally underdeveloped state of theory in spatial studies, and called for additional development in three basic areas of theory, each primarily concerned with the explanation of spatial patterns at distinct scales: the Micro or within structure scale, the Semi-Micro or intrasite site patterning scale, and the Macro or regional scale. There have been many new methods and approaches suggested since Clarke's essay, all though, fit well with his conception of the distinct scales at which information from spatial patterning should be considered.

Three major research directions and the theoretical perspectives that accompany them have become prominent recently that fit especially well into Clarke's scheme: 1.) ethnoarchaeology, 2.) the study of site formation processes, and 3.) attempts to use social and

evolutionary theories to explain spatial processes. Perhaps foremost among these has been the increase in ethnoarchaeological research with an emphasis on understanding the relationships between the presently observable "static" archaeological record and the "dynamic" processes that created it in the past (Binford 1983a). This ethnoarchaeological research has important elements at all of Clarke's theoretical scales, although most of the detailed work has been done at the micro and semi-micro scales (e.g. Binford 1983a, 1986, 1987; Gifford 1978; Whallon 1984). With the increase in ethnoarchaeological studies has come an increasing emphasis and concern with the detailed study of site formation processes on an intrasite level (Schiffer 1976, 1987; Stein 1982; Wood and Johnson 1978). This work is most clearly focused at the semi-micro scale. Although somewhat more obscure archaeologically than the previous two, research perspectives that focus on social and evolutionary processes operating at the macro scale have also been the subject of much work (Dunnell 1980; Hillier and Hanson 1984).

Ethnoarchaeology

Binford's work among the Eskimo (1978a,b) allowed him to suggest several theoretical frameworks in which to consider regional site patterning, intrasite patterning,

and their interplay (Binford 1982, 1983a, 1986, 1987). These schemes were mainly concerned with distinctions between collector and forager based subsistence strategies. Binford has suggested that subsistence strategies be viewed as a continuum, with pure collector and pure forager strategies at either end. Collector based strategies involve moving substantial amounts of food and other raw materials to places where the people involved congregate. These places would be permanent or temporary home bases, depending upon the nature of the resources available. People utilizing collector strategies are often also assumed to practice food sharing, stress group and perhaps 'ethnic' identity, and exhibit territoriality. A foraging strategy on the other hand, requires that people move around in search of food and other resources. Under this strategy, large, stable home base camps or settlements do not exist, or are very temporary. Any real world subsistence strategy would involve elements from each end of the continuum (Binford 1982, 1983a).

In a theoretical paper Binford (1982) suggests that, in essence, varying proportions of the collector and forager strategies in a subsistence system would condition the number of people and length of stay at various types of sites. Changes in the specific nature of the economic use of a given location, and such additional elements as

tool curation and storage patterns would then "cause" large scale archaeologically visible patterns to form at specific sites. Because of the limited amount of the ethnoarchaeological data used to construct this scheme, some applications tend to be essentially indistinguishable from rather straightforward ethnographic analogy based on Binford's Nunamiut data. Unfortunately, this data is generally derived from observations of modern people using non-native technology (e.g. guns, metal implements, canned food, oil, and snowmobiles), whose contemporary subsistence strategies were dependant not only on these items, but also on imported food and other connections with a world market, and whose mobility patterns and subsistence regimes were certainly different in the past. The scale and nature of the effects that these deviations from the prehistoric situation might have on the more abstract principles derived from this data have not been addressed by Binford (but cf. Headland and Reid 1989; Murray and Walker 1988; Schrire 1980, 1984). Despite these problems, which can probably be minimized in application by staying away from overly specific analogic reasoning, the scheme is still the most detailed and encompassing theoretical framework for viewing hunter/gatherers and their spatial processes at semi-micro and macro scales.

Along with his examination of regional level patterning, Binford has proposed a framework for understanding detailed intrasite patterning that occurs primarily within restricted areas in a larger site. Based primarily on expectations of human physical space requirements and body size, this micro scale theoretical framework is perhaps more directly derived from uniformatarian principles than ethnographic observation. Binford has thus provided us with at least the basic outlines of what would probably be accepted by Clarke as a theoretical framework for at the micro, semi-micro and macro spatial scales.

At almost the same time as Binford's work, Yellen provided an example of spatial patterning derived from an independent set of ethnographic observations on the San or bushman peoples of southern Africa (Yellen 1977, 1987; Brooks and Yellen 1987). Yellen (1977) concentrates his attention primarily on residential sites, although some regional scale work is also presented, suggesting that patterning at this level can be seen primarily in terms of the number of domestic units which occupy a site and the length of their occupation. Various differences between what Binford and Yellen each call activity areas can be easily attributed to the nature of the sites examined and the level of discrimination applied to the concept of an "activity" in the behavioral realm. Once these semantic

differences are overcome the two sets of observations seem to reinforce each other quite well, although each is concerned with discourse in distinct causal frameworks. Recently a much greater time depth and broader spatial distribution has been achieved for material supporting Yellen's original contentions (Yellen 1987; Brooks and Yellen 1987). Binford's have remained more restricted temporally.

A number of researchers have also studied the Alywara of Australian (Binford 1986; O'Connell 1987; Spurling and Hayden 1984), providing another source of observations on micro and semi-micro scale processes. These observations also tend to fit well within the larger scheme suggested by Binford, although they differ in detail and some of the similarities seem strained. There are also a number of more limited ethnoarchaeological studies, most of which also tend to show support for the major aspects of Binford's scheme. The societies that have been examined include: Central Americans (Lange and Rydberg 1972), Mexican Americans (Kent 1984), Mayan Highlanders (Hayden and Cannon 1983), East Africans (Gifford 1978), and Bedouins (Simms 1988). Thus from many independent quarters comes support for this basic framework.

Formation Processes

In contrast to the regional subsistence system and body size constraints emphasized in Binford's theoretical approaches, there is what may be called the "formation process approach" to micro and semimicro scale spatial theory. This approach may be broken into two distinct schools of thought, although in general the primary concern is with the nature and type of natural and/or cultural formation processes that acted (or continue to act) at a particular site. It seems useful to make a distinction between those who follow Schiffer, and have a very large scale view of formation processes, and those who proceed from a more restricted geological or geoarchaeological perspective.

Perhaps best exemplified in Schiffer's own work (1976, 1978, 1983, 1987, 1988), the "Behavioral Archaeology" framework should be distinguished from a more general concern with site formation processes that could be extended to cover regional level systems such as those modelled by Binford. Schiffer's main concern is often limited to cultural refuse disposal patterns, and natural disturbance processes which may act to "bias" pre-existing patterns (for extensive catalogs of these agents and their potential effects see Wood and Johnson 1978; Schiffer 1987). This emphasis leads to attempts to reconstruct these formation processes and remove their "bias", thereby

allowing direct behavioral inferences to be drawn from spatial patterning (e.g. Carr 1984, 1985, 1987). Binford (1981) has criticized this as implying a "Pompeii" situation in which the static record can be directly read in behavioral terms after being "unbiased". The implication here is that the archaeological record can be examined as if it represented a frozen moment in time, after the "biasing" processes that affect it have been properly identified and eliminated. It should be clear however, that understanding those factors which underlie a "biasing" formation process is an entirely proper and important research goal, behavioral inference rightfully lies in another realm entirely. For example, within such a framework it may be possible (given an ideal world) to distinguish between the sets of behavioral events (but not necessarily their relationships to regional subsistence strategies) that went into making up a specific type of refuse deposit, if the specific type of dumping behavior is understood and identifiable as a "biasing" process (i.e. the refuse is not simply an activity area resulting from the activity of dumping, as Binford (1986) would have it). It may be best simply to adopt a more general notion of formation process, one which includes both the specific biasing concerns of Schiffer, and the regional level patterning of Binford. Such a consideration would effectively bridge the gap between the intrasite, semi-

micro scale, and regional level, macro scale processes. Schiffer's main contribution may be to shift the focus of ideas about formation process and disturbance away from the very broad entropy level (e.g. Ascher 1966) to specific processes and the patterning which they can produce. Thus the "Pompeii premise" problem can be seen to focus on the process of making inferences beyond identifying formation processes, rather then being inherent in their study.

Taphonomy

There is another, largely different school of thought which is also centered on the notion of site formation processes. The main difference between this set of approaches and that of the Schifferian school, is that formation processes are thought of primarily as taphonomic processes. Taphonomic is a term from Paleontology that refers to those processes effecting and creating an assemblage of bones from the time an animal dies until its remains are recovered (Gifford 1978; Gifford and Behrensmeyer 1977). The use of this approach in archaeology is largely due to the influence of Gifford (1978) and Brain (1981), both of whom were more interested in the effects that various kinds of animals had or have on archaeological assemblage formation, than on cultural patterns of refuse disposal. These processes are

generally considered to be in the realm of "natural transformations", or those not caused by human behavior by Schiffer (1975).

Social/Evolutionary

Moving away from the semi-micro and micro scales of theoretical development in spatial analysis, we find very broad scale attempts to explain human induced patterning as an aspect of cultural or social construction. This approach, as exemplified by Hillier and Hanson (1984) and Agorsah (1988), suggests that spatial organization is best viewed as a coding scheme which reveals, and reinforces for its users the nature of their social structure and their place within it. Hillier and Hansen (1984) give this full play only in connection with modern built space (i.e. buildings), and attach long term evolutionary significance to it. However, the concept is easily generalized as culturally specific meaning given to spatial structures of various types. Agorsah's (1988) concept of social relationships in space following a "local rule", whereby distances between the activity and domestic loci of two or more parties are functions of the social distances between the parties involved, is an excellent example of this concept applied on the intrasite or micro scale.

To Hillier and Hansen, built spaces, the spatial organization implied by them, and their relationships with the peoples who inhabit them, is viewed through an analogy with biological evolution. In their terms built space is seen as serving the same role as the genotype, while social organization is seen as the phenotypic expression of this genotype. This phenotype is read from the spatial organization created by spatial structures (which were, of course, created by the society). This is seen as a way of making these relationships dialectical and participatory rather than linear. While it seems reasonably clear that the biological analogy is somewhat strained, especially as they have not demonstrated these relationships so much as assumed them, the social and participatory aspects of their model are at least interesting attempts to integrate several different types of "causal" agents into the study of spatial patterning. Similar views on evolution in a more traditional biological framework have recently been expressed in Lewontin (1984) and Lewontin and Levins (1985). Such a framework may have very little or no utility when considering low level formation processes. However, in application it would have very clear implications for micro and semi-micro scale patterning, such as: loci patterning in relation to features, specific types of activities, refuse, etc. Thus one would expect differences in such patterns between discrete cultural and

subcultural units, even within similar functional contexts. Although these implications aren't very earth shattering, at least this framework provides a theoretical basis for them beyond common sense.

An important advantage to these frameworks and others like them, is that they do not exclude functional description or explanation, merely embed it within a larger theory. Because of this flexibility and mechanisms allowing change originating as non-functional variation, such a scheme may become important in integrating spatial patterning at both inter and intra-site levels into even larger theoretical frameworks, such as future developments of evolutionary theory.

Conclusions

There have been a number of very promising advances in the theoretical aspects of spatial analysis, and the general understanding of spatial processes since Clark's (1977) essay calling for necessary development. Most important for consideration here are those which concern the micro and semi-micro scales. Among these, the contributions of Binford and Yellen must be seen as the most important. Because of this importance, and their different emphases, they will be discussed in detail in the next section, especially as they relate to a single

critical concept in spatial archaeology: the activity area.

I.3 Activity Areas and Models of Spatial Process

The idea that human behavior in space is organized into "activity areas" is widespread in archaeology in general, and ethnoarchaeology and archaeological spatial analysis in particular. This is especially apparent in the micro and semimicro scale approaches outlined above (e.g. Binford's 1982 body size constraint models, Schiffer's 1975 Cultural formation process models, and Yellen's 1977 San models). Before this concept can be used in creating general models of spatial process however, it requires critical evaluation. A brief look at some of the more recent uses of the concept will, I think, shed some light on its nature, and potential in quantitative study of artifact spatial patterning.

Binford has conducted ethnoarchaeological research oriented towards spatial relationships among artifacts with two distinct groups, the Alaskan Nunamiut, and the Australian Alywara (1978a,b, 1982, 1983a, 1986). Based primarily on his Eskimo research he has proposed the collector-forager continuum scale for characterization of subsistence patterns. This has been used to create expectations for intrasite patterning in various situations (Binford 1980, 1982, 1983a, 1986, 1987).

Relatively detailed ethnoarchaeologically based spatial analyses have been published from only two "types" of Nunamiut site, a briefly occupied hunting stand (the Mask site: 1978b, cf. Whallon 1984), and an adjacent butchering site (1983a). Binford observed that a large number of the activities which went on at both sites were segregated into discrete loci, when specific activities and loci were clearly correlated, they were, together, called "activity areas" (Binford 1983:147). General expectations were that the refuse found in these areas would correspond to the behaviors that took place there, although there need not be unique, monofunctional sets of refuse present.

In contrast to this, although also at the Mask site, some activities took place primarily around a series of hearths (often more than one hearth was in use at a time). In this situation very small refuse from these hearth focused behaviors was dropped in a band around the hearths that corresponded to the seated positions of the individuals (i.e. the drop zone). Larger (or messier) refuse was tossed further from this area. This "toss zone" was located either: 1.) behind the seated individuals away from the hearths or, 2.) across the hearth (in the quadrant where smoke blew and no one was seated), although frequently this kind of positioning was constrained by the presence of large boulders. The size

and nature of the drop and toss zones are explained by reference to body size constraints and the positioning of the people around hearths. Both the drop zone and the toss zone were also referred to as activity areas. In this single case only a few activities took place around the hearths in such a way as to overlap strongly in their spatial utilization.

A similar ring pattern was also claimed to occur for a butchery site (Binford 1983a). The animal being butchered occupied a central area while debris from the process was discarded in a more-or-less circular pattern around it. In this case the entire spatial structure is referred to as an "activity area".

It is relatively easy to see that an "activity area" as used in the Nunamiut examples is a very loose concept, sometimes applied to a limited number of specific areas within a site with little or no distinction made between areas created by only one type of activity and those created by more than one, and sometimes to the site as a whole. The only major common factor in these examples of the use of the term, is that human action definitely created all of the patterning.

In the Alywara case Binford has investigated more long term residential camps and claims that very similar ring models can also be applied, although the models are generally not so directly dependent upon body size

constraints, and the overall camp structure must also include door dumps, other refuse dumps, and peripheral activity areas such as roasting pits (Binford 1986). None of these peripheral zones correspond well with the "ring" model; serving to distort this pattern at the larger campsite level.

From this discussion it should be clear that for Binford an "activity area" is synonymous with behaviorally caused deposition in a broad sense. The notion is clearly not constrained (at least in his later writings) to mean a segregated zone with a uniquely occurring set of tool types or waste products, instead, activity areas are "places, facilities, or surfaces where technological, social, or ritual activities occur" in the broadest sense (1983b:147). Thus I would argue that, for Binford, an activity area is identically constituted in both archaeological and behavioral contexts, and its contents may be broadly multifunctional in composition. Zones which contain unique sets of materials from a single event (or many functionally identical events) and zones which contain many unique deposition sets from a number of moderately or negligibly similar events (such as the hearth zones) are all "activity areas". This implies that archaeologically, any discernable concentration of objects which can be supposed to have been deposited as the result of roughly contemporaneous events is an "activity area".

Because this is such a central concept in most of Binford's consideration of intrasite scale spatial patterning, it carries with it the implication that one should focus on determining just what the "activity" represented in any such "area" was.

In contrast to Binford, Yellen (1987, 1977; Brooks and Yellen 1987) has investigated primarily residential camps among a number of Kalahari San or Bushman groups. He too has suggested a "ring" model but one not so strongly tied to individual body spacing. Yellen suggests that among these people most day-to-day activities in a residential camp take place around either a single family hearth, immediately outside of that family's sleeping structure, or in the common area central to the camp as a whole. Activities requiring more area, shade, occurring over a longer time frame, or which are simply messier will take place away from the family hearth, and generally outside the immediate area of the huts as well (Yellen 1977:126-27). In these cases shade was often seen to have directly determined the areal extent that these areas covered (Yellen 1977:92). Material accumulation directly around the hearths was mitigated by periodic clean up activities that commonly resulted in the formation of specific dumping locations. Thus in general Yellen's model suggests that in a residential camp composed of a number of family units, there would be a roughly circular

or semi-circular group of family huts and hearths. This area defines an intensively used space in which the debris from many activities would be found if they had not been largely removed to dumps. Outside of this would be a peripheral zone containing more extensively used areas and any dumps of material from the intensively used areas.

Yellen's notion of an archaeologically visible activity area then is one of a more-or-less structurally restricted area of deposition which corresponds to the area in which the activity took place. Dumps are not included as activity areas, they are instead those places holding the refuse from activities. He argues that for the central hearth zone many activity areas overlap in space and material used (as well as discarded) and will thus not be individually visible. Only in the peripheral areas will individual behavioral activities perhaps map onto segregated and uniquely occurring sets of materials.

For Binford, any concentration of material is an activity area in either behavioral or archaeological contexts. If its material was dumped (or "structurally disposed") one may recover the "activity" of dumping. By and large activity areas are discretely located and composed. For Yellen, an activity area is the locus of an activity which is a primary producer of waste materials, not one which only combines and relocates existing waste and it is primarily restricted to the behavioral context

rather than the archaeological context. Only rarely would one expect to find clearly defined activity areas in the behavioral sense represented archaeologically. Activity areas may be expected to overlap strongly both in material and loci in some situations. The archaeological implications of these two views are also clear. Binford would expect to find activity areas more or less discretely located in space because they correspond to material concentrations, while Yellen would expect strong overlap in many contexts. The essential differences come down to the functional nature of the materials found in an concentration of objects. For Binford, these materials would be expected to represent a single behavior, and thus at least indirectly, a single function. Yellen, on the other hand would expect many different behaviors, and thus functions, to be represented.

The nature of these two views is very clearly derived directly from the types of ethnoarchaeology situations that were studied. Binford's published observations are based mostly on a completely male, brief, fluctuating occupation of a site used primarily as a lookout for caribou hunting. Only rarely did a single individual stay for any great length of time, and most "activities" were embedded in the process of searching for caribou or other game animals. In contrast, Yellen observed a large number of residential camps, occupied for

from several days to several weeks by effectively the same or a similar group of families. Behavior in this case was habitually organized in space. When Binford investigated a similar situation in Australia, his Nunamiut based models had to be significantly extended and became very similar to Yellen's, although the terms remained essentially the same as those he had used in the Nunamiut cases. Thus Binford's observations may be seen as a special case (restricted time and nature of occupations) within the more broad models proposed by Yellen, i.e. the patterns observed by Yellen can be considered to be composed of redundant and spatially overlapping sets of those found (in the Eskimo cases) by Binford. The differences between Binford's and Yellen's notions of activity area are clear and important. There seems little or no basis for the idea that the two models are the result of broadly dissimilar processes; they are rather the same processes seen at different time and population scales.

I.4 Methods and Approaches

As I have suggested, there has been much development in the more abstract theoretical realms of archaeological spatial analysis. So too, there has been refinement in the methodology of spatial analysis. For convenient discussion this can be broken down into two broadly

distinct types of method: 1.) locational, those methods focused on forming groups of objects based on their distance relationships, and 2.) associational, those methods that form groups based on some measure of object similarity or association. Before 10 years ago, most quantitative spatial analysis was associative in nature, generally concerned with characterizing the global patterning at a site and recovering tools kits. Early forms of Nearest Neighbor Analysis, for example, essentially ignore individual object locations and seek to characterize the global patterning at a site as random, clustered, or uniform (i.e. how closely do objects associate with each other) (Clark and Evans 1954; Dacey 1973; Earl 1976). Searching for associated types (e.g. "tool kits") with regression or factor analysis is a classic example of this type of approach, also usually done at a global scale for a given site or level (Binford 1966, Freeman 1978). In general with these early approaches, very little emphasis was given to the specific locational patterning of the objects at a site, only their association (often as grid square counts) with other objects was considered. When analyses considered locational data, they mostly involved visual examination and comparison of point distribution, density, or contour maps (Leroi-Gourhan and Brezillon 1972).

This earliest, association mode of analysis has been largely abandoned as meaningless in most archaeological situations. However, searching for type associations (either globally or locally) is still seen as valuable. Many of the initial problems with this approach were caused by inappropriate statistical assumptions in the specific methods used (especially with respect to the normality and heteroscedasticity of the distributions involved), the quadrat sample nature of the data, or both. Searching a site for global scale linear correlations between artifact type counts, for example, often requires assumptions which archaeological data cannot commonly meet. In place of these methods, more recent associational approaches commonly use nonparametric correlation statistics, the Chi2 and/or Fischer's exact test statistics, or some other nonparametric similarity/association measure (Patraglia 1987; Hodder 1980; Hodder and Okell 1978; Hodder and Orton 1976, see also Pielou 1977). These methods are still commonly applied to quadrat frequency data; unless specific congruence between the spatial scales of interest and the quadrat scales can be assumed, they still leave something to be desired. Similar problems were also inherent in the older variance/mean (Dacey 1973), local density (Johnson 1977, 1984), and dimensional analysis of variance (Whallon 1974) approaches.

There are a number of recently proposed approaches to the search for artifact associations which overcome the quadrat problem by using nearest neighbor based, global measures of association/segregation (Carr 1985; Whallon 1984; numerous examples in Hietala 1984). The more general problem with these associative approaches, effective exclusion of locational information, is the same problem that confronted many of the older association based approaches.

In contrast to associative approaches, location based methods generally consider information inherent in an object's location initially and proceed to considerations of object association once these patterns are established. Unconstrained clustering (Whallon 1984), for example allows both location and association to affect patterning, although in application it is sometimes quadrat-based and so does not escape problems caused by this. Selection of an appropriate data smoothing factor can also be a problem in using this approach, regardless of the original provenience of the data (Gregg et. al. 1989). Similarly, k-means based locational clustering and subsequent cluster content analysis, as well as methods involving other clustering techniques, allows both object location and association (on both local and global scales) to be characterized (Ammerman and Kintigh 1982; Grimm and Koetje 1988; Koetje 1987a; Simek 1984a, 1987; Simek and

Larick 1983). When based on point provenienced data, these are free from quadrat effects, although assumptions built into the specific clustering techniques can be troublesome.

Carr (1987), and Graham (1979) have suggested the utility of techniques borrowed from spectral analysis, such as the transform of a site's density map into its fourier components. In theory this process would allow the removal of "irrelevant" information, such as that produced by "biasing" formation processes, and allow recovery of the true patterns on either a global or local scale. Aside form the question of whether or not "true" distributions can be recovered after the removal of "biasing" elements, there are two main problems with this basic approach. First, the fit between any particular Fourier component and a particular distribution is not exact, only statistical. It is in effect a "best fit" wave function. Even this only holds true if the distribution is even across space (i.e. " ... the association between two variables is invariant relative to spatial locations." Hietala 1984:280), effectively requiring identical effects on all objects regardless of differences in their locations. The spatial scale effected by a biasing process must be continuous and even across a site (or the portion chosen for analysis) for it to be clearly identifiable with a unique set of Fourier

components and eliminated in this way. Since artifact distributions do not generally fit these requirements, and there is little or no expectation that such distributions as disturbed or "biased" by formation processes will either, it would be necessary to combine a number of Fourier components to represent such non-even distributions across a surface. A reasonable model might even require a distinct set of Fourier components for different areas on a given surface. Thus a set or sets of components must be removed, and the choice of membership is obviously critical.

The second problem concerns the fit between a component set and the effects of a particular (or a set of particular) formation processes. There is simply no guidance available regarding this. Carr (1987) suggests that components which occur at particular scales be eliminated, with little or no empirical justification whatsoever. Thus the analyst must know exactly the scale of the effect(s) to be eliminated and the nature of any deviation from evenness in space <u>a priori</u>, in order to choose "irrelevant" components to eliminate. Needless to say, that much <u>a priori</u> knowledge is unusual. Even if it existed, however, eliminating a particular Fourier component effectively filters out only the objects corresponding to a specific density wave form, it does not thereby "untransform" the remaining assemblage into some

pristine pattern. These methods seem more likely to produce reflections of the density and weight characteristics of an assemblage than of disturbance processes, except insofar as these are interrelated.

Another set of basically locational approaches which has been recently developed is the use of bone and stone refitting patterns (Cahen and Keeley 1981; Enloe 1988; Grimm and Koetje 1989; Marks and Volkman 1983; Rigaud and Simek 1988; see especially the collection in Enloe and Hofman 1989). Although this approach has only rarely been combined with other types of analysis, it is quite promising both as a source of additional (and independent) information which can be used to confirm patterning found using other techniques, and as a source of information about changes in technology and procurement of raw material (Grimm and Koetje 1989; Rigaud and Simek 1988). This approach has been specifically applied to questions regarding the middle to upper Paleolithic transition (Grimm and Koetje 1988), and the functional nature of early hominid sites (Isaac and Kroll 1984; Isaac 1985, Bunn et al. 1980). Although there are some problems yet to be solved, such as the determining the extent of mining and re-use of previously discarded material at any given site, in general the potential of these approaches is very great indeed, especially when combined with even such simple methods as visual inspection of density maps. In a

related vein, functional analysis of tool use-wear patterns can, in combination with technological and locational analysis, create a very complete picture of the technological/ functional processes which occurred at a site. The major problem with these last two approaches has generally been the extremely time consuming nature of the analysis.

Conclusions

While a number of new and promising approaches and techniques have been developed for intrasite spatial analysis, many still suffer from invalidating assumptions and or lack of the necessary background knowledge to use them intelligently. One of the most clear cut difficulties for many of these methods is simply the lack of a series of analyses for comparison. Only rarely has more than one method been applied to a single site (Gregg et al. 1989 is an excellent example of this however), and even more rarely have a series of sites been analyzed using the same or similar methods (cf. Koetje 1987).

I.5 Summary and Conclusions

Advances in both theoretical and methodological aspects of archaeological spatial analysis have been made in the last 20 years. The theory behind most spatial analyses, although concerned with a wide range of

empirical phenomena, is clearly focused at the three different spatial scales (micro, semimicro, and macro) distinguished by Clarke (1977). Similarly, development of both the techniques and methodologies used have advanced. Specific methods and sets of methods for regional, intersite, and intrasite analyses have become fairly well established, although comparable analyses of the same or similar sites is often lacking and sorely needed. Moreover, a clear pattern in intrasite analyses has been their primary focus on spatial patterning in only two horizontal dimensions.

Several main points should be clear from the discussion above. First, there is much unnecessary ambiguity in both the models of human induced material patterning in space, and the "causes" thought to have been involved in its generation. Distinctly different definitions of such (seemingly) fundamental concepts as "activity area", "tool kit" etc., lead directly to much of this. Second, methods that seek to explicitly take into account the types of processes used in particular models, often require more a priori knowledge about specific processes than is reasonably available. Carr's (1987) proposals are the best example of this. Third, and perhaps most important, archaeological spatial analysis has focused on those patterns that may be perceived in the two horizontal dimensions. This is because of the very

close ties between spatial analysis, especially intrasite spatial analysis and ethnoarchaeology. The patterns that we may see in actual sites are not necessarily so restricted in the nature of their variability or generation. Chapter II addresses this issue particularly in more detail.

As a whole this work may be outlined as follows:, in Chapter II, a model of archaeological deposition is developed, and its consequences for the consideration of patterning in three dimensions are derived. In addition, the methods used in the actual analyses are outlined and justified. Chapter III is concerned with the design and analysis of a series of simulated assemblages. Many of the methods outlined in Chapter II are applied to these experimental assemblages and the results abstracted and summarized so that they may provide useful guidance in analyzing the two sites considered in Chapters IV and V. Le Flageolet II and the Grotte XVI are analyzed in detail in Chapters IV and V, respectively, each with very distinct interpretive goals and procedures. General results from these analyses, conclusions as to the utility of the methods and approach, and suggestions for further work are found in the last Chapter: VI.

CHAPTER II

SPATIAL ANALYSIS AND THE DEPOSITIONAL PROCESS: Towards Three Dimensional Characterization

II.1 Modelling Depositional Processes

It is my intention in this section to lay out the basis of a consistent theoretical approach to the consideration of artifact patterning in all relevant spatial dimensions, and the methods and techniques that I intend to use in this process, rather than to actually perform such an analysis. This chapter is divided into three basic parts. First, I develop a general model of artifact deposition and the implications of this perspective for the study of vertical patterning. This is a necessary to structure the actual analyses. Second I outline the practical methods used to carry out the analysis and present the measures of, and derive expectations for, cluster homogeneity and correspondence relationships. Third, I discuss previous spatial analyses using the k-means technique, and the broad scale patterns that they have identified in the archaeological record.

Depositional Processes: Scale and Variation

Deposition process modelling in archaeology can be divided into two clear frames of reference. Concern with

behaviorally induced patterning, and concern with natural, taphonomic processes or often so called "post-depositional" disturbance. Until very recently both have been primarily anecdotal, case specific or framed as "cautionary tales". As a scheme for generally structuring our inquiry into behaviorally induced artifact patterning on the level of regional, intersite processes, and the variables which go into the "making of an archaeological assemblage", the ideas outlined in Binford (1982), Aldenderfer (1977), and Ammerman and Feldman (1974) are perhaps the most useful. Concern is focused on the role of the proximate economic function of a specific location within a larger subsistence organization in creating an artifact assemblage at a given location.

Although the terms are not used, the idea of artifact throughput (i.e. the proportion of objects leaving a location with respect to the number of objects that entered it, or: output / input) or flow are very important in these schemes. As objects are brought into a site, some drop out of the various processes which brought them there or enter new ones and remain, while others continue within the same processes, or are also transferred to different ones and are removed. Different types and combinations of processes result in different rates of artifact loss from the living or systemic context. Differential economic and social uses of a

particular location condition the types of processes and the correlated materials that occur at a site. In essence both contextual and utilitarian concerns structure the nature and abundance of the objects that pass through a defined space or locus, and thus the resulting assemblage. The same factors play a critical role in determining the life cycle state at which objects enter this locus, and decisions that are taken once there as to their future courses.

This scheme is not explicitly limited to two dimensional depositional considerations. Binford's (1982) major point may be that because a site is formed over some amount of time, even in the absence of post depositional "disturbance", what we recover as an single assemblage is a palimpsest potentially deposited at any set of points within this arbitrary timespan, with the subsequent effects of changes in the economic function of the specific location- and with this artifact throughput and depositional patterning. Clearly if sedimentation or other burial processes (including subsequent re-occupation) also occur during this time, site formation, even without considering subsequent artifact movement, must have a vertical aspect. Yet without knowledge of the nature and timing of these contextual changes in site function, neither specific assemblage content nor patterning in space can be predicted. Problems with

equifinality and between-site contemporoneity suggest that only in very unusual situations would such specific regional scale processes be reconstructible.

With this as a general framework there are six main variables of interest to be considered in spatial analysis given a single cultural unit (or volume):

1.) occupational redundancy, the number of occupation events during some arbitrary time that occurred at a site,

2.) zone density, the degree to which, within an occupation, the material remains of behavioral events overlap in space,

3.) structural redundancy, the degree to which the overall spatial patterning is repeated among occupations,

4.) assemblage redundancy, the nature of assemblage similarity between and within occupations,

5.) regional context, the relationship between these factors at any given site, and those at contemporaneous sites on a regional scale, and

6.) sedimentation rates.

By the term "occupation" here I mean a single use of or visit to the site in a behavioral sense, this does not imply its archaeological visibility. This aspect of the model is wholly in the behavioral domain. While clearly the behavioral and archaeological visibility of an occupation may coincide in a more or less direct manner, I shall not require that they do in constructing models of

spatial process. Archaeological sites can be expected to exhibit a continuum of variation on these variables. Although not altogether independent, their full interdependence cannot be expected to manifest itself outside of specific cultural contexts.

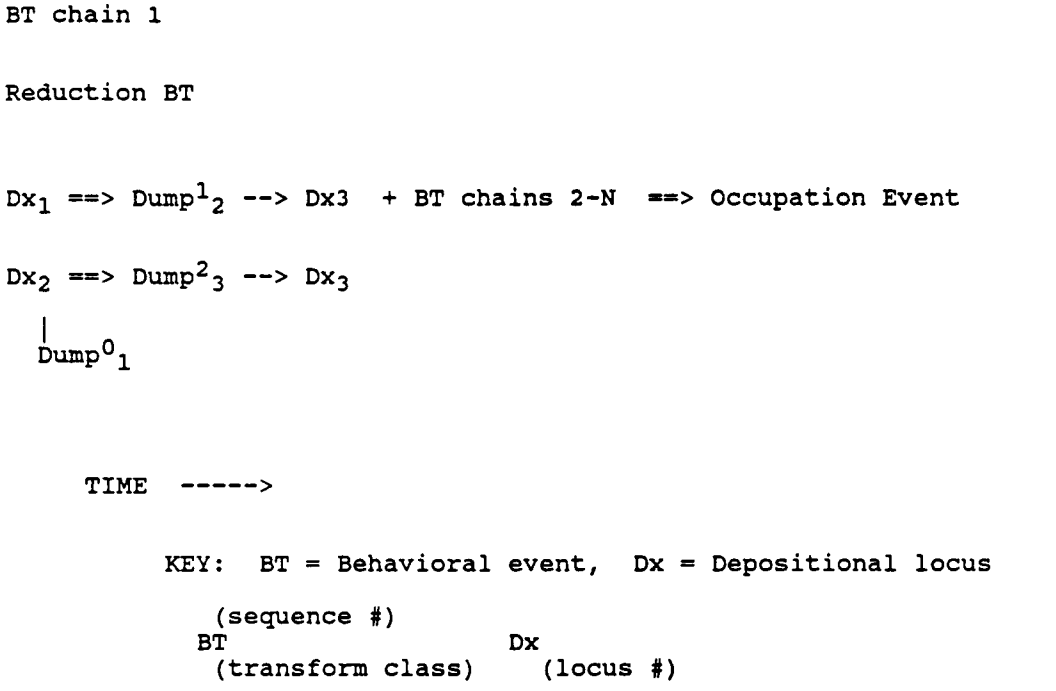
Perhaps the most analytically intractable of all the possible permutations of these variables, is both the least complex and the most frequently discussed: when a low number of occupation events with high occupational redundancy, assemblage similarity, and zone redundancy occur in a low or nonsedimentary context. This is the classic depositional palimpsest on a single topographic surface, there is essentially no distinction to be made between very similar occupational episodes. Without fairly detailed information as to the nature of depositional sequencing among artifact categories, this situation is simply beyond our present ability to deconstruct (it is in effect "always already undeconstructable" in current post-modern jargon). Relaxing the criteria for occupational redundancy and assemblage similarity produces an much more compositionally complex, although similarly difficult to analyses situation. In effect, all such cases are currently visible only as a single occupation event.

The most clear cut cases are those which have high sedimentation rates (relative to the occupation event

timing) as well as high occupational redundancy and assemblage similarity. This situation could be represented by a series of overlapping levels separated by sterile sediment. In the correct circumstances such cases lend themselves to direct comparison within a regional framework.

Intrasite Depositional Processes: The Model

To begin the process of modelling the creation of an archaeological site however, one must start at a much lower level than that concerned with regional processes. This modelling process will focus on discretely bounded events in space and time rather than continuous events. Although this represents some departure from reality, it simplifies matters greatly. The intent here is to establish the outlines of a model of depositional processes that will account for both those situations where consideration of 3 dimensional patterning is necessary (40 cm of undifferentiated sediment at Le Flageolet II, for example) and those in which it would be probably be unfruitful (deposition confined to the upper surface of a horizontal cobble pavement, for example). The model is outlined schematically in figure 2.1.



Dx_3, although behaviorally composed of 2 discrete BT chains would be a single activity area for Binford (or a dump for Yellen.

Figure 2.1 Model deposition based on discrete events. Bt= behavioral event, Dx= deposition.

Behavioral Events

The most basic discrete unit, a behavioral event (or BT), may be thought of as a specific action which is capable of leaving archaeological traces. By definition a BT creates one or more sets of materials which are deposited at specific loci on a topographic surface. These loci are not necessarily uniquely associated with the locus of the event itself, although they may be, nor are they necessarily defined using the same spatial scale. Thus the locus of a BT and the loci at which the material products of a BT are deposited may overlap, but spatial coincidence isn't necessary. A BT is not meant to be synonymous with an "activity area" nor are activity areas meant to be the inevitable result of any BT, but rather a BT includes any such highly constrained patterning if it exists in the situation under consideration. Patterning in the classic activity area fashion is then a subset of the potential types of patterns resulting from BTs.

A BT is also associated with a set of materials that is not deposited as a direct result of the event itself, but which instead is passed directly to other behavioral events without a deposition phase intervening. While this set may be thought of as curated if the time lag between production and deposition is large, it is perhaps more useful to consider it to be the set of use, as opposed to waste products in the short term time scale. For

modelling purposes a behavioral event can be associated with a sequence number, denoting its temporal relationships to other BTs, and a transform class, denoting its general effect on pre-existing materials. The relationship between a single BT and its products is assumed to be such that at least its general nature may be inferred from observation of its products alone, given that it occurs in the absence of other BTs. Thus in essence a BT becomes any event which may practically be distinguished from others by its material products alone, whether as a discretely deposited set or not, and so is not necessarily recognizable directly from either archaeological or ethnoarchaeological evidence.

For modelling purposes behavioral events may be linked to each other, either sequentially or in parallel, i.e. a number of related BTs may operate on each others products either one after the other or simultaneously. They may act solely or partially on each others depositional or use products. A single core reduction with all materials except use products deposited in a single locus, as a distinct deposit within a larger site would be an ideal case of a simple behavioral event. The existence of such an event could be inferred from the archaeological evidence alone. This is quite different from the classical notion of an activity area as used by either Binford (1978, 1982, 1986) or Yellen (1977) (see

chapter I above). For Binford an activity area is (or may be) composed of the discretely deposited materials of many (perhaps only peripherally related in a functional sense) behavioral events (e.g. the activity area around an Eskimo hearth), or only the products of a single activity. For Yellen, an activity area is generally composed of a more restricted set of functionally related behavioral events (i.e. a single behavioral event chain).

To continue with the example, if the core reduction products are removed to a disposal zone (creating a disposal activity area for Binford) a sequentially linked chain of discrete behavioral events has occurred and can be said to have composed the deposited material. In the absence of data tying specific archaeological materials to this process as a whole (such as refits), it would mainly be identified by the dump zone. Material dropping out of the process prior to this might usually be identified as belonging to other BTs, or remain unattached to any specific element of the model. Thus there is always some amount of fuzziness around a BT's material set, and especially around the depositional set resulting from a single BT or BT chain. Additional BTs or BT chains ending in the same deposition locus would not necessarily change the overall character of this area, although they may add to it. Only the behavioral composition and object assemblage of this deposition locus would necessarily

change in this circumstance (i.e. the "dump" above could not thereby be transformed into a knapping activity area, but only the dump of at least a knapping event). Certainly archaeological resolution of the spatial relationships in behavioral event chains composing such an area, and very probably resolution to the discrete locus level can be expected only in very unusual circumstances. As a normal course of events, archaeological resolution of only the final behavioral event (in this example: dumping or clean up) can be confidently expected.

Non-cultural Events and Cultural Byproducts: Alteration Events

Obviously actual depositional environments are not as simple as they have been so far portrayed, as only intentional cultural processes have been discussed and even these in a somewhat naive manner. To move beyond these, a role must be found for both unintended or unconscious cultural and non-cultural processes. Although a very large number of predominantly non-cultural processes that may affect archaeological sites have been discussed in the literature (Wood and Johnson 1978, and Schiffer 1987 provide excellent summaries), most are quite general in their effects, and most would probably be identifiable on both local and global scales only if they were the dominant process(es) forming the record.

Although the number, type and severity of their effects must be context specific, their place within the model presented here is obvious: any deposited materials (dx in fig 2.1) may be subject to them.

In contrast, unintentional cultural effects are more directly related to the nature of the occupation as well as the general depositional environment. The effect of trampling on deposited materials for example, is more directly related to the nature of the continuing or subsequent occupation than would be mass wasting, neither however is fully independent of the other, both are mitigated by the other's major determining factors. Length of occupation, or factors such as heating and additional soil moisture (or its loss) may either contribute towards, or mitigate the effects of certain types of noncultural events. For example, mass wasting may be more common in areas where sediments are not allowed to freeze during an occupation than in those that are allowed to freeze. Very different post depositional movement patterns would probably characterize (in the short term) those areas that were allowed to freeze. At this time we have very little knowledge of the relationships between these types of processes, and thus while their place in the model, and the general nature of their effects are clear, specific effects cannot be included at this time. It seems to make most sense to

include the general class of effects of these processes as separate discrete events bound together in a partial feedback relationship and operating on deposited materials (dx in Figure 2.1). Within a behavioral event chain however, these effects are a function of time lags between deposition by one event and processing by another, should this occur.

Occupation Events

At the next level of complexity up from a behavioral event, an occupation would be composed of some arbitrary number of behavioral event chains and/or sets which occur in an arbitrary length of time and volume of space. Archaeologically, occupation events are perhaps most logically bounded stratigraphically in the absence of more precise information as to the presence or absence of people. Ideally the notion of an occupation should be restricted to a single continuous habitation of the site, but this is not often determinable (even ethnographically), thus its archaeological visibility is generally as problematic as that of the behavioral event chain. The relationship between these two types of event (i.e. behavioral and occupation) can be expected to vary with the type of site involved, the number of actors who inhabit it, and the duration of their stay. Clearly both may be recoverable independently. A site which evidences

no clear stratigraphic breaks that could be assumed to bound occupation events, for example, may have very local evidence of specific behavioral events, whereas another with perfectly distinct levels may not.

Model Implications for Vertical Patterning

What then is the relationship between deposition, as envisioned by this model and vertical patterning? Much as the relationship between behavioral events and alteration events occurs at the depositional loci, so also does the extent and nature of vertical patterning grow from the nature of these loci. All deposition occurs on some topographic surface, it is perhaps more productive to think of this surface as a volume including sediment to the depth of active movement and its upper surface where materials are (normally) deposited. This volume then may be defined by the horizontal and vertical dimensions of the area where objects are being deposited, and of sediment movement. This volume will be referred to as the "active zone". The boundaries of an active zone are not static, they change with disturbance, continued deposition etc. Each behavioral event and occupation may be thought of as occurring within a unique depositional volume as defined by this active zone, although these may obviously overlap to a greater or lesser extent. Each behavioral or occupation event then has, as a consequence

of its occurrence, effects on previously deposited materials. The characteristics of an active zone are determined by the energy input into it by behavioral events, the physical environment in which it exists, and the nature of the sediment matrix (Butzer 1982:193; Gifford 1977; Gifford and Behrensmeyer 1978). In short, a given physical environment and sediment matrix will determine the energy threshold for appreciable movement of objects at a given depth below the surface within the active zone. Different types of behavioral event vary in the extent to which they reach the necessary energy input threshold for a given volume of sediment.

As an example, a set of materials is deposited on a given topographic surface, allowing initial discernment of an active zone and the requisite depositional volume. Subsequent deposition of another set of materials that is wholly or partially overlapping in horizontal space, whether from the same or disjunct behavioral events or occupations occurs into this volume on the now modified (as a result of the initial deposition) topographic surface. This will result in two vertically separable layers, given some error factor, regardless of sedimentation rates or time lags between the depositional episodes. At one extreme, no objects would overlap in space, each would have come to occupy a unique area of the same surface, one set at the first deposition, the other

at the second. The depositional volumes in this case could be identical and the depositional sets would be vertically indistinguishable (i.e. the error factor would be at its maximum). In such a situation the two depositional episodes would only be separable through some time or set marking that was independent of their spatial location (e.g. the nature of the materials, technology of their manufacture, etc.) without this the material remains from these two events could not be separated and the events would necessarily be considered as either identical, or as a single event. At the other extreme, all objects would overlap in space, with the entire second depositional set overlaying the initial set. The depositional volumes would be unique (e.g. the error factor would be at its minimum). In this case the two sets would only be distinguishable vertically: again without independent time marking.

In the absence of further disturbance, given any time difference between depositional episodes there would be some arbitrarily small amount of discoverable sedimentation that would allow the two sets to be distinguished perfectly. However, subsequent behavioral events, and cultural and non-cultural alteration events may be expected to blur clear identification. For example, continuing or subsequent occupation may involve considerable use of the depositional loci, and consequent

modification of the active movement zone in the sediment. In this case, initially unique depositional volumes would become wholly or largely coincident, potentially redistributing materials both vertically and horizontally and rendering discernment of the two depositional sets more difficult or impossible. Alternatively, the nature of the sediments and or objects within them may preclude any movement between the depositional surfaces and any sealed deposits.

This particular process may also be modelled as a discrete one operating in a volume which moves upward over time as sediments accrete, allowing the lower elements to gradually drop out of the active zone from the bottom. Cultural factors (hearth and pavement construction, sediment consolidation), natural factors (sediment matrix, moisture content, catastrophic geologic events), and the nature of the deposited material are clearly involved and interrelated at various levels.

Initial characterizations of the nature of this type of cultural process have centered around trampling experiments in largely unconsolidated matrix (Gifford et.al. 1985; Stockton 1973; Villa 1982; Villa and Courtin 1983) and suggest that relatively small percentages of the deposited materials do much of the moving in a given situation. Movement up to 16 vertical cm is, however, possible in unconsolidated sand (Gifford et al 1985).

Horizontal movement was often more restricted. It has also been noted that initial burial restricts this movement severely.

There have also been a number of both experimental and observational studies of artifact patterning in space with at least implications for three dimensional patterning. Barton and Bergman (1982) suggest that intensive occupation of an Danish Upper Paleolithic site led to a bimodal vertical distribution, large, heavy objects in the upper portions of the site show a horizontal orientation, and no preferred azimuth. Small, light objects, lower in the profile, however, show a non-horizontal orientation. Newcomer and Sieveking (1980), suggest that core knapping in different positions (sitting vs. standing) can be distinguished by dispersion or concentration of knapping remains in the archaeological record. Boeda and Pelegrin (1985) take a similar position. In general, however, there are very few specific patterns that have been identified with a particular process. This is especially true with regard to natural or unintended cultural effects. It has been typical however to identify a preferred orientation with substantial disturbance of some kind, even without a specific causal agent in mind. Schiffer (1987:270), for example suggests: "Generally, the discovery of a patterned orientation is ample grounds for inferring the

occurrence of a noncultural process, such as flowing water". Such assumptions do not eliminate problems of equifinality however, there seem to be no good empirical or theoretical reasons to believe that cultural processes could not induce a "patterned orientation" to objects in some circumstances.

Notice that for this type of process to be modelled discretely, a different time scale from that utilized when considering only behavioral events must be used. This is because of its nature as the cumulative effect of many individual actions. This is an example of a process that is largely visible only when considering occupations, rather than discrete behavioral events.

Natural processes that affect the objects within a site can be modeled similarly to unintended cultural effects. Their place within the scheme is clear (NX in Figure 2.1), but their specific effects are so variable that they cannot generally be determined without site specific information.

Given these factors then, several patterns may be expected. Vertical separation between deposition sets created by distinct behavioral or occupation events can be expected to vary based on their nature, and the nature of sedimentation processes which occur at the site. Given appreciable sedimentation during the events producing deposition sets, considerable vertical spread can be

expected, both within and between occupation events. However, several general predictions can be made on the basis of these assumptions. In the absence of non-cultural disturbance and assuming a relatively homogeneous sediment matrix throughout the depositional volume, the greatest vertical variation can be expected in those volumes whose surfaces receive the greatest usage. Models of camp structure from ethnoarchaeological sources suggest that these volumes should correspond to the areas immediately adjacent to (but not actually including) hearths or other activity focusing features (Binford 1978). The actual volume taken up by these structural features should be very stable, given a single use, although repetitive use of them (especially when evidenced by rebuilding or cleaning) would create greater vertical dispersion. Relatively moderate vertical variation should be exhibited in those volumes corresponding to repetitively used areas away from cultural features. Minimal vertical variation then should be found in volumes corresponding to single use areas. These predictions are supported by evidence from Stevenson's analyses (1985, 1987).

Again using areal ethnoarchaeological studies, a more or less central area of high density and vertical variation would be expected to be surrounded by larger areas of lower artifact density and vertical dispersion,

but showing greater discrete spatial clustering. Even more peripheral would be areas composed of a single artifact cluster, with minimal vertical dispersion, and low or very low artifact density. In the event of an occupation of some arbitrarily small duration, this pattern would be expected to be perturbed by the addition of highly clustered dumps, and perhaps gradual shifting of the original patterns in random directions.

Now that a model of archaeological deposition in three dimensional situations and its implications has been laid out, the methods used to analyze such distributions can be outlined. The next section is concerned with this.

II.2 Methods for Analyzing Three Dimensional Distributions: K-means and Homogeneity.

The implications for vertical patterning of various depositional models discussed in the last section suggest that, when appropriate, such patterning would be best discovered by searching a distribution in three dimensions. However, techniques for searching a three dimensional point distribution for patterning are only poorly developed in archaeological spatial analysis. There are a variety of clustering techniques available for the task, most however, suffer from serious problems. Clustering methods are often described using four dichotomous categories: Sequential or non-sequential,

agglomerative or divisive, hierarchical or non-hierarchical, and overlapping or non-overlapping. The important characteristics for our purposes are the last two. A method that produces a hierarchally structured series of clusters is not generally appropriate for two reasons: first, because such results suggest that the solutions are hierarchically linked or structured, an assumption that we cannot make, and second, because hierarchically structured cluster solutions are by definition non-overlapping. A non-overlapping set of solutions means simply that once an object enters a particular group it is never separated from that group. A method producing clusters that may overlap allows objects to associate freely at different solution levels (i.e. numbers of clusters), their cluster assignments at one solution level are not dependant on their assignment at a previous or subsequent level. A single cluster at a particular solution level is not simply lumped as a whole with another (or others) at the next higher level (Doran and Hodson 1976; Everitt 1980). The K-means algorithm is perhaps the best know of the nonhierarchical, overlapping techniques, and is probably the most suitable for use at this time (Kintigh and Ammerman 1982; Koetje 1987a; Simek 1984a; Simek and Larick 1983).

As applied in 3 dimensions, the K-means clustering algorithm seeks to find a series (from 1 to K) of stable

spheroid clusters, by searching for minima of the global sum of squared error (SSE) statistic for discrete clusters at a particular solution level (Doran and Hodson 1976; Hodson 1971; Kintigh and Ammerman 1982; Koetje 1987a; Simek 1984a). The SSE is calculated as the sum of the squared distances between the cluster centroid and the objects in that cluster. At solution level 2, for example, the 2 cluster solution with the lowest overall SSE measurement is being searched for. The algorithm is a divisive, nonhierarchical, overlapping clustering technique, suffering from few problems with boundaries in its operational space. Thus it avoids problems like "chaining", lumping all members of previously defined clusters together regardless of their actual spatial location, and some of the more notorious boundary problems with nearest neighbor based methods (Doran and Hodson 1975; Kintigh and Ammerman 1982; Simek 1984a). It is aptly suited to this study because of its well understood behavior and established base of applications within the French Paleolithic (e.g. Ammerman et al. 1987; Koetje 1987a; Simek 1984a,b, 1987; Simek and Larick 1983; Simek et al. 1985; Rigaud and Simek 1987).

A graph of the SSE for the observed data and randomized data by solution level against the number of clusters, allows recognition of solution levels with lower than expected SSE values. These are identified by

relatively sharp elbows in the curve of observed SSE vs number of clusters where this curve also falls below that for the randomized data, and are referred to as "optimal solutions". The position and volume occupied by the clusters at a given cluster solution can be represented on distribution maps and projections as a point at the cluster centroid with error bars representing standard deviations in the relevant dimensions.

As in all iterative search procedures, there is no absolute guarantee that the solutions identified in this way represent global rather than local minima of the SSE. It is not, strictly speaking, correct to refer to an "optimal" solution without this guarantee, however this use has become standard. Because the K-means algorithm begins with a unique, random set of cluster centroids for each run, if the same or very similar results are obtained in a number of different runs through the data, the chances of this problem occurring decline dramatically (Koetje 1987a). Although variation occurs, it is usually minimal and the solutions may reasonably be considered robust if similar solutions are obtained in two runs with the object coordinates ordered independently. The number of clusters defined at a particular stage may be thought of as the spatial resolution at that stage, because the study space is being divided into an increasing number of clusters. A major strength of the K-means approach is its

ability to recognize spatial patterns at many scales of spatial resolution independently because it is a non-hierarchical technique (Kintigh and Ammerman 1982; Koetje 1987a; Simek 1984a; Simek and Larick 1983). The patterning at each scale can then be assessed for its role in the depositional history of the site, separately from that at any other scale.

As cluster formation progresses, areas that at low spatial resolution (=few clusters) contained a single, or very few clusters, are broken up into larger numbers of clusters. It is convenient to think of these as "daughter clusters", although they are not hierarchically linked, either to each other, or to preceding clusters. It is this general process of cluster breakup that is of most interest and importance for the homogeneity and correspondence relationships that are developed in the following section. The relationship between any given set of these best-fit clusters and specific depositional events cannot be expected to be simple, or perhaps even real. Differences in the spatial relationships that relate primarily to the distinct scales of horizontal vs. vertical provenience can be overcome in two ways. First, at some level of spatial resolution average cluster size in the vertical dimension will be as small or smaller than the "expected" vertical scale of interest simply as a product of the method. When this is true, a number of

small clusters will show up as a compact group. By definition the actual vertical scale of interest is unknown and variable over space. Second, in the event that this process becomes problematic in any specific application, the vertical scale can be distorted. This process is discussed in more detail in chapter III.

Because K-means clustering seeks spherical clusters it may seem incongruous with the "expected" nature of the archaeological record in three dimensions (i.e. lenticular, or at least non-spherical patterning); this problem is addressed in detail in chapter III. K-means is however, the only well developed, quantitative, locational, spatial analysis method which can be directly applied to fully three dimensional data. The extent to which general "expectations" of the archaeological record may be fulfilled will certainly vary greatly, one of the goals of this work is to determine to what extent such ideas may or may not apply specifically at the sites under consideration here. There is evidence (derived from studies of post depositional disturbance) that grouping of archaeological materials may more reasonably be modelled volumetrically than as a two dimensional surface (Cahen et.al 1979; Gifford et.al. 1985; Patraglia 1987; Villa 1982; Villa and Courtin 1983). K-means clustering does not moreover, produce perfectly spherical clusters, rather it produces discrete point clouds which may be of almost

any shape, depending directly upon the variance inherent in each of the utilized dimensions, again this issue is addressed in more detail in chapter III.

At this stage the interpretive models, as they relate the artifact distribution, features, local topography, and geologic depositional context at the site, become critical. The clustering method alone, only establishes the basic patterning in the site.

Homogeneity Relationships

After establishing the basic spatial patterning at the site, interest shifts to the contents of each individual cluster, and the patterns of cluster content as a greater number of clusters are defined (i.e. spatial resolution increases). To facilitate this investigation, expectations for two sets of variables will be developed. The first set of expectations under consideration here is focused on changes in cluster content homogeneity as the scale of spatial resolution increases (Koetje 1987a; Simek 1984a, 1987). When specific cluster solution levels, or a set of solution levels can be suggested to correspond with a single deposition surface, these expectations may be used to suggest relationships between cluster contents and specific types of depositional event, i.e. behavior such as dumping (Koetje 1987a; Simek 1984a). Figure 2.2 shows four possible relationships between homogeneity and

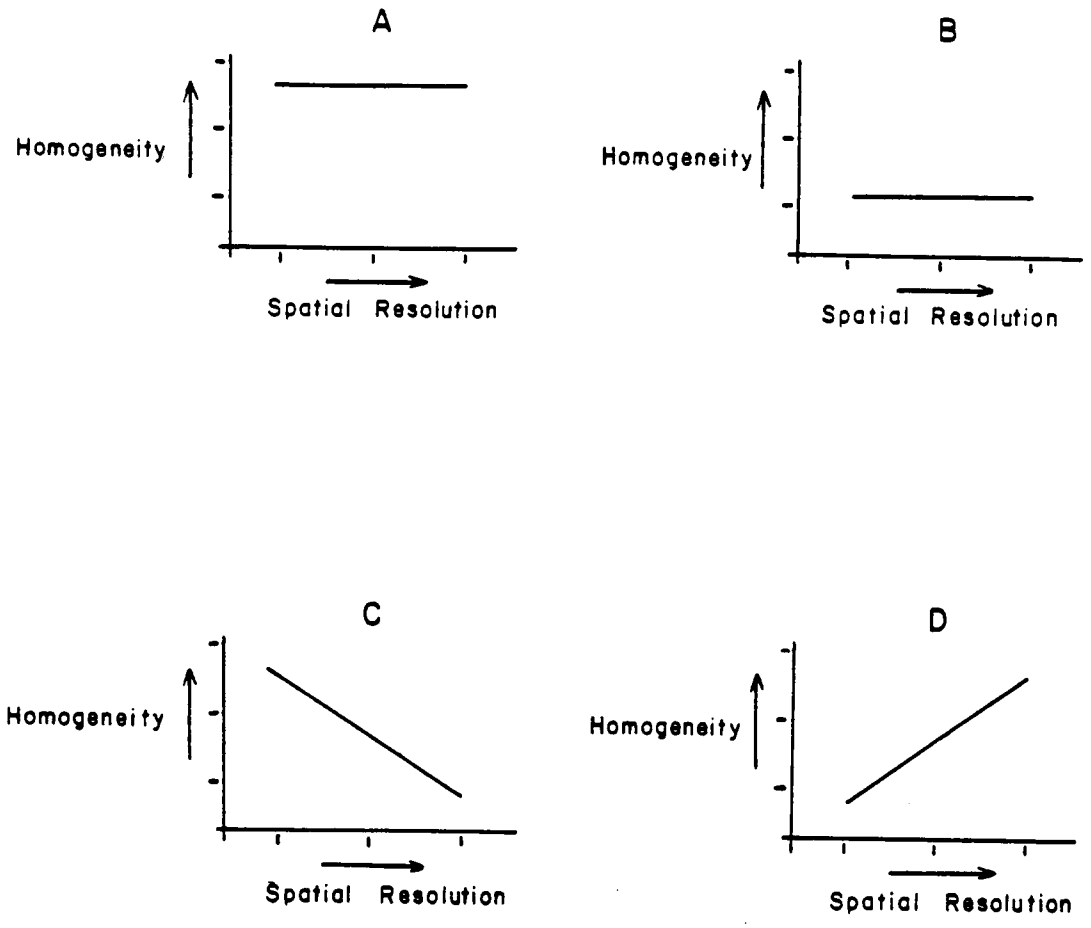


Figure 2.2 Four relationships between Homogeneity and Spatial Resolution (# of Clusters).

spatial resolution, assuming a single deposition surface. When examining the links between specific types of depositional event and homogeneity changes in vertically dispersed clusters when a single deposition surface cannot be warranted, there are two main cases to consider. In the first case the materials are assumed to have originated as deposits on a single surface. Here, post-depositional alteration, not primary depositional patterning would be most important in driving homogeneity patterns, at least at the lower scales of spatial resolution. Traditional bone and stone "type" homogeneity may be less meaningful here than classification by such factors as weight, volume, and largest dimension. In the second case, a group of vertically dispersed clusters are assumed to represent a sample from two or more depositional surfaces. While this "sampling" seems most likely to increase the homogeneity at any given solution level, the exact nature of changes in homogeneity measures will depend on the number and nature of the depositional sets being sampled. These extremes will help to guide investigation of the nature of homogeneity relationships between solution levels in vertically dispersed clusters.

Measuring Homogeneity

There are two distinct extant approaches for measuring artifact cluster homogeneity. Simek (1984) was

the first to identify and use a quantitative measure of homogeneity to analyses artifact clusters. His index (henceforth "RCH" or rank correlation homogeneity) is defined as the percentage of significant positive Spearman's Rho values in a correlation matrix using clusters as cases and artifact class counts as observations. This results in an index with a minimum of 0 and a maximum of 1.0. Because of its base in rank order correlation, this measure is extremely dependant upon the number of cases (i.e. clusters) considered, both because at very low numbers of clusters the definition of significance becomes unclear, and because with a high number of clusters (relative to the number of objects) ties increase, as, in general, do the number of very small differences between class counts. The last two factors may serve to decrease the number of significant correlations possible in some situations, and thus artificially deflate the measure.

Additionally, homogeneity as measured in this manner has no meaning at the level of a single cluster, only globally across a set number of clusters, or within a site. Expectations for the behavior of the RCH measure when used for comparisons between and among sets of clusters (cases) with differing numbers of objects, or when the same finite population is progressively re-allocated into increasing numbers of clusters (the

allocative effect, see Koetje 1987a:29-30) remain unknown. The measure also takes into account only part of the information present in a correlation matrix. Significant positive correlations count towards increasing homogeneity, while significant negative correlations do not count towards increasing heterogeneity.

In response to some of these problems, Koetje in collaboration with Keith Kintigh derived the K and K' measures of Homogeneity (Koetje 1987a:44). The K index is defined as:

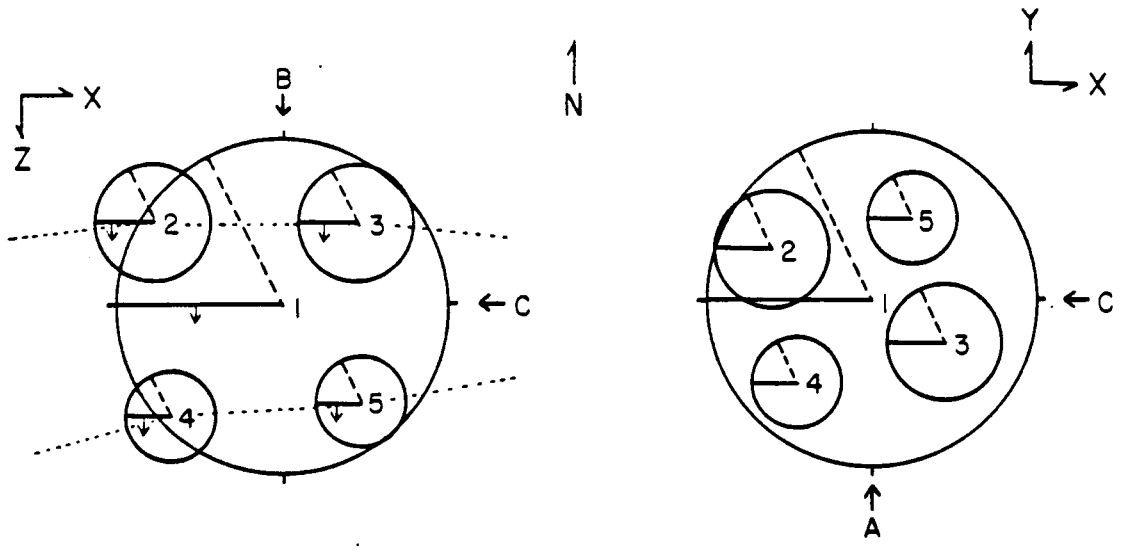
$$K = \frac{\sum_{i=1}^{T} X_i(N-X_i)}{N^2(1-(1/T))} \qquad (2.1)$$

where N objects occupy T classes such that (X1 + X2 + ... + XT) = N. K essentially measures the evenness of a class distribution. It is thus useful for characterizing a single cluster, and for comparing amongst and between two or more clusters. K varies from 0.0, when all objects are in a single class, to 1.0, when the class distribution is perfectly even. The K' index on the other hand, is used as a global measure. It is the average cluster K weighted by the proportion of the total number of objects in each cluster, and defined as:

$$K' = \sum_{i=1}^{C} K_i(n_i/N) \qquad (2.2)$$

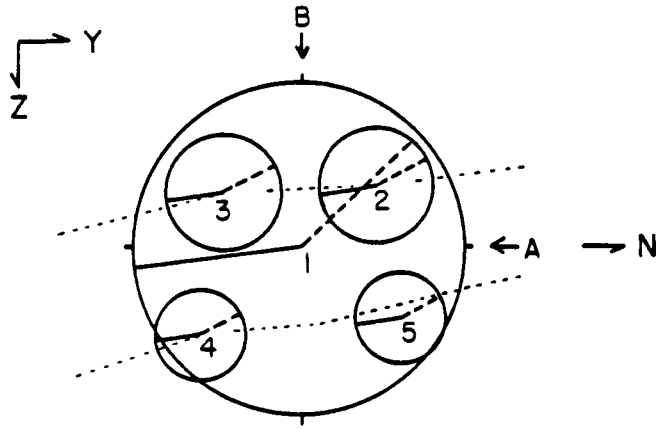
where there are C clusters each with n_i objects, and N total objects. The K and K' indices seem well behaved, and are closely related to both Simpson's C, and the H measures of diversity (see Pielou 1977:291-311), but do not meet some of the requirements suggested as desirable for use in ecology by Pielou (1977:293).

To be usefully interpreted in situations where the same number of objects are progressively distributed or allocated into an increasing number of groups (i.e. clustering), K' must be compared to an expected value for that specific situation (Koetje 1987a:45). This is accomplished by random simulation of the clustering procedure. For each simulated cluster, and each solution from 1 to the given number, clusters are created by randomly drawing objects from a population corresponding to the global class frequency distribution such that no simulated cluster may have more objects than its corresponding observed cluster. This process is carried out separately for some number of trials (typically 500) and the average K' value and its standard deviation are calculated. This allows the expected K' values for a given data set and confidence intervals around them to be plotted (see Figure 2.3). It is deviation from these expected values that is useful for interpreting both global and local homogeneity (Koetje 1987a).



A. FRONTAL PROFILE

B. PLAN VIEW



C. SAGITTAL PROFILE

····· = local topography in profile

——— = intersection line of best fit plane with profile surface, arrows proportional to slope toward viewer

– – – – = average object orientation with respect to grid North

→N = grid North (Y axis)

(2) = rms radius around cluster centroid, # identifies individual clusters

= coordinate axis. X,Y are horizontal Z is vertical

B→ = indicates perspective of view B

Figure 2.3 Example model of correspondence relationships.

A characteristic of the K' measure is that while high K' values imply high similarity among clusters, because of the necessary evenness of their distributions, low K' values imply relatively little about cluster similarity. High K' values are produced only by generally similar, even class distributions among the clusters, while low K' values can be produced by either: 1. a series of uneven, unsimilar class distributions, or 2.) a series of uneven but similar or identical class distributions. Table 2.1 shows why this is true. Given two classes and two clusters, for example, identical K' values could be generated when each clusters' distribution is dominated by a different class in the same or similar proportion, or when the two clusters are identical. The relative inter-cluster distance (RICD) measure was created to clarify these relationships. For each cluster raw class counts were converted to relative percentages of the highest class count. These were then used as N dimensional spatial coordinates, where N is the number of classes. The mean intercluster Euclidian distance in this space was then expressed as a proportion of the largest possible distance between two points in that space, calculated as:

$$MaxDist = SQRT (N * 100^2) \qquad (2.3)$$

RICD reaches a minimum of 0.0 when two clusters have identical proportional representation among the classes, and a maximum of 1.0 when the differences in proportional

Table 2.1 K, K', and mean RICD values for two clusters and two classes in two distinct situations.

cluster	class 1	class 2	K	K'	RICD
A.					
1	20	1	.181		
2	1	20	.181		
				.181	.950
B.					
1	20	1	.181		
2	20	1	.181		
				.181	.000

representation are at a maximum (i.e. the two clusters are at opposite ends of the class proportion space). The mean RICD measures the average intercluster similarity at a given number of clusters, high mean RICD values indicate that average cluster similarity is low, while low mean RICD values indicate that average cluster similarity is high. Each of the situations portrayed in Table 2.1 shows completely different RICD values. Mean RICD values for a series of solution levels can also be compared to mean simulated values, as in the case of K'.

K' and RCH Comparison

K' and the RCH index are attempting to measure the same concept, homogeneity, in fundamentally different ways. High homogeneity, as measured by the RCH value, means that class counts across clusters are more positively rank order correlated than not, within cluster class distribution is not taken into account in any direct manner. As measured by K' and RICD, the concept of homogeneity is widened to include proportional class similarity and class evenness. The two measures make very different assumptions. A class correlation matrix with many positive, significant correlations is not necessarily related to a high K' value for the same clusters, although it should imply lower mean RICD values. Perfect homogeneity (1.0) as measured by RCH (i.e. each class

shows a significant positive correlation with all other classes) for example, implies only a relatively high K' value for that data set, not a value of 1.0. A completely inter-correlated matrix says very little about cluster evenness, except as measured by within class ranks. The opposite however, is not true. A K' value of 1.0 (i.e. within cluster class frequencies are identical) across clusters with different numbers of objects would coincide with a 1.0 RCH value, as all class count ranks would correspond.

Table 2.2 presents the results obtained from analyzing a series of randomly generated clusters designed to help clarify the relationships between the RCH and K' measures of homogeneity. Each trial consisted of 5 clusters of 100 objects each, divided into 5 classes. Class membership was assigned randomly among the 100 objects in a given cluster. The RCH, K, and K' indices were calculated for each trial, and the results correlated. It is clear, that although the two measures RCH and K' are significantly correlated, the relationship is weak (Rho = .339 at $p<.05$). In an attempt to further relate these two measures, RCH was modified to include both positive and negative significant rank order correlations. The resulting index MRCH, is also shown in table 2.2, and is also significantly correlated with K',

Table 2.2 RCH, MRCH, and K' Spearman's RHO correlation matrix from 50 randomly generated cluster solution levels each with 5 clusters, 5 classes, and 500 objects.

	RCH	MRCH	K'
RCH	1.0		
	0.00		
MRCH	.764	1.0	
	.0001	.00	
K'	.339	.515	1.0
	.0160	.0001	.00

but at a substantially higher level (Rho = .515 at $p<.001$). MRCH was defined as:

$$MRCH = .5 + (P/2) - (N/2) \qquad (2.4)$$

where P is the percentage of significant positive correlations, and N the percentage of significant negative correlations in a given matrix. MRCH, like RCH and K' has a minimum of 0.0 and a maximum of 1.0.

This demonstrates, that while these measures differ in detail and emphasis, they are fundamentally related. Homogeneity, as measured by K', RCH, and MRCH can be expected to differ in magnitude, but the fundamental nature of the homogeneity relationships within a particular distribution should be revealed by either measure. The RCH and MRCH measures are used in the analyses below only for comparison, primary reliance will be placed on the K, K' and RICD measures.

Correspondence Relationships

The second set of expectations is used to characterize the shape of the object distribution in 3 dimensions and relate it to depositional events that may be suggested by the patterns of change in cluster homogeneity. Because it is not possible yet to search a large 3 dimensional point distribution for a series of optimal clusters of unknown and/or variable shape, the process must be approximated. Defining clusters in space,

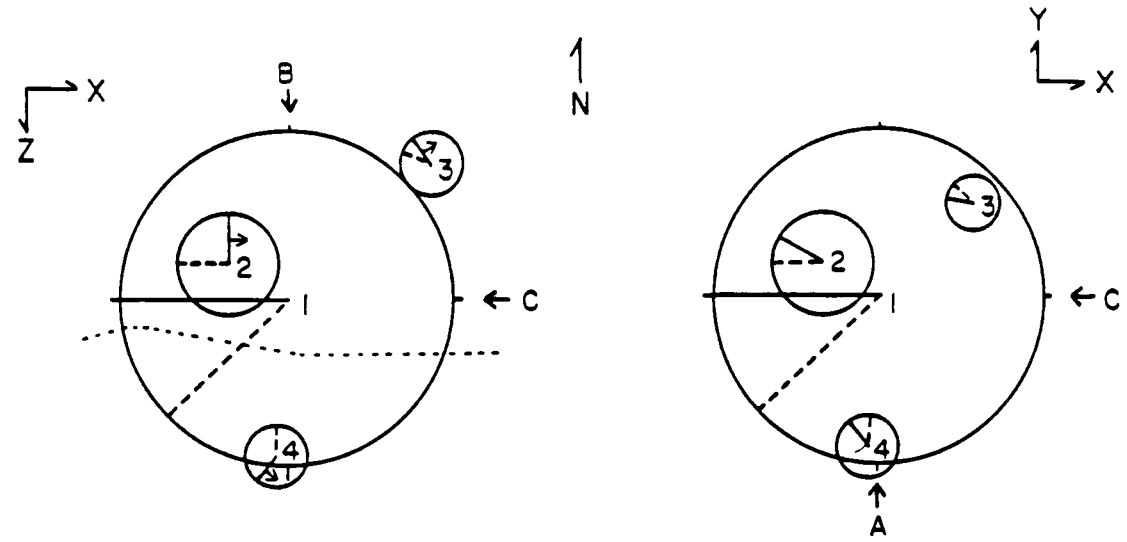
examining successive cluster solutions and their spatial relationships, and relating these to the actual object distribution and orientation, are the basis of this process. Once these relationships are established, they can be placed in the context of site features and local topography.

The first aspect of concern is the extent of vertical patterning among daughter clusters when viewed in profile (see figs. 2.4 a,c, and 2.5 a,c). This may be characterized as structured or unstructured, depending on the extent of topographically related patterning.

The second aspect of concern is the shape of the object distribution within a cluster. In general this may be examined via regression or trend surface analysis, however when the clustering process is effectively restricted to relatively narrow horizontal bands, as in these analyses (see chapter III), these methods are less useful. Instead, within cluster object distribution can be characterized with the standard deviations in each dimension around a cluster's centroid. This is combined with the average object orientation, topography, and structure among the daughter clusters to form a set of expected relationships. Table 2.3 summarizes the possible correspondence relationships between three of these variables. Figures 2.4 and 2.5 show how they can be displayed in combination.

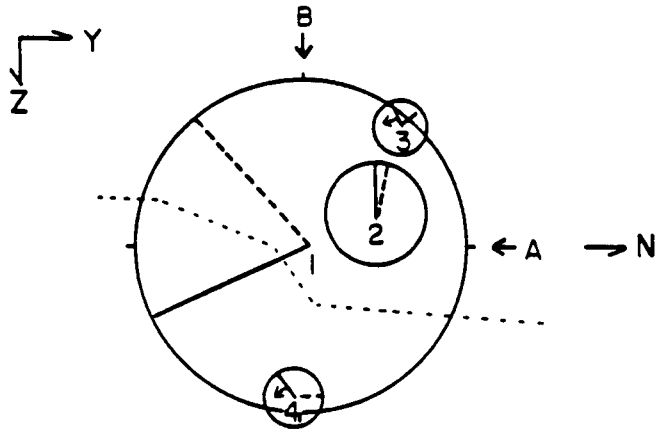
Table 2.3 Correspondence Relationships. Five possible combinations of average object orientation, cluster orientation, and local topographic variation. Stability refers to the maintenance of a single relationship between the factors (e.g. average object orientation always directed across the topographic slope). Each can occur with or without structuring among the daughter clusters.

Model	Expectation:
1	In the majority of clusters, average object orientation and cluster orientation correspond with each other in a stable manner regardless of local topography.
2	In the majority of clusters average object orientation conforms in a stable manner to local topographic variation, while cluster orientation does not.
3	In the majority of clusters average object orientation conforms in a stable manner to cluster orientation, while neither is consistent with local topographic variation.
4	In the majority of clusters, cluster orientation conforms in a stable manner to local topographic variation, while the average object orientation maintains a consistent relationship with neither.
5	There are no stable relationships between any of these variables.



A. FRONTAL PROFILE

B. PLAN VIEW



C. SAGITTAL PROFILE

..... = local topography in profile

——— = intersection line of best fit plane with profile surface, arrows proportional to slope toward viewer

- - - - = average object orientation with respect to grid North

→N = grid North (Y axis)

(2) = rms radius around cluster centroid, # identifies individual clusters

= coordinate axis. X,Y are horizontal Z is vertical

B→ = indicates perspective of view B

Figure 2.4 Alternate example model of correspondence relationships

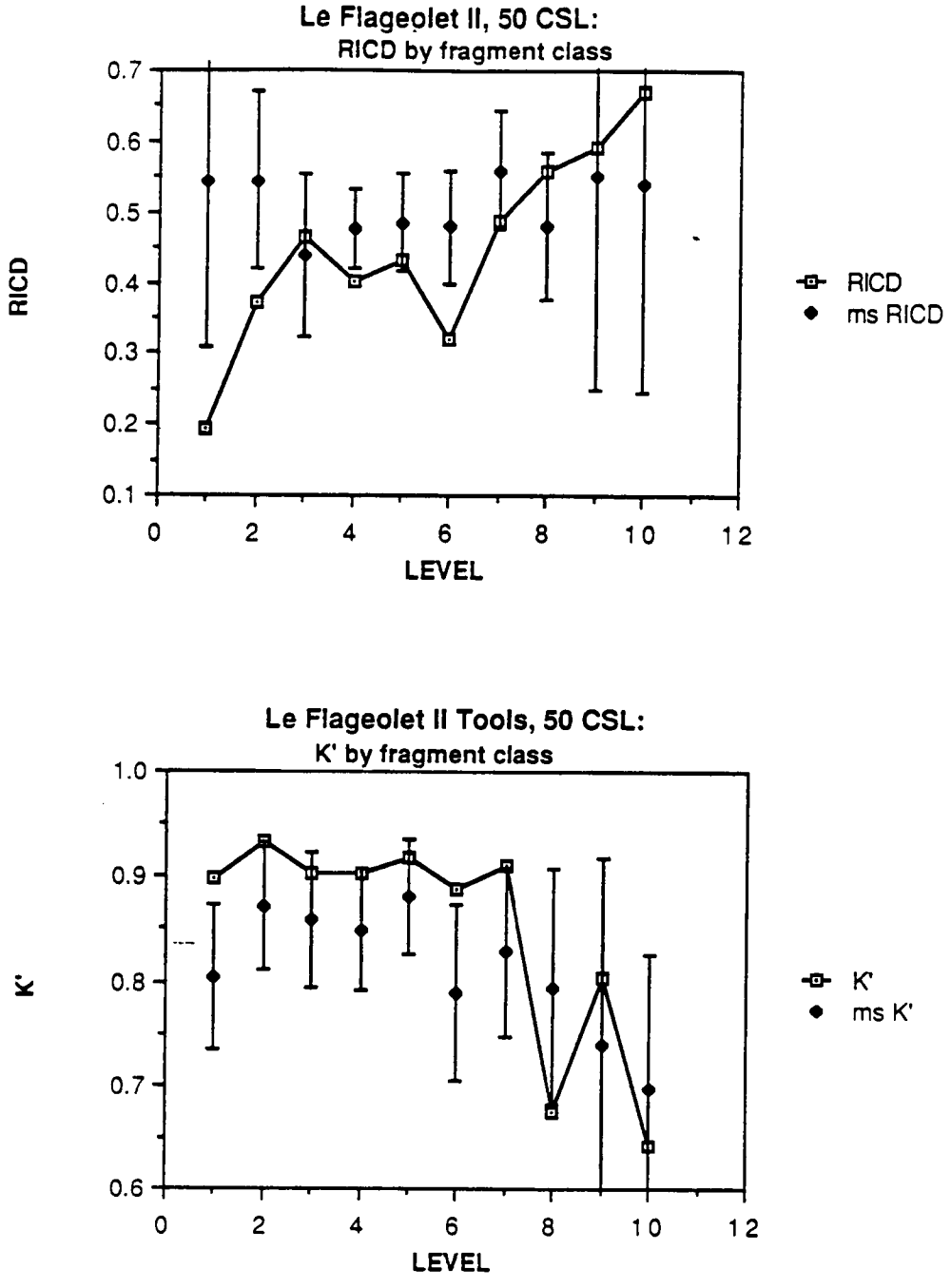


Figure 2.5 Example plot of K' and RICD vs. # of clusters. Error bars around the mean simulated values show a 95% confidence interval.

Correspondence Relationships: Examples

If the expected spatial patterning at a site consists of two discrete horizontal levels each of which had distinctive horizontal distributions an appropriate expectation for the correspondence relationships would be # 1, as shown in fig. 2.4. The original cluster breaks down into daughters so that: 1.) there is clear vertical organization of the daughter clusters, when seen in profile; 2.) the plan view of the original clusters shows a set of non-overlapping daughter clusters when divided into horizontal segments determined by the organization derived from the profile views; 3.) a given cluster's object distribution would be consistent with local features and topography; 4.) the average object orientation for each cluster would be similar, and/or consistent with local topography, and; 5.) these factors would be consistent across increasing spatial resolution. Comparisons would then be made between the actual clustering results, and the correspondence and homogeneity models.

Figure 2.5 shows an example of correspondence relationship 5 (see table 2.1). Here, the daughter clusters show little obvious patterning with respect to either each other or the previous cluster, and no consistency among the average object orientations, the cluster orientations or the local topography. This type

of result might be caused by a number of factors, post-depositional disturbance, multiple occupation events, the nature of the original occupation surface, and the effects of examining small portions of larger patterns all need to be considered. While the first two factors may also be suggested by the homogeneity models, the latter two require further work before they can be supported as specific causes for results of this type.

Incongruence between the cluster orientation, and the orientation of the objects (as shown in fig. 2.5), might be expected to have different causes at different scales. At a small scale this could be the result of depositional surface topography, while at a larger scale, it might be indicative of trampling, or other homogenizing actions.

Aside from the assemblage characteristics that are required by the models discussed above (i.e. object position, character, type, weight, and size) the following contextual factors have important implications: 1.) the location, size, and nature of features at the site, especially the nature(s) of their spatial relationships; 2.) the detailed geology and stratigraphy of the levels included, and their horizontal and vertical variation; 3.) the original depositional context, or as much as can be reasonably inferred from the physical nature of the deposits, especially the contemporary climatic regime; 4.)

physical evidence for large scale post-depositional disturbance; 5.) local topographic variation within the study area.

Defining Occupation Events

Many of the variables used in this study are best defined only in the context of a single set of criteria for the definition of an occupation. This necessitates the development of some relevant definition of an occupation event's characteristics. As an initial attempt at searching for relevant patterns, an occupation may be defined as a set of clusters which are distributed vertically so that the depth variation of their center points: 1.) conforms as a group to local topographic constraints; 2.) is no greater than the depth range of the largest single cluster included in the set, and; 3.) does not result in the division of a single feature between two occupations. The extent to which it will be possible to conform to this standards remains to be seen. Probably, especially in low resolution (= few clusters) solutions, these requirements will not always be met.

Now that the nature of the methods and some relevant definitions have been discussed, previous uses of the K-means technique in archaeological spatial analysis and some of their implication are in order.

II.3 Previous K-means Analyses

K-means spatial analysis as it has been applied to various French Paleolithic rockshelter and open air sites differs in both technique of application and in interpretive goals. All to date however, have been primarily concerned with areal or two dimensional patterning. Various workers (Ammerman et al. 1987; Bricker 1987; Kintigh and Ammerman 1982; Koetje 1987a,b; Grimm and Koetje 1989; Simek 1984a, 1987; Simek and Larick 1983; Simek et al. 1985; Rigaud and Simek 1987) have used the K-means clustering algorithm to create location-based object clusters in two dimensional space and rely on content analyses of these clusters for interpretation. Although detailed use of results in specific analyses differ among these applications, the basic approaches of all users were very similar. Essentially, models of expected diversity or homogeneity in different depositional situations were constructed and then compared to the archaeological situation. In all cases, reasonable fits were found between the models and the archaeological reality. Recently Bricker (1987) has used the K-means clustering technique to act as a density filter as well as a pattern recognition device in his analysis of the two dimensional distribution of the French open-air Chatelperronian site Les Tambourets. His approach and interpretive goals, although somewhat similar

to the above-cited studies, are largely distinct from all other uses of the technique.

K-means based analysis of two Aurignacian levels of the rockshelter site Le Flageolet I (Simek 1984a) found an overall structure very similar to that of predictions derived from Binford and Yellen's models of hunter/gatherer camp spatial structure, i.e. a central hearth based zone of high homogeneity, with a larger, more heterogeneous peripheral zone. This can be seen in terms of two general activity zones. A single hearth focused intensive zone, and a related, extensive zone. General use of space at this site was constrained by the presence of large roof-fall blocks. Some very similar patterns were found at the late Magdalenian open air site of Pincevent, but the extensive zones found at Le Flageolet I was lacking here. In addition though, areas peripheral to the hearths contained occasional small clusters of high homogeneity, interpreted as refuse dumps. Here there were no large scale "natural" constraints on the use of space. The Pincevent analysis was in substantial agreement with that of the original excavators' (Leroi-Gourhan and Brezillon 1972).

Several open air Magdalenian sites from the Isle Valley (France) have been analyzed with K-means based methods (Grimm and Koetje 1989; Koetje 1987a,b). These sites all contained cobblestone pavements, commonly

interpreted as hut or tent foundations. In contrast to the Le Flageolet I and Pincevent, there was no organic preservation, several of the sites had been disturbed by modern agricultural practices, and no hearths could be unambiguously identified. In these cases the spatial patterning of tool clusters and features could not be seen to conform well with expectations derived from either Binford's or Yellen's models. However, cluster content homogeneity patterns did (in general) conform to expectations derived from these models.

Recently, the open air Chatelperronian site of les Tambourets has also been analyzed using K-means clustering methods, however, the specific techniques of its application and interpretation are quite distinct (Bricker 1987). The site is seen as composed of six specific depositional zones arranged around two (probably not contemporaneously occupied) structure "outlines". These zones were divided into: exterior, interior, extensively, and intensively used areas. The interior and exterior zones served primarily to define the structures. Artifact density was used to differentiate the intensive from the extensive use zones. As was the case with the Isle Valley sites, no organic materials were preserved, and no hearths could be located.

Interesting patterns in spatial structure are revealed by dividing the open air sites into two groups:

1.) those containing evidence of hearths (Pincevent), and; 2.) those without hearths (Solvieux level M, Les Tambourets and the Magdalenian Isle Valley sites). In contrast, there seems to be no utility to a division of the rockshelter (Le Flageolet I) and cave (Grotte 15 or Abri Vaufrey) sites analyzed with k-means based techniques.

The analytic techniques followed by Simek (1984a) for Le Flageolet I, Pincevent, and Vaufrey were essentially identical. Spatial patterning at the sites seems to differ largely in that Pincevent covered more area, contained a distinct cultural assemblage, and had no natural constraints. In addition the patterning at Pincevent suggests that more than one spatially distinct hearth (and perhaps tents/huts) may have been occupied contemporaneously (Leroi-Gourhan and Brezillon 1972, but cf. Binford 1983a). This has been interpreted as indicating the presence of more than one social group. In contrast, at Le Flageolet I, a relatively small area containing a number of vertically superimposed hearths has been interpreted as repeated occupation by a single social group (Simek 1984a).

Spatial patterning found in open air sites without unambiguous evidence of hearths is quite different. In the Isle Valley sites (Grim and Koetje 1989; Koetje 1987a,b) there are no large scale spatial patterns

suggestive of hearth focused activities. In general the occupations appear to have been much more brief and seem to have consisted of only one (although in one case possibly two) social unit(s). Instead artifact clusters are structured around the pavement features. In at least two instances patterns suggestive of "door dumps" were found at putative entrances to hypothetical tent/hut structures, however in general clusters often intercepted the pavement boundaries, suggesting that no such superstructure existed (or at least interfered with) artifact deposition. The patterning seen in these sites was not similar to that in Le Flageolet I or Pincevent despite the (similarly) hypothetical existence of tent/hut structures at Pincevent. Nor did it conform well to that suggested at Les Tambourets.

Spatial patterning at Solvieux level M, a Perigordian 5 level, was quite distinct from the Magdalenian sites also found in the Isle valley (Grimm and Koetje 1989). There were no unambiguous hearth locations found at this level, no organic remains, no "natural" constraints on site structure, and no patterning reminiscent of that at other sites analyzed. It was suggested that the patterning at this site might represent a series of independently deposited sets of materials, rather than a single occupation.

Clearly then we have at least five distinct situations in terms of spatial patterning: 1.) Le Flageolet I, hearth focused but with "natural" constraints and large "extensive" areas; 2.) Pincevent, hearth focused, lacking "natural" constraints but with probable habitation structure induced constraints and no large "extensive" areas; 3.) the Isle Valley Magdalenian sites, lacking hearths and natural constraints, but with "habitation" structure (pavement feature) constraints; 4.) Les Tambourets, lacking natural constraints and hearths, with possible structural constraints, and 5.) Solvieux level M, without hearths, natural constraints, or features. These differences cannot be explained by the lack of organic remains at most of the open air sites. If spatial patterning was similar in all cases and differences were due simply to lack of organic materials, the sites without these would be expected to be similar, while they clearly are not. There is little or no evidence for differential natural disturbance at these sites. This leaves differential cultural formation processes (or analytic techniques). Generally differences caused by analytic techniques appear to be minimal, with the exception of Bricker's (1987) analysis of Les Tambourets.

At the regional scale, very little is clearly known about subsistence patterns during the periods under

consideration here (Magdalenian, Aurignacian, Perigordian, and Chatelperronian). Some broad differences are evident, however, they are difficult to relate to the specific patterns of movement and group size which seem to be responsible for the differences seen in these sites. Raw material use in the Perigordian, and the Magdalenian Isle Valley sites, for example, appears to have been focused mainly on local resources (Gaussen 1980; Grimm and Koetje 1989; Koetje 1987a,b), while the Aurignacian of Le Flageolet I contains some material from quite far away (Simek 1984a). While this may imply high mobility, it could as easily imply extensive trade networks (see Geneste 1985, Larick 1983). Neither, however is of particular use in explaining the differences in intrasite patterning. Attributing the differences to differential site functions is also somewhat difficult to do across typologically conceived culture units. Peoples using two distinct sets of tools may have vastly distinct ways of doing identical things. This is a serious enough problem within a culture unit, much less between them.

Site size, and number of tools may be of some help (White 1982). One could reasonably expect both a larger number of distinct activities and a larger overall number of repetitions of these activities at a larger (i.e. more intensively occupied) site. Thus both zone and assemblage redundancy should be relatively high. This

redundancy may be expected to manifest itself as either more clearly differentiated zones (i.e. extensive vs intensive), or as more refuse disposal (i.e. distinct clean up activities and the attendant dumping). Here we have a reasonable inference about some general differences in spatial structure between Les Tambourets, the Isle Valley sites, and Le Flageolet I and Pincevent.

Le Flageolet I was much more intensively occupied than the Isle Valley sites (given that greater numbers and density of artifacts equals higher occupational intensity or longer duration), so its spatial structure would be expected to show higher order structuring, while the Isle Valley Magdalenian sites would be expected to show more loosely ordered structuring. Pincevent, with hearths and an intensity of occupation similar to that of Le Flageolet I could also be expected to show similar structuring. Solvieux level M, with a similar intensity of occupation, but no hearths etc. might also be expected to show similar patterning, however it clearly does not.

While intensity of occupation can be expected to produce and constrain intrasite patterning, it must clearly interact with the site specific features. Thus even similar occupational intensities could be expected to produce differential patterning if the specific cultural features (or cultural use of natural features) varied. This can explain some specific differences between such

sites as Le Flageolet I (with its boulders) and Pincevent (with its possible habitation structures) (Simek 1984a). Both patterning processes are related at the regional subsistence pattern level. The specific use (or function) of a site may be determined by regional patterns of movement, as may the features constructed, and intensity of use. Thus when considering regional scale causation specific sites may be seen as discrete samples of a continuous distribution, the nature of which can be expected to change through time, and with the specific cultural units being considered. At the intrasite level of causation (proximate) however, the features present (both natural and cultural) may be a better explanatory framework. Unfortunately there is no site with both hearths and unambiguous structures present which has been analyzed. Such a site would go a long way toward suggesting which of the two structural influences was stronger.

In conclusion then, spatial structure differences between rockshelter and open air sites can best be seen as produced by the nature of the natural and cultural features present. Attribution to regional or larger scale processes are certainly possible, but given the current sample and its distribution through time it seems unwise to go beyond such general notions as intensity of use. Because sites amenable to two dimensional spatial analysis

are comparatively rare, extending the use of this technique, and the general study of spatial patterns into those situations considered intractable to two dimensional study, is an important part of increasing our knowledge of the range of variation inherent in the use of space during the Paleolithic.

II.4 Summary and Conclusions

Most pre-existing models of artifact deposition are not explicitly structured around consideration of spatial patterning in three dimensions. The model presented above fills this need, allowing relevant implications and predicted characteristics to be considered from a uniform viewpoint. This model suggests that searching an archaeological distribution for clusters based on the spatial location of objects in three dimensions would be a useful approach to understanding site structure and intrasite spatial patterning. The K-means algorithm provides the basis for this process. When combined with modifications to existing measures of cluster content homogeneity and the correspondence relationships, relevant characteristics of the distribution can be identified and examined, and compared to expectations derived from the model. An existing set of two dimensional spatial analyses using similar methods and techniques from the European Upper Paleolithic can be used to place analyses

using these methods into a relevant context of known spatial patterning.

In the next chapter I will outline the design and results of experiments meant to determine the adequacy of these models and methods for the recovery of archaeologically meaningful patterning in three dimensions.

CHAPTER III

A SIMULATION APPROACH TO RECOVERING ARCHAEOLOGICALLY MEANINGFUL LEVELS

III.1 Introduction

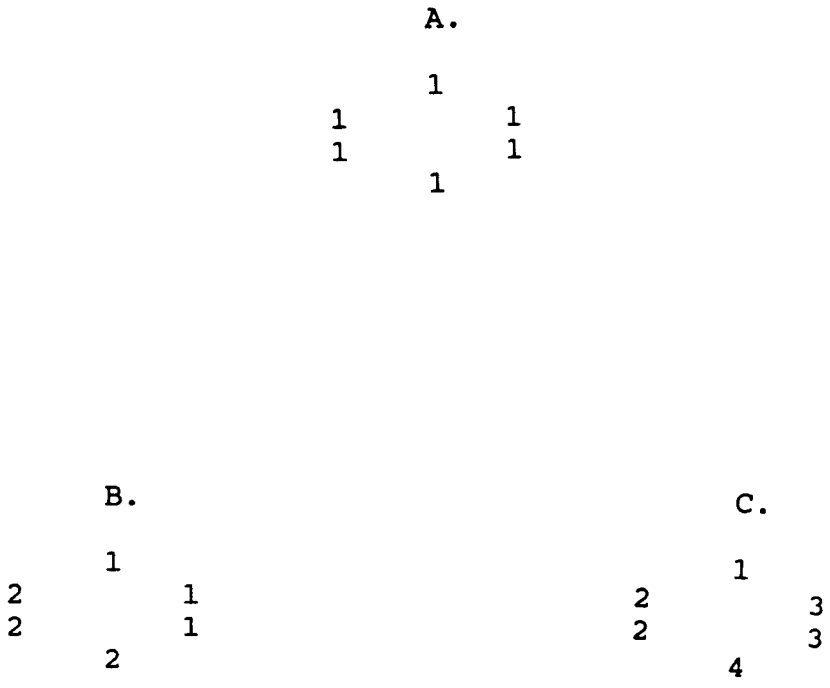
In the last chapter the incongruities between the "expected" nature of three dimensional spatial patterning in the archaeological record, and the mathematical goals inherent in the use of the K-means technique were briefly discussed. In order to demonstrate that modifications to the standard K-means method are able to overcome these problems and produce useful results, a series of simulated archaeological layers were analyzed using various techniques. These simulated distributions include several distinct three dimensional point configurations. This chapter has two main goals. First, to examine the abilities of the K-means technique in situations where the structure of a spatial pattern is known and where that structure varies. This will show the basic concordance between K-means results and the "reality" of site formation processes in three dimensional space. These results may also be used to guide any necessary manipulation or transformation of the spatial relationships prior to the actual analysis. The second main goal of this chapter is to produce estimates of the

error in discriminating between the layers under various experimental parameters. These errors in discrimination are quantified, and the results used to guide the analyses of two sites in chapters IV and V.

II.2 Technical Characteristics of Three Dimensional Spatial Clusters

As with all clustering techniques that attempt to minimize a distance based error measure, the K-means technique tends to find clusters of equal variance in all dimensions, and is often referred to as an "equal variance method" (Everitt 1980, Spath 1985). However, cluster shape is subject to the constraints of the actual data points. In three dimensions an ideal equal variance or unconstrained cluster would be spherical. This characteristic is often seen as the main disadvantage to this type of method (Everitt 1980). For a variety of reasons however, the fact that K-means theoretically seeks spherical clusters is not a fundamentally intractable problem; in fact, it may conveniently be ignored in some circumstances, especially when dealing with relatively high numbers of clusters. When these conditions are not met the problem can be easily overcome through transformation of the space under consideration. For example, at very low levels of resolution (i.e. relatively high # objects/cluster), points grouped

together as one cluster will tend to form a continuous scatter, and thus the cluster will appear relatively spherical. Unless the point scatter is truly continuous however, at some arbitrarily higher level of resolution, the variance inherent in one dimension will be sufficiently low in comparison to the others, that clusters would not be reasonably spherical. This is essentially a random effect. This process is easy to visualize using six points arranged in a hexagram on a plane (see Fig. 3.1). At the one cluster solution, the cluster appears roughly circular. When more clusters are defined, the clusters are not circular. Similarly at some number of clusters the spherical shape of three dimensional clusters will tend to be lost (if it ever existed) simply as an effect of the particular arrangement of points in space. This is certainly a locally variable effect, however, so it cannot be expected to produce non-spherical clusters for the site as a whole at any particular number of clusters. Relying on this effect is clearly not a good choice, as it is a basically distribution dependant random process and may have little or nothing to do with the clustering at "optimal" solutions. Fortunately, sphericity in itself is not so much of a problem as thickness in the vertical dimension, especially relative to our expectations of what an



KEY: Numbers show different clusters with a given solution
A. = 1 cluster solution
B. = 2 cluster solution
C. = 4 cluster solution

Figure 3.1 Cluster solutions showing changes in apparent cluster shape at differing cluster solutions.

archaeological level should look like. Equal variance in all dimensions at a particular scale simply may not fit well with models based on our knowledge of archaeological deposition.

If the nature of the excavated area is such that variation in all utilized dimensions is not similar, clusters formed using equal variance techniques may be seriously distorted as a result. For example, the excavated area of couche IX at Le Flageolet II is 3 x 10 x .65 meters. If the K-means technique is used on the raw coordinate data, equal variance clusters will be comparatively shorter (with respect to the total range available) in the Y dimension (10 meters) then in other directions and thick (again with respect to the total range available) compared to either width (X) or length (Y). This is because variation along the X and Y axes contributes more strongly to the SSE than does variation along the Z axis. In other words, a greater reduction in a cluster's SSE is likely to be gained by dropping an object on the X-Y plane of a clusters centroid, than one on the Z plane, simply because of the larger variation in the X-Y plane.

It would clearly be advantageous to restrict or control this tendency when searching for archaeologically meaningful deposition. At some arbitrary number of clusters this effect will be balanced out by the very low

number of objects included in any cluster, but for a large sample (e.g. >= 300 objects) this point may be difficult or effectively impossible to determine, and may have little or no relationship to the existence of optimal cluster solutions. In general terms then, the problem involves finding potentially meaningful clusters in a space of arbitrary dimensional variation while avoiding the problems of equal variance assumptions. One solution is to utilize some transformation that creates an analytic space with equal variance in all dimensions, while maintaining the relative distance relationships among objects. This "equal variance space" (S1) is an analytic construct, and thus quite distinct from the true space (S0).

Two common transformations are generally used in this type of situation. The first is to replace each coordinate with its Z-score calculated as:

$$Zs = \frac{X - \bar{X}}{S} \qquad (2.1)$$

Where X is the observed coordinate, $\bar{X}$ the mean of a particular coordinate, and S the standard deviation. The second transformation method is to divide each coordinate by its standard deviation. As the result of both transformations the standard deviations of the distributions are equal to 1.0, and the relative distance

relationships within the data are preserved. In such a situation all dimensions contribute equally to cluster formation. By using the z-score transformation, the entire distribution is transformed into a standard space with coordinate means of 0.0 and standard deviations of 1.0. At this stage in the process any other type of transformation is equally acceptable so long as the relative spatial order of the true space is maintained, (i.e. the objects retain their relative distance relationships) and the variance of all dimensions is equalized. Metric equivalency between the true space and transformed space need not be maintained (Everitt 1980).

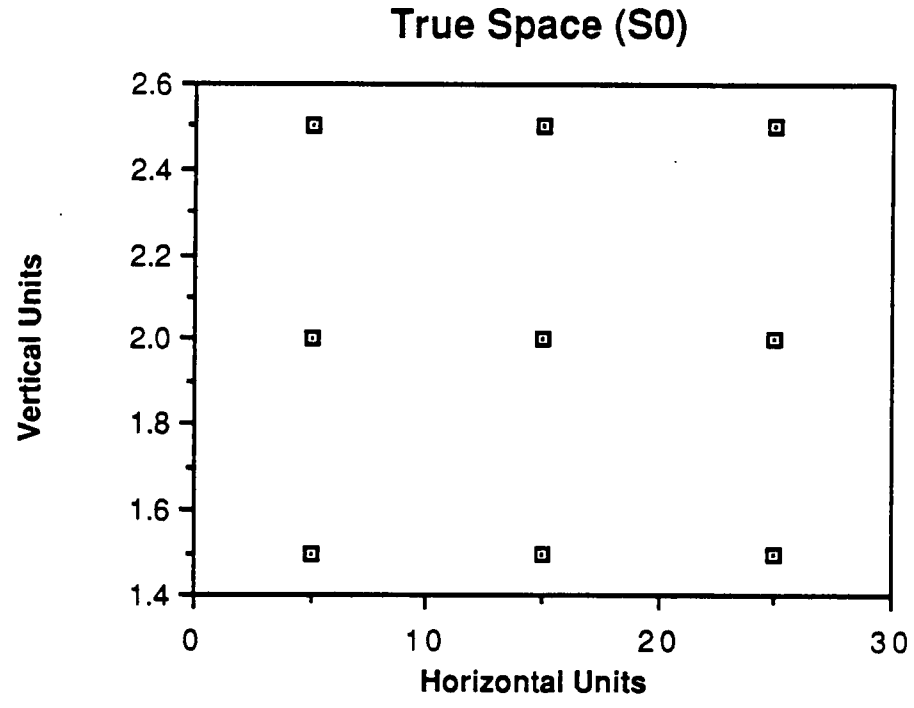
Given transformation into an equal variance space, and some substantial object density, K-means will generally be successful in finding roughly spherical clusters. There are two important characteristics to notice, however. First, any clusters are only as spherical as the data allow; the actual point cloud of any given cluster may take almost any shape because all points are included at a given solution. This has been somewhat obscured by the common use of a circle drawn at one RMS radius (essentially the average standard deviation over N dimensions) around the cluster centroid to represent spatial position and area of a cluster (e.g. Kintigh and Ammerman 1982; Koetje 1987a, Simek 1984a; Simek and Larick 1983) A better representation is a point at the cluster

centroid and error bars showing one or two standard deviations around it in each dimension. Second, the sphericity is only readily apparent in the equal variance space (S1): when cluster contents are mapped back into their true space (S0), much of this sphericity disappears.

Given equal variance in the two horizontal dimensions, for example, and an order of magnitude less variability in the vertical dimension (e.g. 1000 x 1000 x 10), spherical clusters formed in an equal variance space (S1) will appear lozenge or ovate shaped when mapped back into the true space (S0) (fig. 3.2). The SSE contribution of the Z axis (depth) was effectively scaled to equal that of the X and Y axes for the clustering procedure. Given these characteristics the potential of K-means clustering for finding archaeologically valid clusters in three dimensions seems high. In an effort to discover the best parameters for such an effort, a series of test runs were performed on simulated assemblages. These are discussed in the next section.

III.3 Clustering Simulated Assemblages: the Nature of the Variables

A series of experiments were undertaken to enable understanding and prediction of the ability of the K-means technique to recover particular formations under various



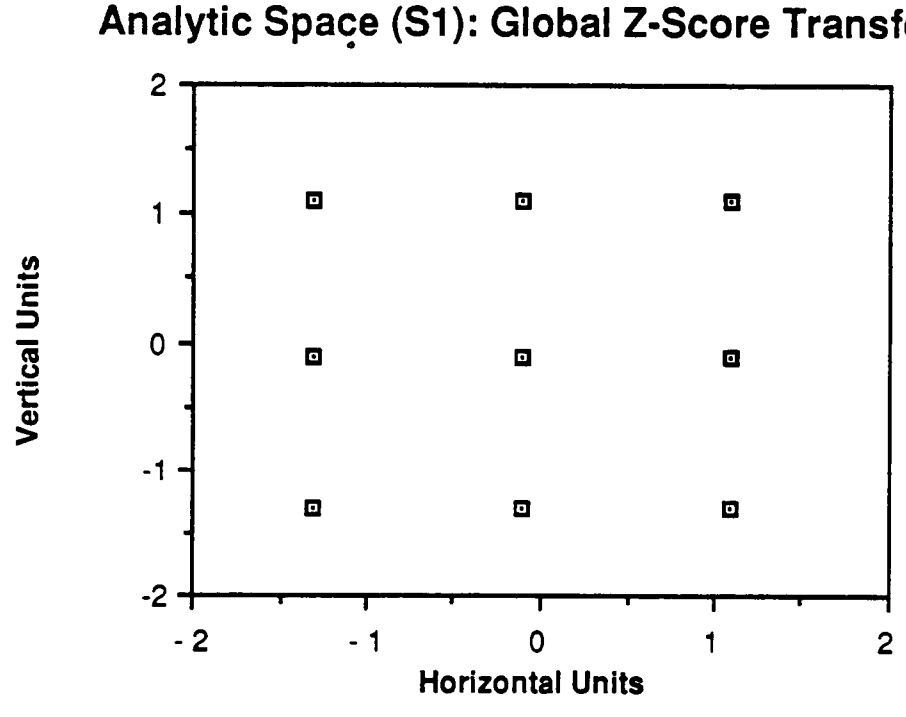


Figure 3.2 Example plot Showing scale differences between the true space (S0) and the equal variance space (S1).

conditions. While there have been a large number of similar experiments designed to demonstrate various properties of clustering techniques (Aldenderfer 1977a; Bayne et al. 1980; Dubes and Jain 1976, 1979, 1980; Everitt 1980; Gower 1967; Kuiper and Fischer 1975; Mezzich 1978; Milligan 1980, 1981; Raghaven and Ip 1982; Sneath and Sokal 1973; Spath 1985, Willett 1987), none have been published that concentrate on clustering in archaeological spatial analysis.

These experiments were designed to explore the effects of four general parameters on the recovery of objects grouped into two or more discrete layers that meet several fairly specific assumptions. The first major assumption is that the ability to recover the layers, or at least to discriminate between them has some meaning, and is the general goal of the process. The second is that the layers to be recovered are largely horizontally oriented, i.e. their extent in the X-Y axis plane is much greater than their extent in the Z axis plane and their slope in the Z axis plane is insignificant. The third major assumption is that individual clusters or groups within a given layer to be recovered are also largely horizontal in orientation. In neither case does this imply that either the layers or clusters have no depth, merely that any slope in the Z axis plane within either is consistent and minimal across the entire distribution.

Thus while sloped distributions are not directly addressed in the experiments below, any distribution with a reasonably consistent slope, or a three dimensional shape that can be described adequately, can be transformed into an effectively horizontal analytic space very easily through various means, and so may be amenable to treatment with the techniques discussed below.

In these experiments, layers were intended to simulate simple (and perhaps typical) archaeological levels, each experiment includes two or more layers. Each layer is roughly horizontal and consists of a unique set of 300 objects distributed in a 1000 x 1000 x 10 unit volume. In each experiment, the parameters were held constant over three sets of layers (two or more layers in each set), each layer a unique set of coordinates. In effect there are three cases for each experiment. The X, Y and Z axis coordinates for each layer set were generated independently of all others, using an NAG Fortran library random number generator available on the UTCC Vax cluster and a predetermined random number seed. Coordinates were in whole units calculated as:

trunc((dm*rnd(rseed))+1) (2.2)

where dm= the maximum number of units in the given dimension, rnd is a random number function returning uniform random variates between 0.0 and 1.0, rseed is the unique random number seed for each layer, and the trunc

function returns the integer portion of a real number. The coordinates have potential ranges from 1 to 1000 for the X and Y axes, and 1 to 10 for the Z axis, inclusive. Technically then, coordinates for the objects within a layer are simply appropriately-scaled pseudo random numbers.

In the standard experiments, objects were formed into from 2 to 60 clusters. Error in discriminating between the layers under a given set of parameters was measured using two indices: number of mixed clusters (#mix), and number of misassigned objects (#miss). At a sampled cluster solution, any cluster which had objects from both layers was counted as a mixed cluster. Any object which appeared in a cluster whose membership was predominantly of the other layer was counted as a misassigned object. In the case of clusters that had equal numbers of objects from both layers, the number of misassigned objects was 1/2 the cluster total. Number of mixed clusters was calculated for every 5th cluster from 60 to 10, and every cluster from 10 to 2 in a given clustering run. Number of misassigned objects was calculated for every 5th cluster from 60 to 5.

The experimental parameters of interest here consisted of: 1. separation between the layers along the Z axis, 2. clustering and concentration of the objects in each layer, 3. spatial transformation technique, and 4. Z

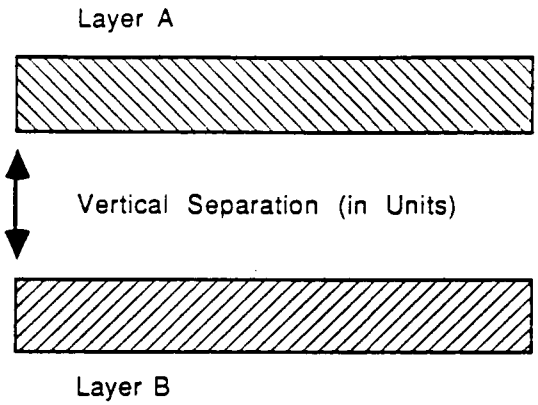
axis expansion factor. Each is discussed in detail below.

1. Layer Separation

Depth was measured on the Z axis as height above zero. Distance separating the layers was independently and systematically varied from 50 to 1 unit(s) for each set of layers. The lowest point of Layer A was set at 101 units above 0, while layer B was moved appropriately (fig. 3.3a).

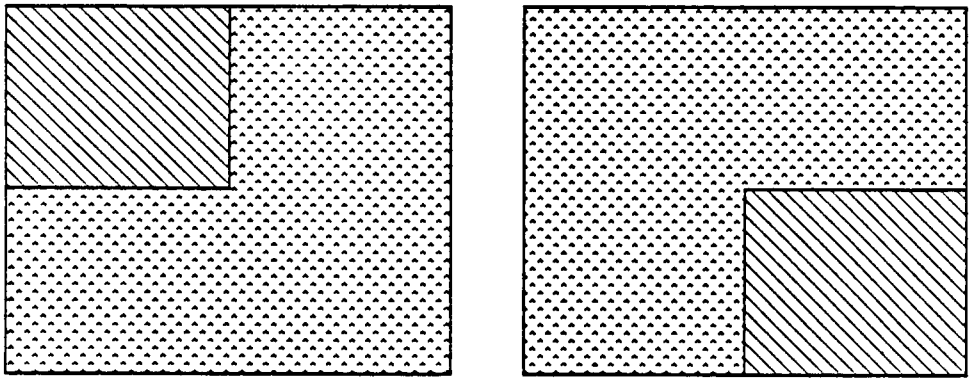
2. Clustering and Concentration

A single experiment could contain both clustered and unclustered layers. Each layer had two variants: clustered and random. A clustered layer was one in which 200 of the 300 objects were randomly assigned to an area 250 x 250 x 10 units in either the lower left or upper right corner of the layer. The remaining 100 objects were randomly assigned to the entire originally defined volume (3.3b). This always resulted in at least one, large scale, visually apparent cluster. When comparing two clustered layers they were said to be clustered adjacently when the concentrations occurred above each other (i.e. in the same corner), and oppositely when the concentrations occurred in opposing corners. Although a truly unclustered layer would be one in which all the objects were equally distant from their neighbors, for these purposes an unclustered layer was one in which all objects



A

B



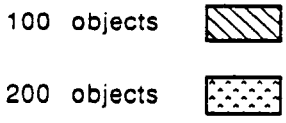


Figure 3.3 Layer separation and layer clustering spatial relationships.

were distributed randomly over the entire volume. This resulted in the formation of small clusters (that may be more or less apparent) at random.

3. Spatial Transformation Technique

Any manipulation of the entire space, as opposed to the manipulation of a single coordinate vector, is referred to as a spatial transformation. Spatial transformations are mappings from one set of dimensions into another. A distinction was made between transformations that are made using only global statistics, and those that require local or within-layer statistics. For global statistics the pooled objects from all layers were used, while for within-layer statistics, they were calculated by layer. Four such transformations were found to be of the most use, and consequently investigated in detail: global z-score and standard deviation, and within layer z-score and standard deviation. In addition, spatial transformation by square, square root, log and multiplication by a constant were more briefly examined (see group 1 below).

4. Expansion Factor

Any multiplication of a single coordinate vector, without equivalent manipulation of the other coordinate vectors, is referred to as an expansion. Various expansion factors were applied systematically to the Z axis coordinate in both transformed and untransformed

spaces when it appeared that they would be likely to increase the ability to discriminate between layers.

III.4 Experimental Results

Experimental Groups

The experiments can be conveniently formed into six groups based on the interpretive goals, and patterning involved in each. Each group consists of a number of series, where a series is all those individual runs in which a common set of experimental parameters was held constant over the layer set variants. That is, the same parameters were applied to the three layer sets generated from different random seeds.

Group 1

This group consisted of largely exploratory runs, in an attempt to establish some basic expectations for the procedures. Both clustered and unclustered layers were used. No transformations were used, but various expansion factors were applied to the Z axis coordinates. They included: Log, square, square root, and division and multiplication by a constant. In general none performed even moderately well with layer separation factors as high as 50 vertical units. In no case was there perfect discrimination (i.e. no mixed clusters or misassigned

objects), and most contained more than 50 mixed clusters at the 60 cluster solution. At cluster solutions with fewer than 30 clusters, it was common for all clusters to be mixed. Number of misassigned objects often amounted to 30-50% of the total in both layers at any given cluster solution. Some improvement on this was achieved with the square and multiplication expansions, especially in those experimental runs that contained clustered layers. Except for extreme cases however, (e.g. multiplication of Z axis by >100) improvement was minimal, and decreasing the separation between layers always resulted in a decrease in the ability of the program to discriminate between them. Details of the group 1 results are not presented, but see table 3.1 for a summary.

Group 2

Group 2 consists of experimental runs that were focused on exploring the effects of the global standard deviation and Z-score transformations on discrimination of two layers with separation factors ranging between 10 and 50 units. All three layer sets and all combinations of clustered and unclustered layers showed the same results regardless of the type of transformation used. Discrimination was invariably perfect after the 4 cluster solution, and often after the 2 cluster solution.

Table 3.1 Summary of experimental results for groups 1-3.

Variable	Group 1	2	3
1.	None	Global: Z-Score S. Deviation	Within Layer: Z-score S. Deviation
2.	1-50 units	10-50 units	1-10 units
3.	yes	yes	yes
4.	Various	none	none
Result:	Very Poor	Excellent to Perfect	Excellent to Perfect

Variable key:

1. transformations
2. layer separation
3. clustered/unclustered layers used
4. Z axis expansion

Details of the group 2 results are not presented, see table 3.1 for a summary.

Group 3

The Group 3 experimental series were focused on the effect of using as much a priori information as possible. In these runs, each layer was transformed by its within layer z-score, or standard deviation. Layer separation was varied from 10 to 1 vertical unit(s). All series, including all combinations of clustered and unclustered layers showed perfect discrimination with layer separations of 2 vertical units or more. When only 1 vertical unit separated the layers, only the z-score transformation series achieved perfect discrimination. The standard deviation transformation runs all had at least one instance of a mixed cluster below the 20 cluster solution, commonly 2 or more, although never more than one in a given solution. There was no apparent patterning with respect to any of the other parameters of interest. The number of misassigned objects in these runs ranged from 5 to 18 (.8 to 3 % of the total number of objects). Again, details of the group 3 results are not presented, but see table 3.1 for a summary.

Group 4

The experimental runs in this group were focused on attempting to increase the ability to discriminate between two layers with vertical separation ranging from 5 to 1 unit(s), using transformations which required only global statistics. A single series in group four includes all three layer sets, and z axis expansion factors from 1 to 26. Clustering in the layers, and vertical separation are held constant in each series. Table 3.2 shows the number of clustered layers and the vertical separation between each layer, by series number.

All runs with 5 units of vertical separation between the layers achieved perfect discrimination at solutions with two or more clusters. Tables 3.3 through 3.7 summarize the results from the Group Four experiment series (# 1-5) with z axis separations of 2 and 1 vertical unit(s). Because there was little variation between layer sets, and discrimination was invariably very good, these tables show the average #mix and #miss for the three layer sets involved in each run.

In Group Four, Series #6 is the most interesting case. Here, both layers are clustered adjacently, and the separation between layers was reduced to 1 vertical unit (i.e. the highest objects in Layer B were at Z = 100, while the lowest objects in Layer A were at Z = 101). Table 3.8 shows #miss and #mix in Series 6 for each of the

Table 3.2 Summary of Group 4 experimental Series.

Series #	# Clustered Layers	Vertical Separation (in units)	Mean #Miss (*)
1	0	2	0
2	0	1	6
3	1	2	0
4	1	1	2
5	2	2	0
6	2	1	3
7	2	2	0
8	2	1	1

* Mean #Miss for a given series at the 30 cluster solution, with a Z-axis expansion factor of 5.

Table 3.3 Group 4 Series #1. Average number of mixed clusters (#mix) and number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 2 units of vertical separation and no clusters in either layer.

	Cluster Solution																		
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
Number of Mixed Clusters																			
1	5	4	4	4	4	4	5	5	2	2	3	0	0	1	2	5	2	1	0
2	0	0	0	1	1	0	0	0	0	1	2	2	2	2	0	1	2	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Number of Misassigned Objects																			
1	10	12	11	11	14	15	15	12	11	5	8				77				
2	0	0	0	1	1	0	0	0	0	8	37				1				
5	0	0	0	0	0	0	0	0	0	0	0				0				
10	0	0	0	0	0	0	0	0	0	0	0				0				

Table 3.4 Group 4 Series #2. Average number of mixed clusters (#mix) and number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 1 unit of vertical separation and no clusters in either layer.

	Cluster Solution																	
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
Number of Mixed Clusters																			
1	9	8	9	9	10	6	7	8	6	5	3	4	2	5	4	5	3	2	1
2	6	6	6	6	6	5	5	4	3	3	2	2	2	1	2	1	2	1	0
5	2	0	1	1	1	1	3	2	2	2	1	1	1	1	0	0	0	1	0
10	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	1	1	1	0
Number of Misassigned Objects																			
1	27	29	29	30	35	33	37	45	37	36	12					94			
2	14	15	16	18	14	18	18	16	16	14	45					36			
5	3	0	2	2	2	2	6	15	15	21	3					0			
10	0	0	0	0	1	1	2	2	0	0	0					48			

Table 3.5 Group 4 Series #3. Average number of mixed clusters (#mix) and number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 2 units of vertical separation and one clustered layer.

	Cluster Solution																		
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
Number of mixed Clusters																			
1	4	3	3	4	4	4	4	5	1	2	0	1	0	2	2	3	4	3	2
2	1	1	1	1	1	1	1	3	2	2	2	1	3	2	1	1	0	0	1
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Number of Misassigned Objects																			
1	6	5	7	9	10	12	12	13	3	3	0					14			
2	1	2	2	2	4	2	2	7	8	3	6					8			
5	0	0	0	0	0	0	0	0	0	0	0					1			
10	0	0	0	0	0	0	0	0	0	0	0					0			

Table 3.6 Group 4 Series #4. Average number of mixed clusters (#mix) and number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 1 unit of vertical separation and one clustered layer.

	Cluster Solution																		
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
Number of Mixed Clusters																			
1	6	6	6	6	6	9	7	6	5	3	5	1	3	3	4	4	4	3	2
2	3	5	4	4	4	4	4	5	5	4	3	3	3	2	2	2	1	1	2
5	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	2	1	1	0
10	0	0	0	0	0	0	1	1	0	0	0	0	0	1	1	1	0	1	0
Number of Misassigned Objects																			
1	14	14	14	13	21	18	13	16	16	13	17					17			
2	8	10	8	9	9	9	8	10	11	19	8					25			
5	2	2	2	2	2	2	2	2	2	4	1					2			
10	0	0	0	0	0	0	6	6	0	0	0					26			

Table 3.7 Group 4 Series #5. Average number of mixed clusters (#mix) and number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 2 units of vertical separation and 2 similarly clustered layers.

	Cluster Solution																		
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
Number of Mixed Clusters																			
1	1	3	3	4	6	6	5	4	4	2	3	2	2	2	2	3	2	1	0
2	0	0	0	0	0	0	1	1	1	2	1	1	0	2	0	0	0	1	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Number of Misassigned Objects																			
1	1	4	4	9	13	13	12	16	16	11	8					68			
2	0	0	0	0	0	0	1	1	5	12	7					0			
5	0	0	0	0	0	0	0	0	0	0	0					0			

Table 3.8 Group 4 Series #6. Number of mixed clusters (#mix) and Number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 1 unit of vertical separation and 2 similarly clustered layers, by layer set.

	Cluster Solution																		
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2

Layer Set Q:

Number of Mixed Clusters

1	9	9	9	7	9	8	10	8	7	6	5	5	5	5	4	4	3	2	1
4	4	4	4	4	3	3	2	2	2	2	2	3	2	1	1	0	0	1	0
8	1	1	1	1	1	1	0	0	2	1	2	2	1	1	1	1	1	1	0
12	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0

Number of Misassigned Objects

1	23	23	23	28	29	29	29	26	32	26	26	49
4	10	10	10	20	4	4	6	5	7	6	4	0
8	2	2	2	2	2	2	0	0	3	4	28	51
12	0	0	0	0	0	0	0	1	2	7	7	27
16	0	0	0	0	0	0	0	0	0	0	0	27
20	0	0	0	0	0	0	0	0	0	0	0	27

Layer Set S:

Number of Mixed Clusters

1	9	9	10	10	8	8	9	7	6	4	4	4	4	4	4	3	2	1	2
3	5	5	4	5	5	4	4	4	3	4	3	3	2	2	2	2	2	1	0
4	3	3	3	2	2	3	3	3	2	2	2	1	2	2	2	1	1	1	0
6	2	2	1	1	1	1	1	2	1	2	2	2	2	2	1	1	0	1	1
8	0	2	2	2	2	2	2	1	1	1	2	2	2	1	1	1	1	1	0
10	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	1	1	0
12	0	0	0	0	1	1	1	1	1	1	0	0	0	0	1	1	1	1	0
15	0	0	0	0	1	1	2	2	2	1	1	1	1	1	1	1	1	1	0
18	0	0	1	1	2	2	2	2	2	1	1	1	1	1	1	1	1	1	0
20	0	0	0	0	1	2	2	2	2	1	1	1	1	1	1	1	1	1	0
25	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0

Table 3.8 con't.

*Z	Cluster Solution 60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
Number of Misassigned Objects																			
1	25	31	30	36	31	31	40	49	39	45	34						68		
4	6	6	5	5	5	6	7	9	10	7	8						60		
6	3	3	4	4	4	4	4	7	4	34	34						34		
8	0	7	7	7	7	7	7	4	4	4	31						29		
10	0	0	0	0	0	0	0	0	0	6	0						29		
12	0	0	0	0	4	4	4	4	4	4	0						29		
15	0	0	0	0	21	21	29	29	29	25	29						29		
18	0	0	4	4	29	29	29	29	29	25	29						34		
20	0	0	0	0	29	29	29	29	29	25	29						34		
25	0	0	0	0	0	0	0	0	0	0	0						60		
Layer Set R:																			
Number of Mixed Clusters																			
1	13	11	11	9	9	9	9	8	8	6	5	6	6	5	4	3	3	1	2
2	5	4	5	5	6	5	6	3	2	2	3	3	2	2	2	2	1	1	0
4	4	3	3	2	1	2	1	3	1	1	1	1	2	2	2	1	1	1	0
6	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	1	0
8	0	0	0	0	0	0	1	1	1	1	1	0	0	0	1	1	1	1	0
10	1	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	0
12	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	1	1	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0
18	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
24	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0
Number of Misassigned Objects																			
1	41	41	43	43	43	43	36	41	38	38	101						31		
2	16	18	20	20	22	20	23	18	9	17	33						82		
4	6	6	7	5	2	4	5	5	8	4	7						32		
6	2	2	2	4	4	2	2	2	3	0	13						68		
8	0	0	0	0	0	0	2	2	5	5	12						68		
10	24	26	26	26	26	26	26	29	28	31	31						68		
12	0	0	0	0	0	0	0	0	0	2	0						68		
14	0	0	0	0	0	0	0	0	0	0	0						31		
18	0	0	0	0	0	0	0	0	0	0	0						68		
24	0	0	0	0	0	0	0	0	0	0	31						31		

three layer sets. In general the ability to discriminate between the layers is reduced in this situation as compared to the other runs in group four. Although the maximum #miss (101) is some 16% of the total number of objects, it is very atypical, and occurs with a Z axis expansion factor of 1. A more typical value would be below 10 for any expansion factor of 2 and above. Clearly then even in the "worse case" this method does a reasonable job of detecting the two layers under these assumptions. Tables 3.9 and 3.10 show the results of the remaining series in group 4.

These data make it possible to generate error estimates for cluster analyses made under particular sets of constraints or assumptions. The surface in figure 3.4 represents the combined #miss results from Group 4 Run 6 as percentages of the total number of objects by Z axis expansion factor and number of clusters. When the data forming this figure are used for a trend surface analysis, there are no significant (at $p < .10$) polynomial surface fits with R values higher than .38. As this corresponds to a fairly low amount of explained variation, expected error rates for a given situation are probably better read directly from the figure, or interpolated from tables 3.3-3.8 than calculated via the regression equations.

Table 3.9 Group 4 Series #7. Average number of mixed clusters (#mix) and number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 2 units of vertical separation and 2 oppositely clustered layers.

	Cluster Solution																		
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
Number of Mixed Clusters																			
1	2	2	2	2	2	3	2	2	2	2	1	2	3	2	2	3	2	3	2
2	0	0	0	0	0	1	0	0	0	1	2	2	2	2	1	0	0	0	0
5	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Number of Misassigned Objects																			
1	4	4	4	4	4	5	5	5	5	5	1				20				
2	0	0	0	0	0	1	0	0	0	2	5				0				
5	0	0	0	0	0	0	0	0	1	0	0				0				
8	0	0	0	0	0	0	0	0	0	0	0				0				

Table 3.10 Group 4 Series #8. Average number of mixed clusters (#mix) and number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 1 unit of vertical separation and 2 oppositely clustered layers.

	Cluster Solution																		
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
Number of Mixed Clusters																			
1	2	2	3	3	3	4	4	3	3	2	1	3	3	2	3	3	2	3	2
2	0	0	0	0	1	1	1	2	4	4	2	2	3	3	2	1	1	0	2
5	0	0	0	1	1	1	1	1	1	1	2	2	2	1	1	0	0	1	0
8	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	0	1	0
Number of Misassigned Objects																			
1	4	4	8	8	8	10	9	8	11	5	2					21			
2	0	0	0	0	1	1	1	4	7	8	7					7			
5	0	0	0	1	1	1	1	1	2	3	4					0			
8	0	0	0	0	0	0	0	0	1	0	0					1			

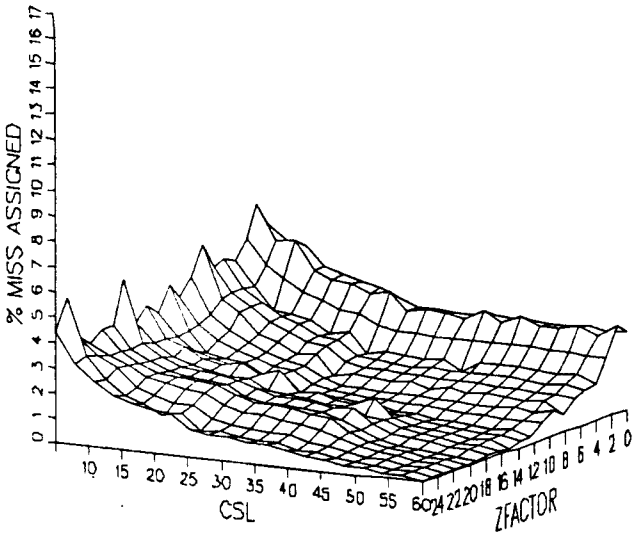


Figure 3.4 Three dimensional error surface #miss as percentage of the total number of objects present by Z axis expansion factor (ZFACTOR) and Cluster Solution (CSL). This plot shows the combined results from the Group 4 experimental series.

Group 5

The experimental runs in Group 5 were designed to test the effect of changing the characteristics of the distributions in each layer on the ability of the program to discriminate between the layers. When only two layers, of equal thickness and with equal numbers of objects in each are used with the Z-score transformation and any substantial vertical separation (as was the case in all the previous experimental groups), the global mean Z coordinate is likely to fall in the empty space between the layers. If this is true the layers may be distinguished perfectly simply on the basis of the sign of their Z coordinate in the transformed space (S0), layer A having positive sign, and layer B negative. If this is the driving force behind the programs ability to discriminate between the layers, it should fail when given layers that are not symmetric around their global mean Z coordinate. Two separate series were created to test this idea: the "asymmetric" series consisted of two layers (A and B), each ten units thick where layer A had 500 of the 600 total objects, and layer B the remaining 100 objects (fig. 3.5a). The "thick" series also had two layers A and B, each of which had 300 objects, but layer A was 20 units in depth while layer B was only 10 units in depth (fig. 3.5b). In both cases the mean global Z coordinate is well within layer A.

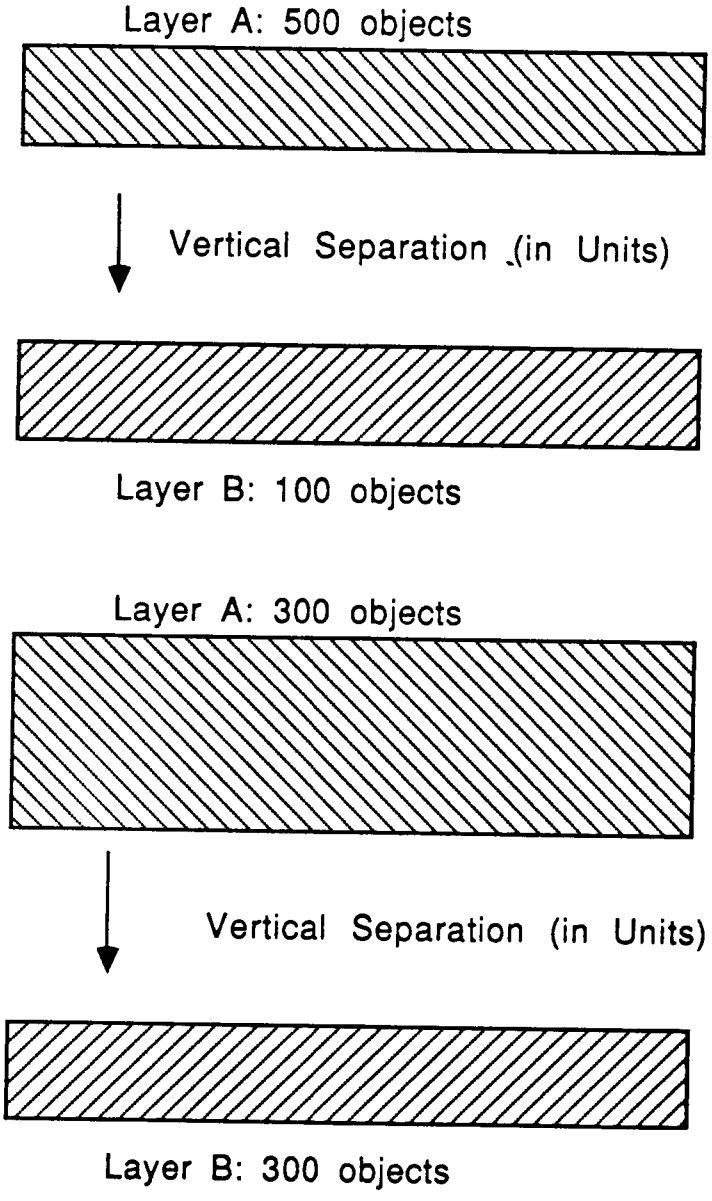


Figure 3.5 Relative thickness and object counts for the: A.) "Asymmetric", and B.) "Thick" experimental series.

Tables 3.11-3.15 present the #mix and #miss from the "asymmetric" and "thick" series respectively. In each case error is increased relative to that from similarly unclustered layers whose distributions were symmetric around the empty space separating the two layers (e.g. Group 4, Series 1 and 2: see tables 3.3 and 3.4), but differences were generally minor. There seems to be no drastic degradation of the ability to discriminate between layers under these circumstances. This is consistent with the idea that distributional symmetry is not the main factor used to discriminate between the layers; and while it seems clear that the existence of this condition is generally favorable, it is not a necessary condition for a successful result.

Group 6

The Group 6 experiments were designed to extend the conditions under which error rates may be estimated to those involving three separate layers. Tables 3.15-3.18, present the #mix and #miss for the three series involved in group six. It should be clear from comparison with the other tables that error rates are generally twice as high (and in some cases higher) as they were in similar 2-layer situations, especially when the vertical separation is reduced to 1 unit. Note however, that generally the

Table 3.11 Group 5 Asymmetric series. Average number of mixed clusters (#mix) and number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 2 units of vertical separation and 2 nonclustered layers.

	Cluster Solution																		
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
Number of Mixed Clusters																			
1	4	4	4	4	7	5	4	5	4	1	0	1	1	2	4	5	3	2	0
2	0	0	0	0	2	1	0	0	0	0	2	2	1	2	0	0	2	0	0
5	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Number of Misassigned Objects																			
1	9	9	11	8	16	15	13	22	21	1	0				36				
2	0	0	0	0	3	2	0	0	0	0	22				0				
5	0	0	0	0	0	0	0	8	8	0	0				0				
8	0	0	0	0	0	0	0	0	0	0	0				0				

Table 3.12 Group 5, asymmetric A series. Average number of mixed clusters (#mix) and number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 1 unit of vertical separation and 2 nonclustered layers.

	Cluster Solution																	
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
Number of Mixed Clusters																			
1	4	4	4	5	4	4	4	4	4	1	1	1	2	4	3	4	3	3	2
2	2	2	1	1	1	1	2	2	3	3	4	3	2	2	2	2	1	1	0
5	1	1	1	2	2	2	2	1	1	2	3	1	1	2	1	1	1	1	0
8	1	1	1	1	1	1	2	2	1	1	0	0	0	0	1	1	1	1	0
10	1	1	2	2	2	2	2	2	1	1	0	0	0	0	1	1	1	1	0
12	1	2	2	2	2	2	2	2	1	1	0	0	0	0	1	1	1	1	0
14	0	0	0	2	2	2	2	2	2	1	0	0	0	0	1	1	1	1	0
16	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Number of Misassigned Objects																			
1	8	8	10	11	11	10	10	9	12	9	9				26				
2	5	5	6	6	6	6	6	9	13	11	13				16				
5	1	1	1	6	6	6	6	5	7	8	6				6				
8	1	1	1	1	1	1	6	6	6	6	0				6				
10	1	1	6	6	6	6	6	6	6	6	0				6				
12	1	6	6	6	6	6	6	6	6	6	0				6				
14	0	0	0	6	6	6	6	6	6	6	0				6				
16	0	0	0	0	0	0	0	0	0	6	0				6				
18	0	0	0	0	0	0	0	0	0	0	0				0				

Table 3.13 Group 5, Thick 1 Series. Average number of mixed clusters (#mix) and number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 2 units of vertical separation and 2 nonclustered layers.

	Cluster Solution																	
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
Number of Mixed Clusters																			
1	8	9	8	6	5	4	5	4	5	7	5	4	4	4	4	4	3	2	1
2	4	4	4	5	5	5	4	4	3	2	2	1	2	2	3	3	2	0	1
5	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	0	1	1	1
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
Number of Misassigned Objects																			
1	19	22	22	17	13	12	14	6	14	23	38					98			
2	10	10	10	13	12	14	13	13	14	11	9					24			
5	2	2	2	2	2	2	0	0	6	5	21					0			
8	0	0	0	0	0	0	0	0	0	0	0					12			
10	0	0	0	0	0	0	0	0	0	0	0					12			

Table 3.14 Group 5, Thick 2 Series, Layer Set A. Number of mixed clusters (#mix) and number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 1 unit of vertical separation and 2 non-clustered layers.

	Cluster Solution																	
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
1	9	9	7	6	6	6	9	9	7	7	6	4	4	4	4	3	3	2	1
2	7	6	5	5	5	4	5	3	5	3	2	2	3	2	3	3	2	2	1
5	2	2	2	2	3	3	3	2	2	2	2	1	1	1	1	1	1	0	1
8	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	0	1
10	2	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
12	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
14	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	1
16	0	2	2	2	1	1	0	1	0	0	1	1	1	1	1	1	1	0	1
18	0	1	0	1	1	1	0	0	0	0	1	1	1	1	1	1	1	0	1
20	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	1

Number of Misassigned Objects

1	18	27	23	21	25	27	20	29	29	30	57	105
2	17	15	15	14	15	16	19	16	20	15	21	36
5	6	6	5	5	11	16	16	9	8	20	22	12
8	4	6	8	8	8	9	9	9	9	6	5	12
10	4	5	5	11	6	6	8	8	8	4	22	12
12	4	4	8	4	4	4	4	7	7	4	12	12
14	0	0	0	0	0	0	4	12	12	12	12	12
16	0	8	8	8	6	6	0	5	0	0	12	12
18	0	4	0	6	6	6	0	0	0	0	12	12
20	0	0	0	0	0	0	0	0	0	0	12	12

Table 3.15 Group 5, thick 2 Series, Layer Set B. Number of mixed clusters (#mix) and number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 1 unit of vertical separation and 2 non-clustered layers.

	Cluster Solution																		
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
1	10	11	10	10	11	8	9	8	8	7	5	5	4	4	4	3	3	2	1
2	5	6	6	4	5	6	5	5	5	3	3	4	3	2	2	3	2	1	1
5	3	4	4	3	3	3	2	2	2	2	2	2	2	2	2	1	1	0	1
8	2	2	1	1	1	2	2	1	2	1	1	1	1	1	1	1	1	0	1
10	1	1	1	1	2	2	2	1	1	1	1	1	1	1	1	1	1	0	1
12	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	0	1
14	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	1
16	1	1	1	1	1	2	1	1	1	1	1	0	0	0	0	1	1	0	1
18	0	1	1	0	0	0	1	1	1	1	1	1	0	0	0	1	1	0	1
20	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	1	0	1
Number of Misassigned Objects																			
1	39	43	41	39	41	40	35	28	59	67	57				72				
2	12	17	17	11	13	29	20	21	45	41	9				38				
5	10	12	9	10	10	13	9	3	11	8	16				14				
8	8	8	6	6	6	8	8	6	13	15	14				14				
10	4	4	4	4	9	9	9	14	14	17	18				14				
12	4	4	4	4	4	5	13	14	14	14	14				14				
14	5	5	5	5	5	5	5	5	14	14	18				14				
16	3	3	3	3	4	6	14	14	14	14	18				14				
18	0	2	2	0	0	0	14	14	14	14	18				14				
20	0	0	0	0	0	0	4	14	14	14	18				14				

Table 3.16 Group 6, Three 1 Series. Average number of mixed clusters (#mix) and number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 2 units of vertical separation and 3 nonclustered layers.

	Cluster Solution																		
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
Number of Mixed Clusters																			
1	19	17	14	15	14	16	14	13	9	13	10	9	8	7	6	5	4	3	2
2	7	8	7	8	8	8	7	8	8	4	5	5	4	3	2	4	1	0	2
5	1	2	2	3	3	1	1	1	0	0	0	0	0	0	0	1	1	0	2
8	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	1	2	0	2
10	0	0	0	0	0	1	2	1	1	1	0	0	0	0	0	1	2	0	2
12	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	0	1
Number of Misassigned Objects																			
1	60	51	44	49	44	50	56	36	59	90	149				212				
2	15	16	18	22	29	33	32	40	51	45	26				45				
5	2	4	4	5	4	1	2	1	0	0	0				38				
8	0	0	2	2	2	2	3	3	3	0	0				35				
10	0	0	0	0	0	5	6	1	1	7	0				35				
12	0	0	0	0	0	0	0	0	1	0	0				0				

Table 3.17 Group 6, Three 2 Series, Layer Set A. Number of mixed clusters (#mix) and number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 1 unit of vertical separation and 2 non-clustered layers.

	Cluster Solution																	
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
Number of Mixed Clusters																			
1	23	23	22	20	20	17	18	14	5	13	10	9	8	7	6	5	4	3	2
2	12	12	12	12	12	10	10	8	9	7	6	5	6	6	6	4	3	3	2
5	7	6	6	6	7	8	7	7	5	4	3	3	3	3	2	2	2	0	2
8	1	1	1	1	1	2	4	4	2	2	0	0	0	1	1	2	2	0	2
10	3	2	1	2	2	2	2	2	3	1	2	1	1	1	0	1	2	0	2
12	6	6	6	6	5	3	3	3	3	2	2	2	2	2	2	2	2	0	2
14	5	5	5	5	4	3	3	3	3	2	2	2	2	2	2	2	2	0	2
16	5	5	5	5	3	3	3	2	2	2	2	2	2	2	2	2	2	0	2
18	5	5	5	5	4	4	2	1	1	1	1	1	1	1	1	1	2	0	2
20	3	2	2	0	0	0	0	1	2	1	1	1	1	1	0	1	2	0	2
22	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	1	2	0	2
24	0	0	0	0	0	0	0	1	2	1	1	1	1	1	0	1	2	0	2
26	0	0	0	0	0	0	0	1	2	1	1	1	1	1	0	1	2	0	2
Number of Misassigned Objects																			
1	73	79	75	84	81	84	71	63	108	144	193						172		
2	31	35	40	46	48	59	68	67	77	94	57						58		
5	16	16	16	16	22	34	33	38	48	54	17						71		
8	3	3	3	3	3	9	17	14	8	4	75						63		
10	8	7	3	8	8	8	8	10	15	7	12						59		
12	24	24	27	27	23	24	24	24	23	29	30						75		
14	19	19	19	19	18	19	22	22	22	29	30						75		
16	18	18	18	18	12	18	23	29	29	29	30						75		
18	17	17	17	18	18	19	12	12	12	12	12						59		
20	6	2	2	0	0	0	0	17	29	12	12						59		
22	0	0	0	0	0	0	0	0	12	12	12						59		
24	0	0	0	0	0	0	0	17	29	12	12						59		
26	0	0	0	0	0	0	0	17	29	12	12						59		

Table 3.18 Group 6, Three 2 Series, Layer Set B. Number of mixed clusters (#mix) and number of misassigned objects (#miss) by cluster solution and Z axis expansion factor at 1 unit of vertical separation and 2 non-clustered layers.

	Cluster Solution																	
*Z	60	55	50	45	40	35	30	25	20	15	10	9	8	7	6	5	4	3	2
Number of Mixed Clusters																			
1	21	21	20	20	18	16	14	12	14	13	9	9	8	7	6	5	4	3	2
2	16	14	14	13	13	12	11	12	8	8	7	6	6	6	4	4	3	3	2
5	6	7	7	7	7	7	7	6	7	5	3	3	2	2	3	2	3	0	2
8	7	6	4	4	5	5	5	5	4	2	1	1	1	2	1	1	2	0	2
10	5	5	3	3	3	3	3	2	1	1	0	1	1	2	1	1	2	0	2
12	6	6	5	5	3	3	3	2	2	1	1	1	1	1	0	1	2	0	2
14	4	4	5	4	3	3	3	3	3	1	1	1	1	1	0	1	2	0	2
16	2	3	4	4	4	4	4	3	2	2	2	2	2	2	2	2	2	0	2
18	1	1	1	2	2	2	2	3	2	2	2	2	2	2	2	2	2	0	2
20	1	1	1	2	2	2	2	3	2	2	2	2	2	2	2	2	2	0	2
22	1	1	1	1	1	1	0	0	1	1	2	2	2	2	2	2	2	0	2
24	0	0	0	0	0	0	0	0	1	1	2	2	2	2	2	2	2	0	2
26	0	0	0	0	0	0	0	0	1	1	2	2	2	2	2	2	2	0	2
Number of Misassigned Objects																			
1	69	68	72	68	70	72	64	67	78	108	144						224		
2	45	48	56	56	53	57	62	65	67	71	55						96		
5	18	24	34	33	33	37	42	41	48	39	42						83		
8	28	29	21	13	16	27	38	35	34	15	8						51		
10	18	20	11	9	10	10	10	3	2	8	0						51		
12	28	28	26	26	27	21	21	20	20	21	21						51		
14	20	20	26	26	23	23	23	26	35	16	21						51		
16	5	15	21	20	33	33	33	35	39	45	45						89		
18	2	2	2	20	20	20	20	35	39	43	45						89		
20	2	2	2	2	2	2	0	0	43	43	45						89		
22	2	2	2	2	2	2	0	0	22	22	45						89		
24	0	0	0	0	0	0	0	0	22	22	45						89		
26	0	0	0	0	0	0	0	0	22	22	45						89		

number of miss assigned objects does not exceed 30 for expansion factors greater than five, and that this represents less than 5% of the total number of objects.

III.5 Discussion

General

Several points seem clear as a result of the clustering experiments. First, the use of within layer z-score and standard deviation transformations is the best solution to the problem of discriminating between two or more layers regardless of their vertical separation. This relies however, on a priori knowledge about the layers that is quite specific, requiring a high-confidence layer assignment for each object. This makes it equivalent to separate analyses done within each layer. The value of a more holistic approach given such knowledge is in: A.) exposing those areas or volumes in the site that might have questionable layer attributions, may be mixed or, are anomalous in some other sense, and B.) allowing subsequent analyses to crosscut couche or layer boundaries in these areas. Minimally then, besides providing the initial portion of a location based spatial analysis, this approach might be used to either create from scratch, or to help produce a replicable verification of, more traditionally defined layer or couche boundaries,

especially in those situations where such boundaries are not visually apparent. In essence such a use would examine within versus between layer variation, with outlying groups targeted for closer examination. These outlying groups of objects might correspond to either: 1.) distinct depositional levels, or depositional/disturbance episodes within a particular sediment layer, 2.) differential post-depositional behavior of material classes within a single sediment layer, or 3.) objects that have been mislabeled.

The second main point to be gleaned from the experimental results is that using global z-score transformations and Z axis expansion factors between 2 and 30 can be nearly as successful as within layer transformations in discriminating between the layers regardless of vertical separation or layer characteristics. This procedure, however, does not require any a priori layer assignment. Expected error rates are somewhat higher than those produced when using transformations based on within layer statistics, but within reasonably acceptable limits in almost all cases. This is especially important considering the very minor amount of prior knowledge (e.g. no reliable layer assignments) required to use global transformations. The experimental results demonstrate that for a variety of circumstances, Z-axis expansion factors of five or

greater almost always lead to error in object assignments of approximately 5% or less (of the total number of objects). Only very infrequently was this error rate in fact greater than 1%. While this is not insignificant, it is certainly acceptable, especially for situations that involve a single recognized cultural unit.

There are several interesting characteristics that become apparent through comparison of the various experimental groups. One of the most striking is that, in nearly all those experimental series having a vertical separation factor of one, as the Z-axis expansion factor increases between 2 and approximately 8, the #mix and #miss always drop steadily. In many cases however, the error rates rise again with Z-axis expansion factors between 8-10 and 15-18, producing very similarly shaped surfaces in the result space (see figure 3.4). This seems to be characteristic of nearly all layer sets, and may be connected with the standard layer depth, which was nearly always 10 units. It may be significant that for the Thick 2 series, in which layer A was 20 units in depth and Layer B was 10 units in depth (see tables 3.11-3.15), this characteristic increase in the #miss is found at a higher Z-axis expansion factor than is typical of the other experimental series. Although a weak correlation is fairly clear, there seems to be no good mathematical reason for this phenomenon, nor is there a consistent

increase in #miss only at a expansion factor of 10. Rather, the precise occurrence of the increasing error rate varies considerably within an experimental group, i.e. with different random coordinate sets. There is also a suggestion of a relationship between this phenomenon and the number of objects occurring at the layer boundaries, but there is no clear statistical tie. It may also be that this characteristic is related to the differences in the original variance among the coordinate axis. Variation along the Y axis is, for example somewhat more than ten times higher than variation along the Z axis, although the X:Z axis variance ratio is only 4.6:1.

At this point then it cannot be determined whether this is a result of the process, the data, or a unique combination of both. Consequently we cannot tell if it should be expected of non-simulated data. Because this increase in discrimination error seems to occur unpredictably with expansion factors between 10 and 20, the best solution seems to be simply to keep expansion factors used in analysis below 10, in the absence of some other criteria to be used in error measurement.

Another characteristic of the experimental results as a whole is that there is an apparent trade off that must be made between increased ability to discriminate between layers and what may be called "induced horizontal banding". As the Z-axis expansion factor increases,

clusters at any given solution tend to be more restricted in their vertical extent. While this is the key to discrimination between layers (especially with very small separation distances), it also leads directly to extremely thin clusters in proportion to their length and width. In extreme cases (i.e. expansion factors above 15 or so), and at a low number of clusters, the thickness of a given cluster will tend towards the (total vertical range)/(number of clusters). There is effectively only one cluster for each unit of vertical range, especially when the horizontal extent of the distribution is also small. In this situation, only when the number of clusters exceeds the total vertical range (in # of measurement units) will there be more than a single cluster per vertical unit. This can be a major problem if optimal solutions also tend to be at low resolution layers and the total vertical range of the object distribution is of a similar size. In this situation a reasonable trade off must be made between expected discrimination error and horizontal banding.

While there is no immediately obvious method for measuring banding, it is very clear when profile or projection plots (e.g. scattergrams of the Z vs. X, or Y axes) are examined with clusters marked in unique colors or symbols. More than one cluster existing in a single horizontal band creates a mixed pattern, that is very

apparent visually. Figure 3.6 shows a cluster solution with heavy horizontal banding, while figure 3.7 shows the same distribution at a subsequent solution with more than one cluster on a given horizontal plane. This effect does not seem to be a general problem, it can arise only under a fairly specific set of circumstances, and seems to have no connection with optimal solutions as determined by lower than expected drops in the SSE values at a given solution (see chapter II). Nevertheless, this too seems to suggest that Z axis expansion factors should generally be less than the range from 10-15. Importantly, this range is consistent with that avoiding increasing error rates as mentioned above.

The simulation based experiments presented in this chapter indicate generally that these methods are appropriate for spatial analysis that explicitly takes into account three dimensional patterning in those situations where the targeted layers to be recovered (or perhaps created) can be assumed to be roughly horizontal. In most of these situations, potentially meaningful layers may be recovered with error rates of less than 5% of the total number of objects. These methods, then, may be used to discover and characterize in a quantified, replicable manner, the basic spatial patterning at a site in three dimensions. It is possible that different clustering

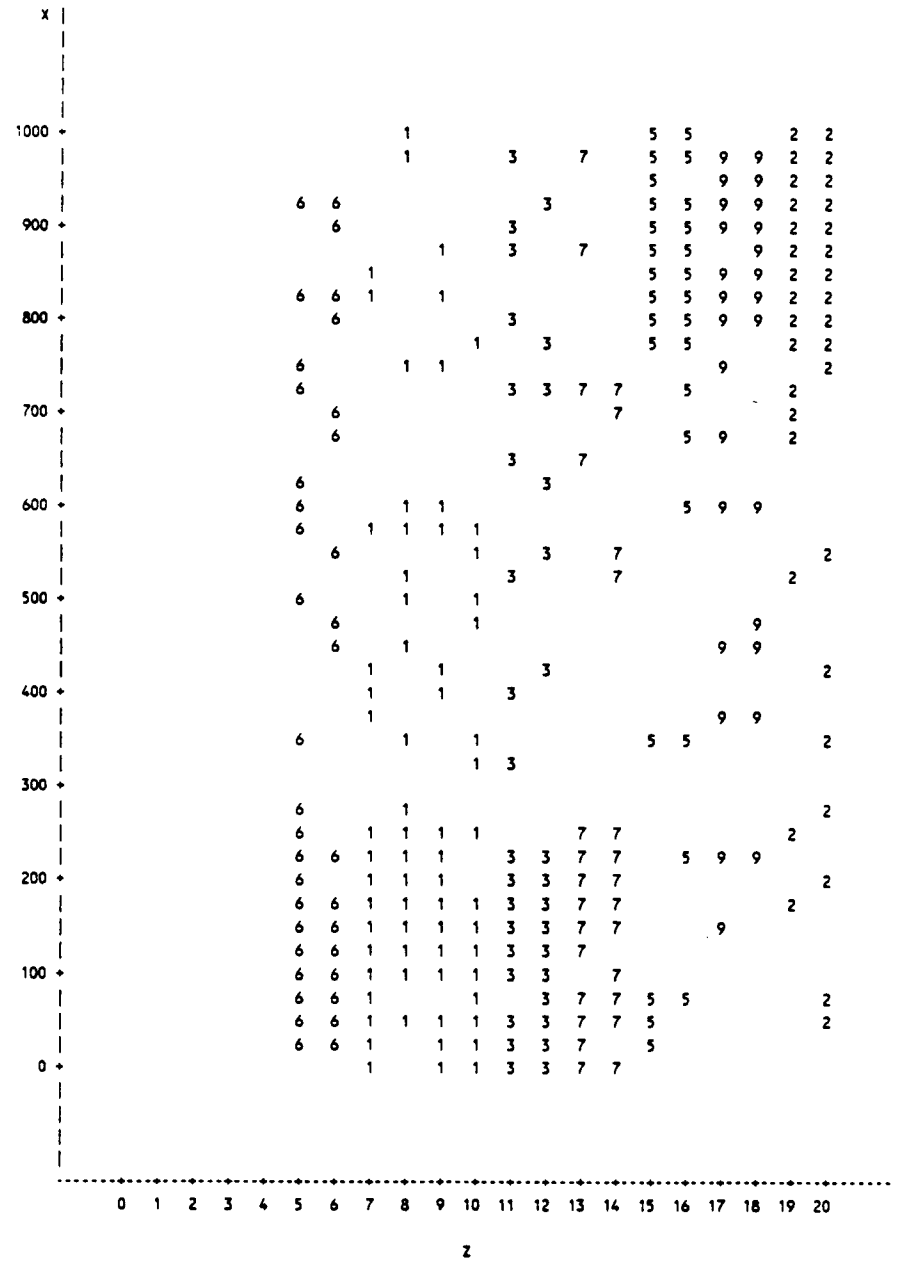


Figure 3.6 Cluster projection showing "induced horizontal banding" effect.

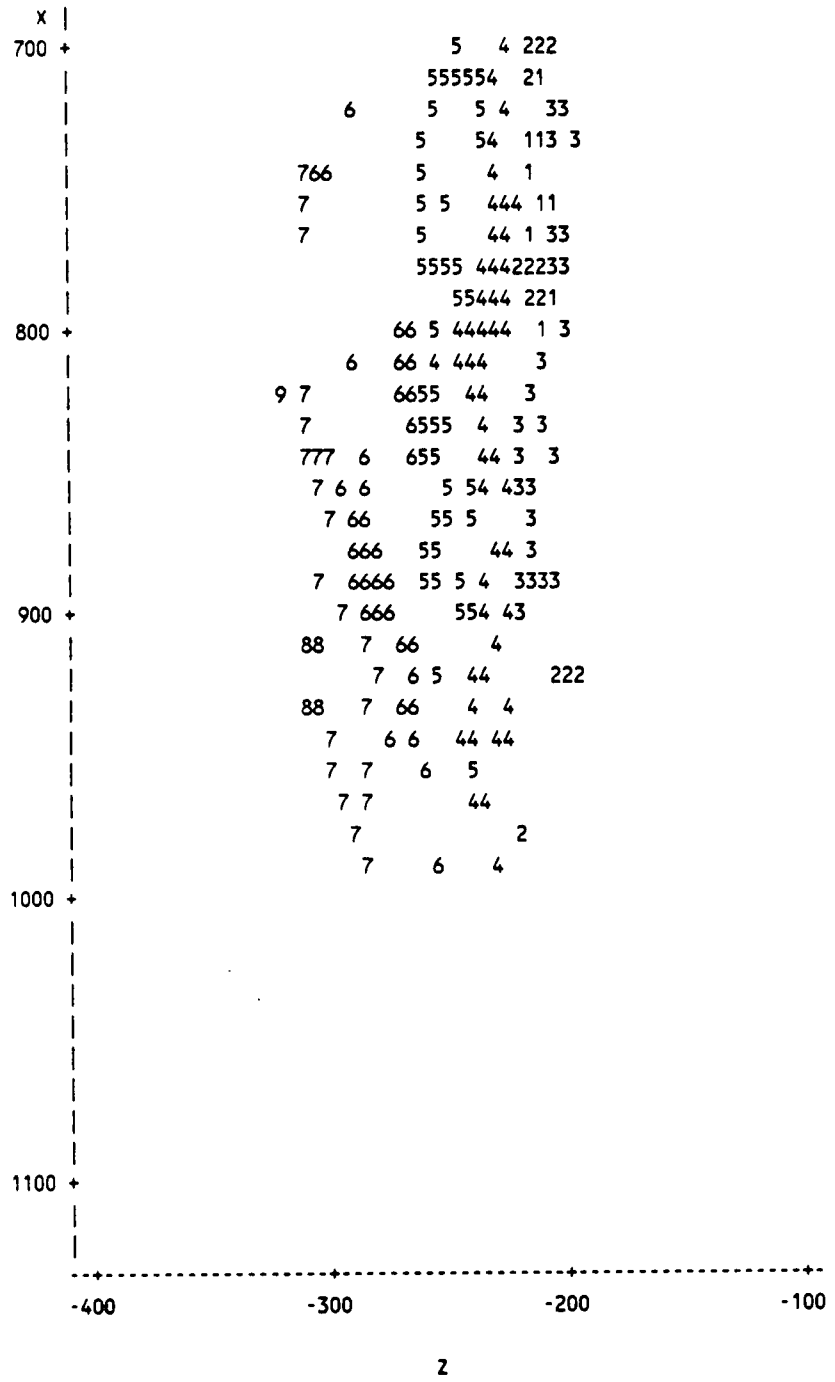


Figure 3.7 Cluster projection showing no "induced horizontal banding".

algorithms are appropriate for situations in which the layers targeted for recovery are not sufficiently horizontal and cannot be consistently transformed into a horizontal analytic space (i.e. slopes are not able to be adequately characterized over the entire distribution), or when individual clusters within larger layers are not largely horizontal, especially if the slopes of individual clusters vary substantially.

It remains then to apply these methods to real archaeological situations in the light of the models developed in the preceding two chapters. Chapters IV and V present analyses of two very different sites with just this goal.

CHAPTER IV

CASE I: LE FLAGEOLET II

IV.1 Introduction to the Site

Le Flageolet II is a rockshelter site located in the Dordogne region of Southwestern France (figs. 4.1-4.2). It was excavated between 1966 and 1976 by teams from the Direction des Antiquites Prehistoriques d'Aquitaine, under the direction of Jean-Phillipe Rigaud. Twelve geologic layers or couches were described in a series of preliminary reports published together in 1970 (Delpech 1970; Laville 1970; Rigaud 1970, 1982). Couches I-VIII, and X-XII contain very sparse Upper Paleolithic materials attributed to the Magdalenian time period (fig. 4.3). These couches are not considered further here because of their very low object counts and frequent disturbance. Couche IX contained the most objects by far; it consists of approximately 80 cm of largely undifferentiated sediment in a 10 x 3 meter excavated area (see fig. 4.2). Artifactual materials are distributed throughout this volume. In addition there are at least two hearths located at different levels, and in the upper portion a cobble and limestone pavement (Fr.: pavage or dallage). The presence of these three relatively intact features argues for the lack of any catastrophic disturbance processes at this site, as do the sedimentological

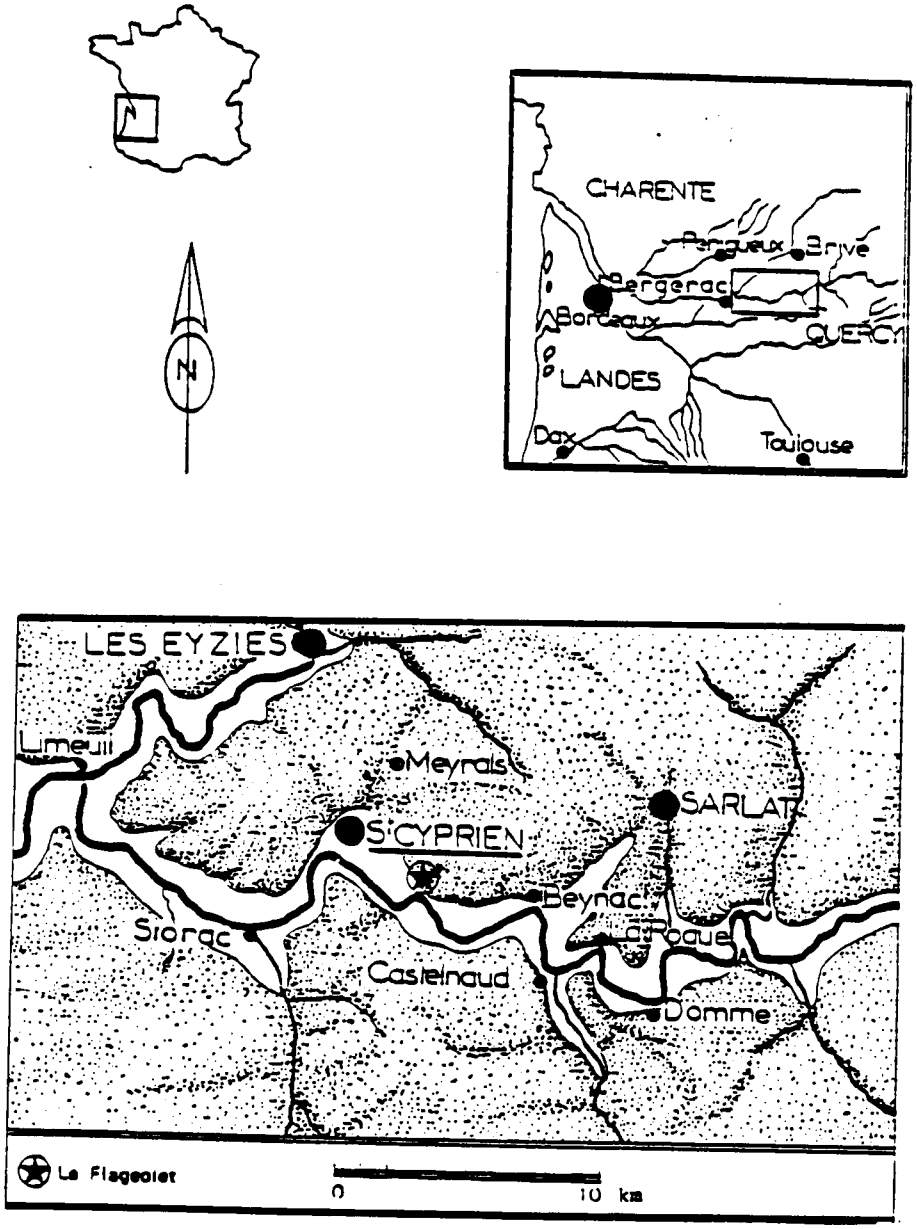


Figure 4.1 Location of Le Flageolet II. Reproduced from Rigaud (1982), with permission.

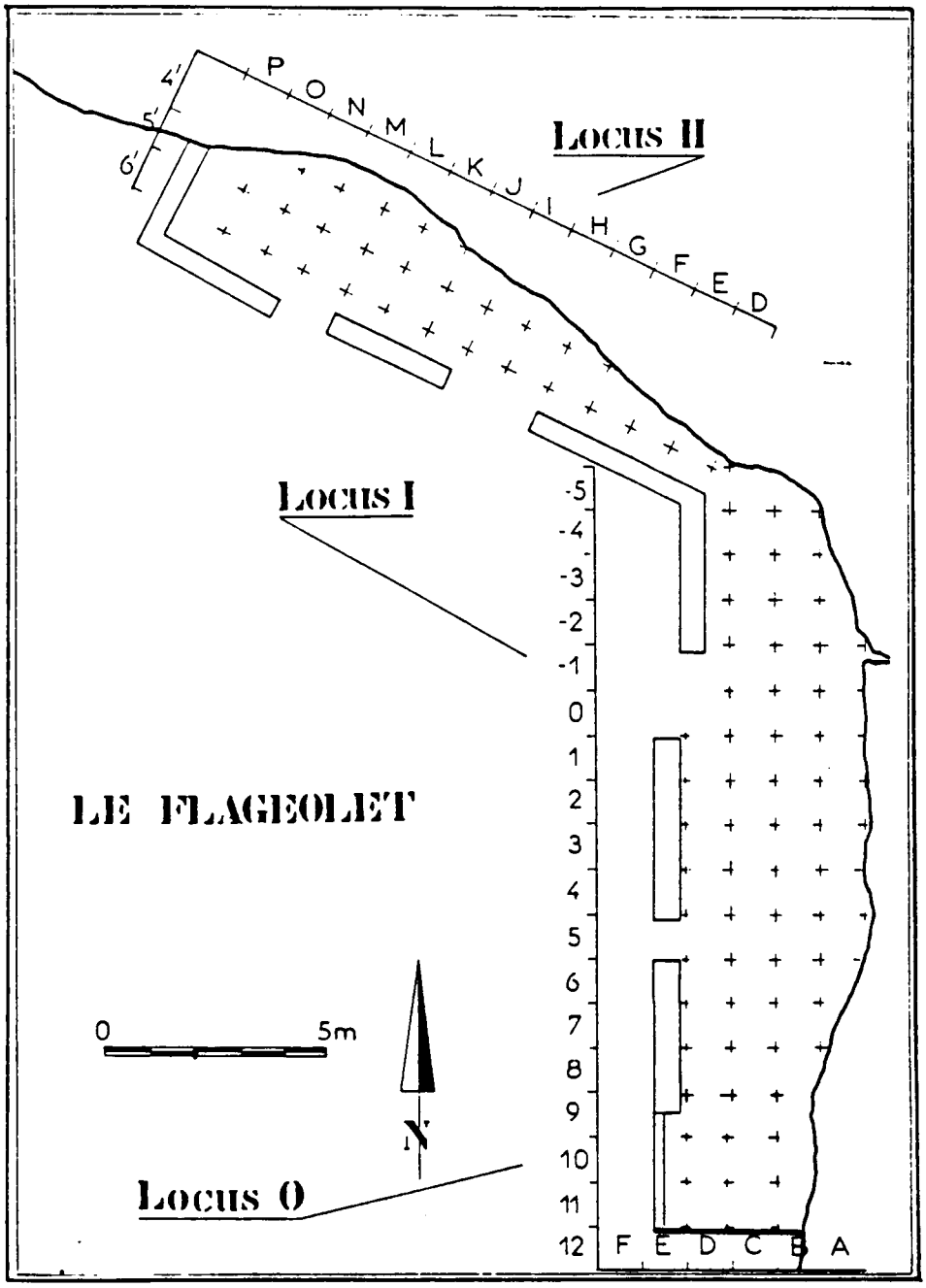


Figure 4.2 Plan map of Le Flageolet II. Reproduced from Rigaud (1982), with permission.

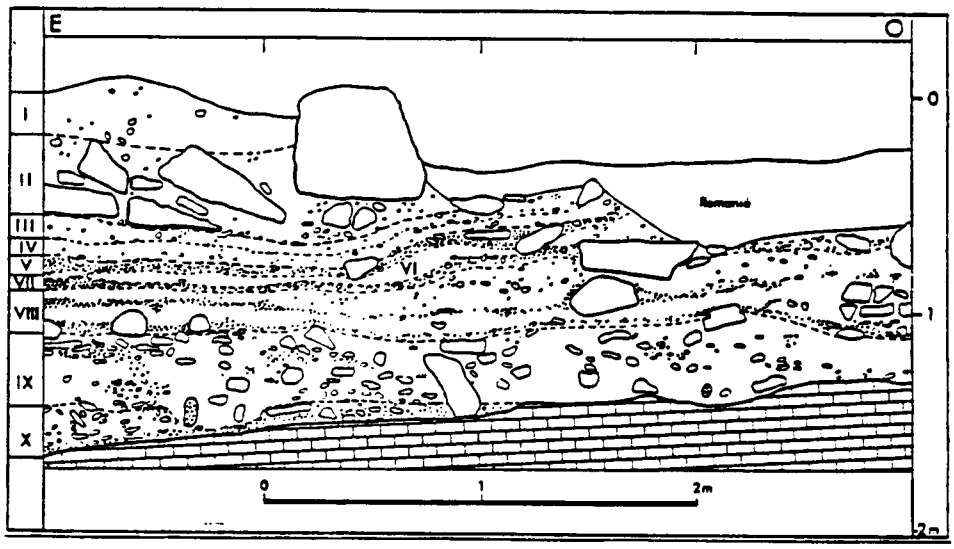


Figure 4.3 Stratigraphic section from Le Flageolet II. Reproduced from Rigaud (1982), with permission.

analyses (Laville 1970). An internally consistent series of three radiocarbon dates, establishes the time range during which the couche IX materials were deposited. upper (14110 + 690 B.P., Ly 917) and lower (15250 + 320 B.P., Ly 918) radiocarbon dates span approximately 1000 yrs (Rigaud 1982). Artifactual materials do not display any obvious vertical clustering upon initial inspection. The site then appears to be a typical case of overlapping deposits laid down over a possibly lengthy time span, which has suffered from little site-wide catastrophic postdepositional disturbance.

On the basis of the flint tools, this level has been classified as belonging to the Magdalenian V phase, although the radiocarbon dates and chronostratigraphic correlations place the level several thousand years prior to other assemblages with the same attributions (Laville et al. 1980:330; Rigaud 1970, 1982:399-410). Exact chronological and stratigraphic relationships among a variety of Magdalenian sites in the Southwest of France are somewhat controversial, because of its late industry but early dates this level is one of the most clearly contradictory that exist.

There are several areas within the site that evidence substantial disturbance, probably the result of shelter use by historic peoples and the construction of a small house and other buildings at the site. The upper

central portion of the excavated area contains a single large pothole, approximately 3 x 2 x .5 meters in volume (see fig. 4.2). Clearly large portions of the material once present are gone. The rest of the site, however, is intact with little or no obvious evidence of either large scale disturbance, or similar excavation.

Recorded Data

Couche IX contains some 12000 objects, 9342 of which have full three dimensional point provenience: 816 retouched flint tools; 3486 non-tool (i.e. unretouched) flint flakes or flake fragments; 2044 non-tool flint blades or blade fragments; and 2996 bone fragments, mostly Caribou (Rangifer tarandus). As data for the present analyses, the 3 dimensional provenience of each object, its technological and tool class, clock azimuth, length, width, and weight were recorded. Fragment or technological class was assigned, and length, width, and weight were recorded directly from the objects. Tool types for most of the flint tools had been previously assigned by J.-Ph. Rigaud (1970, 1982). Formal faunal identification and analyses are complete for less than half of the bone material (Delpech 1970), and are discussed in more detail below. Azimuth was reconstructed from maps of each square made during the excavation. Because this process was very error prone, azimuth was

recorded to the nearest 5 degrees (by protractor) and considered accurate to the nearest 15 degree increment from -90 (eastward) to +90 (westward) degrees, with 0 at grid north along the Y or frontal axis. This results in 12 azimuth categories, 6 positive and 6 negative. In addition, another variable, "density", was created by combining the length, width and weight such that:

$$\text{Density} = \text{Weight} / (\text{Length} * \text{Width}) \quad (4.1)$$

This is actually approximate density, as the measurement only takes into account the rectangular area of an object, rather than true volume. It is easily calculated however, compared to actual density, and can be assumed to be proportional to true density.

IV.2 Site Specific Modifications

It is clear from ethnoarchaeological accounts, that, distinct artifact groups, e.g. bones and stone tools may not receive similar treatment by humans (Binford 1978, 1986; Yellen 1977). Stone tools, in various stages of manufacture, use and discard, are extensively curated in some contexts, while the same is only very rarely true of animal bones. Similarly, debitage or debris from stone tool manufacture is only rarely curated in any meaningful sense. There is no good reason then, to expect a priori that these distinct material classes should exhibit the same types or scales of spatial patterning (Binford 1981a,

1978; Rigaud and Simek 1988). Consequently the materials from couche IX where analyzed in four separate groups: retouched stone tools, non-tool (i.e. unretouched) blades, non-tool flakes, and bone.

As objects subject to human manipulation, stone tools and bones may be clearly differentiated from each other and from the other groups. However the use of non-tool blades and flakes as separate classes requires some justification. Several recent microwear studies of Upper Paleolithic materials from France have suggested that unretouched blades may commonly have a primary tool use: cutting meat and hide (Moss 1983; Symens 1986; Vaughan 1985). They should not be lumped in with retouched tools for spatial analysis however, because they are relatively expedient to produce compared to the additional manufacturing and time investment expected for retouched tools. As more-or-less heavily retouched blades, most of the Upper Paleolithic flint tools are a specifically selected subset of all blades, and subject to distinctly special human processing, perhaps especially the microblades (Wise 1982). This also means that a large number of unretouched blades will probably not have a primary tool use; but rather will be debitage. These factors make unretouched blades a distinctly mixed category having elements connecting it to both debitage and (expedient) tool selection and use. These microwear

studies show unretouched flakes, on the other hand, as primarily debitage, much more rarely having been used as unmodified cutting tools, as compared to unretouched blades. Because of the unique processing required to make each class of object, and the unique place that each holds as part of subsistence, tool use, and other activities, the spatial patterns of each of these classes should reflect the distinct processes that each goes through. Because of the very low number of significantly worked bones, they were not broken down farther into categories reflecting tools/art and debitage. There are then, two material classes that should reflect the processes that both essentially expedient and more curated tool types undergo (retouched tools and non-tool blades), one that should show primarily stone tool debitage processing (non-tool flakes), and one that should show a mix of those processes that effect bone debitage and tool/art objects (bone).

At a global scale, spatial patterns from all four material classes should be largely distinct, given that the material classes actually represent distinct treatments and processes, and that there have been no global scale post-depositional processes acting to eliminate such patterns. If, on the other hand, all spatial patterning is essentially identical across material classes and depth, it argues for either massive

restructuring of the site on a global scale, or extremely well patterned behavior conditioning all aspects of material culture and use of the same site for roughly 1000 years.

All of the analyses of couche IX materials were carried out from 1 to 50 clusters, using the global Z-score transformation and a Z-axis expansion factor of 5. These were chosen based on the results presented in chapter III. A Z-axis expansion factor of five should result in an error rate of between 0 and 4% of the total number of objects in finding separate, largely horizontal levels (if they exist) in a given analysis, depending upon the exact assumptions that a particular set of data can meet (see tables 3.3-3.18). Because of the relatively unknown nature of the data and the analytic techniques, I thought it best to be conservative and accept a somewhat greater range of discriminant error estimates with the low expansion factor, than to risk unknown types of errors by using very high expansion factors despite the much lower estimates of discrimination error (see chapter III above).

In previous uses of the K-means technique, the log(%sse) vs. number of clusters plot was used to pick optimal solutions for further analysis. Those solutions whose log (%sse) figures fell substantially below both the expected level (i.e. dropped sharply from one solution to

the next) and a similar plot derived from randomizing the data, were chosen as optimal solutions. In the case of the Le Flageolet II analyses however, this log(%sse) plot is largely flat after 10 clusters, although in every case it was below that obtained from the randomized data. As a consequence, a plot showing the log of the difference between each pair of % SSE values (LN (%sse1 - %sse2)) is used for this purpose (see fig. 4.4). On these plots, peaks occur at solutions that precede a large drop in % sse. These peaks represent "elbows" on the more commonly used plots, and optimal solutions. It becomes apparent when inspecting these plots that there are occasionally small areas with a large number of peaks. On figure 4.4, the section between 30 and 40 clusters is an excellent example. These areas are usually very similar from one solution to the next. In order to avoid inconsistency and needlessly complicated analyses, only those peaks preceded by at least two lower points were accepted as optimal solutions. Returning to figure 4.4, the relevant area contains only two optimal solutions- at 34 and 38 clusters.

The next section begins the analysis of three dimensional spatial patterning of the materials in couche IX from Le Flageolet II. Results of the tool analysis will be presented in detail. Non-tool blade, non-tool flake, and bone analyses will be more briefly summarized.

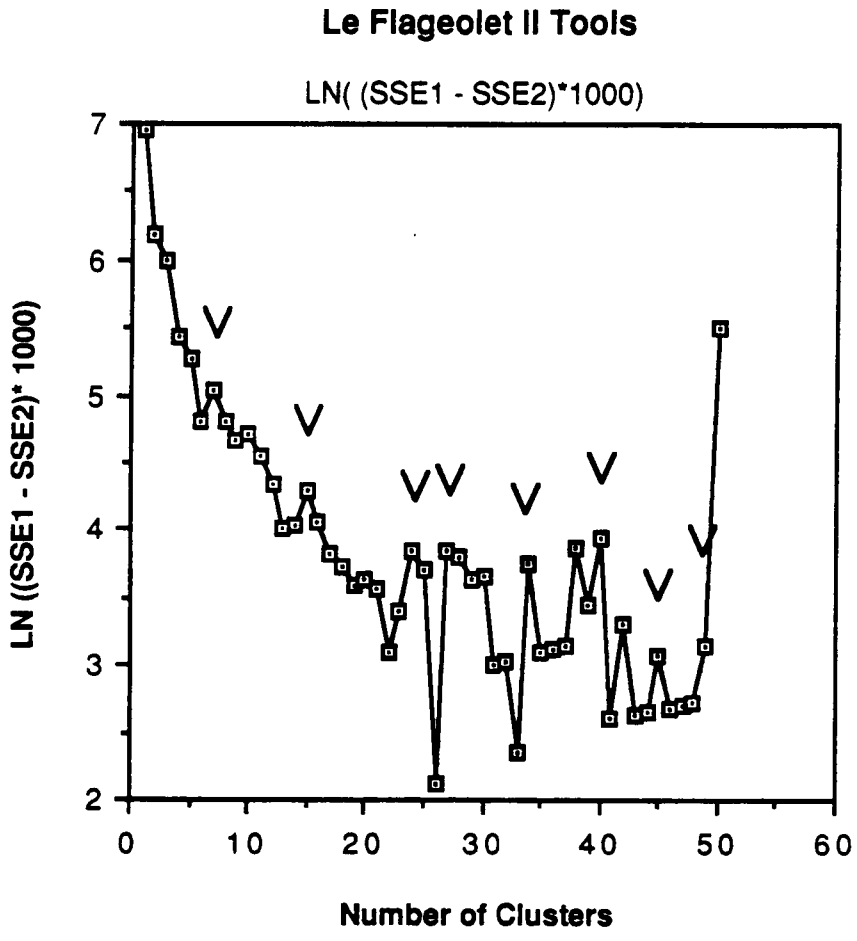


Figure 4.4 Le Flageolet II Tools, LN((sse1-sse2)*1000). Optimal solutions are indicated at the 8, 16, 25, 28, 35, 39, 46, and 50 cluster solutions.

IV.3 Analyses

Site Wide Patterns

Initial investigations involved mainly correlation and Chi squared association statistics, in an attempt to examine object attribute patterning with depth. The attributes azimuth, weight, length, width, and density are common to all objects at Le Flageolet II, and so may be compared globally. Weight, length, width and density for each object, by material class were correlated with object depth using Spearman's rank order correlation statistic. No results significant at $p < .10$ were obtained. The relationships between an object's depth and azimuth measurements were investigated using the Chi squared statistic. Azimuth measurements organized into 12 categories (every 15 degrees around grid north), showed no significant Chi square relationships ($p < .10$) with depth category when depth was organized into classes consisting of every 2, 5, 10, and 15 cm. Similarly, there were no significant Chi square relationships ($p < .10$) between azimuth and any of the other measured attributes when organized into appropriate classes.

The lack of patterning between the measured attributes for each object and their depths suggest that there has been little or no large scale post-depositional vertical movement of objects.

Global Homogeneity by Tool Class

Retouched tools from Le Flageolet II were initially grouped into 11 tool classes (defined in table 4.1), each representing a number of similar types. The objects were then clustered, and optimal cluster solutions identified from the %sse differences curve (Fig. 4.4). Peaks in the curve identifying optimal solutions occurred at the 8, 16, 25, 28, 35, 39, 46, and 50 cluster solution levels. Calculation of the observed and simulated K' and RICD indices by tool class for these solutions as a whole results in the plots shown in Figure 4.5. Comparing the observed K' values for the global solution with the mean simulated values and their 95% Confidence Interval (henceforth CI), show the observed values to be generally high, and substantially above those derived from simulated clustering of data with the same class frequency distribution. When compared with the T-Test (Zar 1974:228-229), the slopes of Pearson product-moment regression lines for the observed and mean simulated K' data are not significantly different (at $P < .001$). Mean RICD values for the global solution are quite low and always lower than the expected values. A T-test on the slopes of regression lines calculated for the observed

Table 4.1 Tool Class definitions for the Le Flageolet II analyses. Tool type numbers follow the Type du Paleolithique Superieur (1972) from Le Tensorer (1981).

Class	Types	Contents
1	1-18	Grattoirs
2	20-29	Percoirs/Becs
3	19,30-46	Burins
4	50,51,54,55,56,65,66, 68-70,92,96-102	Points
5	53,57-60	Truncated Elements
6	61,62,74-76,105	Misc. Retouched Pieces
7	72,73	Notches
8	77-82	Microliths
9	84-88	Backed Bladelets
10	83,90,91,93-95	Bladelets
11	63,64,103,104	Heavily Retouched Blades

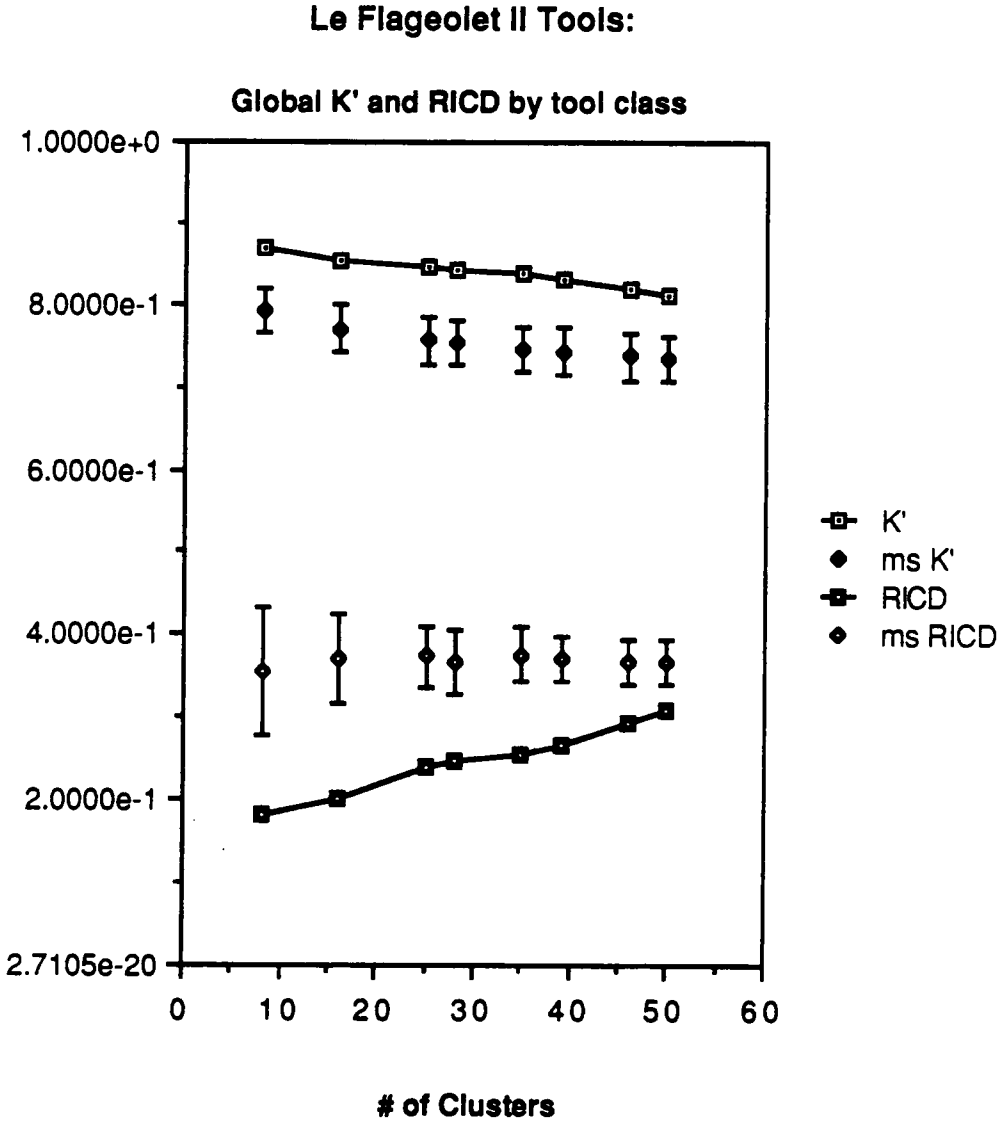


Figure 4.5 Le Flageolet II tools, global K' and mean RICD by tool class.

mean RICD and mean simulated RICD, however, shows that the two slopes are significantly different at $p < .05$. Clearly differences in class proportion by cluster increase more quickly than expected as the number of clusters increases (see fig. 4.5).

Calculation of RCH, and modified RCH values by tool class (see chapter II), from the global class correlation matrix using clusters as cases, results in somewhat different curves (Figure 4.5). While both curves are similarly flat (no significant difference in slope at $P < .001$), the RCH curve is low, and the modified RCH curve is moderately high. Simek's (1984) interpretation of the RCH curve is based primarily on their overall shape, in this case the RCH curve would fit well with his expectations for low but relatively stable homogeneity relationships across the entire couche (i.e. no change with increasing numbers of clusters). The modified RCH curve suggests a similar relationship, but a higher level of homogeneity. Note that all homogeneity measures (K', RCH, MRCH) have suggested essentially stable relationships with increasing number of clusters.

Global Homogeneity by Fragment Class

Table 4.2 shows the fragmentation classes for the Flageolet II tools. When homogeneity is calculated using

Table 4.2 Technological class definitions for Le Flageolet II flint objects. In order to maintain comparability between the material classes (i.e. tools, and non-tool blades and flakes) no distinction is made between blank types.

Class	Definition: Fragment Type
1	Proximal
2	Medial
3	Distal
4	Indeterminate
5	Complete

these classes, the resulting curves are substantially similar to those resulting from the tool class analyses (Figure 4.6). Again K' is high, and above and similar in slope to the curve of simulated mean values. Observed mean RICD is always lower than mean simulated RICD, and is positively sloped, while the mean simulated curve is essentially flat. The main differences between the two sets of curves is that technological class homogeneity and mean RICD always have greater magnitude then the tool class measures.

Global Attribute Correlations

In addition to the homogeneity analyses by tool and technological class, the relationships between measured object attributes were examined by cluster and solution level. In an effort to examine the potential for major disturbance on a global scale, and provide a background for the correlations by cluster for couche IX, tool attributes were correlated by arbitrary levels created at intervals of 5 and 10 centimeters along the vertical axis. The within-level means of four object attributes (weight, length, width, and density) were calculated and correlated with their mean within-level depth, as was the modal azimuth (happily, in all cases modal azimuth was a unique value). Table 4.3 presents these results by arbitrary

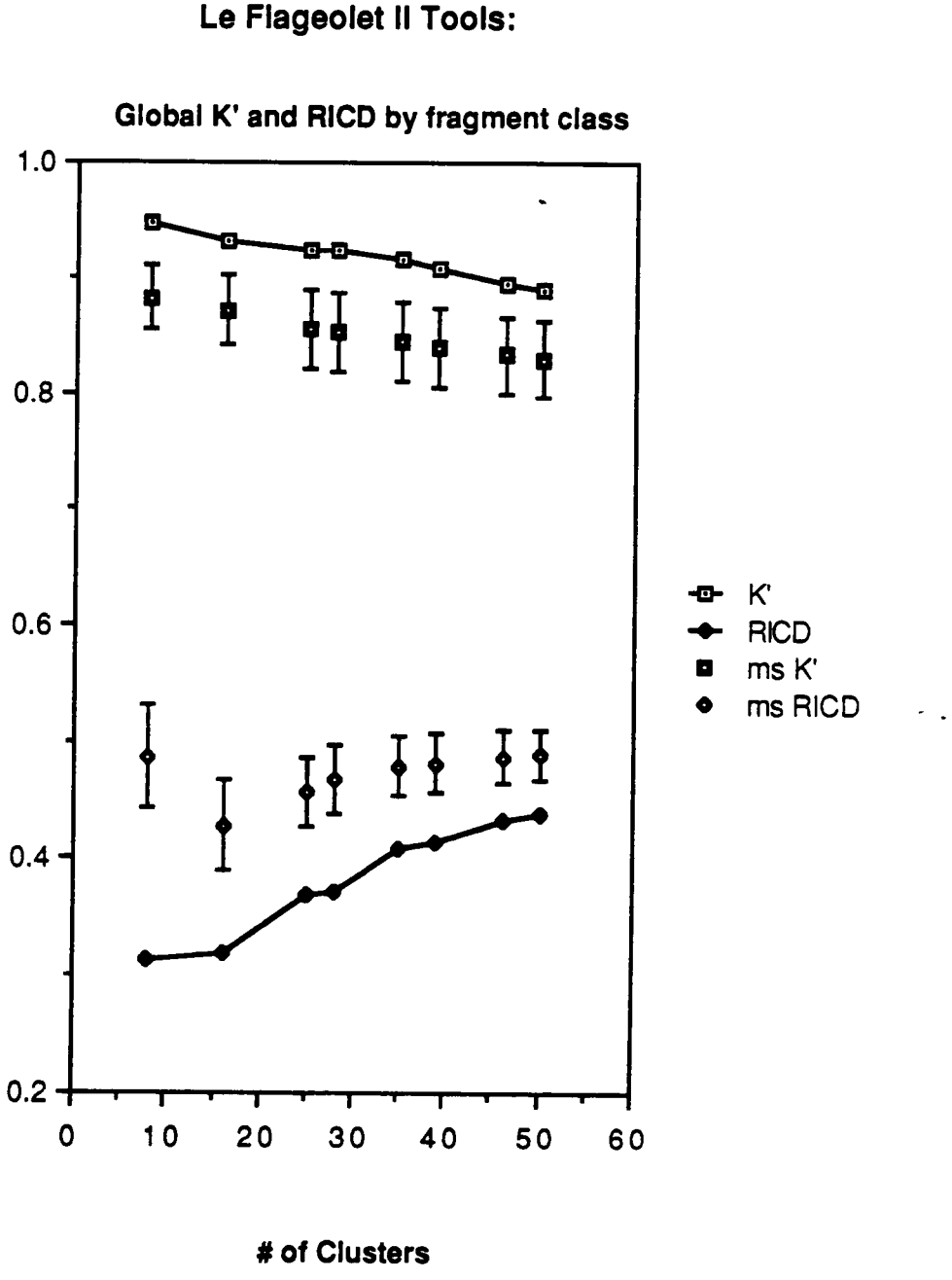


Figure 4.6 Le Flageolet II tools, global K' and mean RICD by fragment class.

Table 4.3 Spearman's rank order correlations between mean attribute measurements and mean arbitrary level depth for Le Flageolet II tools.

Level thickness (cm)	depth with:	Rho	P
5	Width	.40	.09
	Density	.58	.01
10	Density	.54	.08

level for the lithic tools. The most consistent relationships are between mean within-level depth and density. Width was also significantly correlated with depth, but only when the arbitrary levels were 5 cm thick. The correlations increase in strength with decreasing level thickness. These results suggest very little patterning between depth and width on a global scale, and are consistent with the lack of patterning found between an objects depth and measured attributes for the overall assemblage. While this is generally true, mean object density clearly increases with mean within-level depth.

Table 4.4 presents the results of correlation by cluster solution of within-cluster mean weight, length, width, density, and modal azimuth against mean within-cluster depth and its standard deviation. The major consistent relationships with depth involve width and density. All correlations behave similarly: decreasing in strength with increasing numbers of clusters. The correlation between width and depth for example, decreases from .66 at 8 clusters to .32 at 50 clusters. Clearly all four variable means tend to increase with mean within-cluster depth, however as ever smaller clusters are defined this relationship weakens and eventually disappears with the exception of the density correlation. Within-cluster depth standard deviation, as a measure of

Table 4.4 Spearmans rank order correlations between mean within cluster depth and within-cluster depth standard deviation, and mean within-cluster object attributes significant at the .10 level for Le Flageolet II tool analysis by cluster solution.

CSL	Depth with	RHO	P	Depth S.D.	RHO	P
8	Azimuth	-.78	.03	Length	-.78	.02
	Width	.66	.07	Width	-.66	.07
16	Azimuth	-.48	.05			
	Length	.48	.05			
	Width	.55	.02			
	Density	.51	.08			
25	Azimuth	-.54	.004	Length	-.38	.05
	Width	.49	.01	Width	-.37	.06
	Density	.40	.04	Density	-.41	.04
				Azimuth	.33	.09
28	Length	.33	.07			
	Width	.51	.004			
	Density	.50	.006			
35	Length	.28	.09			
	Width	.48	.002			
	Density	.46	.005			
39	Length	.28	.07			
	Width	.32	.04			
	Density	.36	.02			
46	Density	.29	.04			
50	Density	.27	.05			

the vertical extent of a given cluster also shows several fairly consistent relationships, although only within specific spatial scales, rather than globally. At solution levels between 8 and 25 clusters, length and width are strongly negatively correlated with depth SD., while at the 25 cluster solution density is moderately negatively correlated with depth SD. and azimuth is moderately positively correlated. When these relationships are present in more than one solution, they also show a trend towards decreasing strength with increasing numbers of clusters. Negative correlations between the attributes and within-cluster depth standard deviation suggest that horizontal groups may be largely responsible for these trends.

Results of the global level analyses suggest that most clusters are substantially similar in content and class distribution at all solution levels, and that differences between and among clusters increase only slightly with increasing numbers of clusters. These results are supported by both inspection of the individual cluster K values and class distributions, and the stability of the class correlation relationships by solution level. Attribute correlations with within-cluster depth and depth SD, suggest that both width and density generally increase with depth when grouped by clusters. In contrast modal Azimuth tends to decrease

with within-cluster depth. The changes occur despite the relative stability of the tool class relationships. This suggests that it is the physical nature of the tools themselves which changes with depth, rather than simply their type classes. Tool class stability with increasing numbers of clusters implies that both structural and assemblage redundancy may be expected to be relatively high, while the attribute correlations with within-cluster depth suggest that important changes in the nature of the technology or tool functions are changing.

Homogeneity by Level

To address this issue in greater detail, the tool clusters may be broken into a series of levels based on their spatial relationships. An attempt was made to be as consistent as possible with the provisional definition of an occupation given above (see chapter II). This was not always possible however. Inspection of the cluster positions and volume (as shown by the cluster centroids and standard deviations around them in various projections in figures 4.7-4.8), suggests that there may be a number of distinct levels in couche IX. Table 4.5 shows the number of objects, number of clusters, K' and mean RICD values when calculated by level for each of the optimal solutions. Because each solution redefines the extent of

Table 4.5 Level characteristics for the Flageolet II tool assemblage.

CSL	Level	# objects	# clusters	Tool class K'	Tool class RICD	Fragment Class K'	Fragment Class RICD
8	1	111	2	.866	.189	.944	.189
	2	320	2	.889	.180	.972	.215
	3	296	2	.879	.131	.955	.235
	4	89	2	.813	.209	.828	.551
16	1	94	2	.865	.168	.932	.209
	2	427	6	.875	.191	.965	.250
	3	259	6	.857	.193	.914	.266
	4	36	2	.693	.189	.613	.454
25	1	34	2	.833	.199	.899	.195
	2	112	3	.869	.236	.941	.441
	3	282	7	.867	.223	.956	.287
	4	233	6	.839	.242	.936	.325
	5	131	5	.830	.258	.858	.409
	6	24	2	.741	.211	.729	.449
28	1	34	2	.833	.199	.899	.195
	2	112	3	.869	.236	.941	.441
	3	273	7	.865	.214	.955	.292
	4	238	7	.833	.246	.939	.303
	5	136	7	.808	.270	.845	.421
	6	23	2	.762	.216	.756	.444
35	1	24	2	.833	.199	.899	.195
	2	65	3	.860	.302	.932	.373
	3	218	7	.871	.196	.950	.352
	4	234	8	.837	.236	.939	.373
	5	124	4	.823	.241	.926	.204
	6	78	4	.862	.259	.894	.372
	7	53	5	.717	.291	.704	.606
	8	10	2	.618	.131	.643	.671
39	1	34	2	.833	.199	.899	.195
	2	65	3	.860	.302	.932	.373
	3	209	7	.871	.221	.955	.328
	4	110	5	.839	.277	.896	.401
	5	168	7	.805	.265	.914	.400
	6	113	4	.865	.237	.915	.249
	7	90	7	.775	.278	.811	.493
	8	17	2	.748	.391	.803	.592
	9	10	2	.618	.131	.643	.671

Table 4.5 continued

CSL	Level	# objects	# clusters	Tool class K'	Tool class RICD	Fragment Class K'	Fragment Class RICD
46	1	24	2	.833	.199	.899	.195
	2	65	3	.860	.302	.932	.373
	3	189	8	.848	.217	.929	.425
	4	129	7	.842	.276	.897	.387
	5	156	8	.810	.298	.913	.420
	6	176	10	.805	.283	.900	.409
	7	40	4	.667	.322	.674	.559
	8	17	2	.748	.391	.803	.592
	9	10	2	.618	.131	.643	.671
50	1	34	2	.833	.199	.899	.195
	2	65	3	.860	.302	.932	.373
	3	143	7	.821	.317	.904	.466
	4	204	12	.824	.332	.904	.401
	5	127	7	.814	.292	.917	.432
	6	112	6	.781	.262	.888	.319
	7	64	5	.841	.313	.911	.489
	8	40	4	.667	.322	.674	.559
	9	17	2	.748	.391	.803	.592
	10	10	2	.618	.131	.643	.671

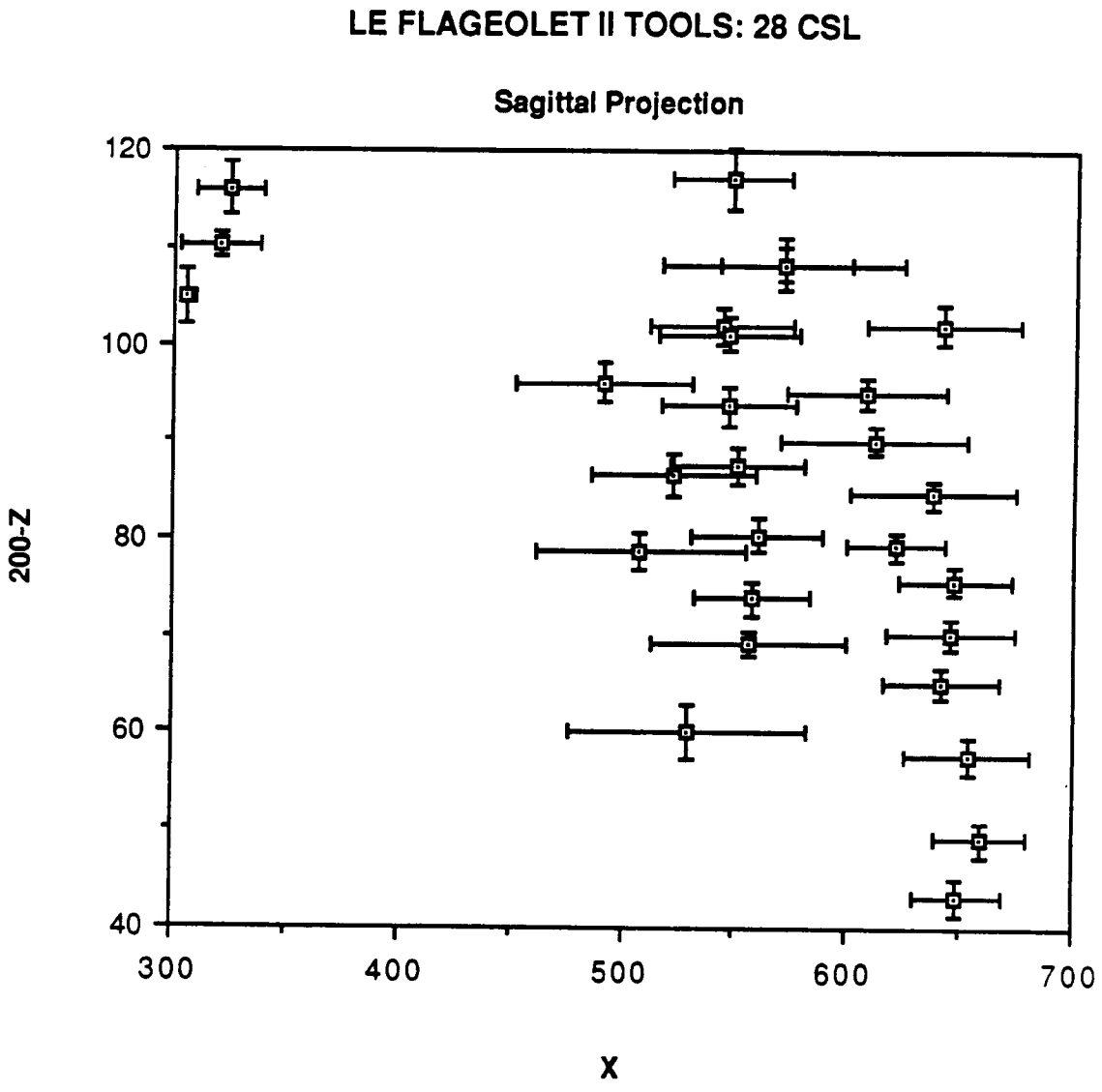


Figure 4.7 Le Flageolet II tools, sagittal projection of cluster centroids with error bars showing 2 standard deviations around the mean value on each axis.

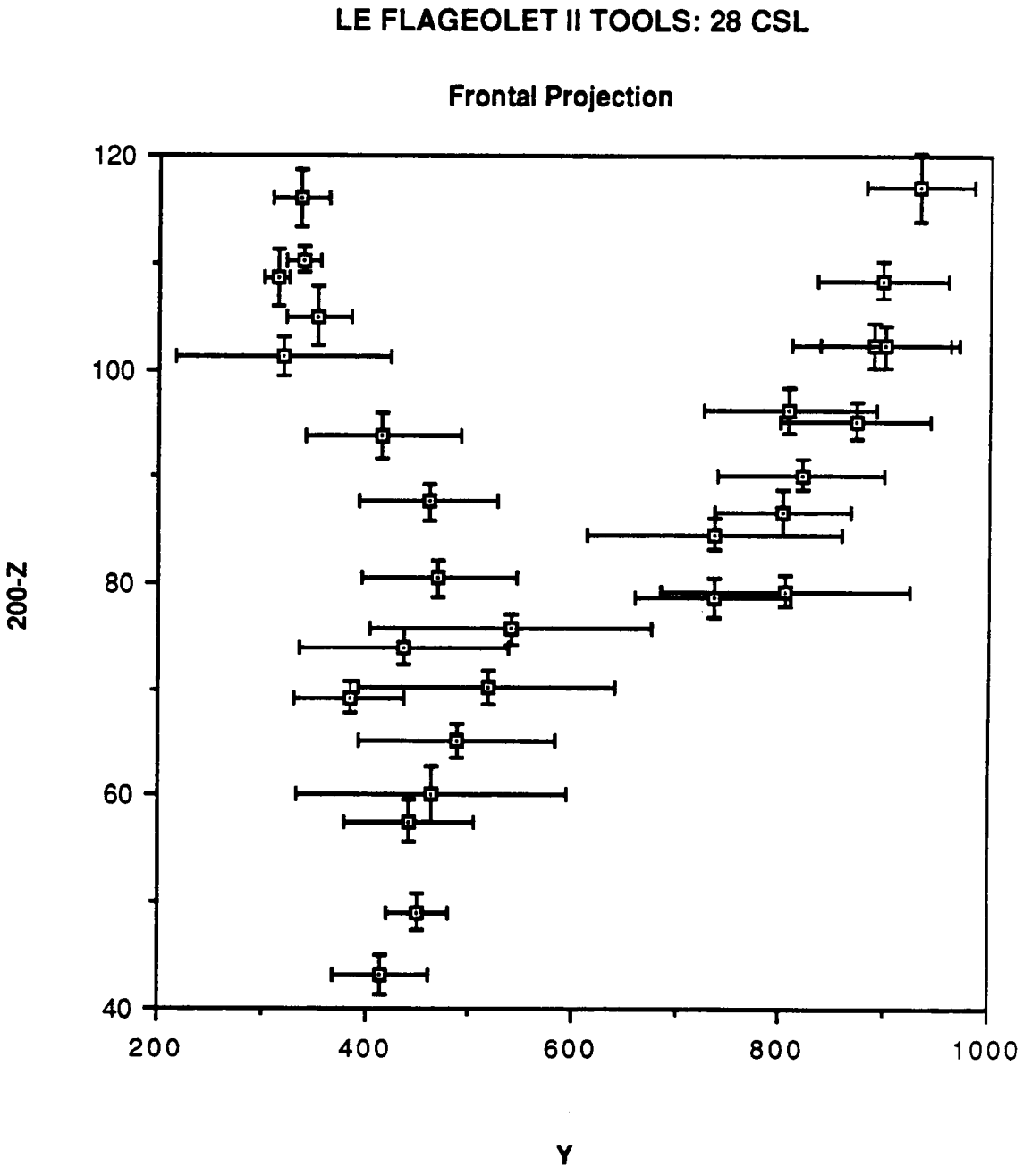
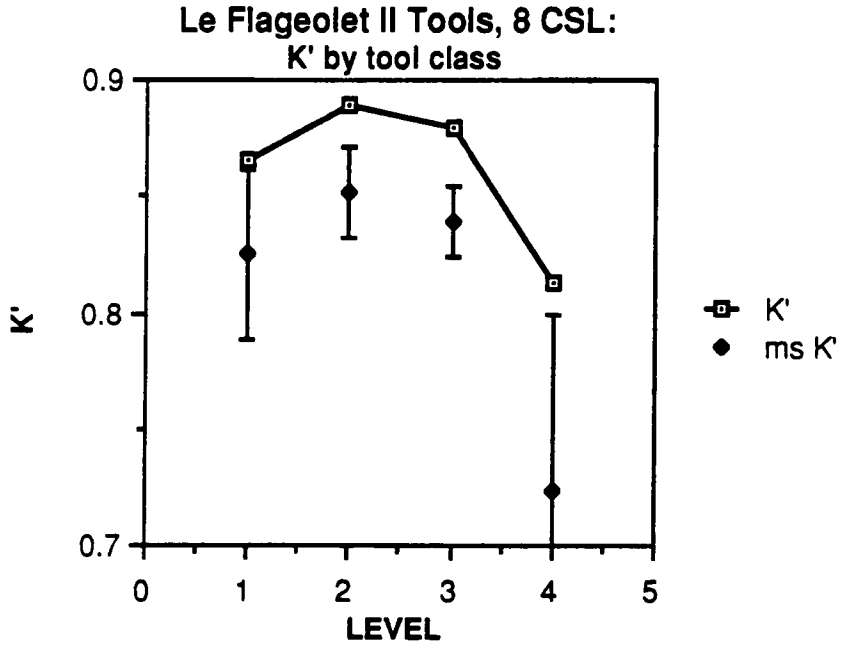


Figure 4.8 Le Flageolet II tools, frontal projection of cluster centroids with error bars showing 2 standard deviations around the mean value on each axis.

each cluster, and its relationships to the other clusters, each may have a unique number of visually apparent levels.

Figures 4.9-4.16 show the observed and mean simulated K' and RICD for each level using the tool class. In this case, both K' and mean RICD were calculated using only the clusters within each level at each cluster solution. The homogeneity relationships evidence a clear trend: decreasing with increasing number of levels. When viewed as a series, overall homogeneity across cluster solutions, can be seen to be above the mean simulated values for the lower solution levels (8 and 16), and to gradually become more mixed into the 95% CI around the mean simulated values in the higher solutions (46 and 50 csl). Similarly, the observed mean RICD is initially always lower than the mean simulated values, often very much so, becoming more mixed only gradually. At the 46 and 50 cluster solutions however, the observed mean RICD values are substantially above the mean simulated value for level 8, and very close in level 9.

Figures 4.17-4.24 show the observed and mean simulated K' and RICD for each level using the fragmentation classes. While these curves generally exhibit the same properties as the tool class curves, there are substantial differences. First, the degree of



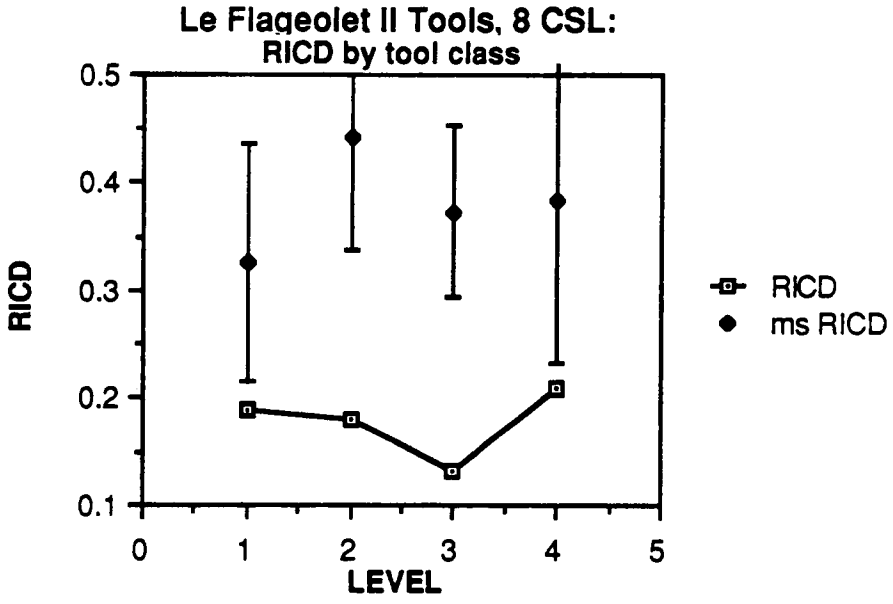
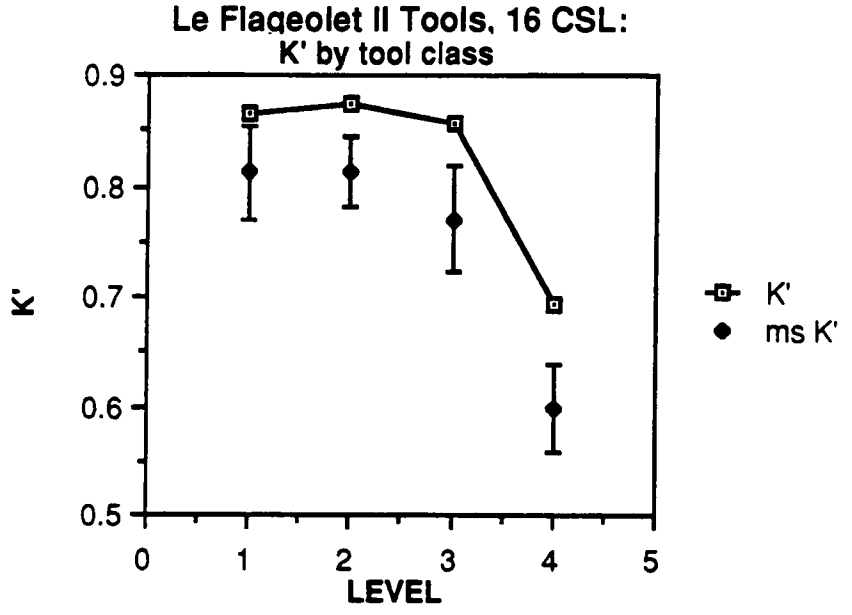


Figure 4.9 Le Flageolet II tools, K' and mean RICD by tool classes and level for the 8 cluster solution.



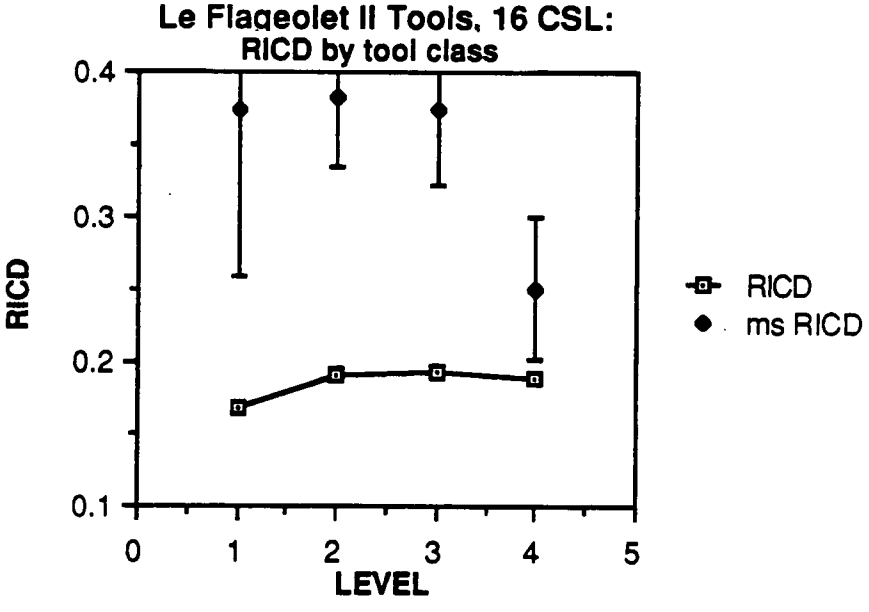
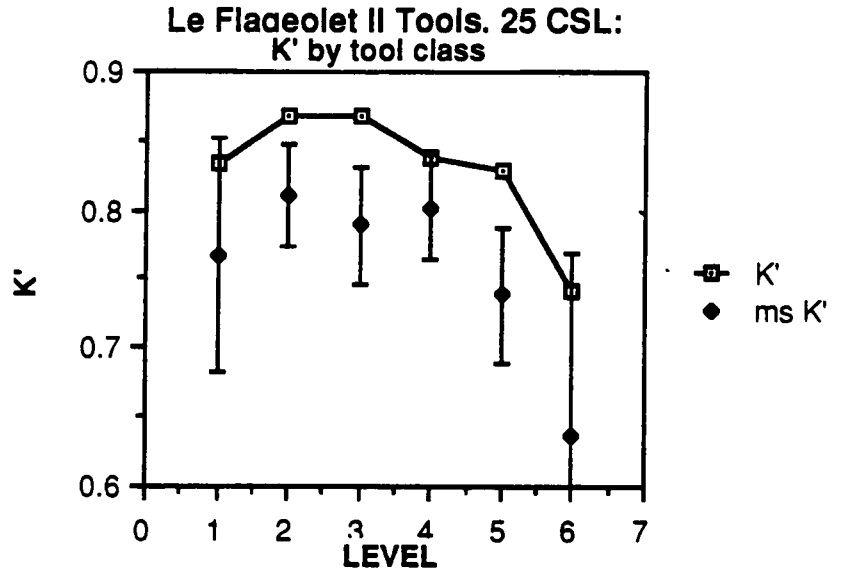


Figure 4.10 Le Flageolet II tools, K' and mean RICD by tool classes and level for the 16 cluster solution.



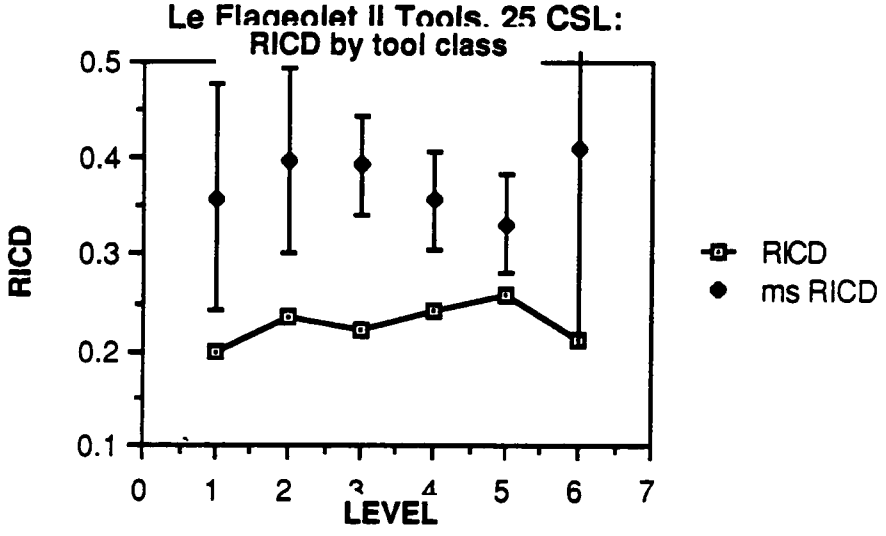
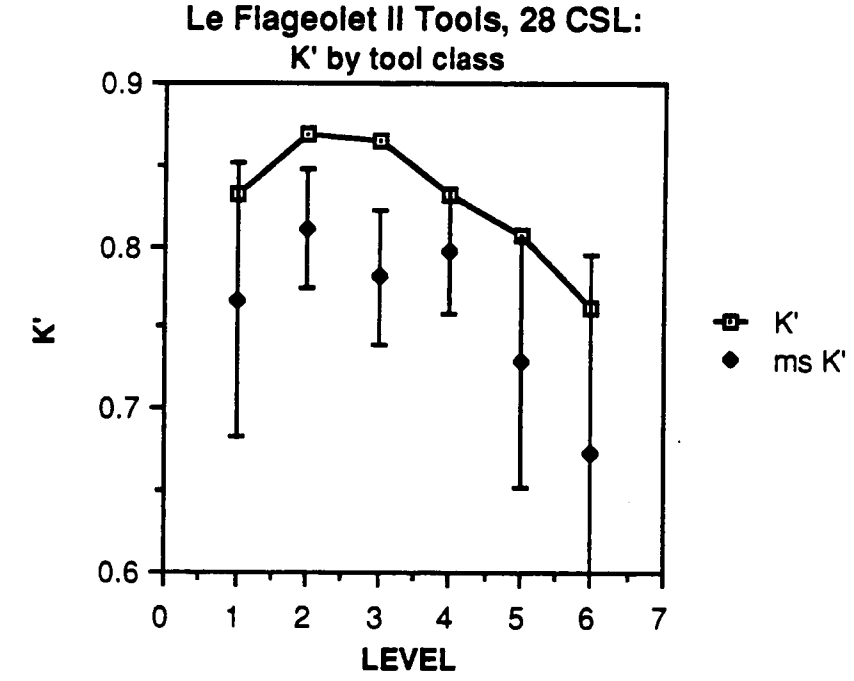


Figure 4.11 Le Flageolet II tools, K' and mean RICD by tool classes and level for the 25 cluster solution.



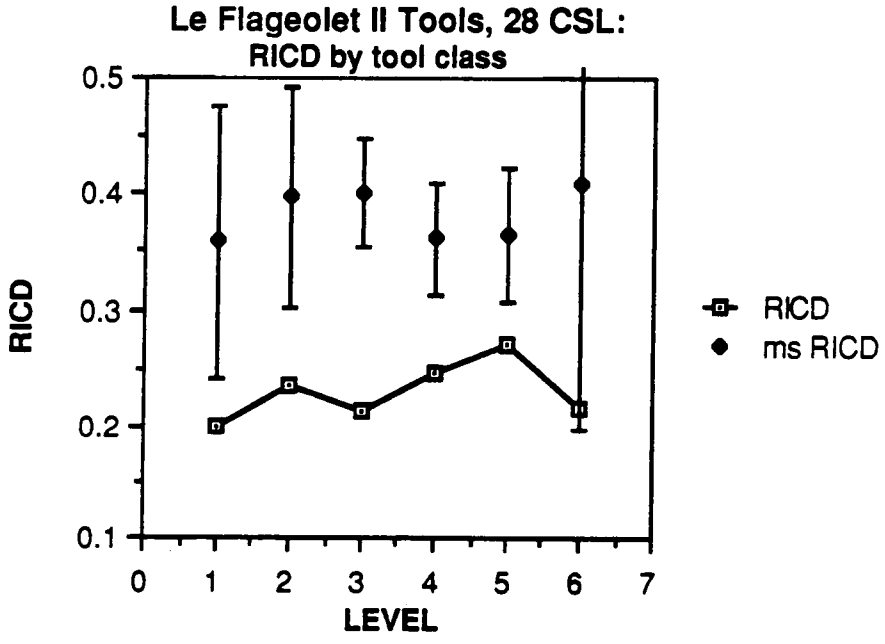
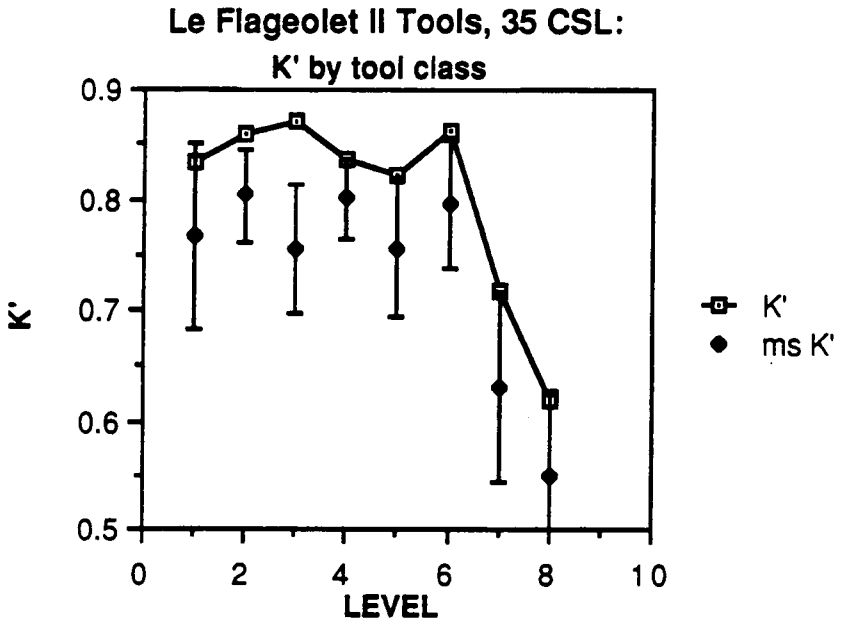


Figure 4.12 Le Flageolet II tools, K' and mean RICD by tool classes and level for the 28 cluster solution.



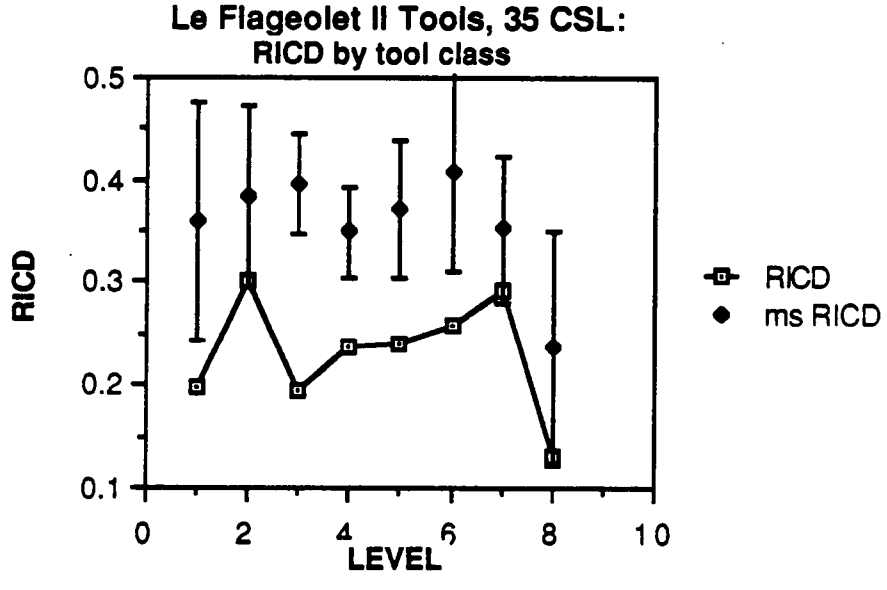


Figure 4.13 Le Flageolet II tools, K' and mean RICD by tool classes and level for the 35 cluster solution.

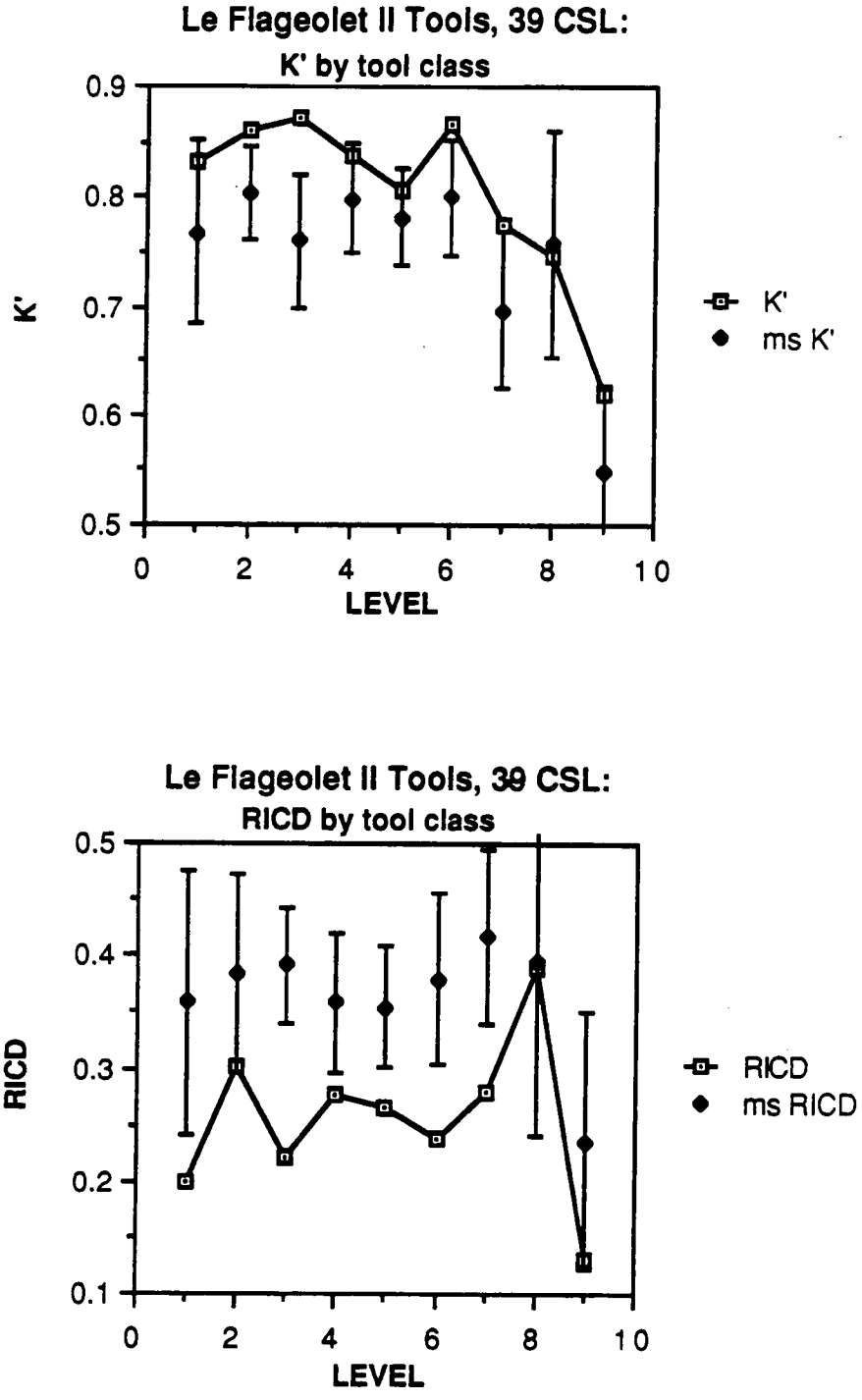
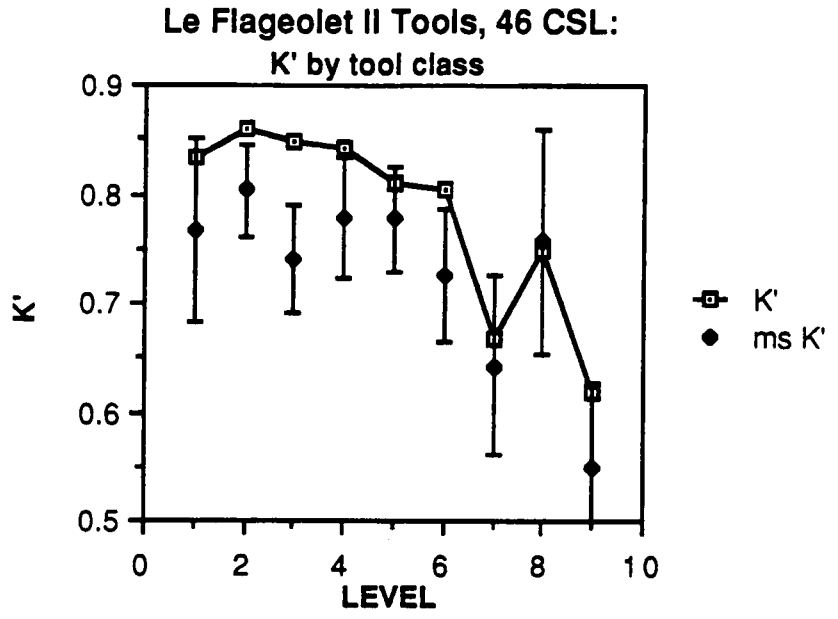


Figure 4.14 Le Flageolet II tools, K' and mean RICD by tool classes and level for the 39 cluster solution.



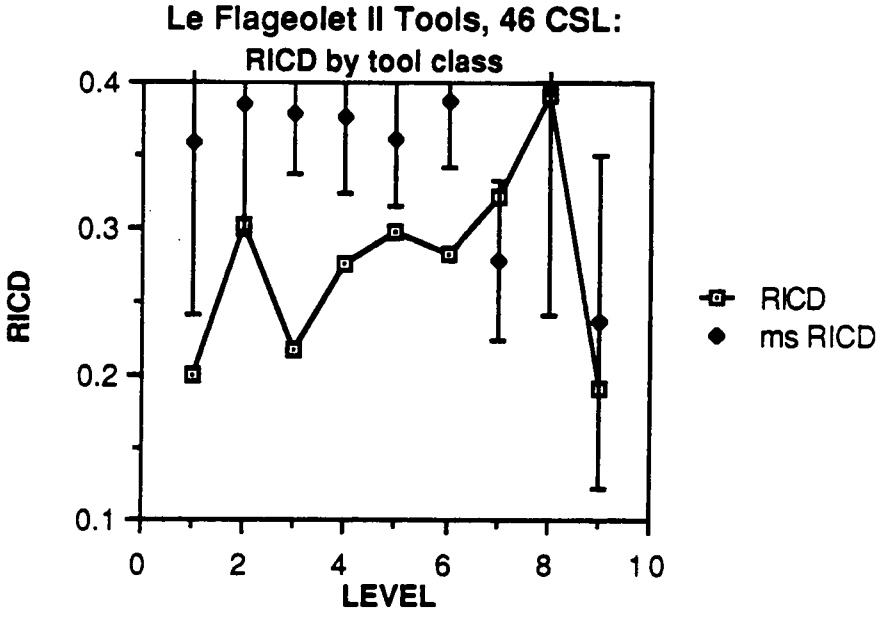
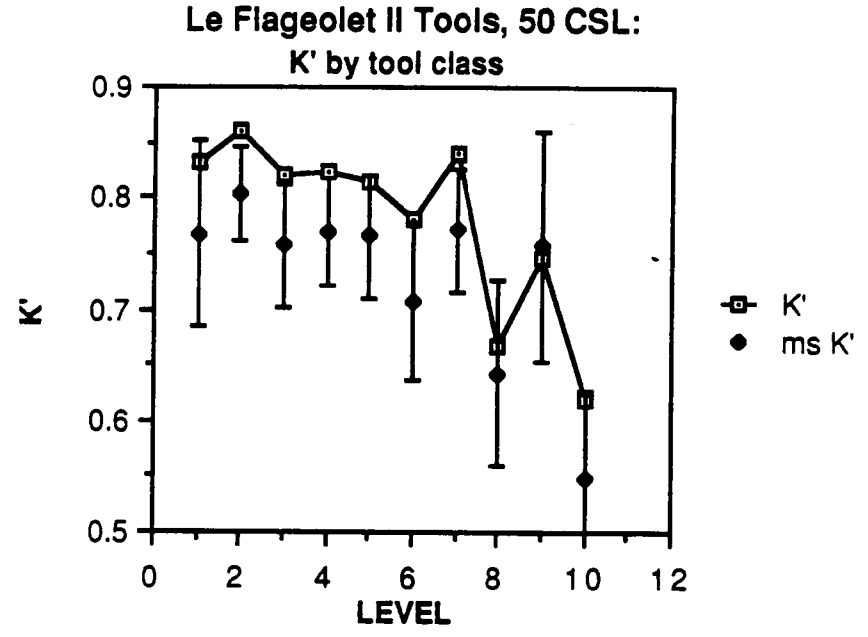


Figure 4.15 Le Flageolet II tools, K' and mean RICD by tool classes and level for the 46 cluster solution.



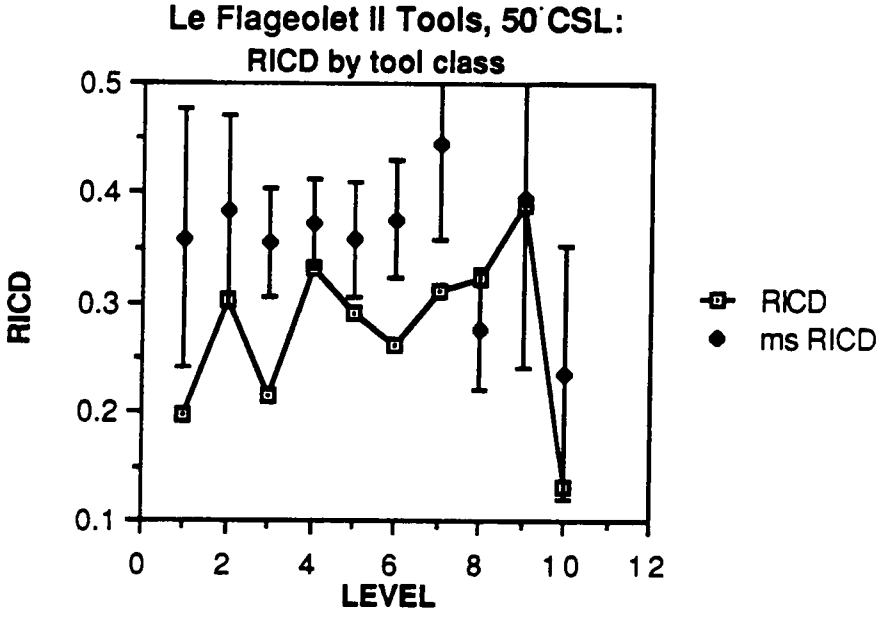
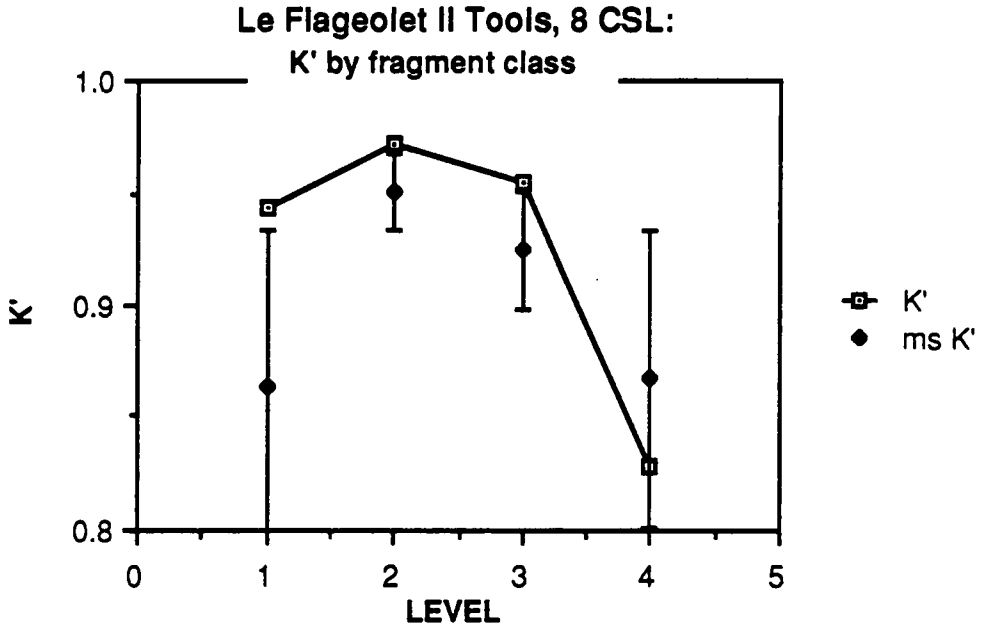


Figure 4.16 Le Flageolet II tools, K' and mean RICD by tool classes and level for the 50 cluster solution.



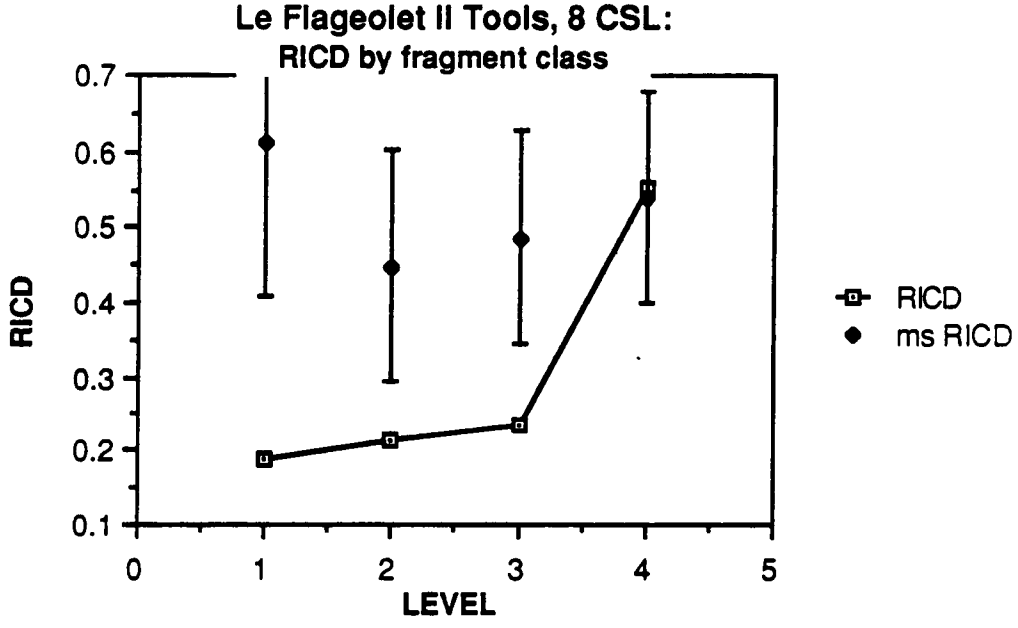


Figure 4.17 Le Flageolet II tools, K' and mean RICD by fragment classes and level for the 8 cluster solution.

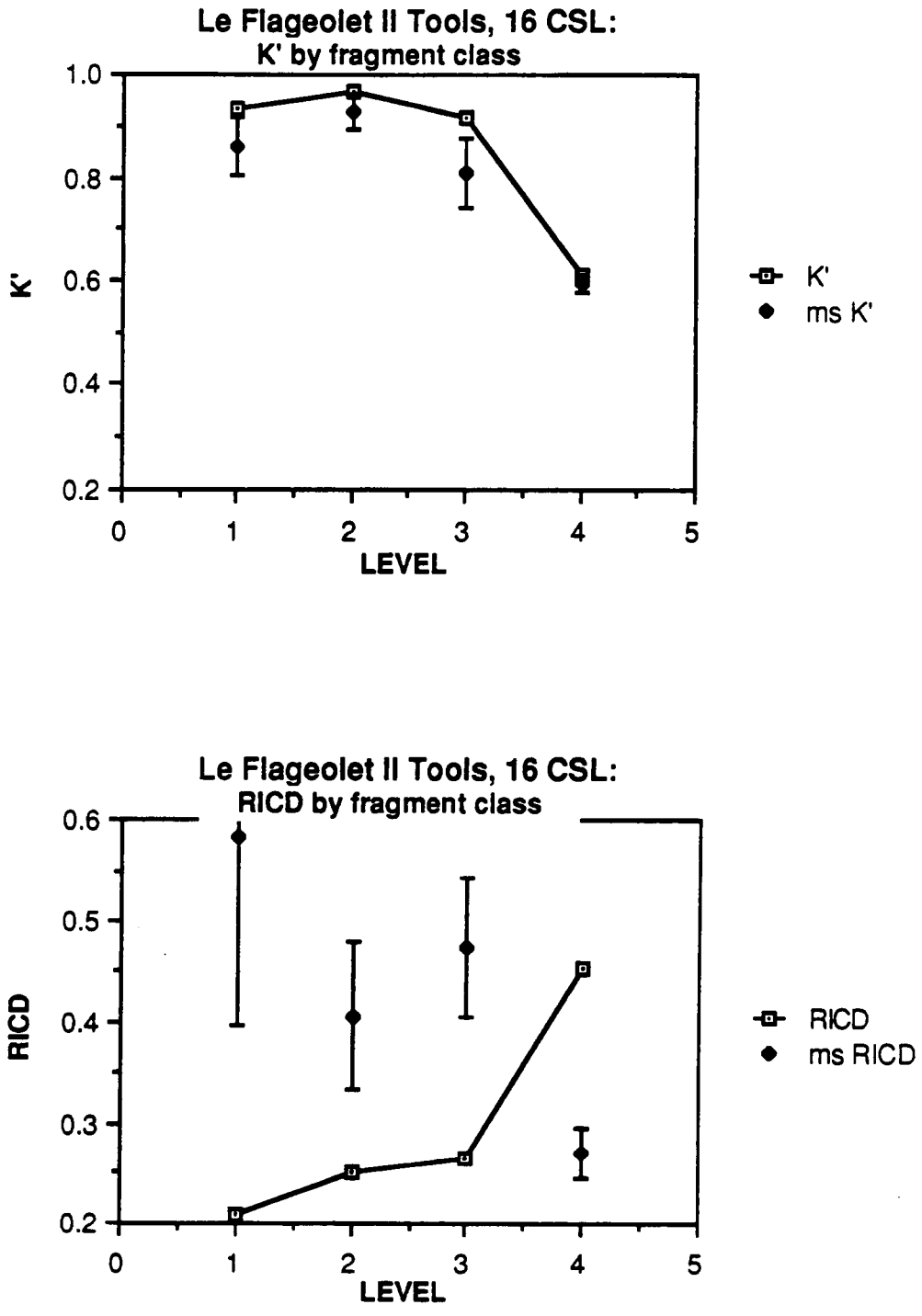
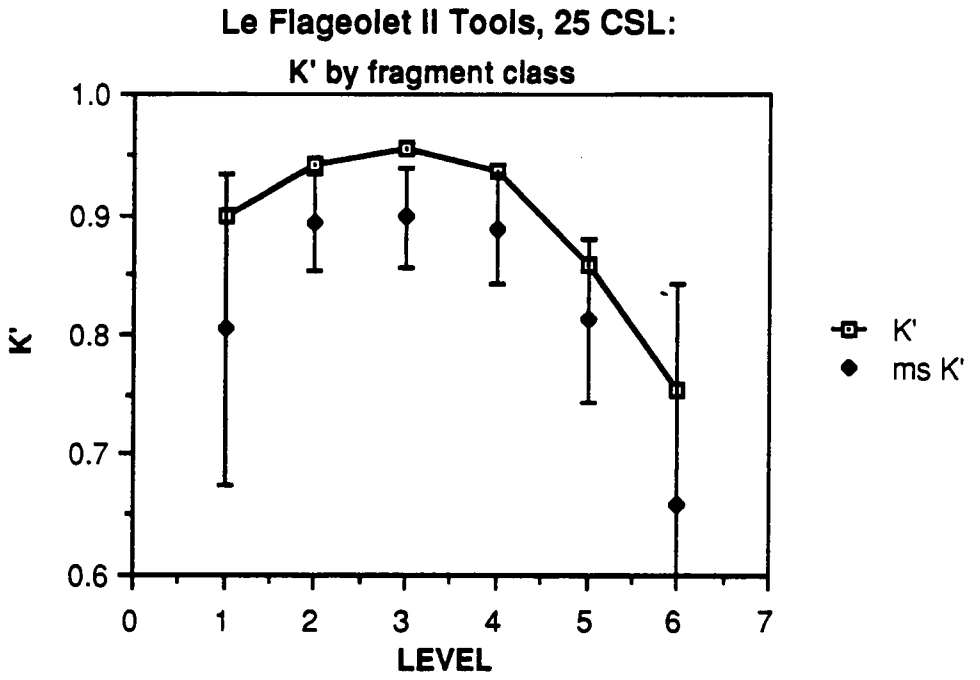


Figure 4.18 Le Flageolet II tools, K' and mean RICD by fragment classes and level for the 16 cluster solution.



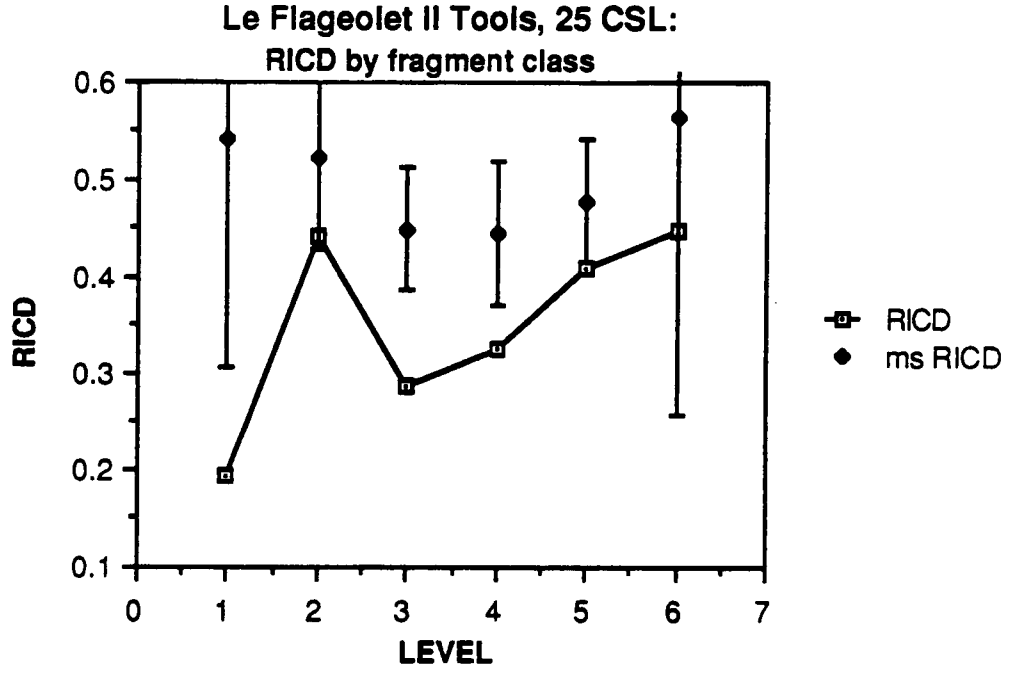


Figure 4.19 Le Flageolet II tools, K' and mean RICD by fragment classes and level for the 25 cluster solution.

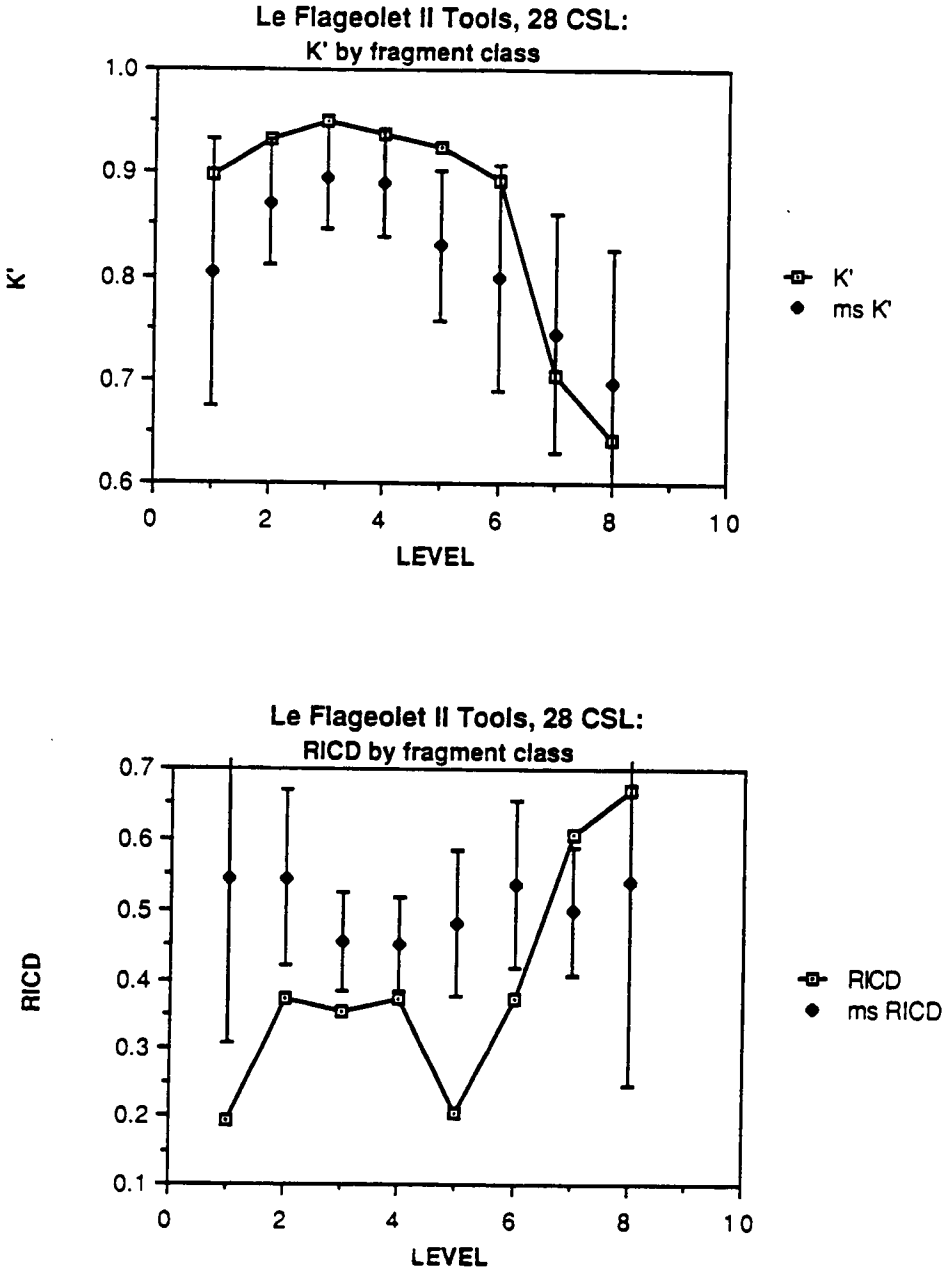


Figure 4.20 Le Flageolet II tools, K' and mean RICD by fragment classes and level for the 28 cluster solution.

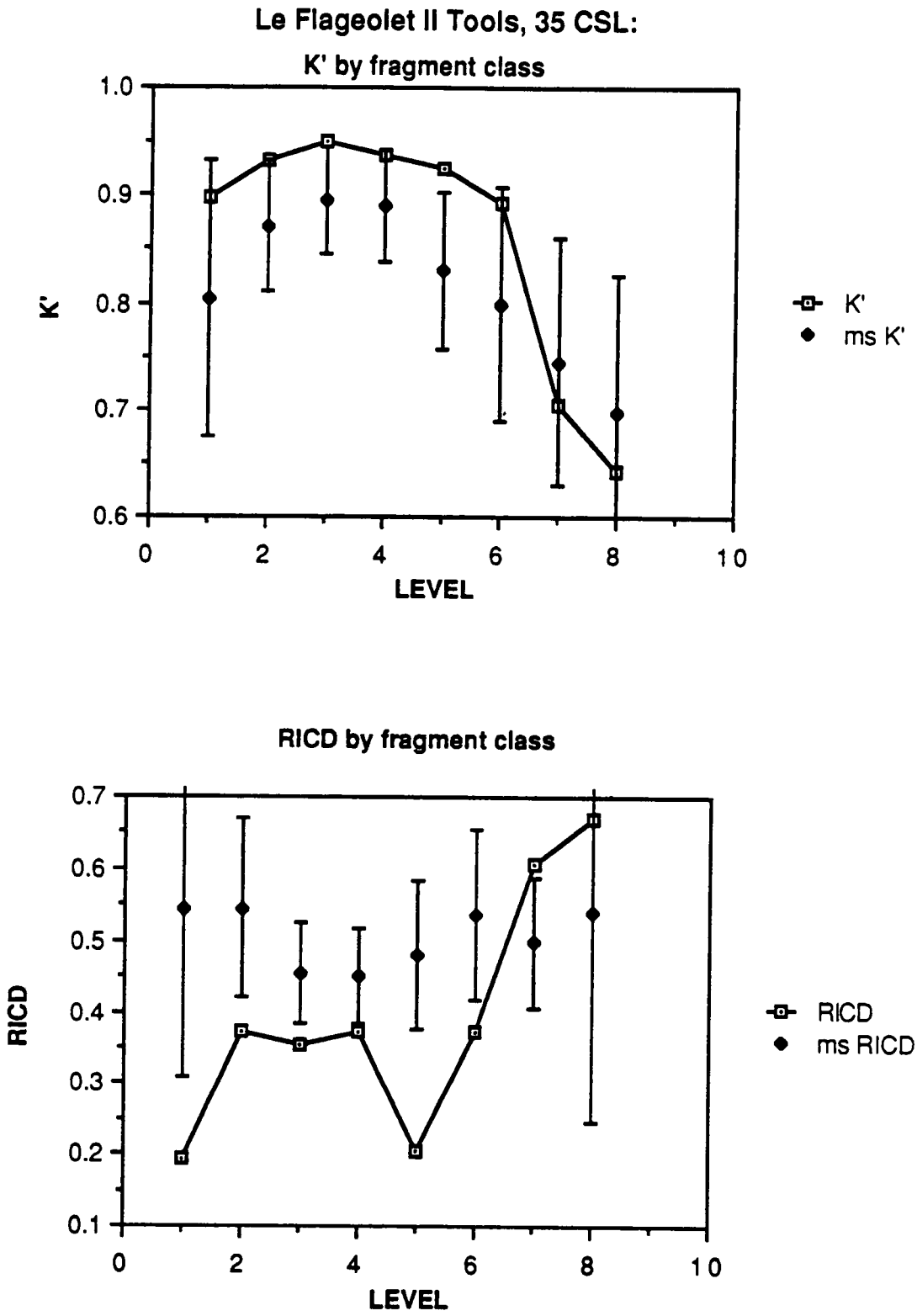


Figure 4.21 Le Flageolet II tools, K' and mean RICD by fragment classes and level for the 35 cluster solution.

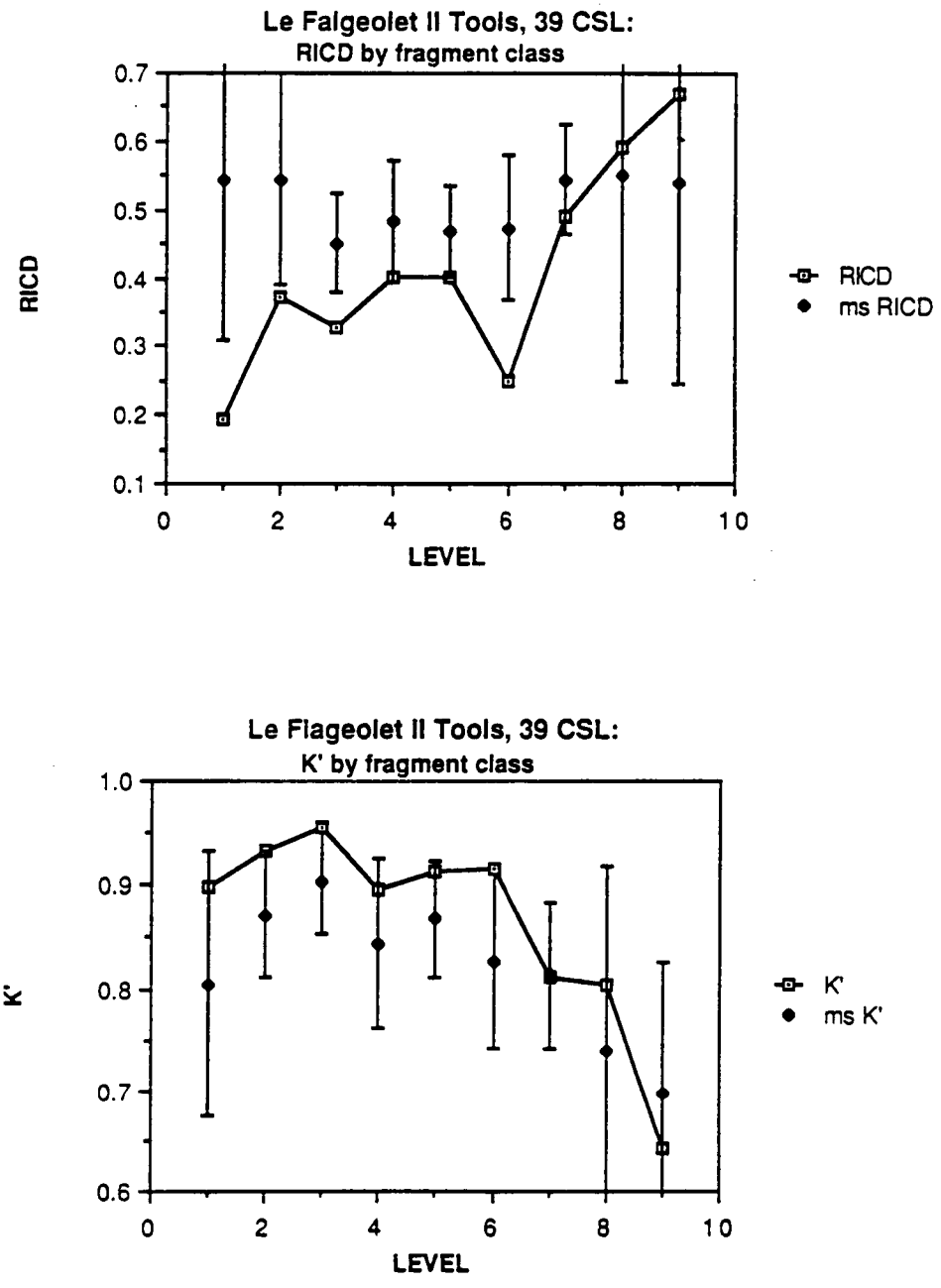


Figure 4.22 Le Flageolet II tools, K' and mean RICD by fragment classes and level for the 39 cluster solution.

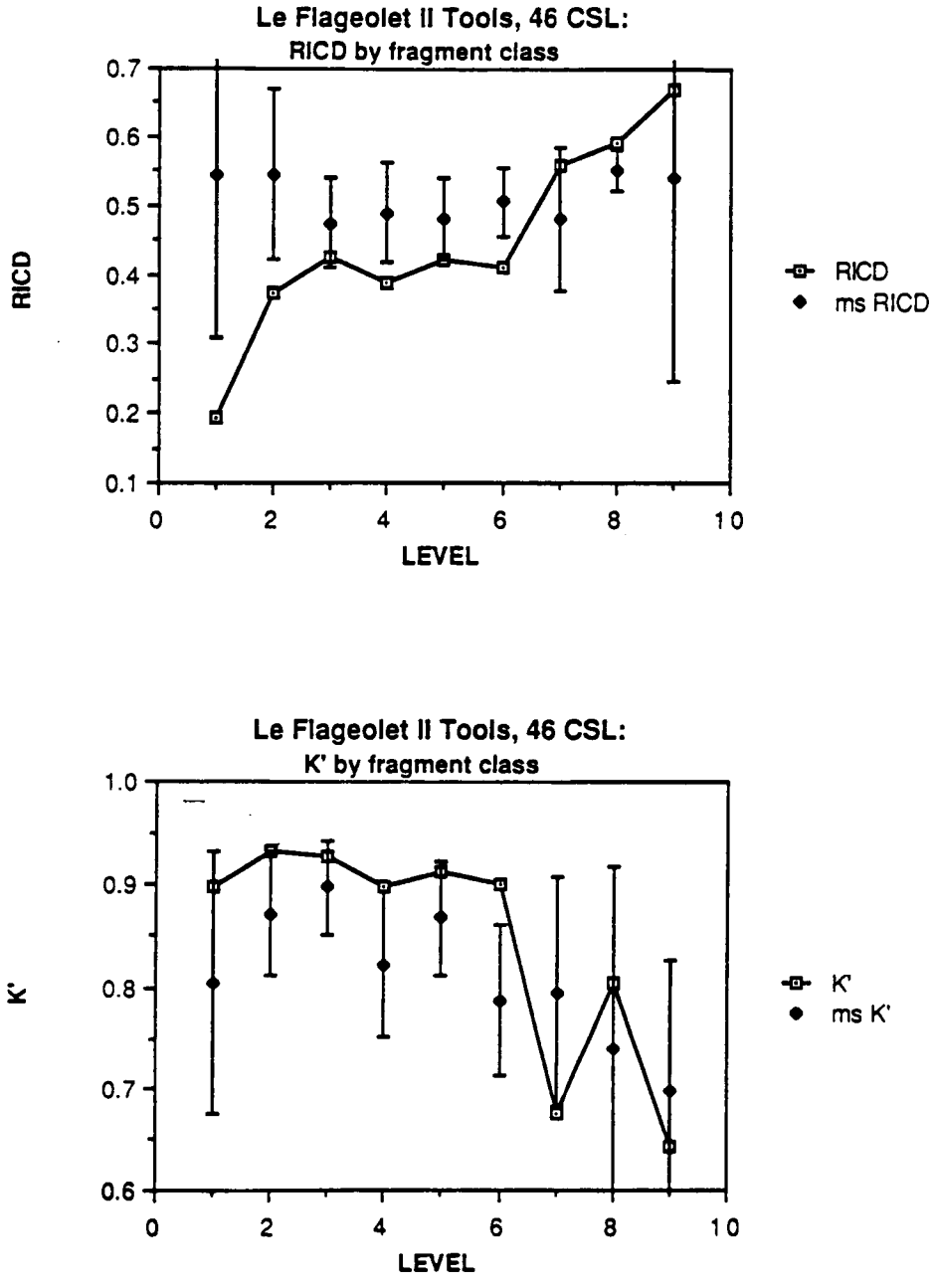
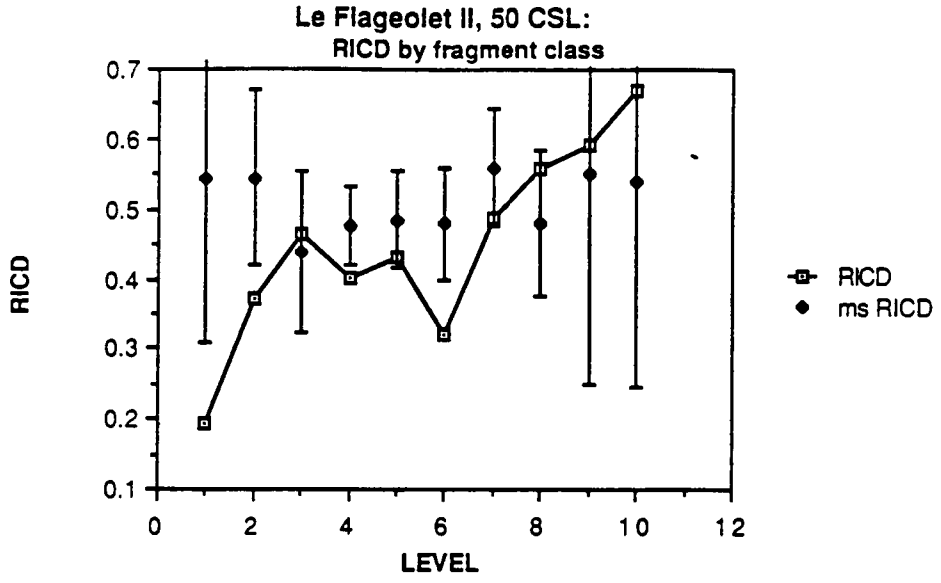


Figure 4.23 Le Flageolet II tools, K' and mean RICD by fragment classes and level for the 46 cluster solution.



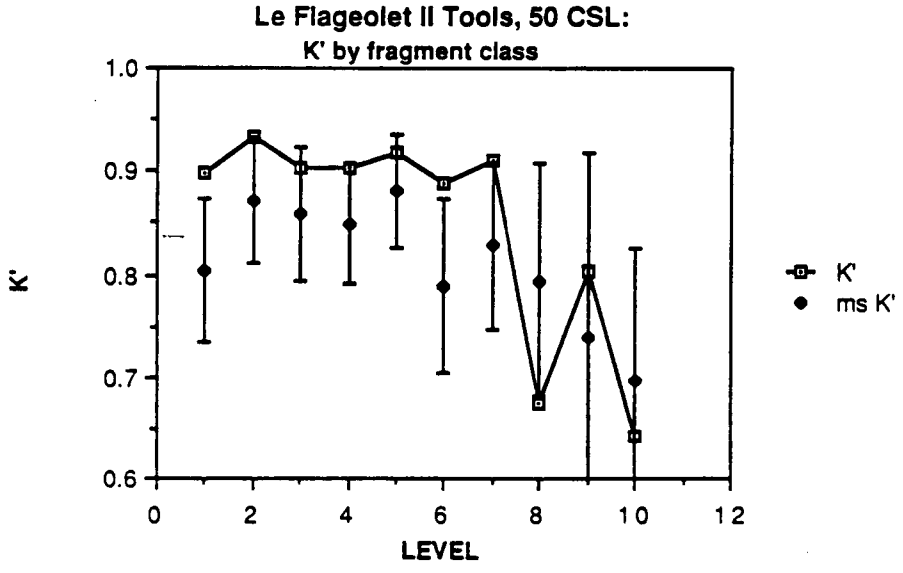


Figure 4.24 Le Flageolet II tools, K' and mean RICD by fragment classes and level for the 50 cluster solution.

mixing with the mean simulated values is less predictable across the cluster solutions. Second, there are a number of instances in which the observed values are substantially below the mean simulated values, and one in which the observed value falls below the lower 95% CI boundary (level 7 in cluster solutions 46 and 50, Figs. 4.23 and 4.24). The mean RICD values by fragmentation class also show a number of exceptional cases, most notably, level 4 in cluster solution 16, and level 7 in cluster solution 35.

Discussion

Overall homogeneity results when analyzing the tool classes suggest that that nearly the entire excavated volume has a very homogeneous class distribution, regardless of the type of division made. Exceptions to this are the relatively isolated upper most areas (upper left and right corners in Fig. 4.8), that do not contain much material. This situation breaks down however, when levels are defined. Within-level homogeneity tends to decline with increasing numbers of clusters and levels. The level creation process then, tends to create subdivisions of the site volume that show a less even tool frequency distribution, perhaps reflecting a less mixed, or more intact deposition set. Those levels with the lowest overall homogeneity, when calculated by either tool

or fragment classes are highest in the stratigraphic profile. The mean RICD values seem to support this conclusion. Overall mean RICD values show that most clusters are only moderately similar in class frequency (mean RICD values between .31 and .45), mean RICD by level however, fluctuates drastically. Some clusters within a single level are very similar, many only moderately so, and some very dissimilar (i.e. mean RICD values between .13 and .70).

If the level creation process can be assumed to have created or recovered subgroups of the assemblage that correspond (at least roughly) to single occupations, these results would suggest that either: 1.) the nature of the activity patterning in the occupations changes with depth, or 2.) the clustering process produces fewer clusters that sample from more than one occupation as the number of clusters increases. In either case the patterning within levels clearly changes with depth. In the next section, spatial patterning from the non-tool blades will be examined in a effort to clarify these results.

Non-Tool Blades

Global Homogeneity

Unretouched blades from Le Flageolet II were clustered out to the 50 cluster solution. Examination of the %sse differences curve (Figure 4.25) shows optimal solutions at the 19, 25, 31, 35, 40, 40, and 49 cluster solutions. Calculation of the K, K', and RICD measures for these cluster solutions using technological classes (see table 4.2) results in the curves shown in figure 4.26. Observed K' values are very high, show almost no slope, and are always above the simulated values and their 2 standard deviation range. Mean simulated K' values also show little slope. Observed mean RICD values, in contrast, are relatively low, and have a distinct positive slope. Mean simulated RICD values, on the other hand, are moderate in value and show little or no slope. These curves suggest that while cluster homogeneity is relatively high and stable across clusters, proportional frequency differences become more pronounced as the number of clusters increases. This relationship is consistent with that found for the tools.

Global Attribute Correlations

Correlations between the mean within-level attributes and mean level depth for the arbitrary 5, and

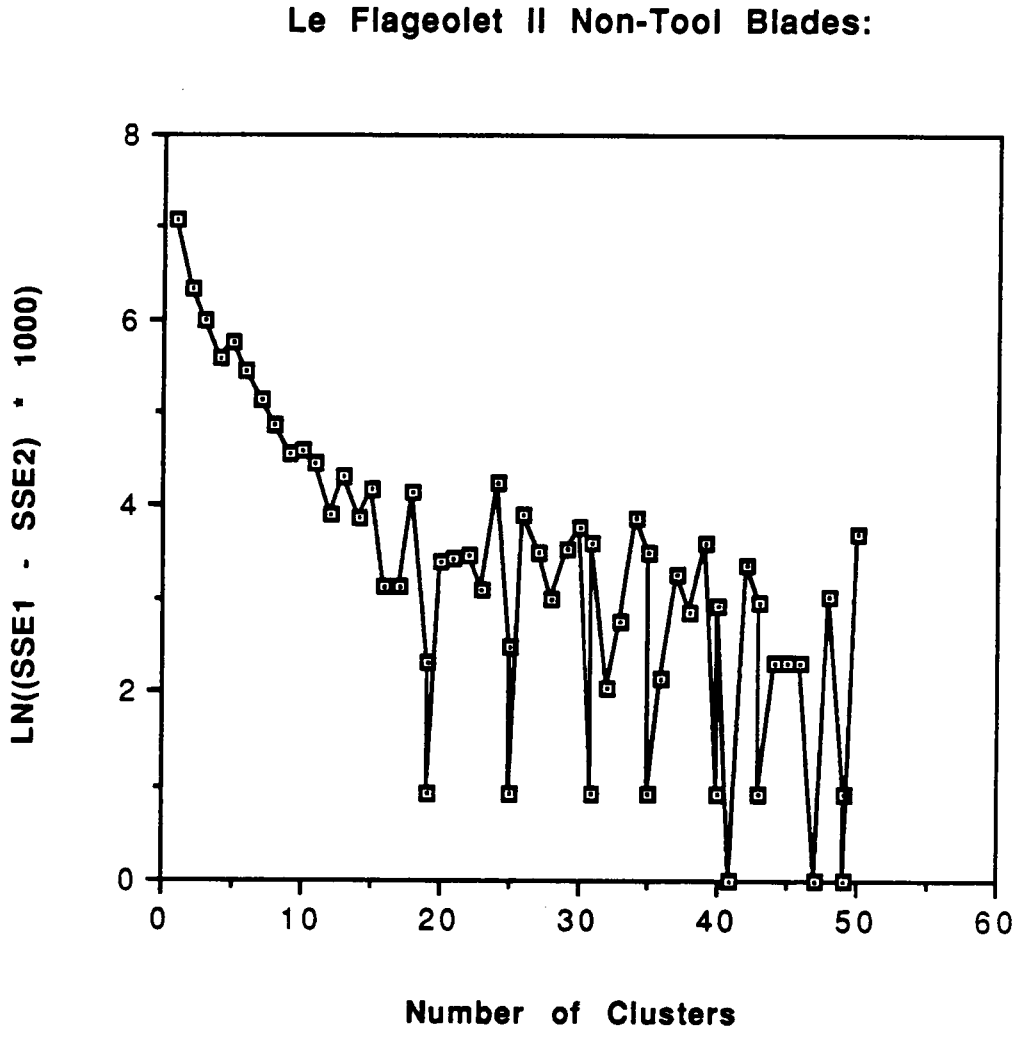


Figure 4.25 Le Flageolet II non-tool blades, LN((sse1-sse2)*1000). Optimal solution are indicated at the 19, 25, 31, 35, 40, 43, and 49 cluster solutions.

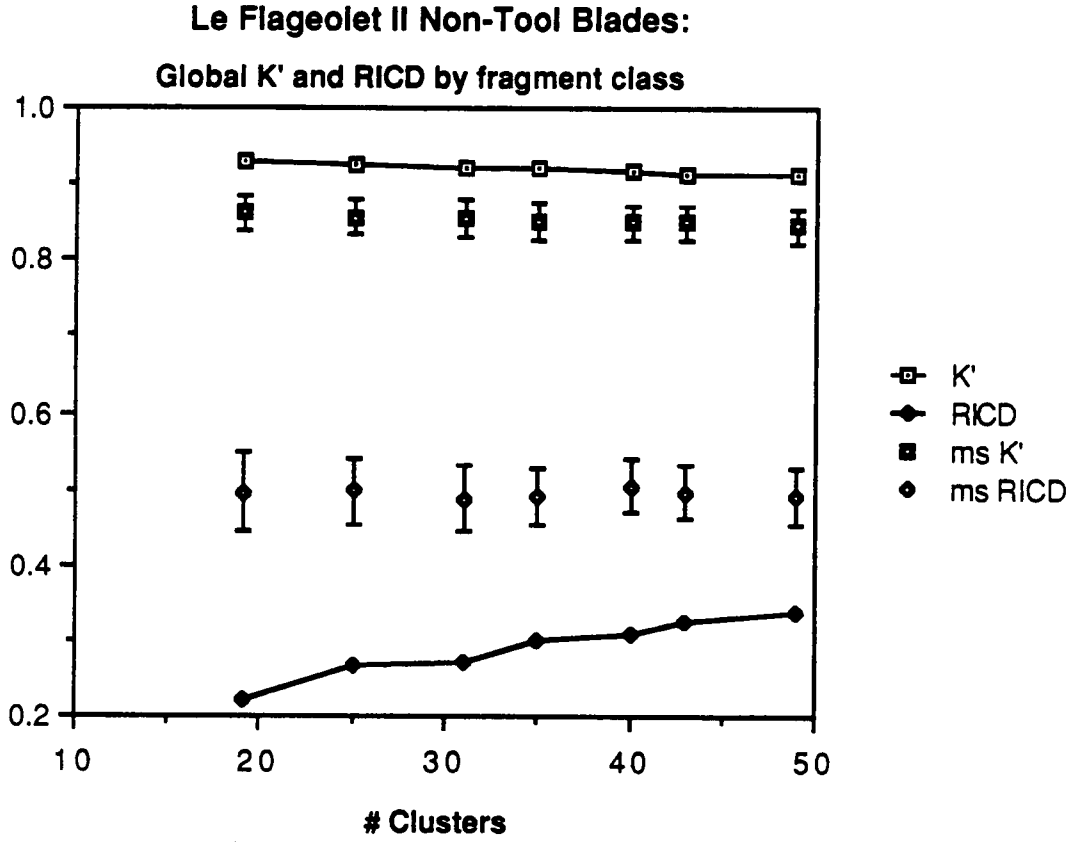


Figure 4.26 Le Flageolet II non-tool blades, global K' and mean RICD by fragment class.

10 cm levels are presented in table 4.6. Nontool blades show strong relationships between mean level depth and attribute for the 5 and 10 cm arbitrary levels, although decreasing in strength with an increase in the number of cases and a decrease in level thickness.

In contrast to the tool analyses, nontool blades also show a substantial number of consistent, relatively strong correlations between the measured attribute means and mean within-cluster depth. Table 4.7 presents these results that were significant at $p < .10$. While there is a tendency for the correlation strength to decrease with increasing numbers of clusters, the decline is slight, and even at the 49 cluster solution level most correlations are still strong (i.e. Rho= .45-.60). Azimuth, although negatively correlated with depth, also shows this decrease in strength. Correlations between the mean attributes and mean within-cluster depth standard deviation, show similar trends, but are more rare and always much lower, as well as generally not being significant at $p < .05$. In a major change from the tool results, there are no negative correlations with depth standard deviation. In general these results suggest strong relationships between the measured attributes and mean within-cluster depth, but little or no consistent relationship with a direct measure of cluster thickness.

Table 4.6 Spearman's rank order correlations between mean attribute measurements and mean arbitrary level depth for Le Flageolet II nontool blades. Azimuth represents modal rather than mean azimuth.

Level	Depth with:	RHO	P
5	Weight	.46	.05
	Length	.46	.05
	Width	.57	.01
	Density	.49	.08
10	Weight	.71	.02
	Length	.71	.02
	Width	.91	.000
	Density	.73	.02

Table 4.7 Spearmans rank order correlations between mean within-cluster depth and within-cluster depth standard deviation, and mean within-cluster object attributes significant at the .10 level for Le Flageolet II nontool blade analysis by cluster solution level.

CSL	Depth with	RHO	P	Depth S.D.	RHO	P
19	Azimuth	-.66	.001			
	Weight	.68	.02			
	Length	.64	.000			
	Width	.78	.000			
	Density	.67	.001			
25	Azimuth	-.40	.000	Length	.35	.08
	Weight	.60	.001			
	Length	.53	.006			
	Width	.72	.000			
	Density	.60	.001			
31	Azimuth	-.48	.005	Weight	.47	.006
	Weight	.59	.000	Length	.45	.01
	Length	.47	.006	Density	.45	.01
	Width	.61	.000	Azimuth	-.33	.06
	Density	.56	.000			
35	Azimuth	-.43	.009	Length	.30	.07
	Weight	.60	.000			
	Length	.50	.002			
	Width	.63	.000			
	Density	.58	.000			
40	Azimuth	-.37	.01	Length	.30	.05
	Weight	.57	.000			
	Length	.52	.000			
	Width	.62	.000			
	Density	.56	.000			
43	Azimuth	-.35	.01	Weight	.27	.07
	Weight	.51	.000	Length	.31	.04
	Length	.48	.000			
	Width	.62	.000			
	Density	.53	.000			
49	Azimuth	-.37	.005	Weight	.24	.09
	Weight	.48	.000	Length	.25	.07
	Length	.48	.000			
	Width	.53	.000			
	Density	.52	.000			

Homogeneity by level

The distribution of nontool blade clusters seems to break down well into between 5 and 12 levels depending on the cluster solution (see Figs. 4.27-4.33). When calculated by level, K' shows a tendency to be very high, generally above .90, but to stay within the .95% confidence interval around the mean simulated value for a substantial number of levels at all cluster solutions. Typically only one or two levels show observed K' values outside of the 95% CI boundaries around the mean simulated values. While no observed K' values drop below the mean simulated values, several are close. It is also exceptional that several of the low resolution levels contain only a single cluster. The observed mean RICD values, on the other hand, are generally spread between low and moderate values, often below the mean simulated values and their 95% CI, but show an increasing tendency to become more mixed with the mean simulated values as the number of levels increases. Only a few, isolated levels show observed values close to or above the mean simulated values, and none are above the upper 95% CI bound around them. In two instances, the observed RICD for a particular level exceeds .5 (level 12, CSL 49, and level 10, CSL 43).

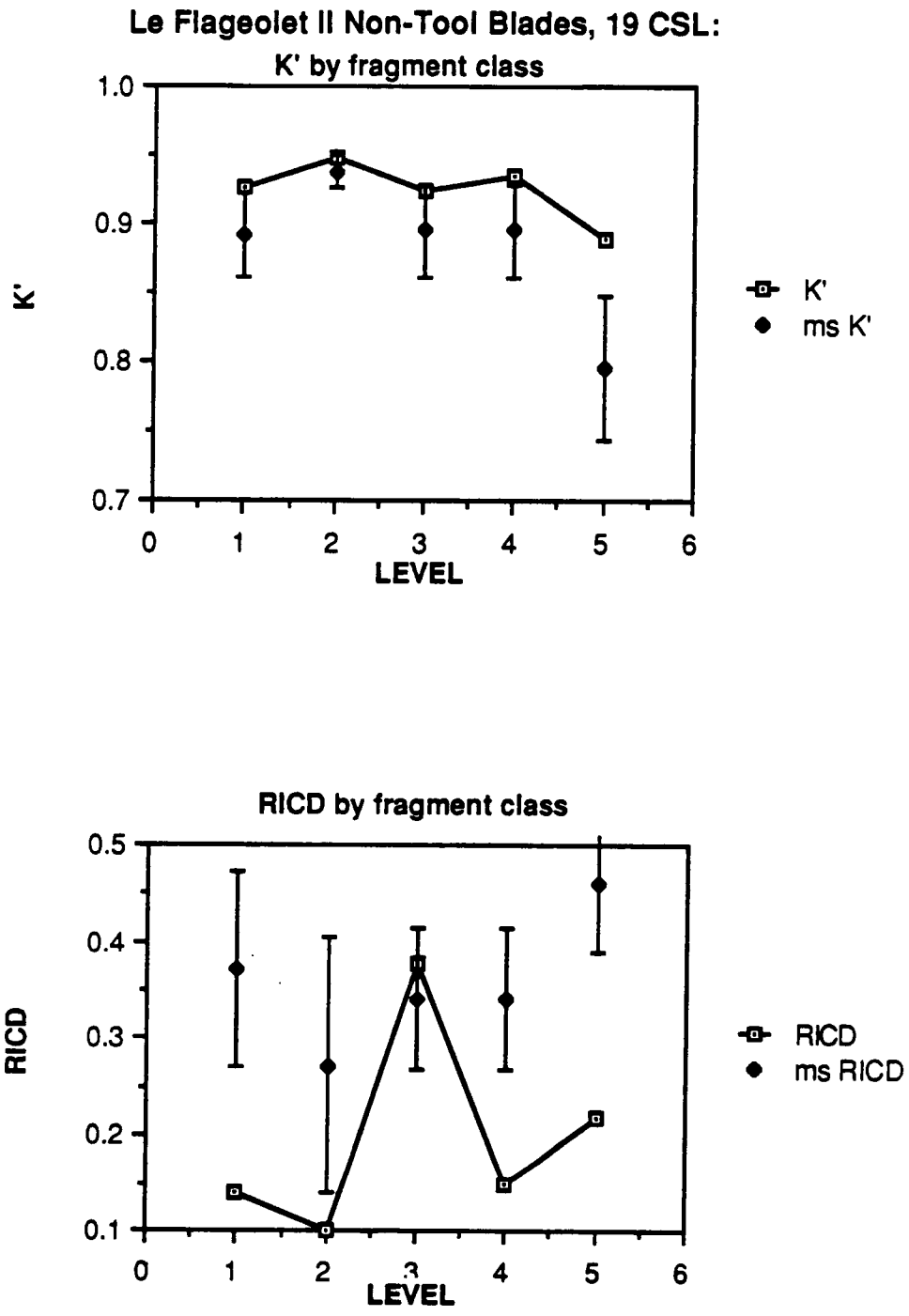


Figure 4.27 Le Flageolet II non-tool blades, K' and mean RICD by fragment class and level for the 19 cluster solution.

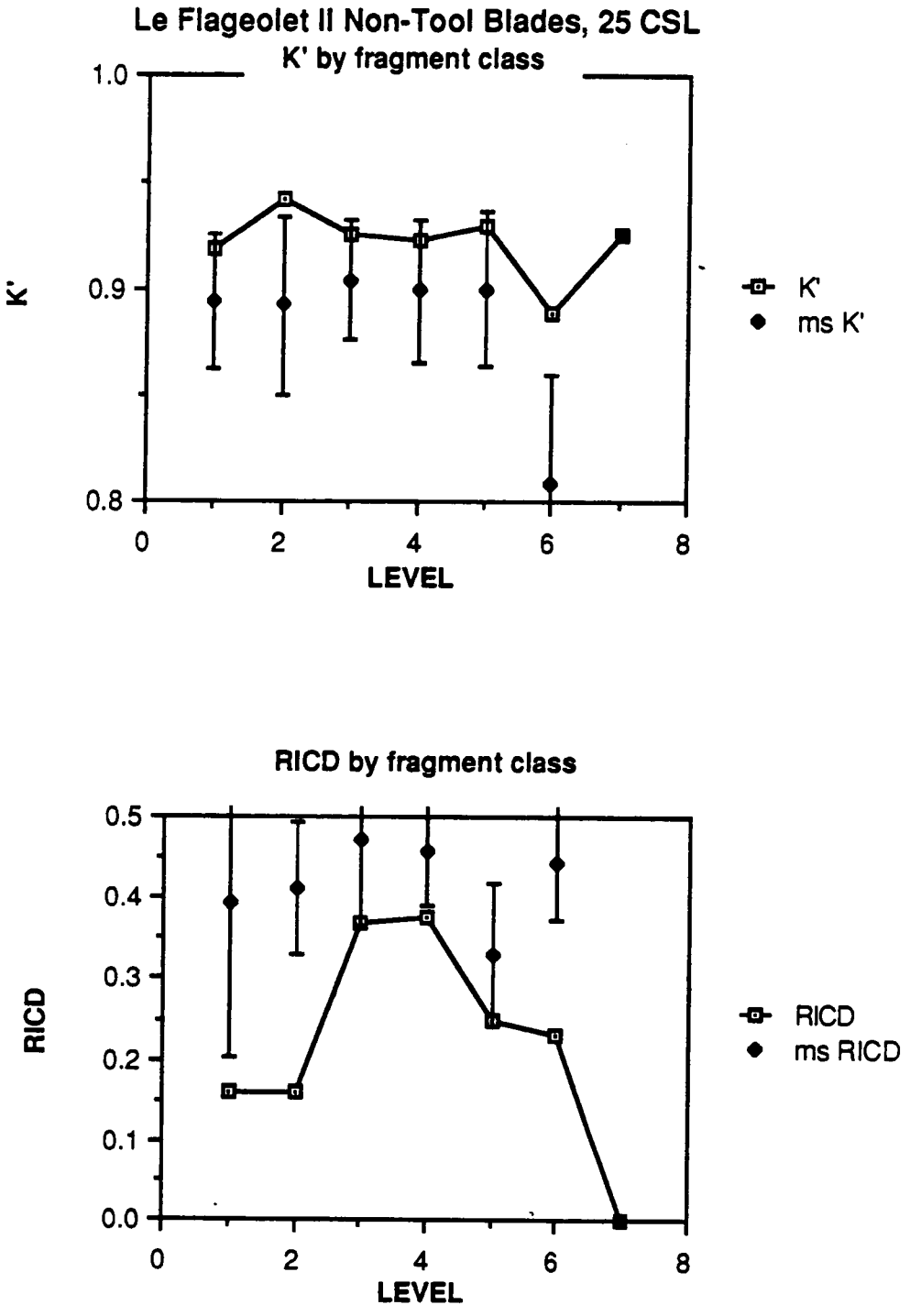


Figure 4.28 Le Flageolet II non-tool blades, K' and mean RICD by fragment class and level for the 25 cluster solution.

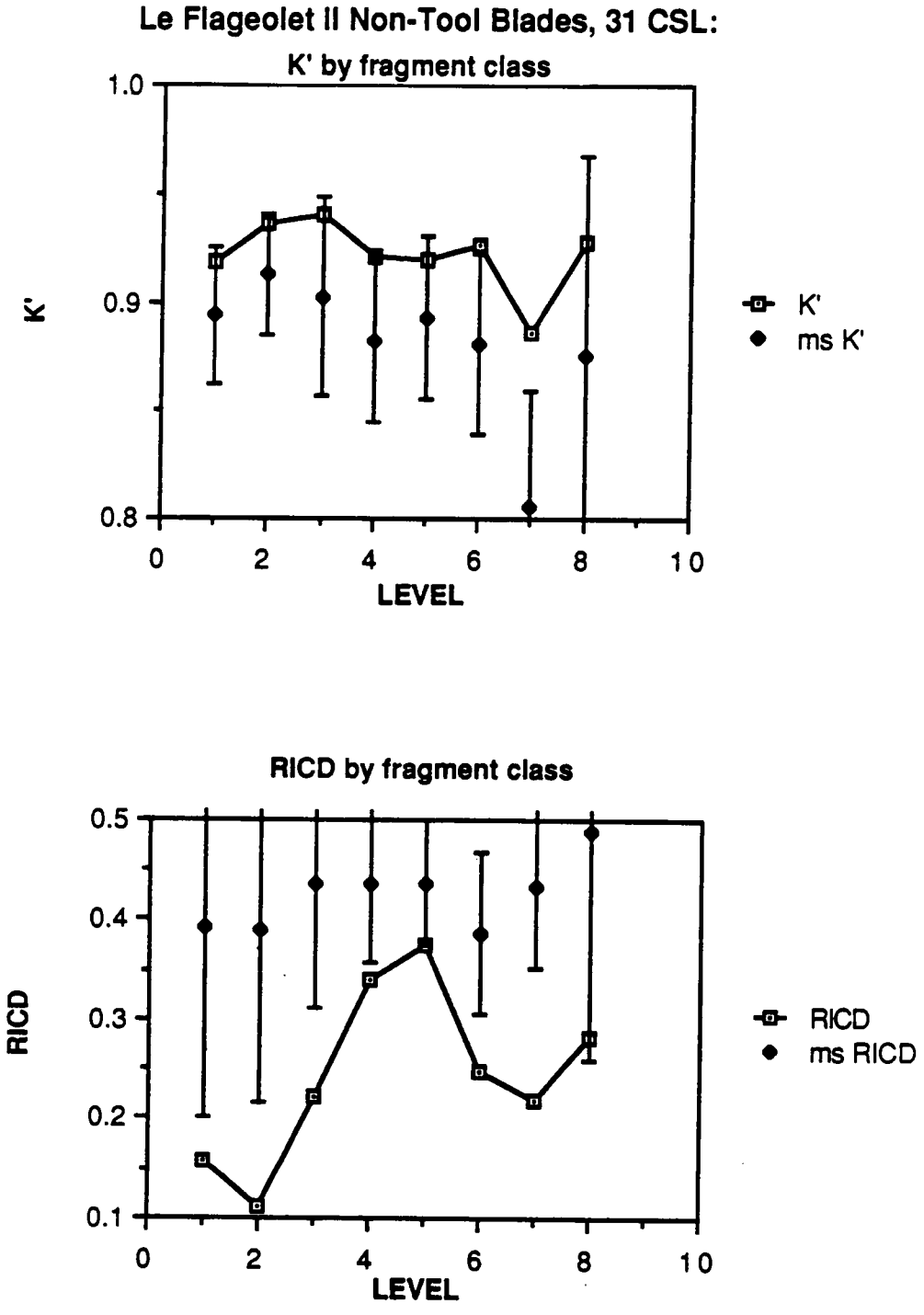


Figure 4.29 Le Flageolet II non-tool blades, K' and mean RICD by fragment class and level for the 31 cluster solution.

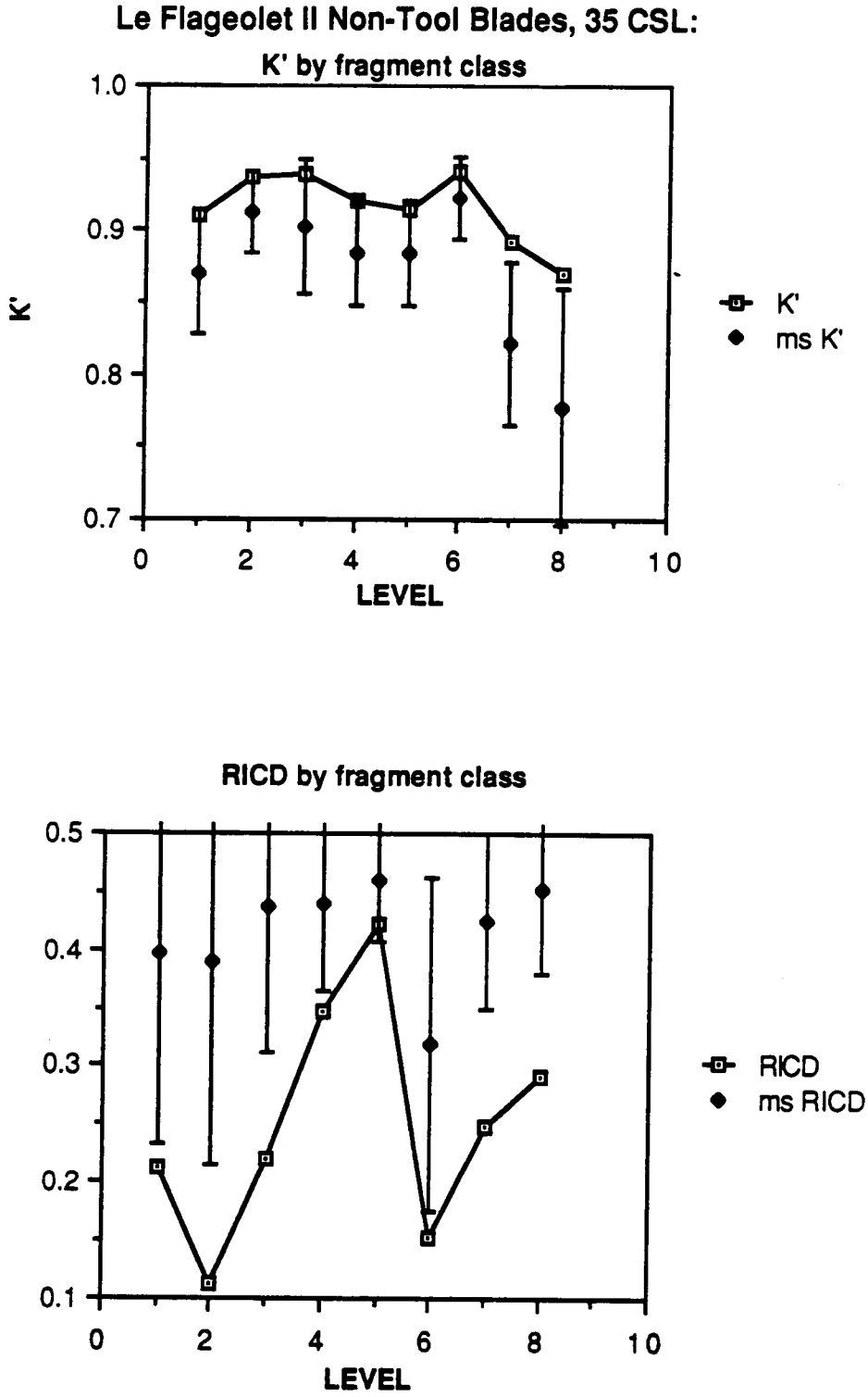


Figure 4.30 Le Flageolet II non-tool blades, K' and mean RICD by fragment class and level for the 35 cluster solution.

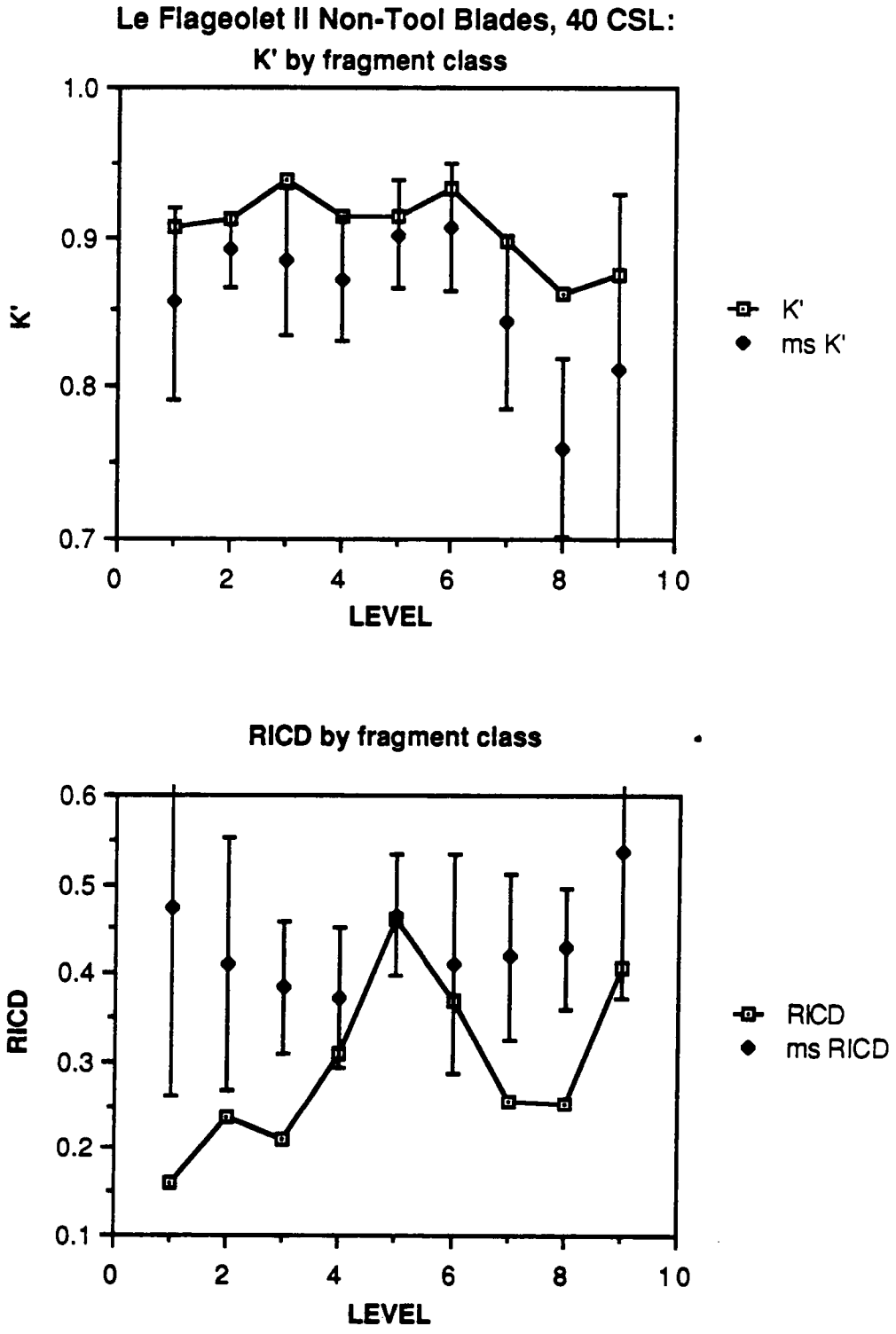


Figure 4.31 Le Flageolet II non-tool blades, K' and mean RICD by fragment class and level for the 40 cluster solution.

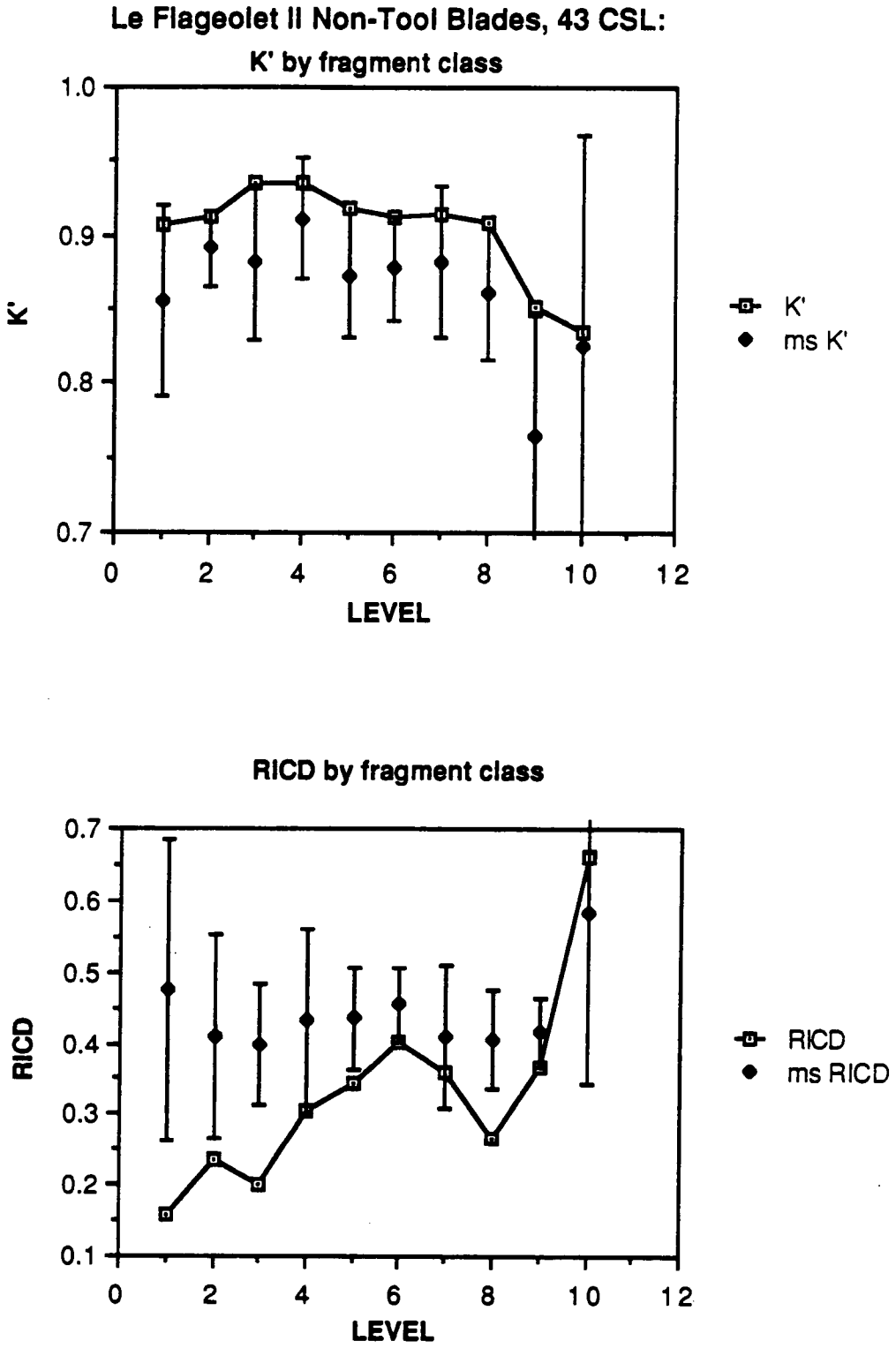


Figure 4.32 Le Flageolet II non-tool blades, K' and mean RICD by fragment class and level for the 43 cluster solution.

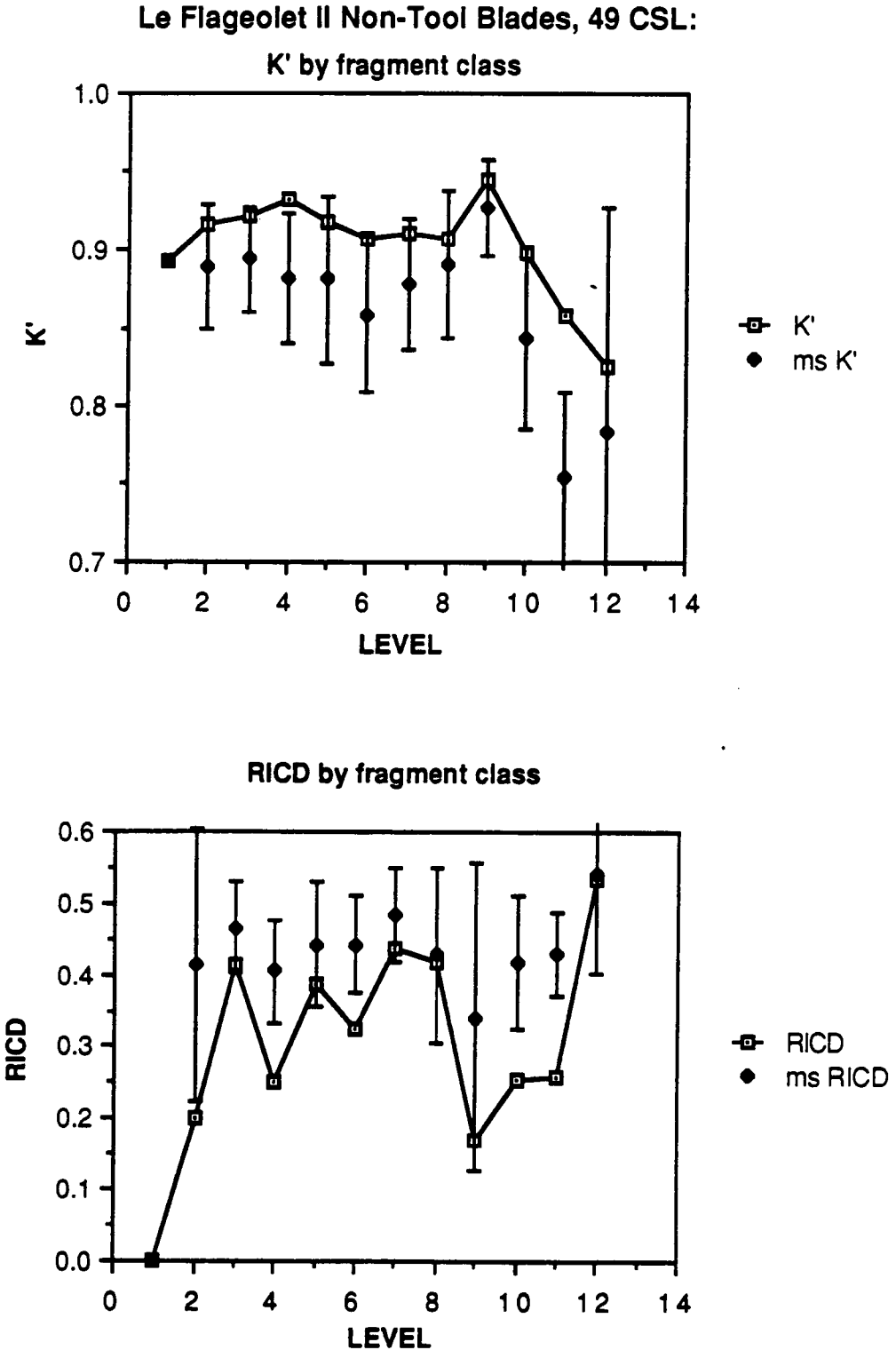


Figure 4.33 Le Flageolet II non-tool blades, K' and mean RICD by fragment class and level for the 49 cluster solution.

Discussion

Non-tool blades show several interesting relationships. When calculated by level observed K' values are very high, generally above .90; they are also most frequently within the 95% CI around the mean simulated values. This relationship appears stable, i.e., observed values do not continue to drop but maintain their level. However, they conform to the magnitude range expected as a property of the measure itself. Observed mean RICD values by level behave very differently. Thus while the homogeneity measure suggests that these objects display properties similar to those of randomly created clusters, the class frequency proportions (RICD) do not support this. Both K' and RICD behave very differently when calculated globally. Attribute correlations, on the other hand behave similarly whether calculated by arbitrary level or by cluster, although azimuth is involved only in the correlations by cluster. In general these relationships seem to suggest that both structural and assemblage redundancy may be low or moderate.

In general then, these results suggest that the distribution of non-tool blade fragment classes is not well structured in space. There are however, clear changes in the nature of the objects themselves with depth. These are similar to the changes with depth found for the tool classes, and again suggests that the tool

production sequence and, perhaps, the functions of the lithic materials, change through time. In the next section, non-tool flakes are analyzed. This material class is generally associated only with the production of stone tools, rather than with their production and use.

Non-tool Flakes

Global Homogeneity by Fragmentation Class

Non-tool Flakes were clustered out to 50 clusters. Optimal solutions were identified from the %sse differences curve (Fig. 4.34) at the 12, 17, 23, 29, 41, 44, and 49 cluster solutions. Calculation of the K' and mean RICD values for these solutions results in the curves shown in figure 4.35. The observed K' values are relatively low, although always much higher than the 95% CI around their corresponding mean simulated values. Both the observed and mean simulated K' values show similar, insignificant slope as the number of clusters increases. A notable characteristic of the mean simulated values is their very narrow 95% CI. This, and the very low magnitude of the measures appears to be largely the result of the very small number of objects in class # 4: indeterminate (n= 6). Most clusters then have a zero for this class, lowering their homogeneity drastically.

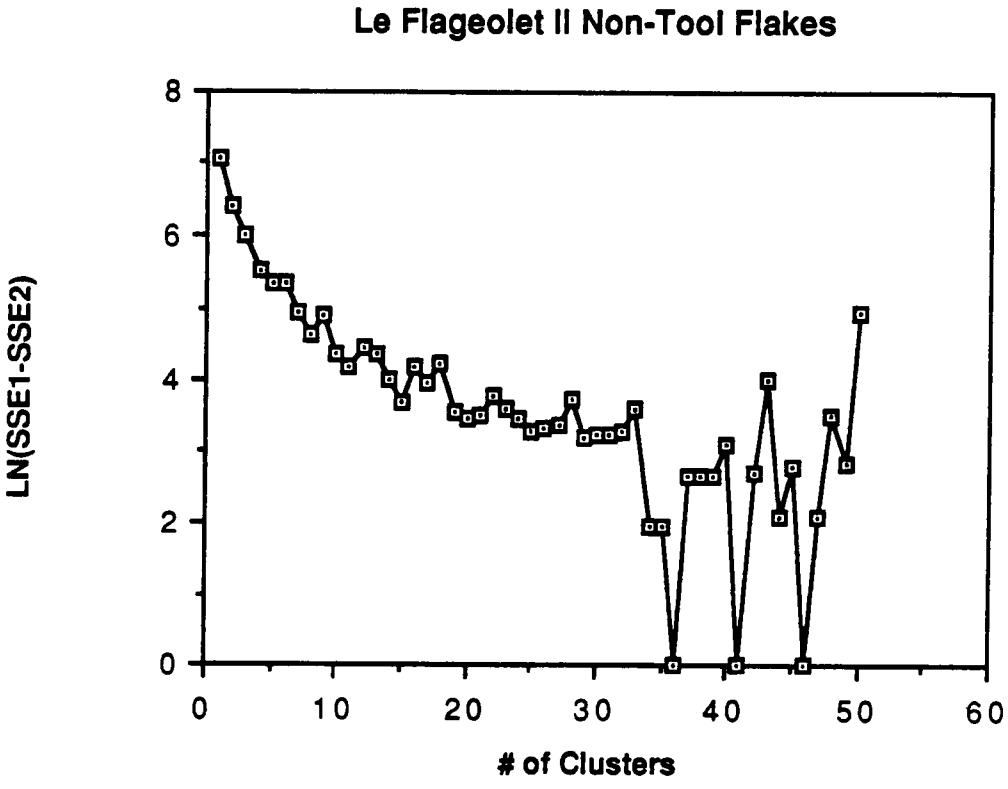


Figure 4.34 Le Flageolet II non-tool flakes, LN((sse1-sse2)*1000). Optimal solution are indicated at the 12, 17, 23, 29, 41, 44, and 49 cluster solutions.

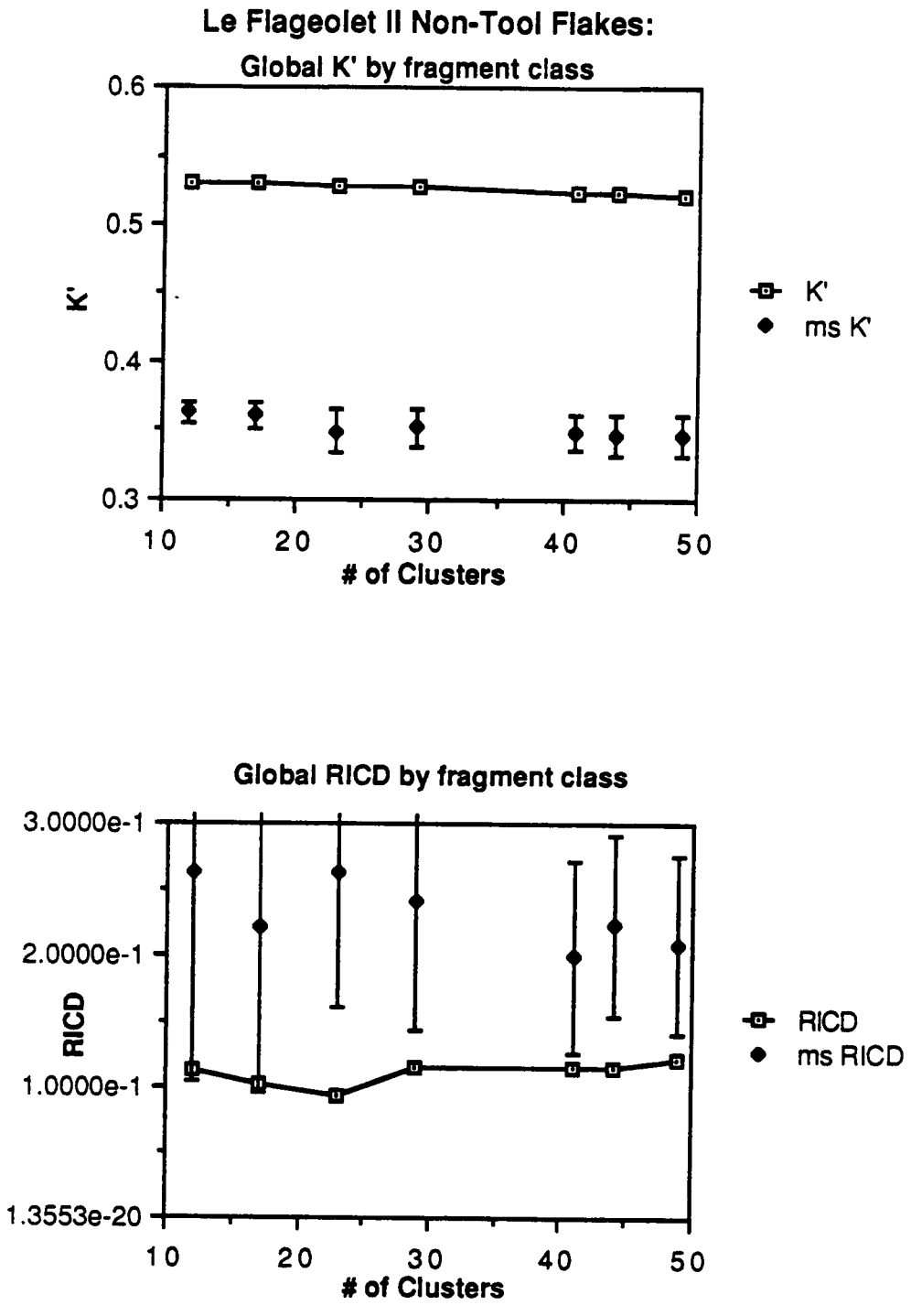


Figure 4.35 Le Flageolet II non-tool flakes, global K' and mean RICD by fragment class.

Observed mean RICD values are also very low. Although initially within the 95% CI around the mean simulated values, after the 17 cluster solution, they are substantially below the mean simulated CI. Observed mean RICD values exhibit a very slight positive slope, while the mean simulated values show a slight negative slope with increasing numbers of clusters. The slopes of regression lines calculated for each of these measures are not statistically different at $p < .10$. In contrast to the confidence intervals around the mean simulated K' values, simulated RICD values are widely scattered around their means. The global K' and mean RICD analyses suggest relatively low, although very stable, homogeneity and effectively no tendency towards increasingly dissimilar clusters, as spatial resolution increases.

Global Attribute Correlations

Table 4.8 presents the Spearman's rank order correlations significant at $p < .10$ between the within-level means of the measured attributes and the mean within-level depth for the arbitrary 5 and 10 cm levels. No relationships were significant at the 10 cm level thickness, although all attributes except for azimuth were moderately correlated with mean within-level depth at the 5 cm level thickness.

Table 4.8 Spearman's rank order correlations significant at p<.10 between mean attribute measurements and mean arbitrary level depth for Le Flageolet II nontool flakes. Azimuth represents modal rather than mean azimuth.

Level	Depth with:	RHO	P
10	No significant correlations		
5	Weight	.64	.002
	Length	.56	.01
	Width	.45	.05
	Density	.62	.004

Table 4.9 shows the result of spearman's rank order correlations between mean within-cluster attribute and mean within-cluster depth. In contrast to the within-level correlations, these relationships fit the more familiar pattern. Initially strong correlations show substantial decreases in strength with increasing numbers of clusters, but little correlation with within-cluster depth sd. In general these patterns are suggestive of strong, stable relationships between the measured attributes and mean cluster depth.

Homogeneity by Level

Inspecting the cluster projection plots for the non-tool flakes suggests that they may be profitably broken down into from 6 to 12 levels depending on the cluster solution level. Figures 4.36-4.42 show the resulting K' and RICD curves for these levels at each optimal cluster solution. With four exceptions (level 6 csl 12, level 8 csl 29, level 9 csl 41, and level 10 csl 44) observed K' values for each level and cluster solution are substantially above the mean simulated values. No particular trend is readily apparent. However, close examination suggests that the observed values may tend to rise slightly compared to the mean simulated values as the number of levels and cluster solutions increases. In

Table 4.9 Spearmans rank order correlations between mean within-cluster depth and within-cluster depth standard deviation, and mean within-cluster object attributes significant at the .10 level for Le Flageolet II nontool flake analysis by cluster solution.

CSL	Depth with	RHO	P	Depth S.D.	RHO	P
12	Azimuth	-.88	.000			
	Weight	.55	.05			
	Density	.55	.05			
17	Azimuth	-.56	.01			
	Weight	.59	.01			
	Density	.60	.01			
23	Azimuth	-.59	.002	Azimuth	.36	.08
	Weight	.58	.003	Weight	-.36	.08
	Length	.38	.07	Length	-.49	.01
	Density	.55	.006	Width	-.46	.02
				Density	-.35	.09
29	Azimuth	-.61	.000			
	Weight	.43	.01			
	Density	.36	.05			
41	Azimuth	-.45	.003			
	Weight	.43	.004			
	Length	.34	.02			
	Width	.30	.05			
	Density	.38	.01			
44	Azimuth	-.43	.003			
	Weight	.46	.001			
	Length	.37	.01			
	Width	.33	.02			
	Density	.38	.009			
49	Azimuth	-.49	.000	Density	.24	.08
	Weight	.44	.001			
	Length	.35	.01			
	Width	.33	.01			
	Density	.39	.005			

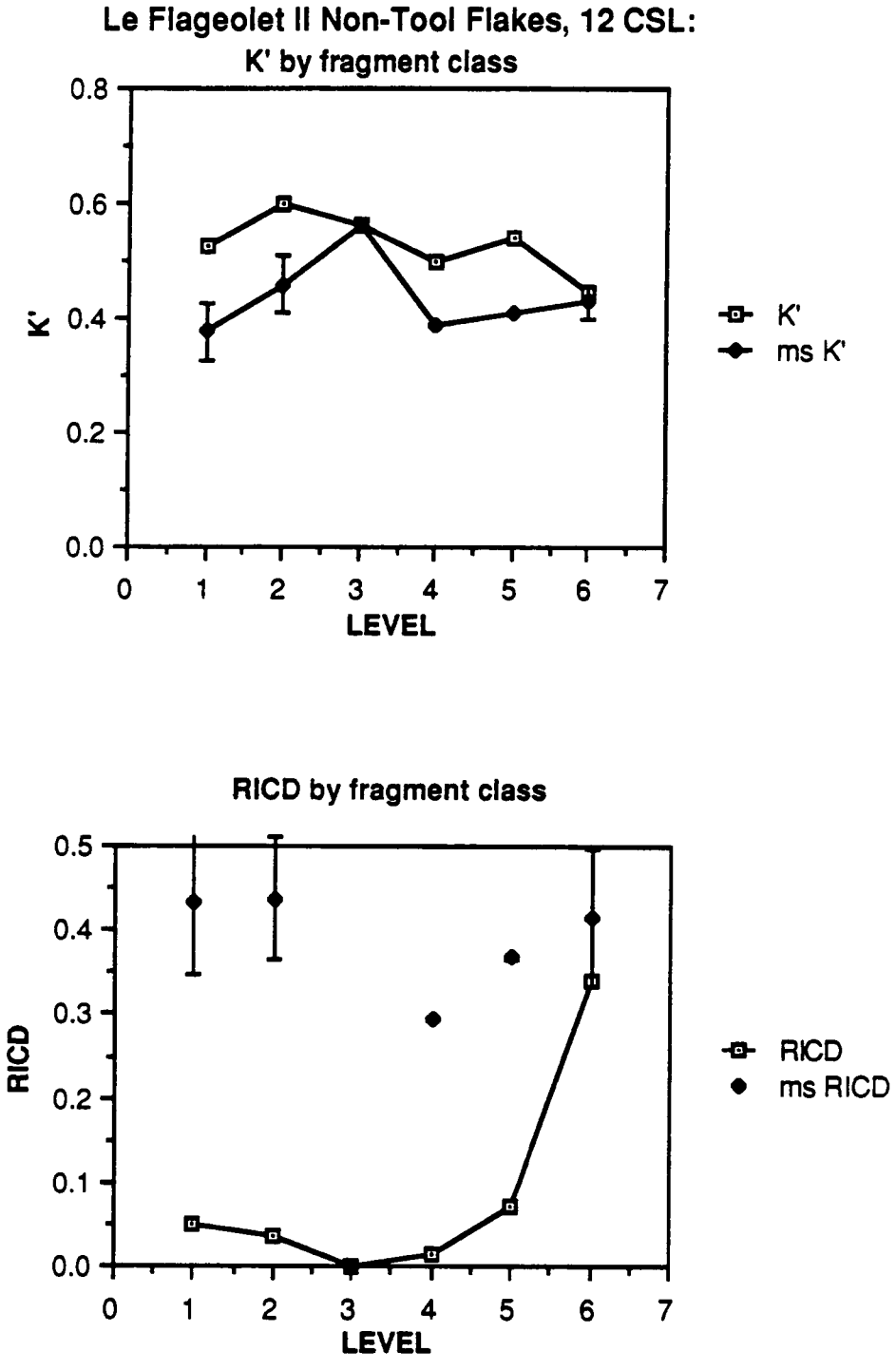


Figure 4.36 Le Flageolet II non-tool flakes, K' and mean RICD by fragment class and level for the 12 cluster solution.

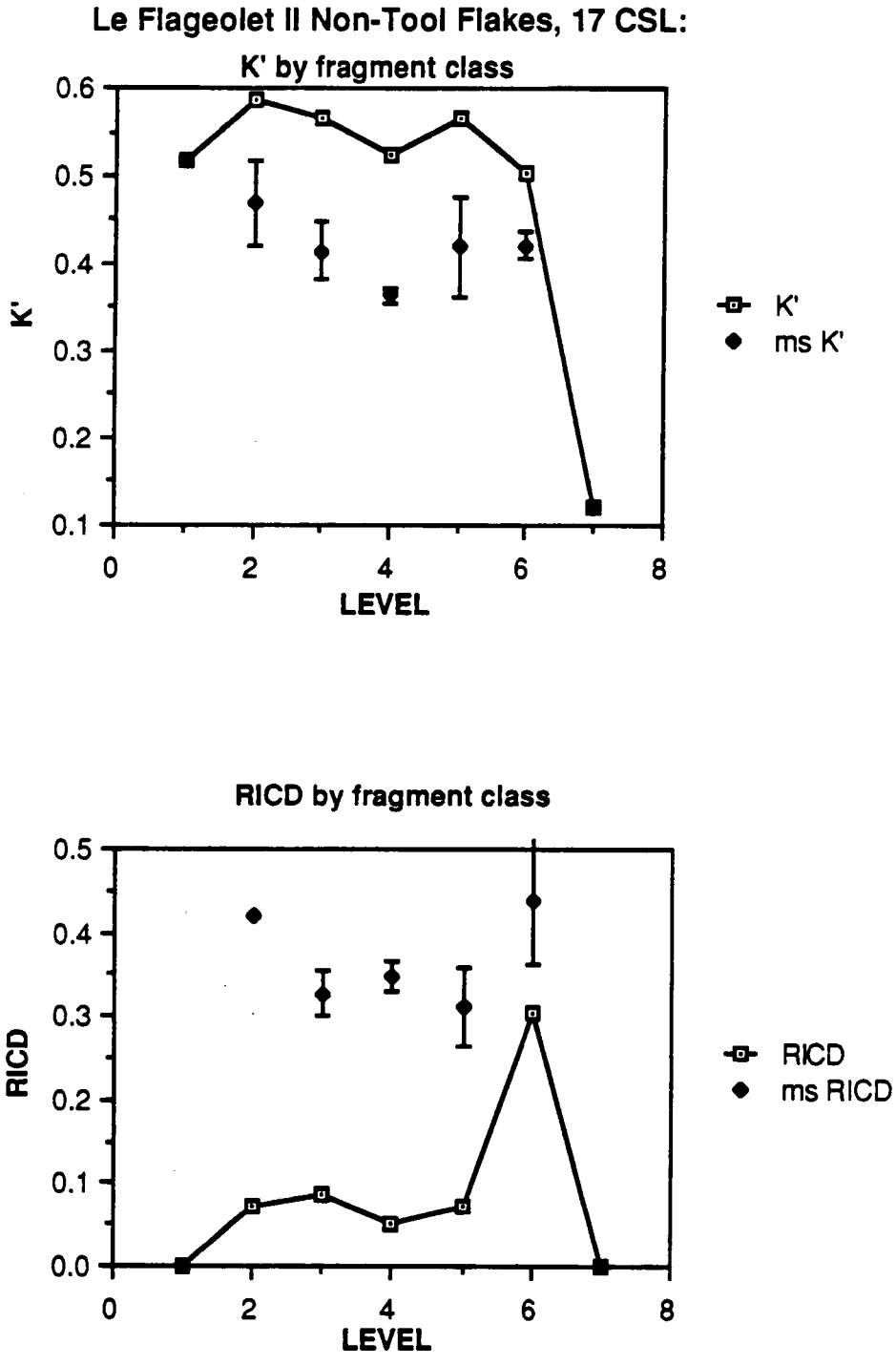
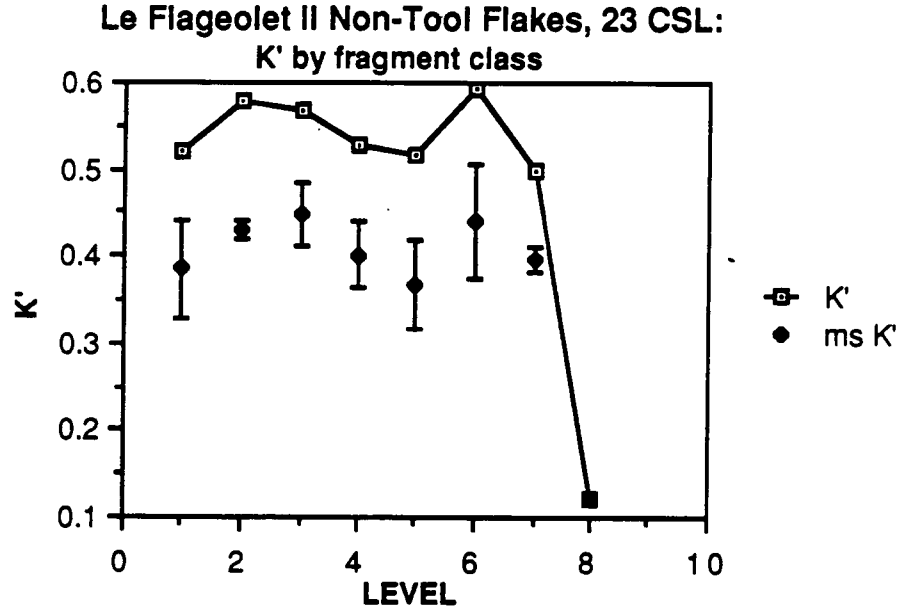


Figure 4.37 Le Flageolet II non-tool flakes, K' and mean RICD by fragment class and level for the 17 cluster solution.



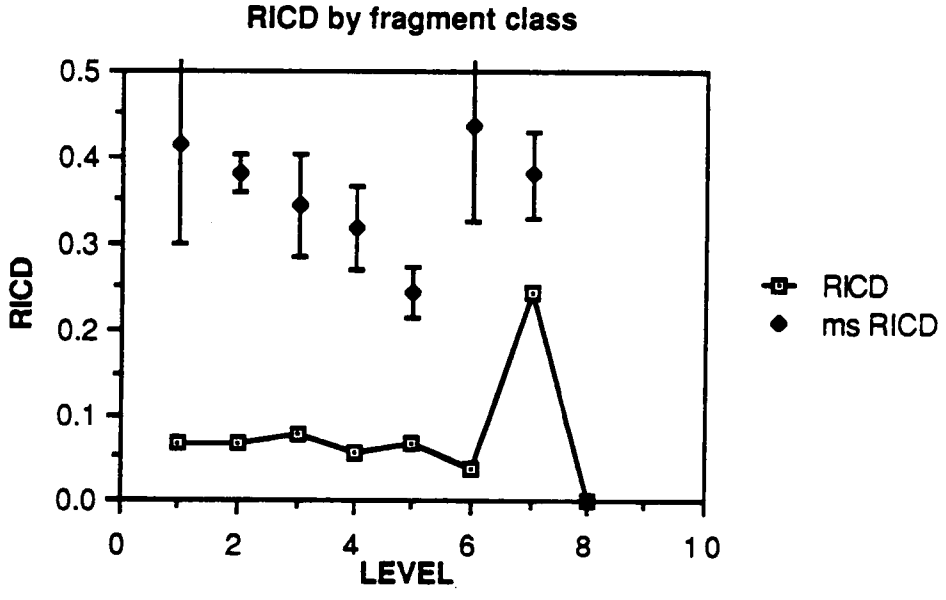
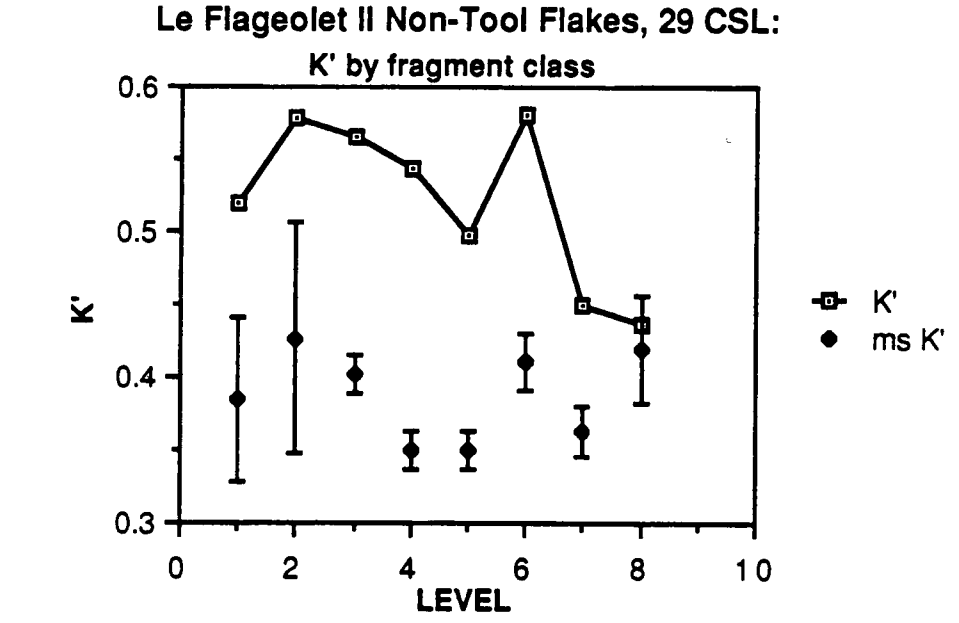


Figure 4.38 Le Flageolet II non-tool flakes, K' and mean RICD by fragment class and level for the 23 cluster solution.



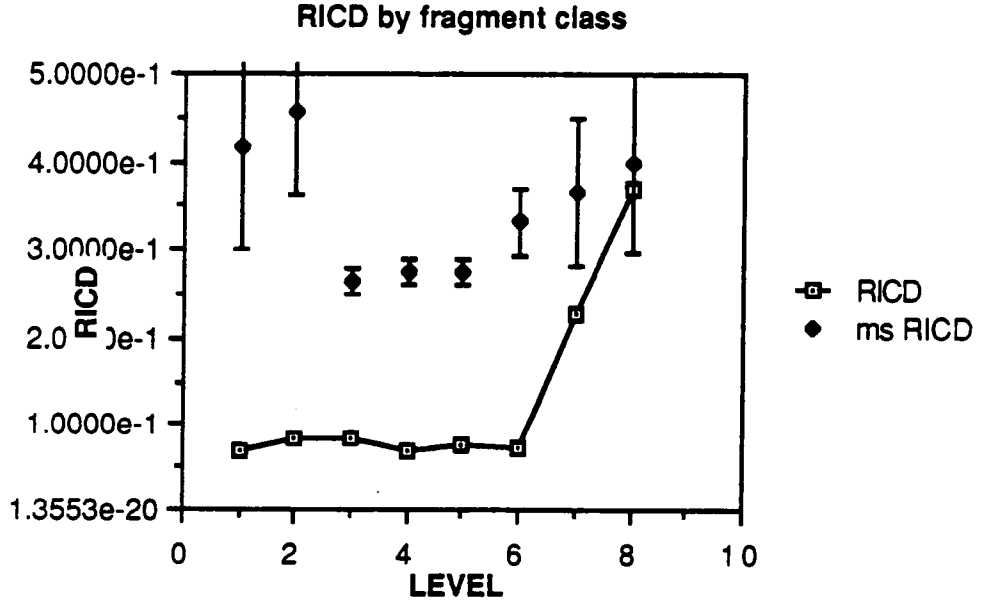


Figure 4.39 Le Flageolet II non-tool flakes, K' and mean RICD by fragment class and level for the 29 cluster solution.

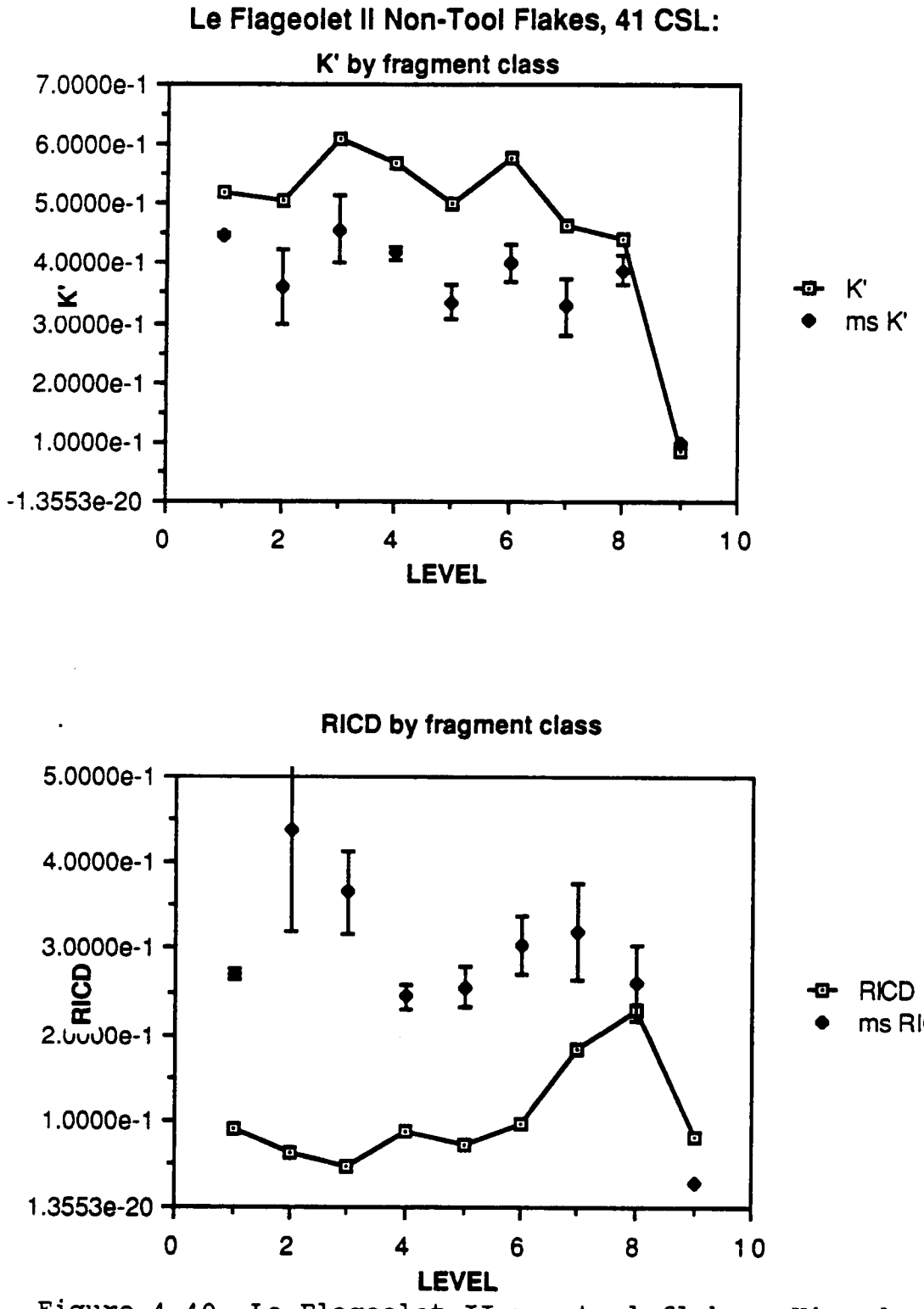


Figure 4.40 Le Flageolet II non-tool flakes, K' and mean RICD by fragment class and level for the 41 cluster solution.

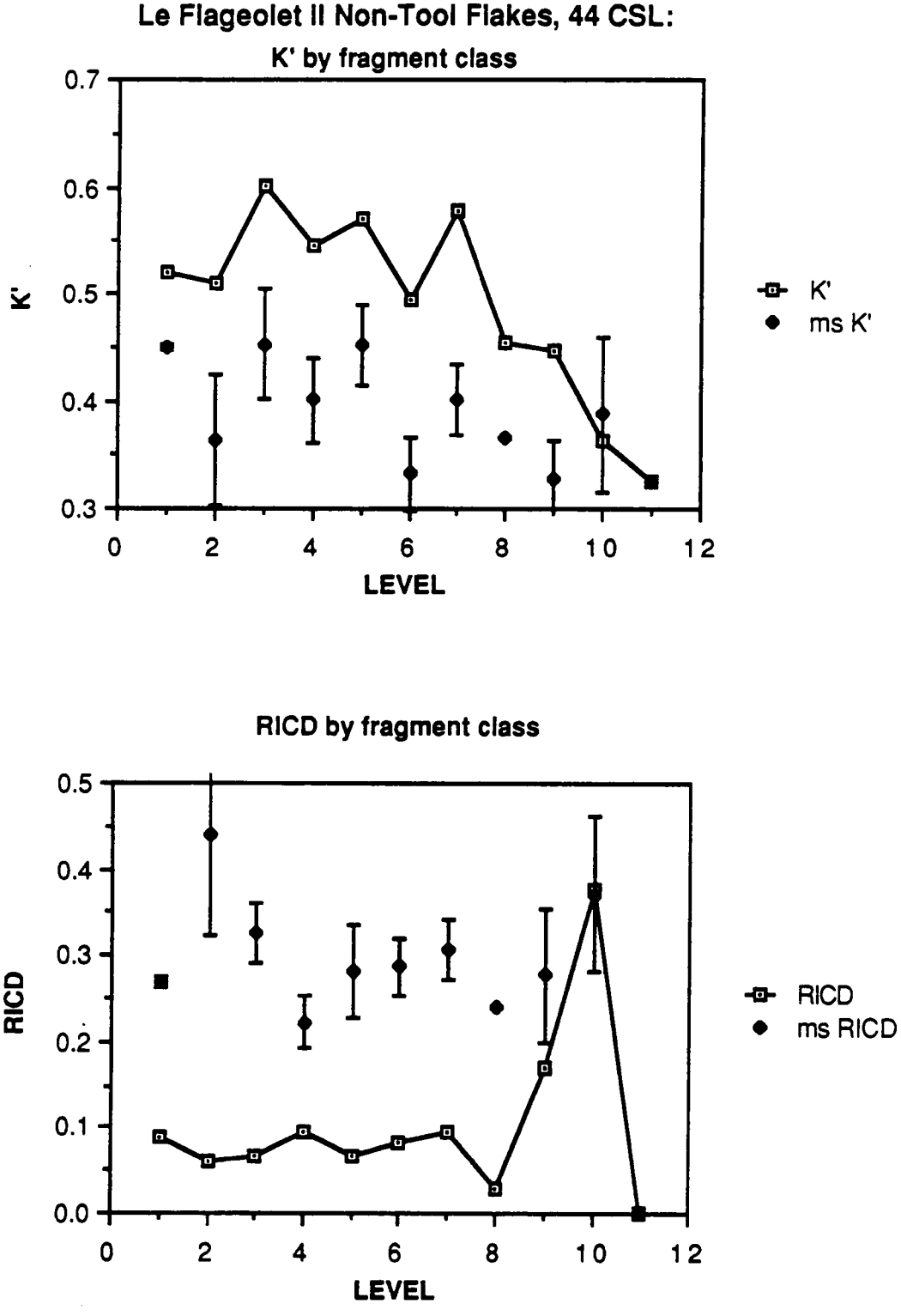
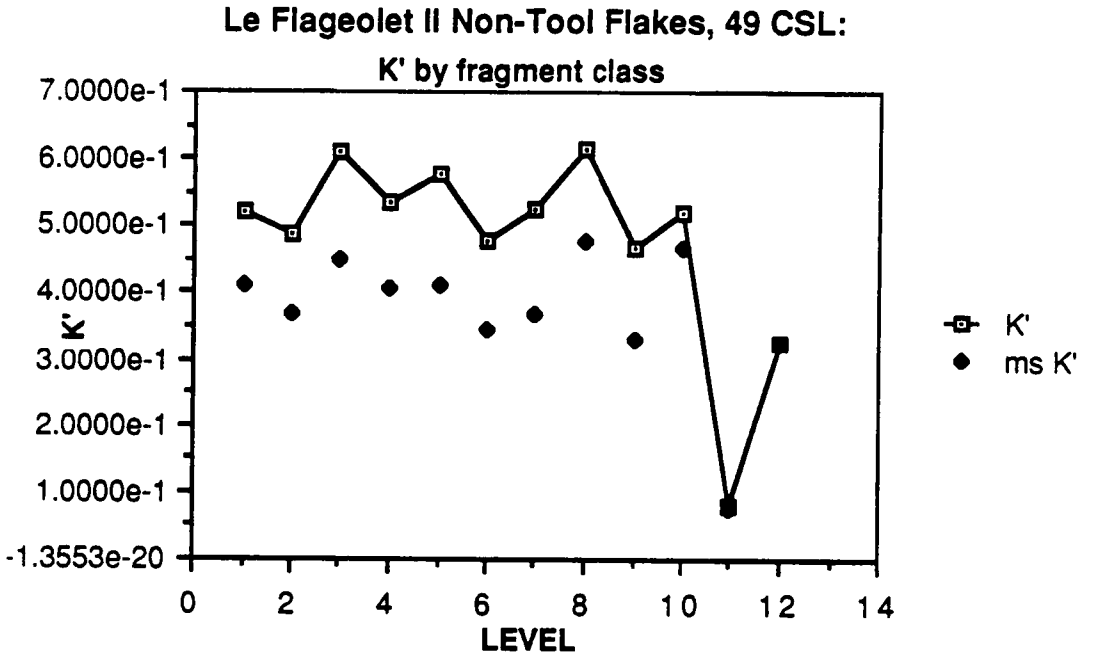


Figure 4.41 Le Flageolet II non-tool flakes, K' and mean RICD by fragment class and level for the 44 cluster solution.



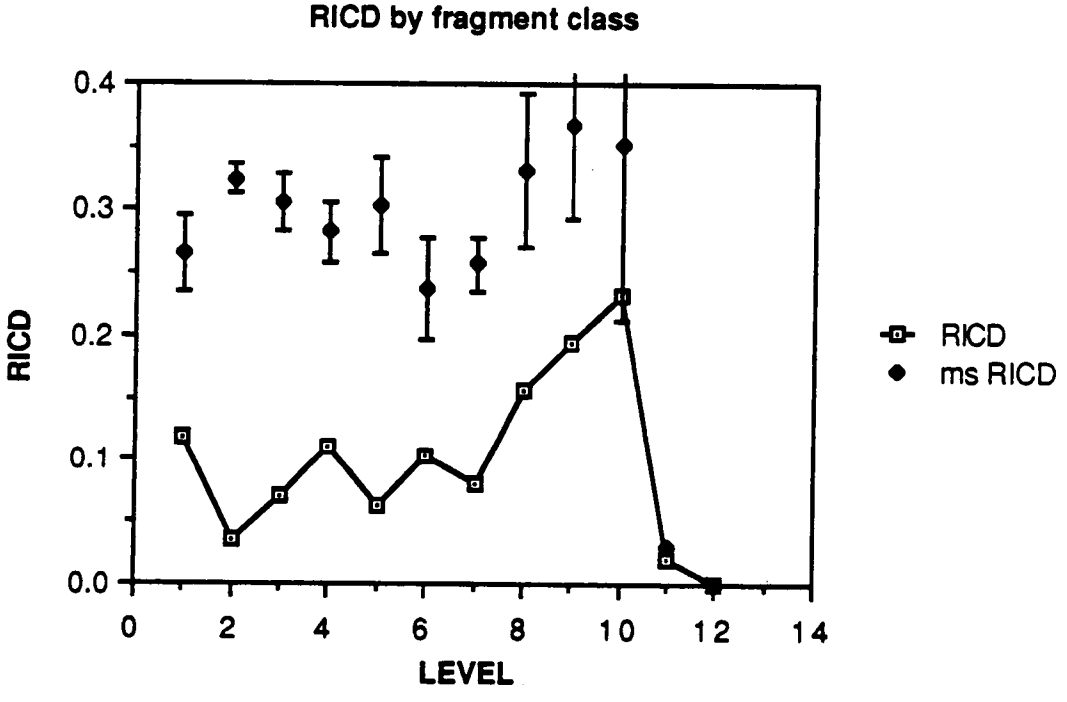


Figure 4.42 Le Flageolet II non-tool flakes, K' and mean RICD by fragment class and level for the 49 cluster solution.

general, the pattern still may be described as showing higher than expected values (although only moderate in an absolute sense) and stability in values across solutions. It is particularly surprising, then, to find 2 levels whose observed K' falls below the mean simulated values (level 9 csl 41, and level 10 csl 44). Also noteworthy is the great variation evident in the 95 % CI around the mean simulated values, particularly as this contrasts sharply with the global homogeneity curve (Fig. 4.35 above).

Observed mean RICD values, by level and cluster solution, are generally very low (below .10), and far below the mean simulated values, with one or two exceptions per cluster solution. These exceptional levels generally correspond with the levels showing K' values falling within the 95% CI around the mean simulated K' values. As was the case with the K' confidence intervals, those for the mean simulated RICD values, show extreme variability.

Discussion

Non-tool flakes also show several interesting patterns. Apparently strong relationships between the measured attributes and depth by cluster, that remain substantial with increasing numbers of clusters suggests that these relationships may have much to do with the overall patterning. Especially as they contrast sharply

with the arbitrary level correlations, which only appear in the 5 cm levels. Global homogeneity relationships are relatively low, but stable and very high above their expected values. Homogeneity by level shows nearly identical relationships. Global RICD measures on the other hand, are very low and stable, but in most cases barely below their expected values. RICD by level shows radically different patterns. In most cases RICD by level is very low, and far below the expected values, suggesting that within level clusters remain extremely similar in class proportions. This is consistent with the much higher than expected K' values by level.

The distribution of non-tool flakes is clearly not well structured over either the site as a whole, or the individual levels created in this analysis. Instead, they are considerably more mixed than would be expected if clusters were formed at random. This is somewhat surprising if the fragment class of a flake is assumed to be the result of random processes. These results imply that both assemblage and structural redundancy should be relatively high. In the next section the bone distribution is analyzed. Because of bones' probable status as refuse, they might be expected to exhibit patterns similar to that found for the non-tool flakes.

Bones

Class Definitions

A relatively small portion of the faunal remains from Le Flageolet II have been identified as to either anatomical part or species. Most of the identified material was excavated between 1967 and 1971, and is from the uppermost portion of the site. Because the identified faunal materials do not form a reasonable sample from the entire excavated volume and I am not competent to complete the identification, genus, species and general anatomical part classes do not play a further role in this analysis. Instead, the bone objects were classified as to their degree of fragmentation. This classification scheme does not involve the usual proximal/distal distinctions that require identification of anatomical part. It is instead based on the percentage of a complete cylinder (in the ideal case of a long bone shaft) that a given object evidences in cross section. Table 4.10 shows the class definitions. This scheme has the advantage of being applicable to all bone fragments, rather than being restricted to the identifiable pieces. In general, the majority of bone objects were long bone shaft fragments, although considerable numbers of skull, mandible and rib fragments were also present. The vast majority of the complete class (# 1 in table 4.10) were phalanges, ribs,

Table 4.10 Flageolet II bone fragmentation class definitions. Class definitions are based on the percentage of a complete cylinder that an object shows in cross section. Objects are placed in the highest category possible.

Class	Definition:
1	whole or complete cylinder, including but not limited to complete bones.
2	1/2 to < whole cylinder
3	1/3 to < 1/2 cylinder
4	1/4 to < 1/3 cylinder
5	irregular peace
6	flat fragment
7	indeterminate

or teeth. More than 90% of the objects identified to the species level were reindeer (Rangifer sp.), although some horse, red deer, and a variety of small mammals are present (F. Delpech, personal communication 1987).

Global Homogeneity

The bone objects from Le Flageolet II were clustered out to 50 clusters. Examining the %sse differences curve (Figure 4.43) shows optimal solutions at the 7, 14, 17, 24, 31, 36, 42, 46, and 49 cluster solutions. The observed K' values for these solution levels (Figure 4.44) are high, and always above the 95% CI around their corresponding mean simulated values. Observed K' and mean simulated K' values both show similar, slightly negative, but clearly present slope. The confidence interval range around the mean simulated values is relatively narrow. Observed mean RICD values, are on the other hand, moderately low in general, and always substantially below the mean simulated values. In contrast to the mean simulated values, which show no obvious slope, observed mean RICD values show a pronounced positive slope (fig. 4.44). A T-test for slope differences using the slopes of regression lines calculated for each of these measures shows that the observed and mean simulated curve slopes are significantly different at $p < .05$. These curves suggest a relatively high homogeneity relationship that

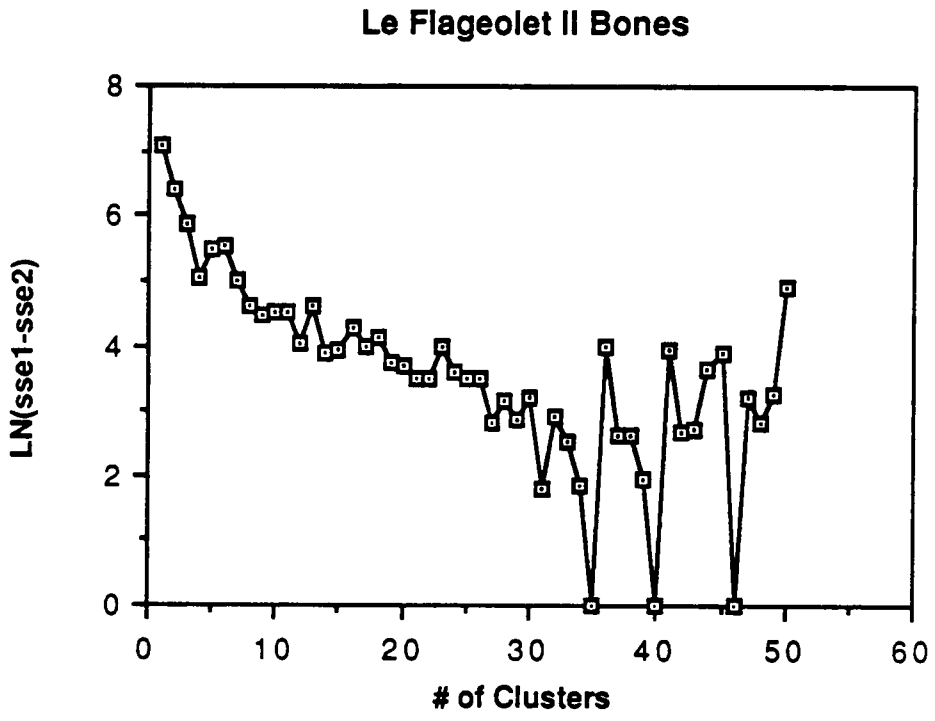


Figure 4.43 Le Flageolet II bones, LN((sse1-sse2)*1000). Optimal solutions are indicated at the 7, 14, 17, 24, 31, 36, 42, 48, and 49 cluster solutions.

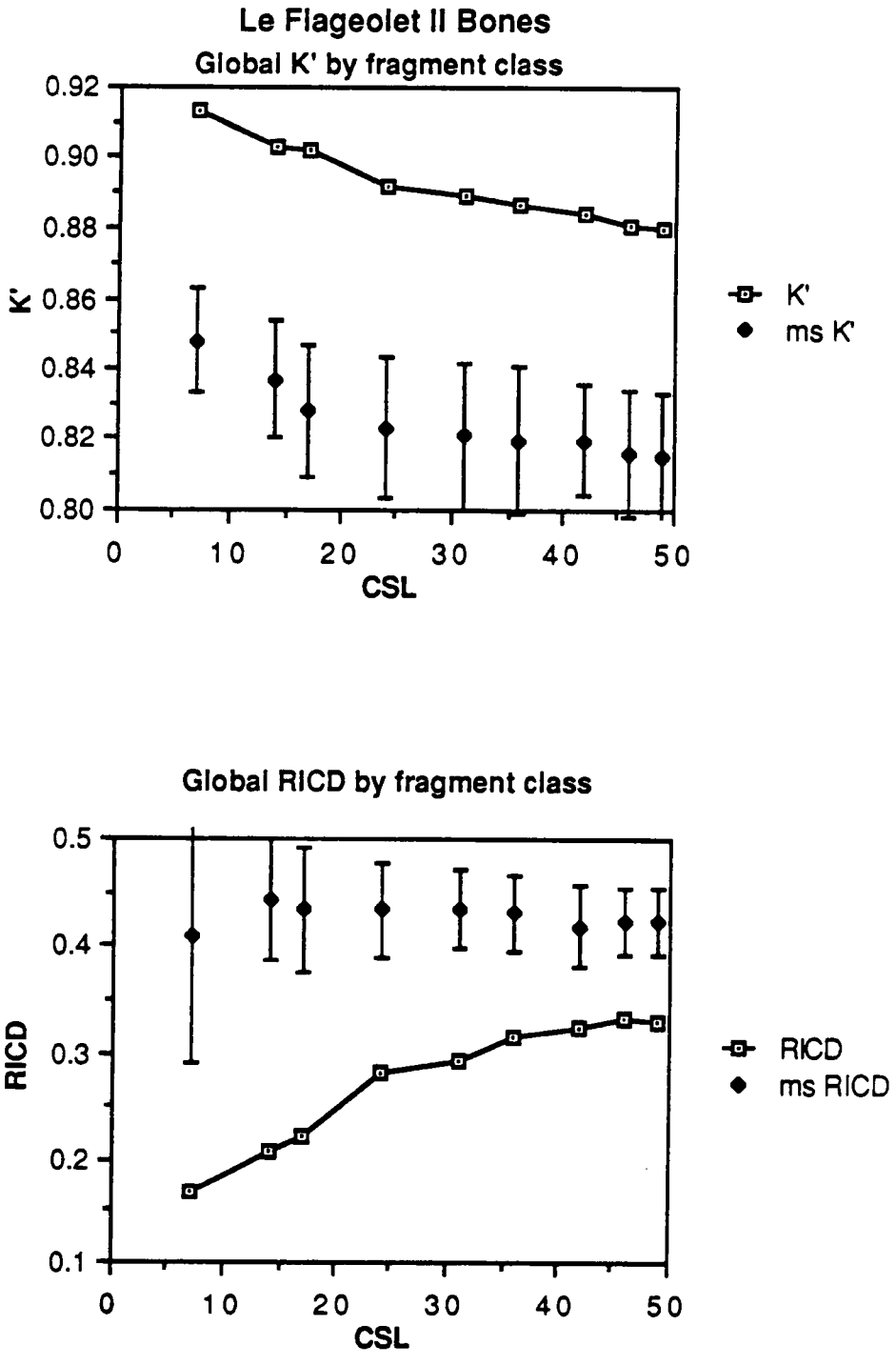


Figure 4.44 Le Flageolet II bones, global K' and mean RICD by fragment class.

decreases slightly with increasing number of clusters. Cluster similarity, in contrast, decreases dramatically with increasing numbers of clusters.

Global Attribute Correlations

Table 4.11 presents the result of Spearman's rank order correlations between mean within-level measured attributes and mean within-level depth for both the 5 and 10 cm arbitrary levels. All significant correlations are moderate or strong, and negative for both the 5 and 10 cm levels. There were no significant correlations between depth and either azimuth or length. Weight, width and density, however, were consistently correlated with depth in both the 5 and 10 cm levels. As has become the normal pattern, correlation strength decreases dramatically with increasing numbers of levels (i.e. form 10 cm levels to 5 cm levels).

In accord with the arbitrary level correlations, correlations between mean within-cluster attribute, and mean with-cluster depth are also all negative (table 4.12). Here, the most consistent relationship is between depth and density, which is represented in all cases except for the 36 cluster solution. Weight and azimuth show some correlations, but only at particular ranges of spatial resolution. Weight is only correlated with depth at the 17 cluster solution, and azimuth only at the 42-49

Table 4.11 Spearman's rank order correlations significant at p<.10 between mean attribute measurements and mean arbitrary level depth for Le Flageolet II bones. Azimuth represents modal rather than mean azimuth.

Level	Depth with:	RHO	P
10	Weight	-.81	.003
	Width	-.56	.08
	Density	-.84	.002
5	Weight	-.44	.05
	Width	-.59	.007
	Density	-.53	.01

Table 4.12 Spearmans rank order correlations between mean within-cluster depth and within-cluster depth standard deviation, and mean within-cluster object attributes significant at the .10 level for Le Flageolet II bone analysis by cluster solution level.

CSL	Depth with	RHO	P	Depth S.D.	RHO	P
7	Density	-.85	.01			
14	Density	-.75	.001	Density	.51	.05
17	Weight	-.41	.09			
	Density	-.64	.004			
24	Density	-.56	.003	Density	.49	.01
31	Density	-.37	.03	Density	.50	.003
36	-			Azimuth	.29	.08
	-			Density	.30	.07
42	Azimuth	-.27	.07	Azimuth	.44	.003
	Density	-.33	.03	Weight	.37	.01
	Density	.44	.003			
46	Azimuth	-.29	.04	Azimuth	.38	.008
	Density	-.36	.01	Density	.35	.01
49	Azimuth	-.31	.02	Azimuth	.42	.002
	Density	-.36	.01	Weight	.33	.01
				Length	.24	.08

cluster solutions. Again, correlation strength generally declines with increasing number of clusters, although both the density and azimuth correlations begin to rise again at the 46 and 49 cluster solutions. Correlations between depth sd and attribute (table 4.12) also show some interesting patterns. Here, density is positively correlated with depth sd in all solutions except for the 17 cluster solution. Azimuth, weight and length only appear after the 36 cluster solution. Again, correlation strength generally declines with increasing number of clusters, but this decline is not smooth. These results suggest that the measured attributes generally decrease in magnitude as depth increases, while simultaneously increasing as a function of cluster thickness.

Homogeneity by Level

The distribution of bone object clusters seems to break down into between 4 and 12 levels, depending upon the number of clusters in a given solution. When calculated by level K' values are generally above their corresponding mean simulated values (see figures 4.45-4.53). In solution levels 7-31, the observed K' values seem to trend upwards, away from the mean simulated values. At the 36 cluster solution however, they first become mixed with the 95 % CI around the mean simulated

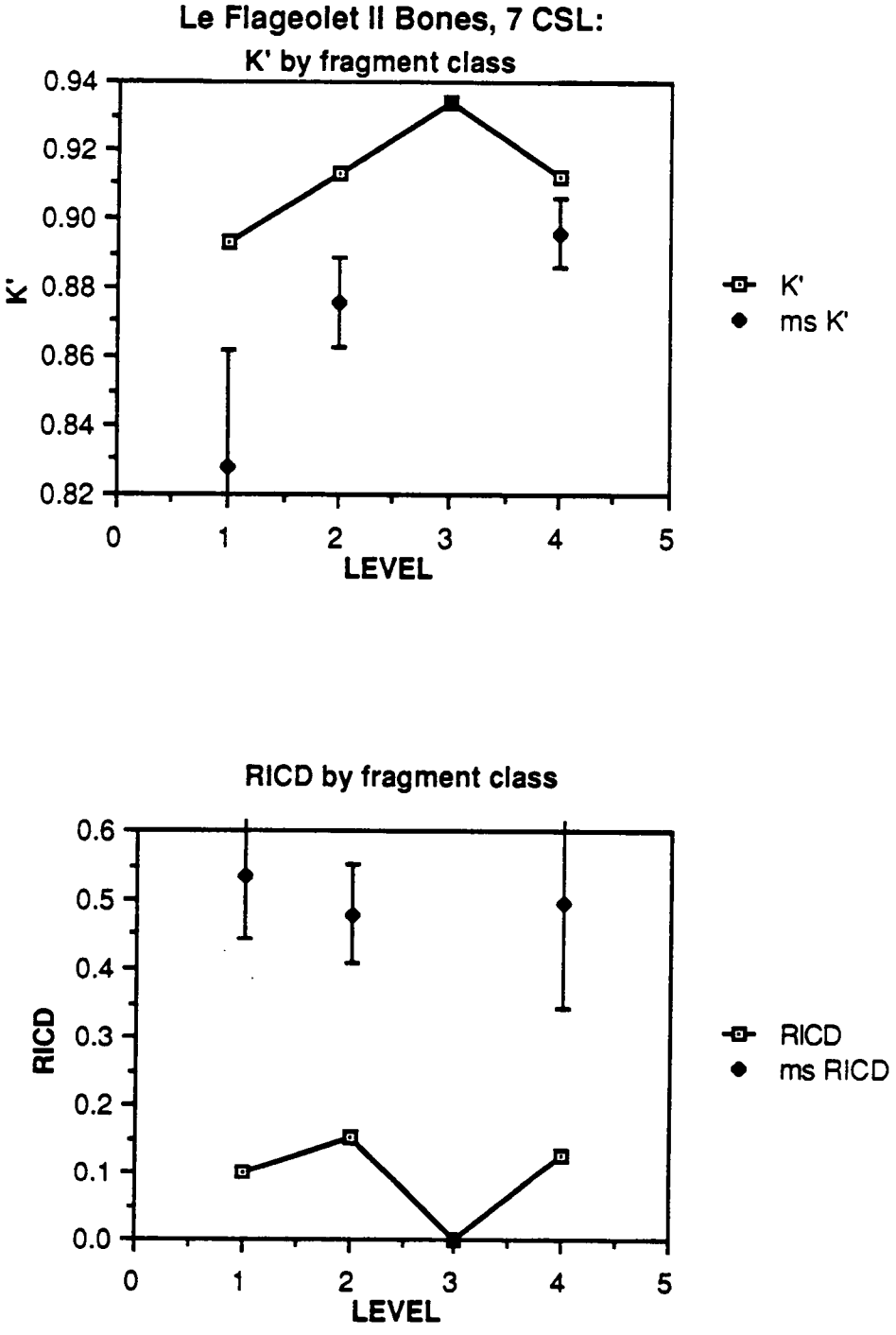
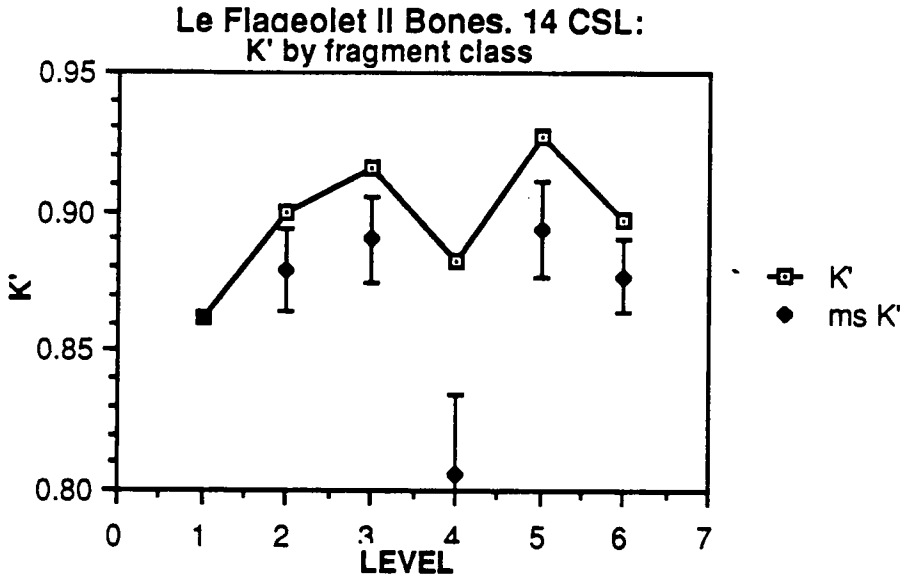


Figure 4.45 Le Flageolet II bones, K' and mean RICD by fragment class and level for the 7 cluster solution.



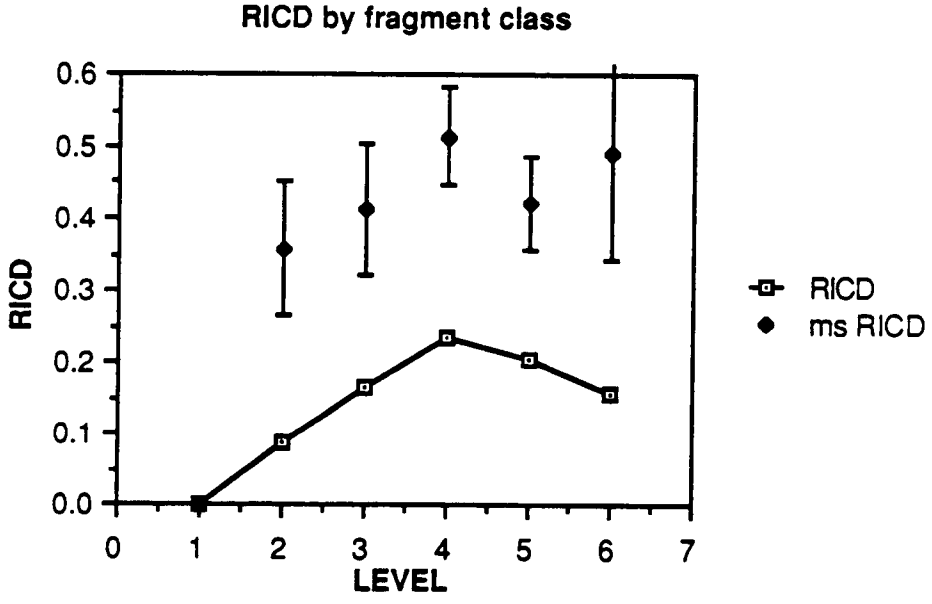


Figure 4.46 Le Flageolet II bones, K' and mean RICD by fragment class and level for the 14 cluster solution.

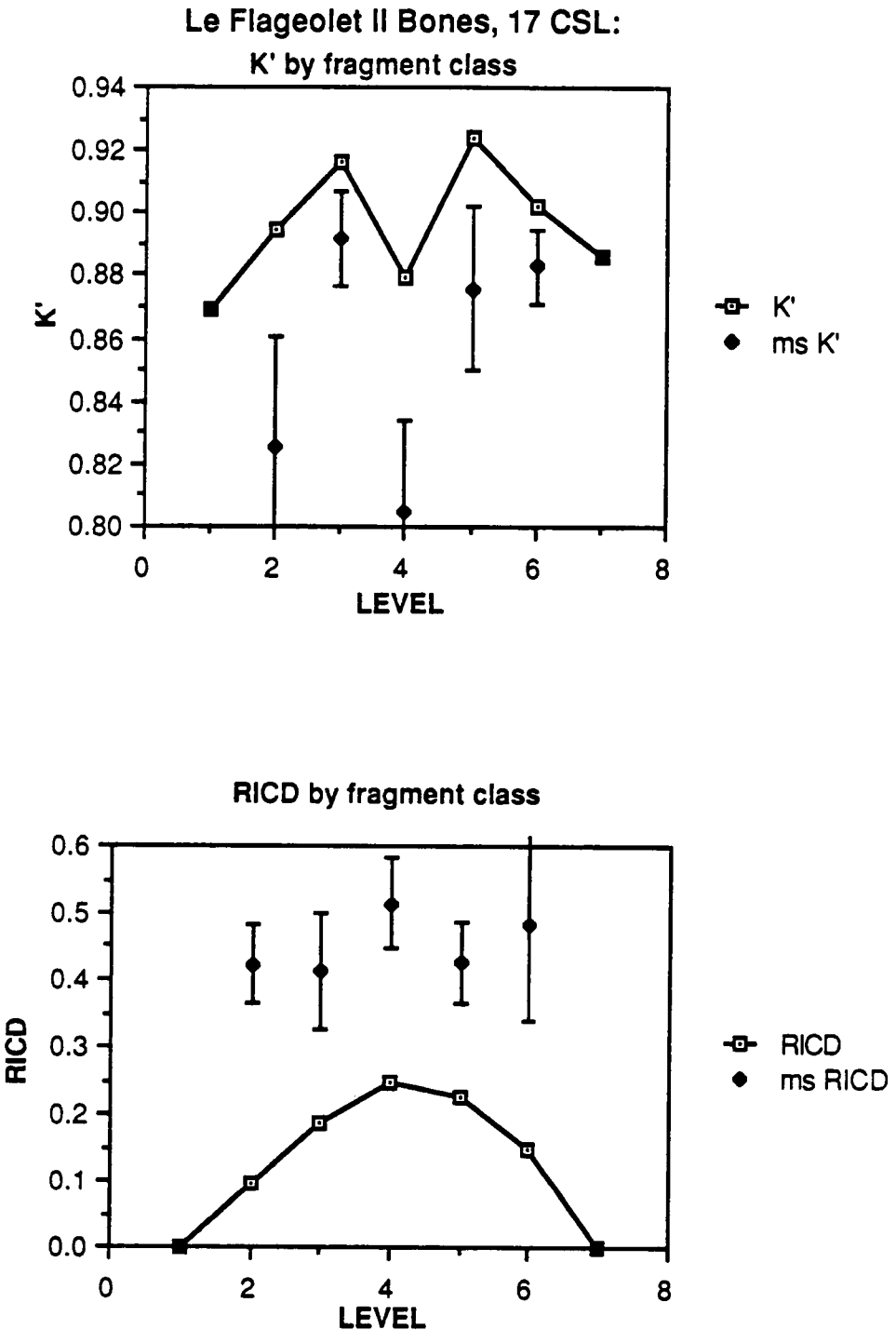


Figure 4.47 Le Flageolet II bones, K' and mean RICD by fragment class and level for the 17 cluster solution.

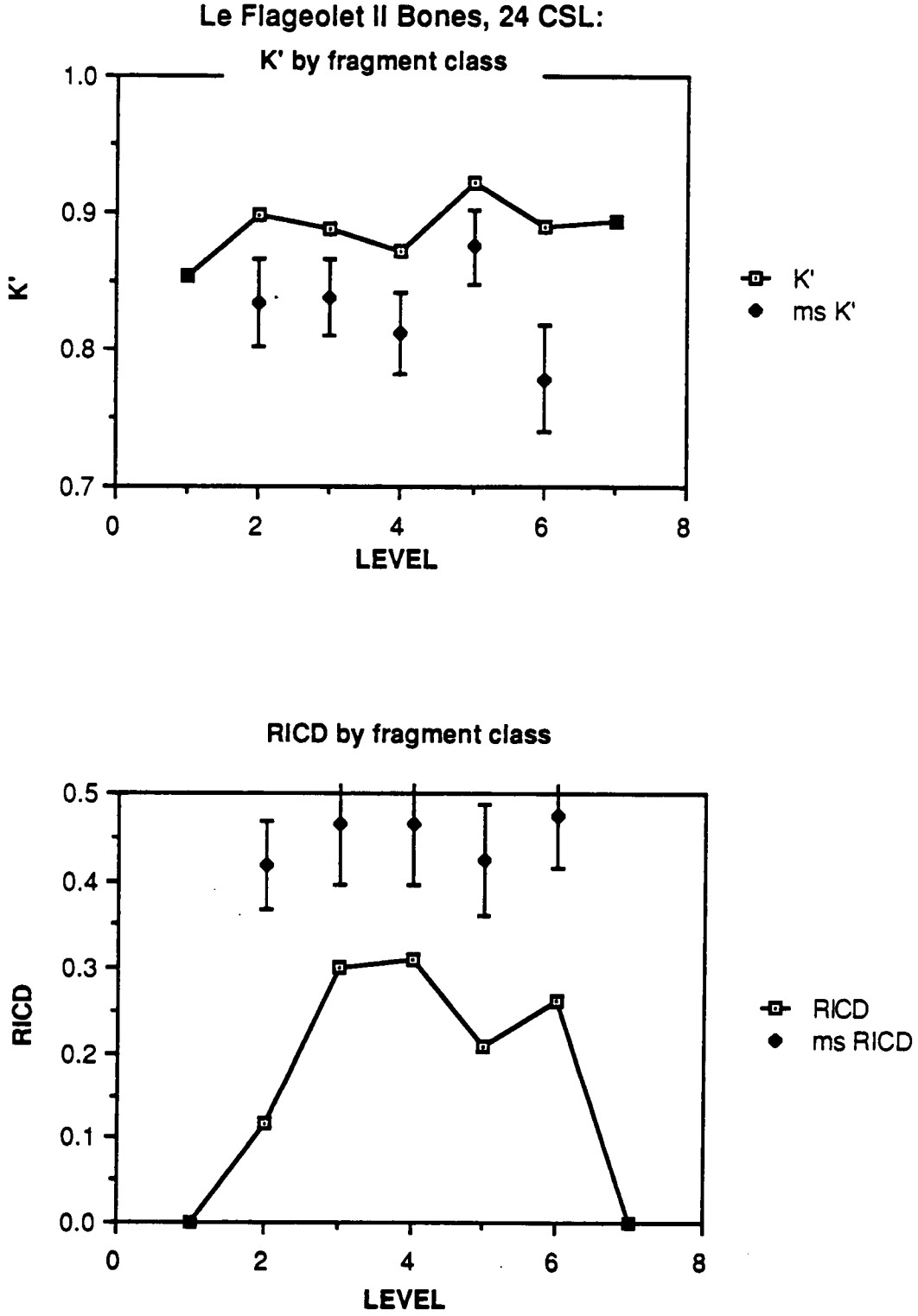
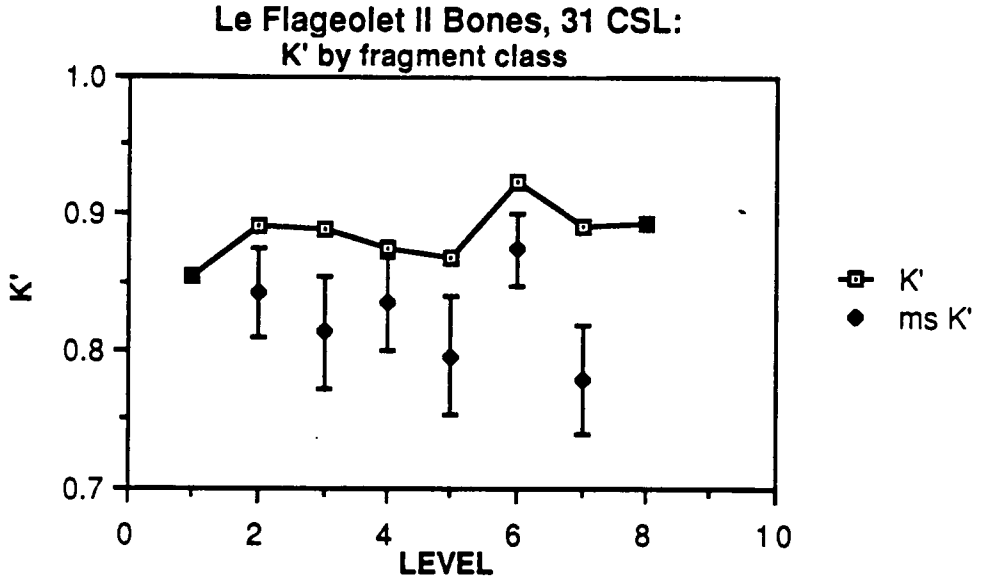


Figure 4.48 Le Flageolet II bones, K' and mean RICD by fragment class and level for the 24 cluster solution.



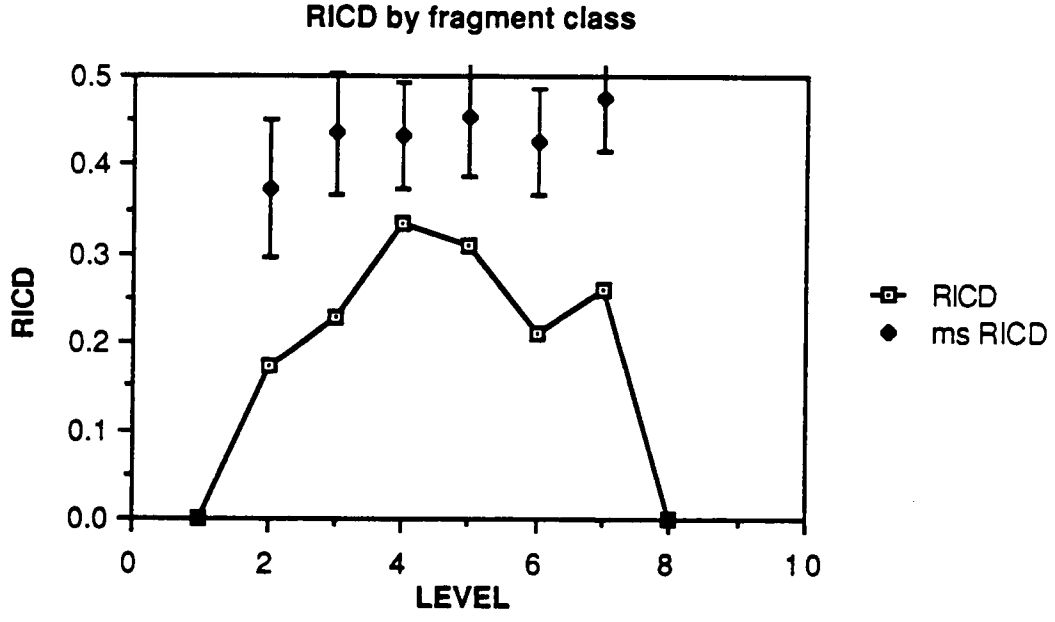


Figure 4.49 Le Flageolet II bones, K' and mean RICD by fragment class and level for the 31 cluster solution.

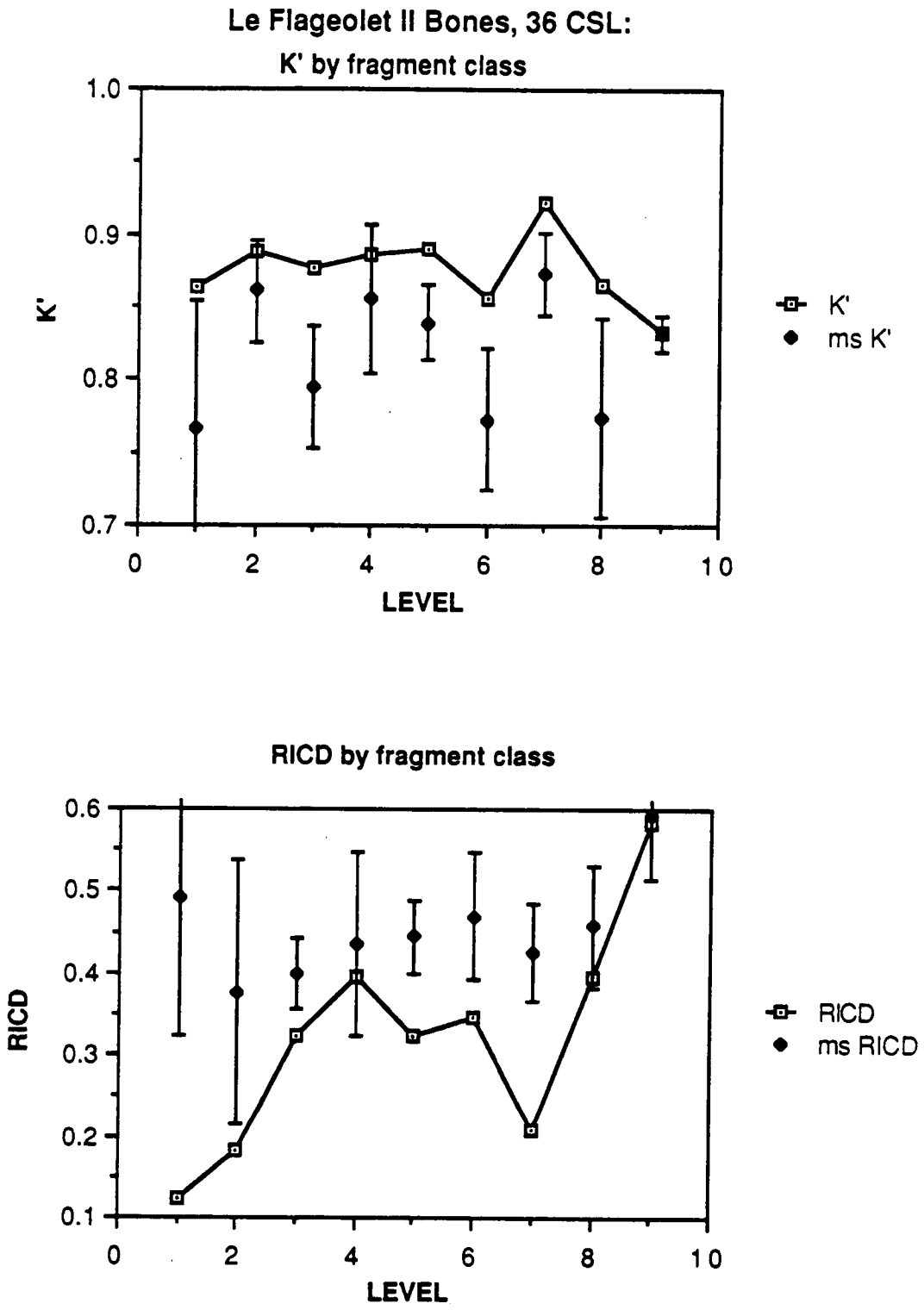


Figure 4.50 Le Flageolet II bones, K' and mean RICD by fragment class and level for the 36 cluster solution.

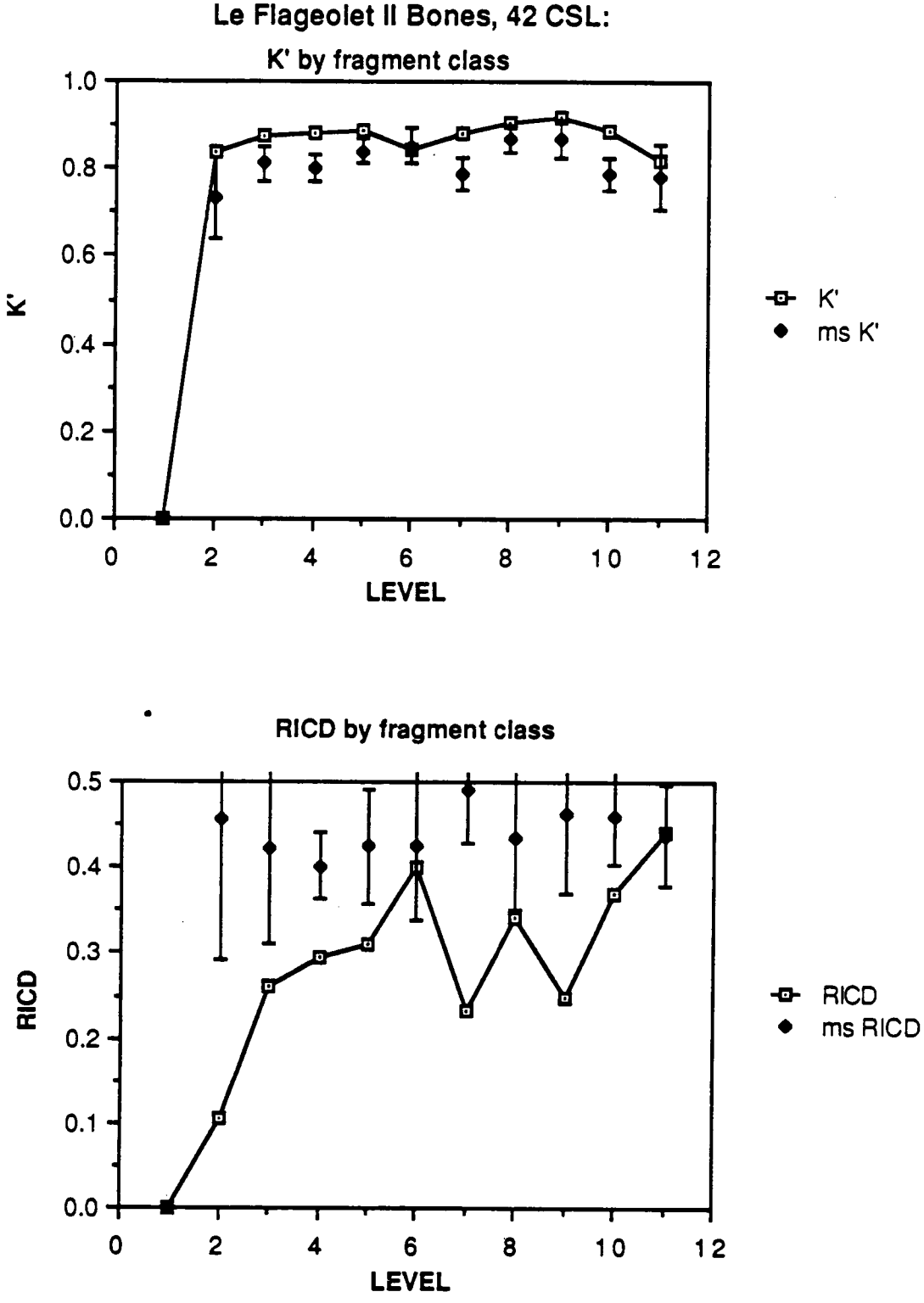


Figure 4.51 Le Flageolet II bones, K' and mean RICD by fragment class and level for the 42 cluster solution.

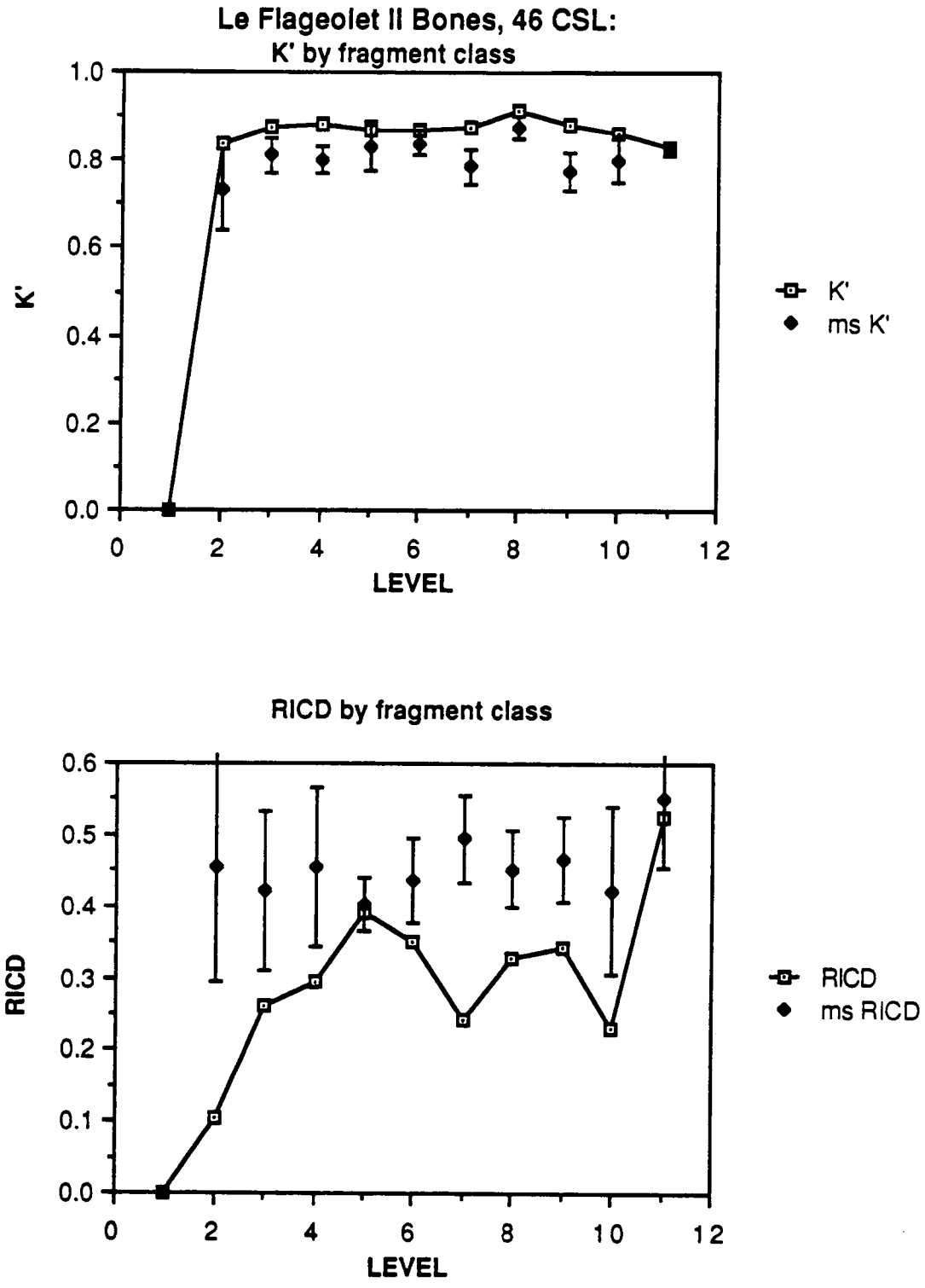


Figure 4.52 Le Flageolet II bones, K' and mean RICD by fragment class and level for the 46 cluster solution.

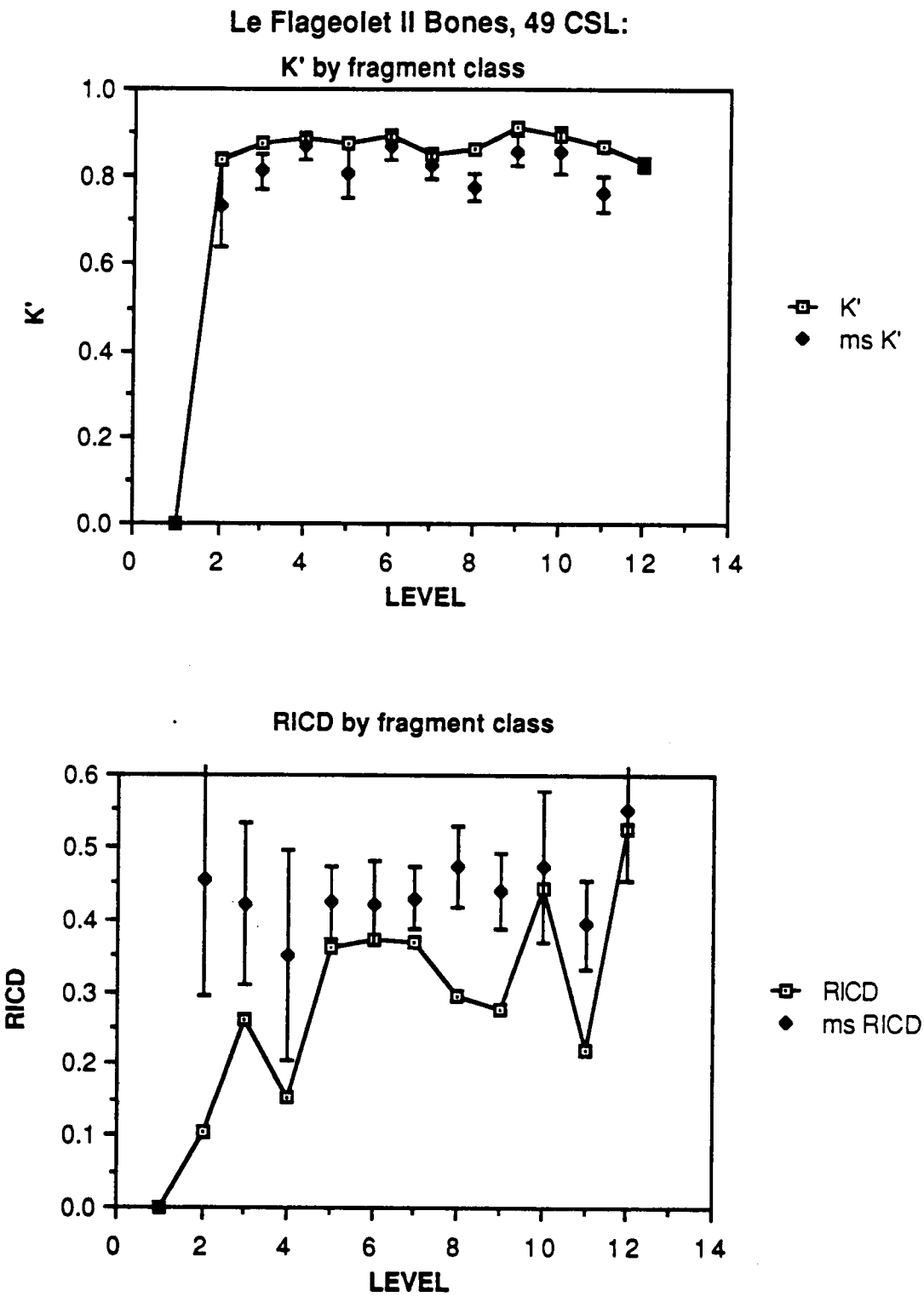


Figure 4.53 Le Flageolet II bones, K' and mean RICD by fragment class and level for the 49 cluster solution.

values. This trend increases as the number of cluster increases, although those levels that do not fall into the 95% CI seem to remain substantially above it, and perhaps trend upwards. There are no cases of the observed K' falling below the lower bound of the 95% CI, however level 6 in the 42 cluster solution is noteworthy in that its observed K' value falls below the mean simulated value.

Observed mean RICD values behave similarly. For solutions between 7 and 31 clusters, the observed mean RICD curves are always below the mean simulated values and their 95% CI. These figures may be somewhat misleading because most include two levels containing only one cluster and thus 0.0 RICD values. After the 36 cluster solution however, these disappear and the observed mean RICD values begin to become more mixed into the 95% CI around their mean simulated values. In no case does the observed mean RICD rise above the upper bound of the 95% CI around the mean simulated values, but level 11 in the 42 cluster solution level is above the mean simulated value.

Discussion

Overall homogeneity results for the bones suggest that while in general the distribution is more homogeneous than expected, cluster similarity decreases drastically, although still ending up below expected levels. When the

site is broken down into levels, homogeneity results again suggest higher than expected homogeneity, at least at cluster solutions below 36 clusters. From 36 to 49 clusters, homogeneity relationships seem to decrease in magnitude, and cluster similarity to decrease much more dramatically. These solutions contain the only cases of mixing between observed and mean simulated K' or RICD. In each case there is a definite correspondence between levels for which the observed K' is within its expected range, and those for which the observed mean RICD is within its expected range. This correspondence does not hold up in detail however. For example, although the observed K' value for level 6 in csl 42 is below the mean simulated value, the corresponding mean RICD value is not above its mean simulated value. Exactly the opposite holds for level 11 in csl 42.

Attribute correlations also show interesting trends above and below the 36 cluster solution. Azimuth, weight, and length show, with one exception, their only significant correlations with either mean within-cluster depth, or depth sd at the 36 cluster solution level or above. Clearly a major distinction can be made between solutions above and below 36 clusters.

Bone fragment classes do not appear to be well structured in space, when calculated globally and by level, homogeneity relationships suggest a substantial

degree of mixing. This is generally true for the site as a whole, despite the changes after the 36 cluster solution. Bone density is negatively correlated with within-cluster depth, a pattern opposite of that found for the other material classes. This suggests distinctive patterning. The next section discusses and compares the results of all four material classes.

Comparisons

Optimal Solution Levels

Comparing the optimal solution levels (figs. 4.4, 4.25, 4.34, 4.43) of the four material classes that were analyzed separately shows several similarities. Although in detail the % sse plots are very different, most material classes seem to have optimal solutions either at or very close to the 24, 31, 42, and 49 cluster solutions. Solutions below 24 clusters seem highly variable across the material classes, as do solutions between 24 and 42 (with the exception of 31 clusters). This implies a high degree of similarity in the relevant scales of spatial patterning, suggesting that at least on a gross level similar processes or constraints were operating on all material classes to structure the three dimensional space at Le Flageolet II. This implication leads to the hypothesis that structural redundancy for

this site should be moderate if not high, assuming that similar high level spatial processes were operating in most or all occupations of the site.

Global Homogeneity

Two distinct patterns of global homogeneity are evident across the material classes. The first, which occurs only with the non-tool flakes (Fig. 4.35), is low in an absolute sense, and flat across clusters, but very high relative to the expected values. The second, which is apparent in all other material classes, shows high homogeneity both absolutely, and in comparison with expected values, but is substantially lower compared to the expected values than the relationship among the non-tool flakes. Given the expectations developed for this and similar measures by Koetje (1987a) and Simek (1984), high homogeneity relative to the mean simulated values might be expected when considering a three dimensional distribution. This is because clusters defined in three dimensions should probably include a more diverse set of materials than those defined on a two dimensional "living floor", thus global homogeneity would be high. Differences in the absolute magnitude of homogeneity among material classes are easily related to the overall class frequencies, but differences in magnitude relative to expected values can not relate to this factor.

These two patterns evident in the homogeneity relationships seem fundamentally distinct, and suggest that non-tool flakes (primarily lithic debitage), are more homogeneously distributed than tools (when examined either by typological or fragment classes), non-tool blades, or bones. Bones, probably also primarily waste, might be expected to show very similar patterns, but they do not. If these patterns are created by human action, they may be the result either of different disposal patterns or the nature of lithic reduction patterns. Distinctions between these "causes" probably cannot be made through this type of analysis alone.

Attribute Correlations

In most cases there are a number of consistent, moderate or strong correlations between the object attributes and within- level and cluster depth. This might be taken to imply massive disturbance and mixing. However, trampling and disturbance studies in general most frequently show no clear correlation between these attributes and depth. This is especially true with respect to object weight. Thus the existence of these relationships cannot be taken to imply this presumptively. The intact features at this site argue against extensive reworking of the deposits by natural phenomena. Furthermore, at Le Flageolet II the correlation

relationships do not remain consistent across material classes. If weight or density and depth correlations alone implied serious vertical mixing, the relationship would be expected to be either consistently strong, or at least consistently in the same direction across various material classes. This is not the case here. Mean within-cluster weight, length, width and density are uniformly positively correlated with within-cluster depth for all lithic material classes, but weight and density are negatively correlated with depth for the bone materials. To explain this with a single natural disturbance process as a cause one would have to suggest a process that moved objects both upward and downward simultaneously according to some weight or density threshold. Dense bone objects would have to "float" upwards, while dense lithic objects would simultaneously "sink". Such a process seems unlikely.

Given the lack of evidence for major vertical movement presented by the intact features and very low number of vertically oriented objects, a more reasonable model for differing density correlations by material class might be differential removal from the site by material class and density, rather than vertical migration by density. Negative correlation between bone density (but not size or weight) and depth suggests several possible "causes"; differential in-place chemical decomposition or

weathering, and/or decreasing frequency (or length) of occupation with depth. The last seems likely given the presence of a cobble pavement in the upper portions, and only isolated hearths in the lower portions of the site. The implication then is that only the more dense (but not large or heavy) bone fragments would tend to survive intensive occupation, either as a result of the human activities or their unintentional byproducts (e.g. trampling, increased Ph etc.). This is consistent with studies showing that density is a factor in bone preservation in general, as well as recovery in ethnoarchaeological situations (Binford and Bertram 1972; Gifford 1977; Gifford and Behrensmeyer 1978).

Differential survival by density in the face of distinct occupations intensities may also be a reasonable explanation for positive weight, size, and density correlations with depth for the lithic materials. If the upper pavement portions of the site were occupied more intensively, they might be cleaned more thoroughly. In this case, large masses of lithic materials would be removed, while smaller ones might be lost, or less likely to be removed. Also to be considered is the extent of disturbance in the upper portion of the site. If objects were originally distributed differentially by density in the horizontal plane, (i.e. large, heavy, dense lithic material, and low density bone material occurred most

commonly in the upper central portion of the site), the removal of substantial amounts of the upper central part of the site could explain these trends. A large central hearth or hearth complex in this area would be a good reason for such horizontal patterning to have existed. In any case it seems clear that because there appear to be no reasonable explanation based on natural processes, explanations should center on differential removal or survival rather than vertical migration.

Perhaps as interesting are patterns among the correlations with within-cluster depth standard deviation. Tools, and non- tool flakes show moderate to strong negative correlations with this measure of cluster thickness. In both cases the majority of these correlations occur at or near the 25 cluster solution. They are of similar magnitude, and include the attributes of length, weight and density. Most other solutions in these cases show no correlations with within-cluster depth SD and the measured attributes. While there is no obvious explanation for this phenomenon, it suggests horizontal banding by weight and density class, which may be evidence for restricted, local vertical movement. It may, as easily however, be connected to distinct occupation or formation events, especially as it is restricted to particular spatial scales.

While both non-tool blades and bones show moderate positive correlations with depth SD, the attributes are usually different in each case. Non-tool blades typically show low positive correlations between length and weight, and depth SD, while bones most frequently show somewhat higher correlations between density and azimuth, and depth SD. In the case of non-tool blades mean size, while in the case of bones, mean density tend to decrease with decreasing cluster thickness, again suggesting horizontal banding by these factors, but here the spatial scales do not appear as restricted. Instead these relationships occur at most or all cluster solutions.

Homogeneity by Level

Homogeneity by level does not seem to evidence the same kind of patterning as the factors discussed above. With the exception of the K' patterns of the non-tool blade and non-tool flake material classes, each pattern is unique. Non-tool blades and flakes show similar K' patterns when these are calculated by level. In both cases K' is relatively stable with increasing numbers of clusters and levels, but their magnitude relative to the expected values are quite different. RICD patterns are very different in each case however. In general homogeneity and mean RICD by level seem to show different patterns for each material class.

IV.4 Conclusions

Different parts of this analysis have suggested distinct implications for the variables identified in the model developed in chapter II. Similarity among optimal cluster solutions suggests that similar large scale spatial processes are acting on all the material types at specific spatial scales. This implies that structural and perhaps assemblage redundancy should be moderate or high for different occupations at the site. These implications are supported generally by the high global homogeneity values (relative to their expected values) for all material classes, and the generally similar attribute correlations across cluster solution levels. They are perhaps contradicted in part by the evidence from features for increasingly intensive site use through time. Yet such increases in occupation intensity do not necessarily require a change in site structure. It would not be surprising to find that the addition of a pavement did not fundamentally shift the use of space in a relatively restricted area. Similar pavements from the Magdalenian in open air contexts show a wide variety of spatial structures (Koetje 1987a,b). Direct comparison of the spatial structure between the levels containing the pavement and other levels in this site are generally pointless because of the disturbance in the upper levels.

In general terms the Late Magdalenian utilization of Le Flageolet II seems to have changed substantially and perhaps dramatically through time, although the types and fragmentation patterns of lithic tools and debitage produced, and fragmentation patterns of bone waste are substantially similar throughout the site. The distributional similarity of the materials suggests that the same general pattern of site use was carried on through the entire potential occupation period (c. 15800 to 13500 B.P.). Early occupations involved no major, surviving architectural structures beyond fire hearths. In later occupations of the same general pattern, as evidenced by faunal remains and the lithic tool assemblage, at least one surviving pavement was constructed. This is possibly indicative of increasing occupational intensity, an interpretation that is supported by the bone and lithic density correlations by cluster depth, but may also be related more simply to climatic changes (Koetje 1987b), or both. The physical attributes of the materials included in the early and later occupations appear to have changed through time as well, although how this may relate to their function or use is unclear. In the case of the lithic materials, this may be related to changing patterns of the lithic reduction process itself, or more simply to the locations were particular phases of this activity were carried out.

The methods used to analyze this site appear to have been very successful in generating patterns that could not have been found through other approaches. Correlations by arbitrary level for example showed little or nothing. It is clear from the cluster projections, (Fig. 4.7-4.8) that largely horizontal clusters were produced, and that these may be fruitfully combined into levels that produce interesting patterns. In many respects however this site represents an ideal case for this type of analysis, the position of most objects was recorded in three dimensions, vertically oriented objects were clearly noted, and the excavated area was restricted to the portion of a rockshelter behind the dripline so "target" levels could be assumed to be largely horizontal. In the next chapter, a similar analysis will be performed on a site in which the "target" levels cannot be so easily assumed to be horizontal.

CHAPTER V

CASE II: THE GROTTE XVI

V.1 Introduction and Site Specific Modifications

The Grotte XVI is one of at least 22 caves and rockshelters along the Le Conte Cliffs overlooking the Ceou river valley in the Dordogne region of SW France. Excavation under the direction of Drs. Jean-Philippe Rigaud and Jan Simek was begun in 1984 and is continuing (Rigaud et al. 1989). The site is composed of a deeply stratified series of deposits containing materials ranging from the Mousterian to the late Magdalenian (see figs. 5.1-5.3). As currently understood there are ten major stratigraphic units ("couches" in French) in the Grotte XVI (table 5.1).

This analysis is restricted to the front and lower portion of the excavated area in the Grotte XVI, consisting on the X or frontal axis of units H-K, and on the Y or sagittal axis of units 1-10 (see figure 5.2). Some 40 square meters are involved with depth ranging from 1 to 3.2 meters. Towards the interior of the cave, excavation consists only of a single 1 x 10 meter trench connecting the main chamber with the gallery (see figure 5.2). Because of their restricted excavation as of 1989, neither this trench nor the gallery are considered further

Table 5.1 Stratigraphic layers (couches) at the Grotte XVI. A "*" in the CLASS column indicates that a couche was not present in the analyzed volume of the site.

Major stratigraphic units (Couches)

COUCHE	CULTURE	CLASS
0	Upper Magdalenian	*
1	Magdalenian (?)	*
A superieur	Late Solutrean	3
A base	Late Aurignacian	2
B	Mousterian	4
C	Mousterian	5
D	Mousterian (Quina retouch)	6
E	Mousterian	7
F	Middle Paleolithic	8
G	Middle Paleolithic	9
Solifluction	Solutrean (?)	10
A	Solutrean (?)	1
Abi	(?)	11

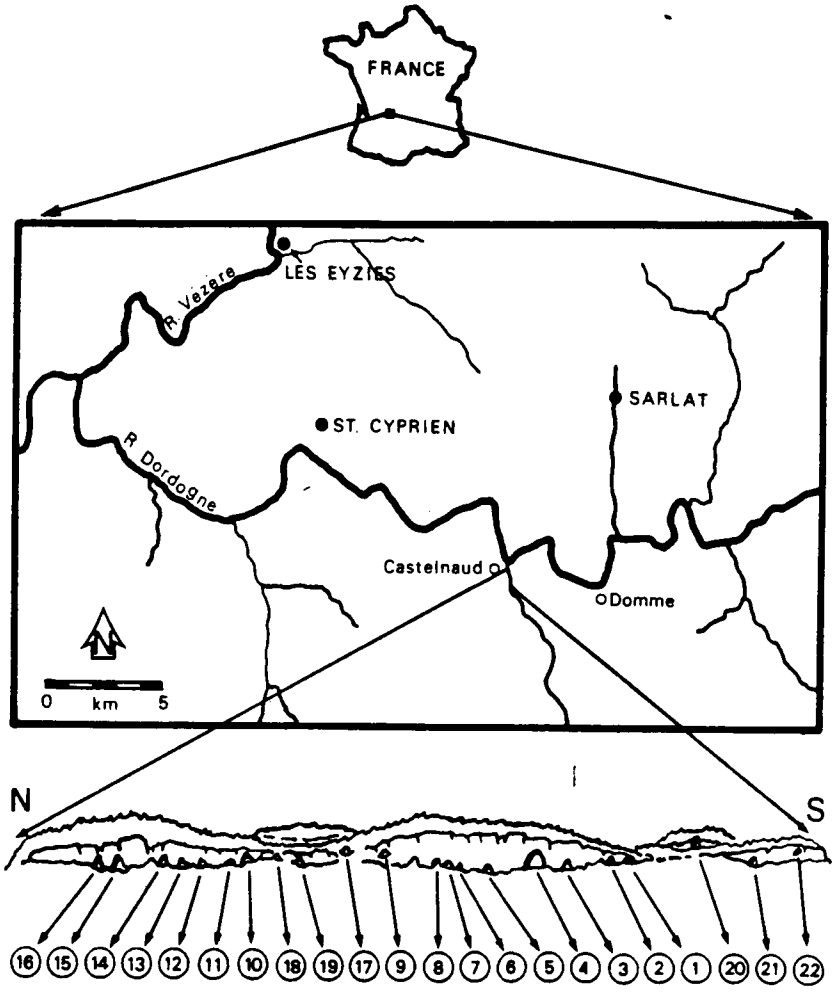


Figure 5.1 Location of the Grotte XVI.

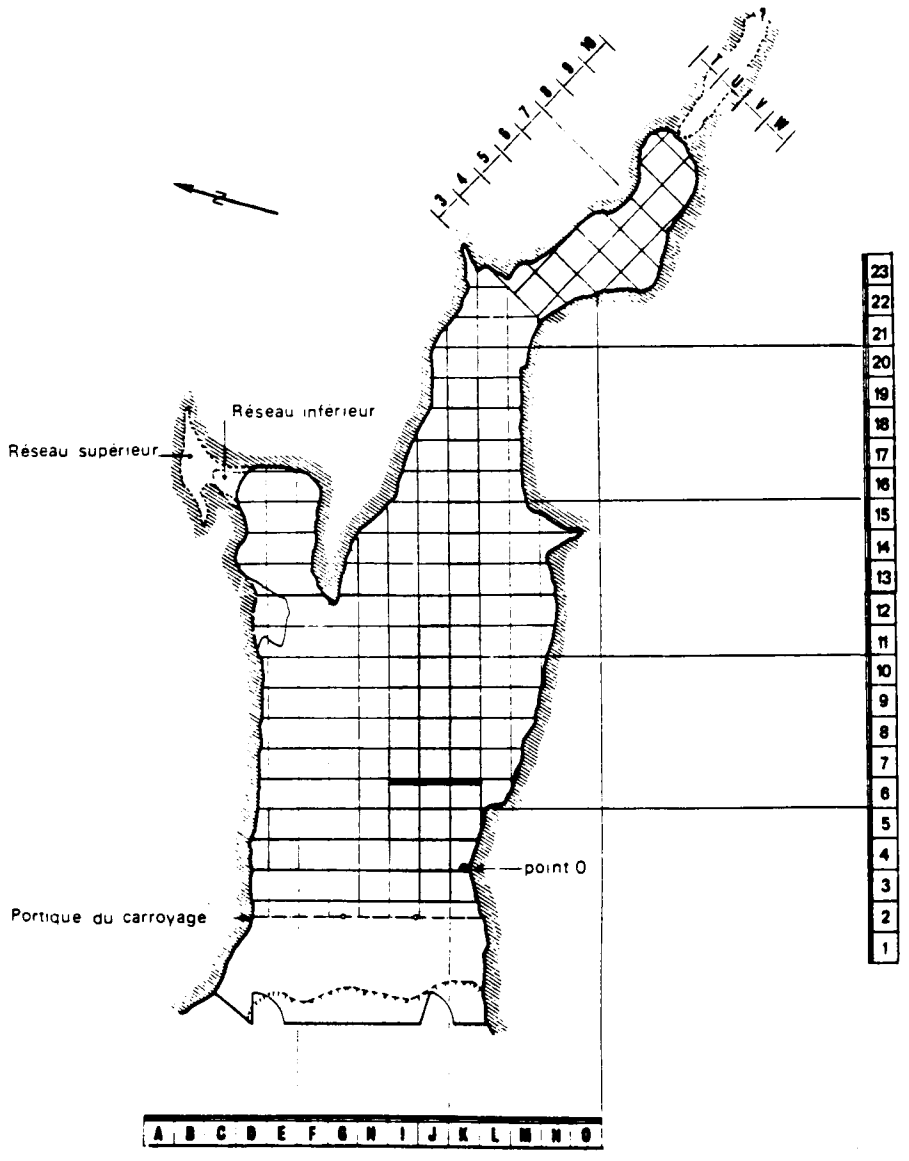


Figure 5.2 Plan map of the Grotte XVI showing the coordinate system and excavated areas. Reproduced from Rigaud et al. (1989), with permission.

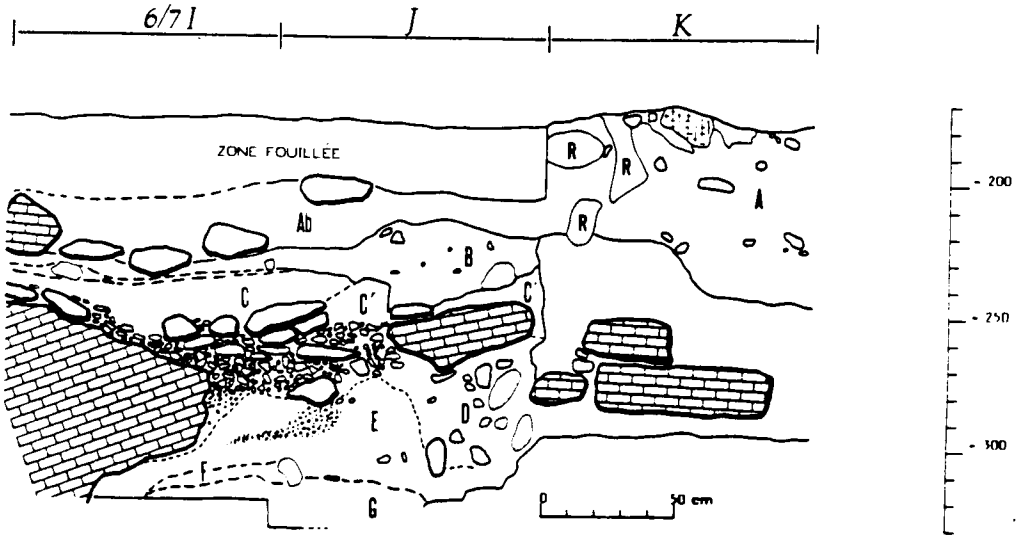


Figure 5.3 Frontal stratigraphic section for the Grotte XVI. Reproduced from Rigaud et al. (1989), with permission.

here. Couches A-G occur in the volume analyzed here. In addition, material currently labeled as couche "A", couche "Abi" (for A base infra), and "solifluction" occur in the analyzed volume. The proper place of these materials in the stratigraphic sequence is in doubt because of either their problematic nature, the restricted nature of the current excavation, or both. This is not then, to be a full fledged attempt to characterize spatial patterning at this site so much as to explore the contributions that these methods can make towards understanding the deposits at a site in three dimensions, and how this can contribute to their excavation.

This analysis does not include the same examination of patterning with respect to measured attributes for each object that was the case in the Le Flageolet II analysis. For these purposes there is only one major attribute common to all objects beyond their position in three dimensional space: material type. Three separate sets of objects were used. Bone and lithic material were analyzed separately, and as part of the consideration of all the objects. Weight, technological nature, and fragmentation were recorded and are available for some 90% of the lithic objects. For most bone objects genus and species, anatomical part, and fragmentation are known. In addition, position with respect to horizontal was recorded for each object. Two distinct sets of analyses were done.

Bone, lithics and the complete set of objects were clustered using both the within-couche standard deviation transformation, and the global z-score transformation. Flint objects were selected for a series of analyses using the global z-score transformation and various Z-axis distortion factors. Analyses of the entire assemblage and the bone materials using the global z-score transformation were restricted to a distortion factor of 5.

Figures 5.4-5.5 show frontal and sagittal projections of the entire assemblage from a 50 cm wide section of the excavated area. Objects in these figures are marked by their couche assignment. Two main points are clear from examination of these figures. First, both frontal and sagittal projections show that some couches (particularly 3, 4 and 5) have distinct slopes, and that these slopes are not uniform in either degree or direction. Second, it is clear that several couches show particularly irregular outlines, and often extend into those immediately over or underlying them. This is most evident in the frontal stratigraphic section. As a direct consequence of these points, any given horizontal band drawn across these projections is likely to contain objects assigned to two or more couches, and in extreme cases perhaps as many as five or six. The generally sloped and uneven couche boundaries are probably the result of at least three distinct processes: inclusion of

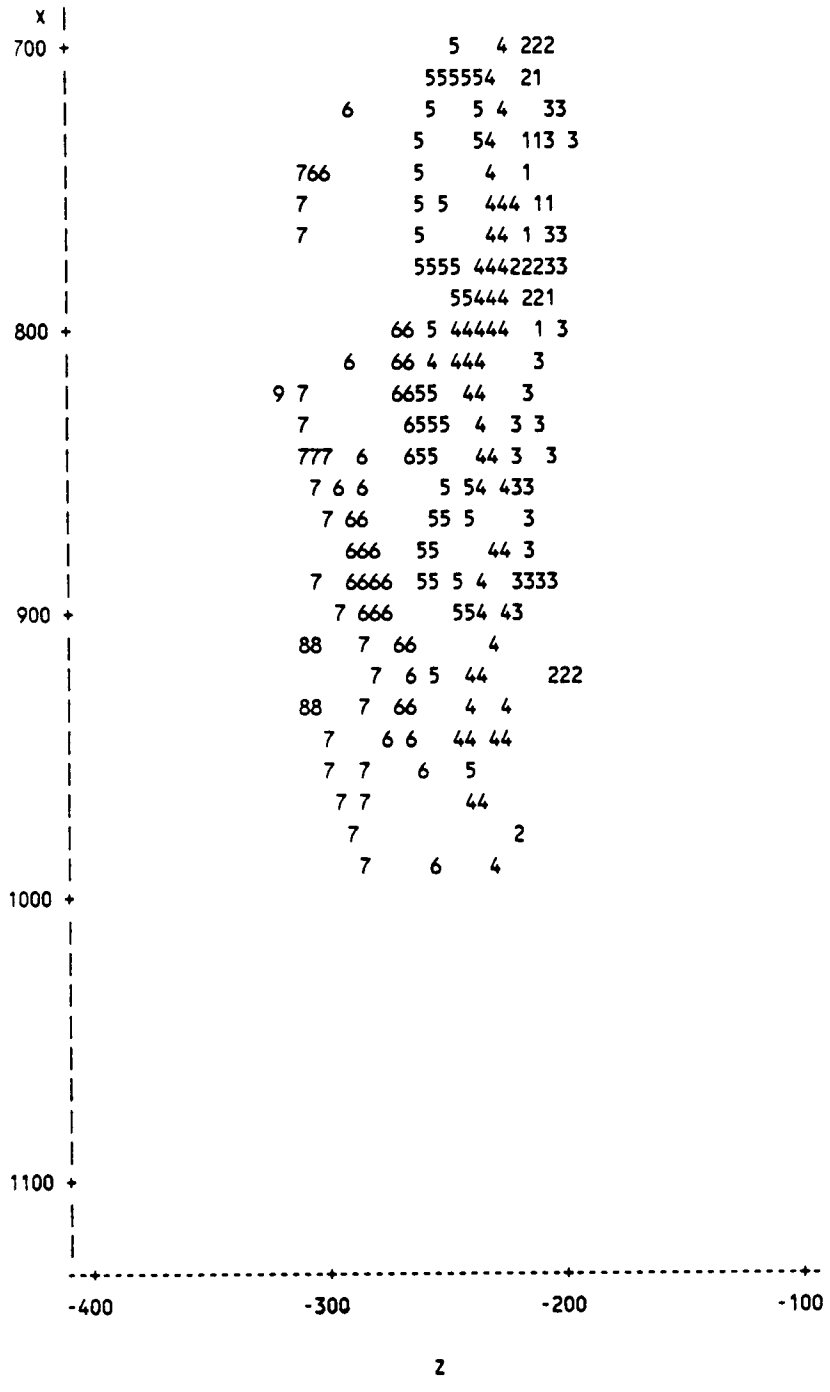


Figure 5.4 Frontal projection of archaeological materials from the Grotte XVI. Numbers indicate couches (see table 5.1).

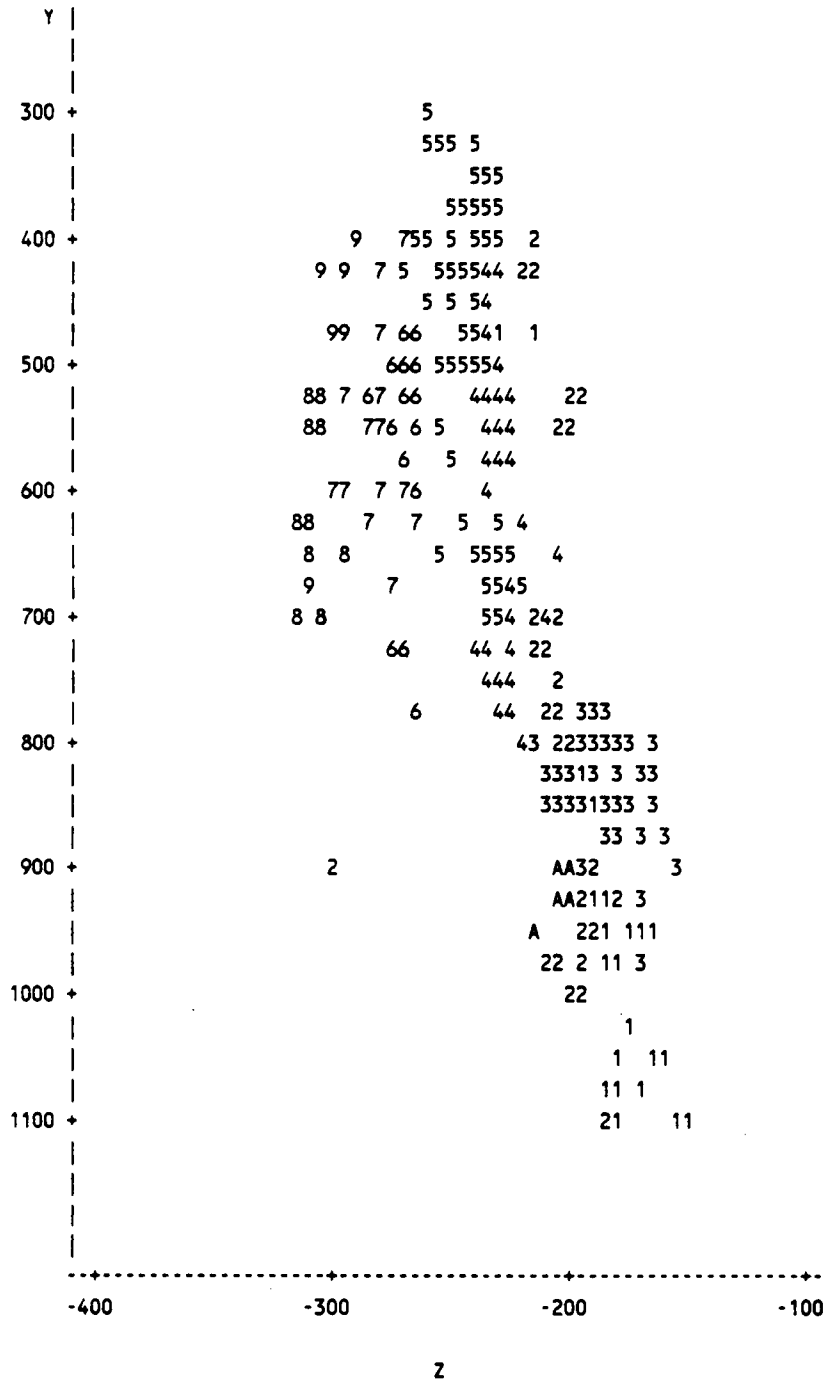


Figure 5.5 Sagittal projection for archaeological materials for the Grotte XVI. Numbers indicate couches (see table 5.1).

a couche tentatively labeled "solifluction" in this analysis, several large rock fall episodes that have effected various parts of the excavated area, and the incomplete nature of the excavations.

Inclusion of the "solifluction" couche causes problems immediately because it occurs in several distinct areas and within at least two previously defined couches, however there are relatively few objects in this category. Similarly the relationships between some of the more well defined couches have yet to be clarified. The exact relationships between the couches labeled "A", "As", "Ab", and "Abi" (see table 5.1 for the class key used in Figs. 5.4-5.5) are unclear in many places at the moment, and so while they were included as discrete entities they may in fact be largely identical. At the same time however, because of the rock falls and other procesess, it is clear that the couches within this site are by no means horizontal, nor are they relatively similar in slope over the excavated area. They are not with a few exceptions, indistinct or arbitrarily defined.

Given the horizontality assumptions inherent in the use of the global z-score transformations, and the tendency for Z-axis distortion factors to restrict cluster membership to horizontal bands (at least in extreme cases), these techniques would seem to be largely inappropriate for use at this site without extensively

transforming the spatial coordinates of each object. Some of the obvious object patterning in the profiles and the distinct nature of each of the 11 defined couches should cause problems for transformations based on within level statistics as well however. Well defined separation of the "solifluction" areas and couches As, A, Ab, and Abi, may be difficult or impossible because in some sections these are thoroughly intermixed. The focus of the remainder of this chapter will be on the utility of these methods in characterizing the patterning evident in three dimensions at this site, and the uses that this knowledge may be put to in these circumstances, particularly with respect to the solution of stratigraphic problems and guidance for the next excavation sequence.

The couches and material found within them span somewhat more than 40,000 years (by radiocarbon dates) and the two major periods in the later Paleolithic (Middle and Upper). These periods can and often do contain many objects with distinctly patterned technological, typological, or natural (in the case of faunal material) attributes. The goal of this research is not to address these distinctions, but to discover methods to characterize the spatial patterning of the objects. For this reason, many of the more obvious characteristics of the materials were ignored. Particulars are discussed in more detail in the relevant sections. When dealing with

lithics for example, blade versus flake distinctions, and typological classification of the retouched lithics were not used. In general, patterning along these variables would almost certainly reflect Upper vs. Middle Paleolithic technological patterns more than anything else. Questions of the continuity of broadly defined functional tool types or faunal exploitation patterns across the Middle/Upper Paleolithic boundary at this site are beyond the scope of this project, and perhaps inappropriate at this stage of the excavation.

V.2 Analyses

Complete Assemblage

Homogeneity by Couche

In all, the front portion of Grotte XVI contains some 4077 provenienced objects. When clustered out to the 50 cluster solution, inspection of the %sse differences plot (Figure 5.6) for the complete assemblage using within-couche standard deviation as the transformation technique shows optimal solutions at the 17, 30, 33, 38, 43, and 48 cluster solutions.

Because the K' index measures (among other things) the evenness of a cluster's class distribution, these values can be used to compare the distribution of couches

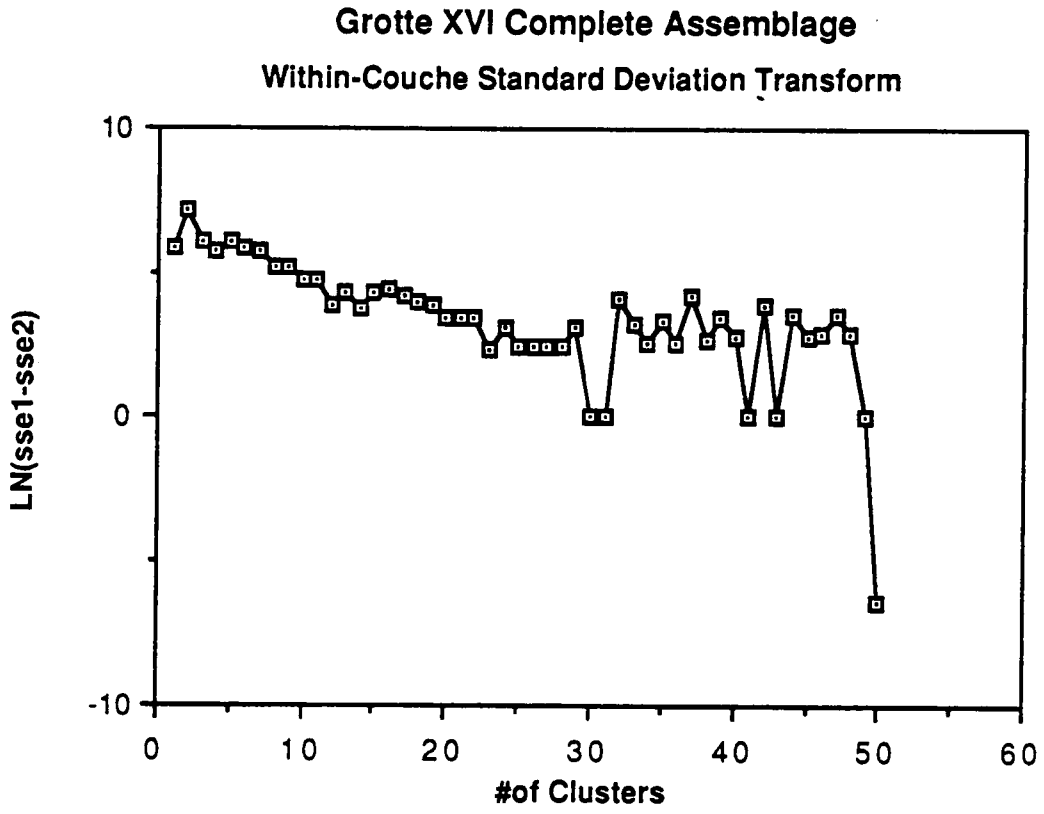


Figure 5.6 Grotte XVI complete assemblage, LN((sse1-sse2)*1000) using the within-couche standard deviation transformation. Optimal solutions indicated at the 17, 30, 33, 38, 43, and 48 cluster solutions.

across clusters, if couche assignment is considered as an object's class. Clusters that contain objects from only a single couche would have K values of 0.0, while those containing equal numbers from all represented couches would have K values of 1.0. Extremely low or 0.0 K' values then, indicate relative success in creating clusters that contain objects from very few or a single couche at a particular cluster solution. K' here is not being used to predict or evaluate specific depositional structures, but rather to measure the success of a cluster solution in recovering predefined couches. RICD statistics are somewhat harder to interpret in this case, as when many clusters have only a single class represented each cluster is at an extreme corner (e.g. with coordinates 0,0,100 or 0,100,0 in a three class space--see chapter II) of the class frequency space, and so the mean RICD value may well be moderate or even high. Very low mean RICD values would suggest that a single class was present and perhaps numerically dominant in many clusters. Very high values, on the other hand would indicate that many or most clusters contained a single, uniquely occurring class. This situation would probably arise only at solutions with low numbers of clusters, similar in range to the number of classes.

Figure 5.7 shows the K' and mean RICD values for the optimal solutions using couche assignment as class.

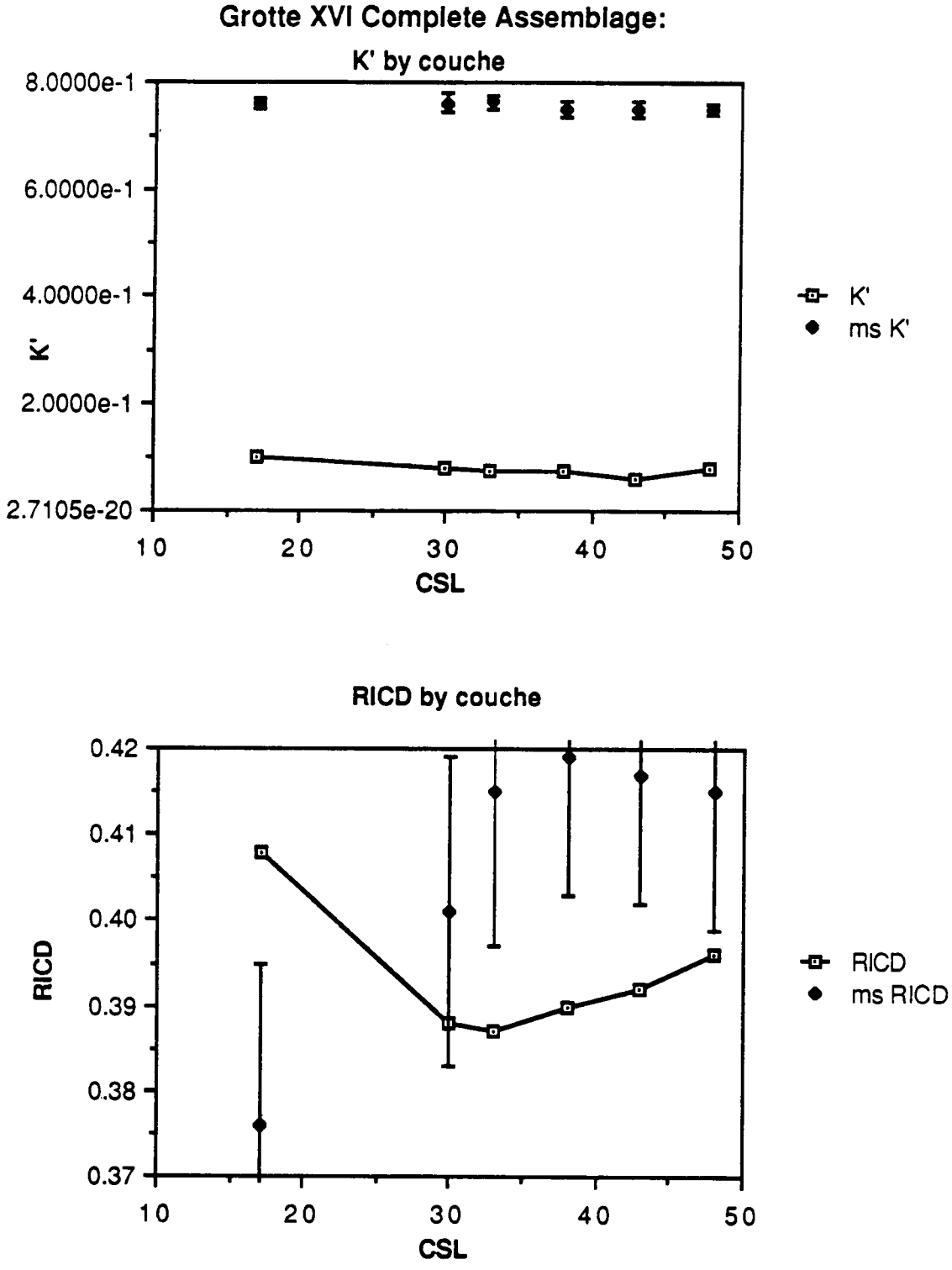


Figure 5.7 Grotte XVI complete assemblage, global K' and mean RICD by couche using the within-couche standard deviation transformation.

Observed K' values are extremely low, typically lower than .1, and far lower than their corresponding mean simulated values. This reflects the largely unmixed nature of the majority of the clusters. The mean RICD values behave interestingly. Although initially above 95% CI around the mean simulated values, after the 30 cluster solution they all fall below the 95% CI, but remain moderate in strength. Examining the individual clusters shows that most contain objects from a single couche, although a few contain objects from 3 or more. Thus when RICD values are calculated most clusters are at extreme ends of the couche frequency space, and relative intercluster distances tend to be either 1 or 0.

Figures 5.8-5.9 show the % sse plot, K', and mean RICD values for the complete assemblage when using the global z-score and Z axis distortion factor of 5 as the transformation technique. In this case, optimal solutions are found at the 16, 25, 28, 35, 44, and 49 cluster solutions. Notice that there is some similarity to the number of clusters defined as optimal when using either the within-couche standard deviation transformation, or the global z-score transformation. Using the global z-score transformation technique, K' values are moderate in strength, and although well below their corresponding mean simulated values, are still substantially higher than those for the standard deviation

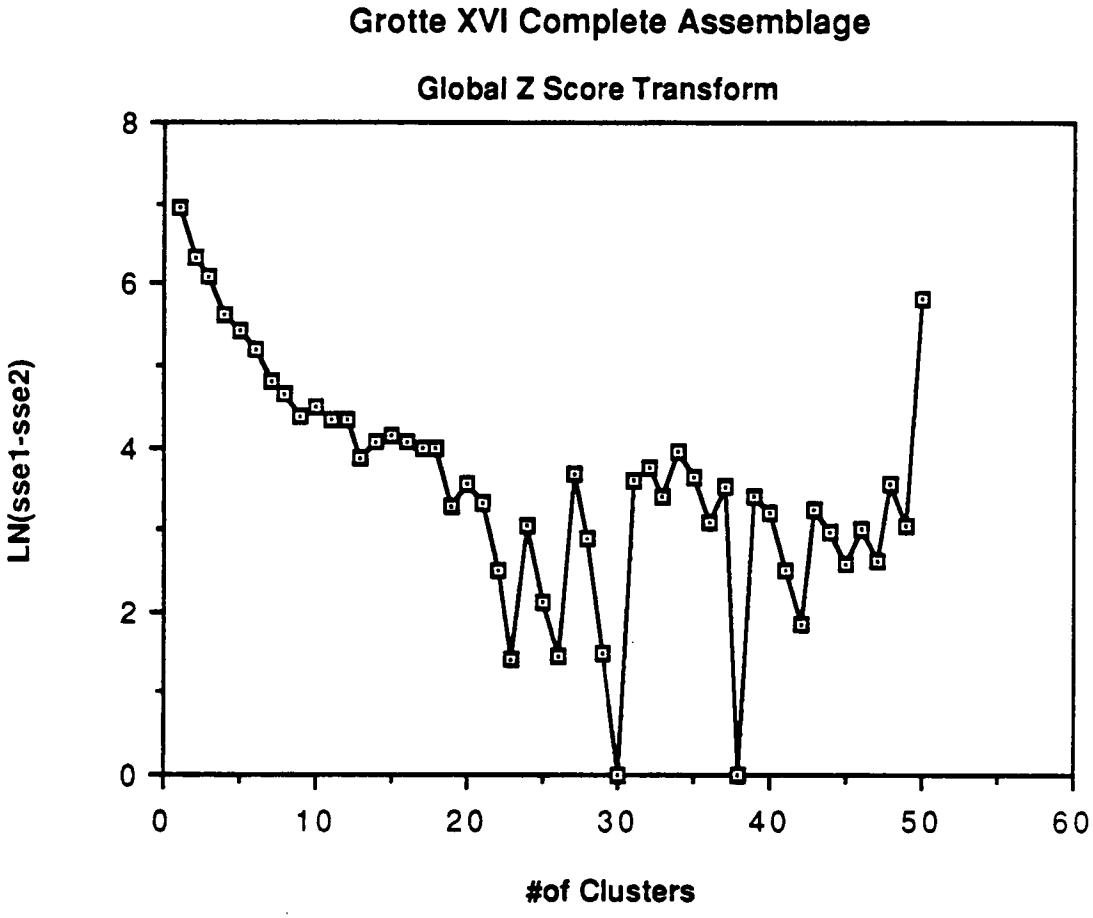


Figure 5.8 Grotte XVI complete assemblage, LN((sse1-sse2)*1000) using the global z-score transformation. Optimal solutions indicated at the 16, 25, 28, 35, 44, and 49 cluster solutions.

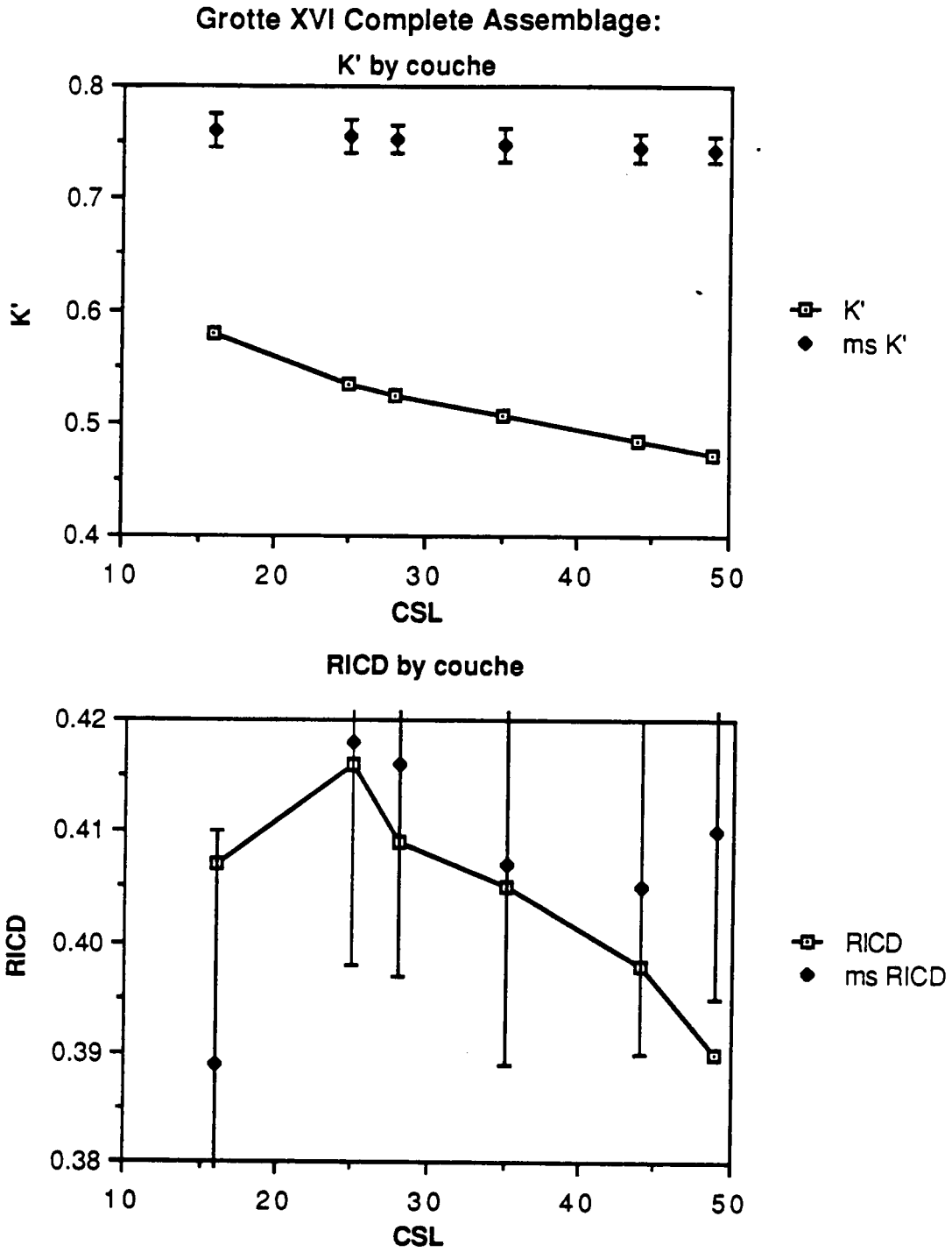


Figure 5.9 Grotte XVI complete assemblage, global K' and mean RICD by couche using the global z-score transformation.

transformation technique. This suggests that clusters frequently contain objects from more than a single couche. Examination of the individual clusters confirms that this is the case. Observed mean RICD values are moderate, and with one exception well within the 95% CI around their mean simulated counterparts. Clearly the K' values suggest relatively more mixed clusters, while the RICD values are more ambiguous. Observed mean RICD values do distinguish the cluster solutions created using these two types of transformation, but unlike the K' values, only through their slope and relation to their mean simulated values and not by differences in absolute magnitude.

Couche Discrimination Error

Because the couche assignments are known and presumed to be substantially correct, it is possible to use the same measures of level discrimination error that were used for the experimental assemblages in chapter III. Table 5.2 presents the number of mixed clusters and misassigned objects for the optimal solutions of the complete assemblage by transformation technique. Clearly the standard deviation transformation results in lower error solutions, the highest error rate using this transformation is only 6.1% of the total number of objects, while the lowest attained with the global z-score transformation was 30.5 % of the total. Differences in

Table 5.2 Various level discrimination error measures for the Grotte XVI complete assemblage: by transformation and optimal cluster solutions.

CSL	#mix	#miss	#miss / #mix	#miss / Total	(#miss/cluster) / Total
Within-Couche Standard Deviation Transformation					
16	7	249	35.5	6.1	
25	10	186	18.6	4.5	.45
33	10	185	18.5	4.5	.45
38	9	200	22.2	4.9	.54
43	11	126	11.4	3.0	.28
48	11	225	20.4	5.5	.50
Global Z-score Transformation and Z-axis Expansion of 5					
16	16	1647	102.9	40.3	2.5
25	23	1546	67.2	37.9	1.6
28	25	1487	59.4	36.4	1.4
35	30	1431	47.7	35.0	1.1
44	38	1335	35.1	32.7	.8
49	42	1284	31.4	30.5	.7

the number of misassigned objects are close to an order of magnitude.

Despite the large differences in error rates from the two transformation techniques, similar trends are evident in each case. As the number of clusters increases both the number of misassigned objects and the mean number of misassigned objects per mixed cluster tend to decline. The detailed behavior of these two measures is very different however. For example, while #miss tends to decline steadily with increasing numbers of clusters when using the global z-score transformation, the use of within-couche standard deviations #miss fluctuates widely, although at generally very low levels (between 6 and 3 percent of the total number of objects).

Bone Objects

Homogeneity by Couche

More than 50% of the total number of objects are bones (2129 of 4077 total). When clustered using the within-couche standard deviation transformation, optimal solutions were identified at the 10, 19, 22, 27, 36, and 47 cluster solutions (Figure 5.10). Observed K' values for these solutions are extremely low, and far lower than their corresponding mean simulated values (Figure 5.11). This suggests that very few clusters are mixed to any

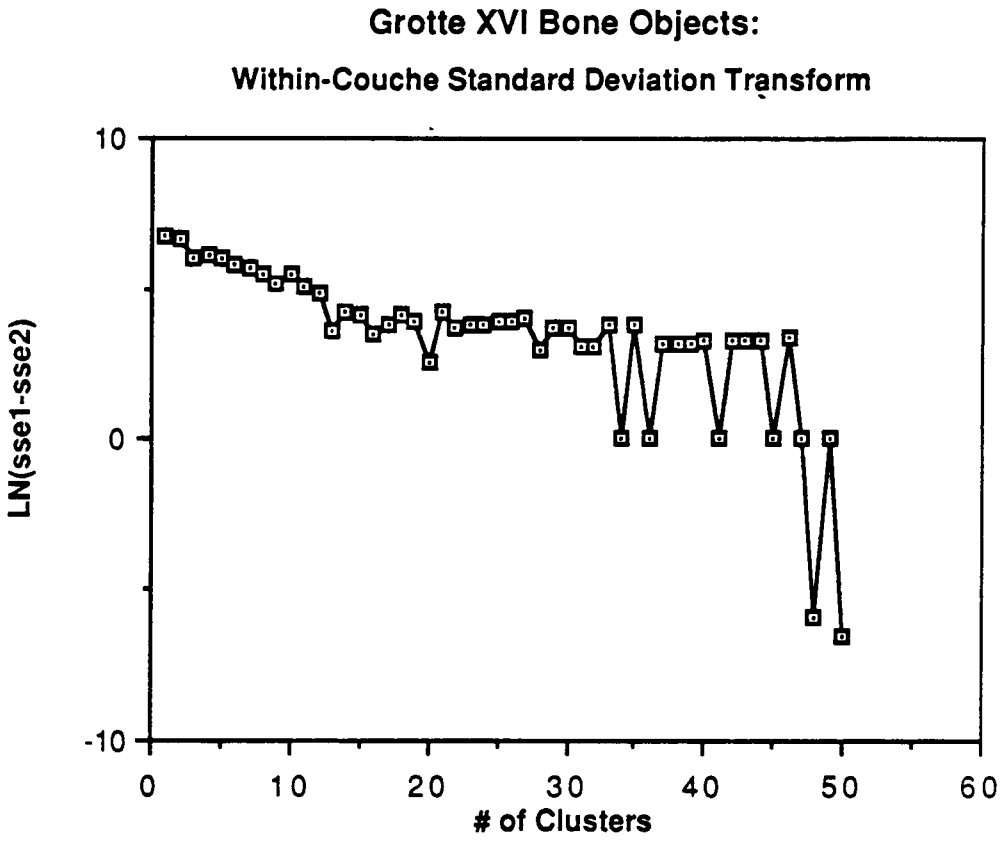


Figure 5.10 Grotte XVI bone assemblage, LN((sse1-sse2)*1000) using the within-couche standard deviation transformation. Optimal solutions indicated at the 10, 19, 22, 27, 36, and 47 cluster solutions.

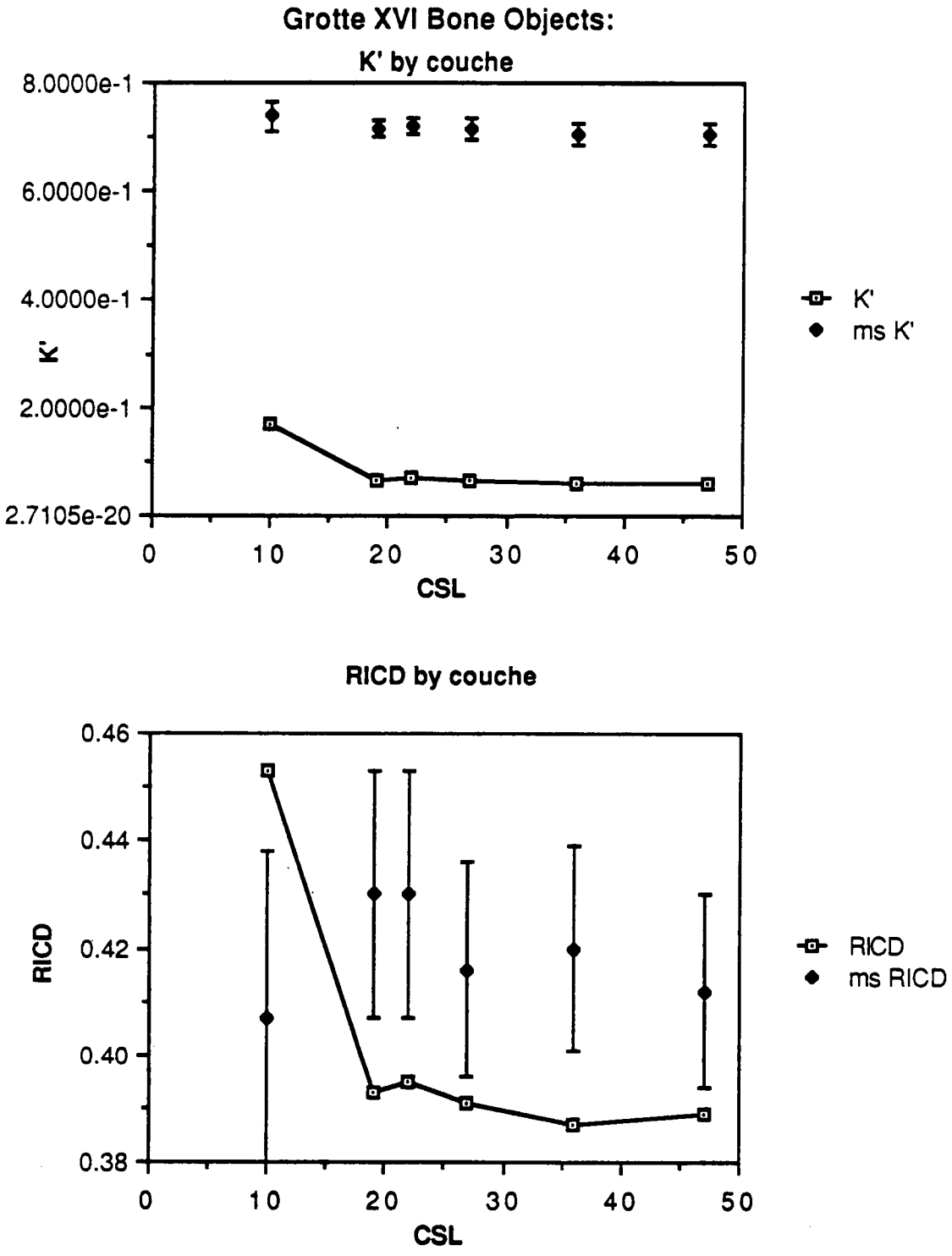


Figure 5.11 Grotte XVI bone assemblage, global K' and mean RICD by couche using the within-couche standard deviation transformation.

substantial degree. Observed mean RICD values are initially moderate in strength although higher than their mean simulated values and the 95% CI around them, but between the 10 and 19 cluster solutions fall below the lower 95% CI boundary values (Figure 5.11). Subsequent solutions show essentially identical mean RICD values.

When clustered using the global z-score transformation, on the other hand, optimal solutions are found at the 14, 19, 23, 34, 38, 41, 44, and 47 cluster solutions (Figure 5.12). Notice that while several solutions have the same or nearly the same number of clusters as did the optimal solutions using the within-cluster standard deviation transformation, there are more solutions identified as optimal in this case. Figure 5.13 shows the observed and mean simulated K' and RICD values for these clusters. Observed K' values using this transformation are all of moderate strength, and although well below their corresponding mean simulated levels and the 95% CI around them, do not attain the extremely low values found for K' when using the within-cluster standard deviation transformation. This suggests that a substantial number of clusters in each of these solution levels contains objects from 2 or more couches. Observed mean RICD values are moderate in strength and always within the 95% CI around the mean simulated values, although in the initial solutions they are at the extreme

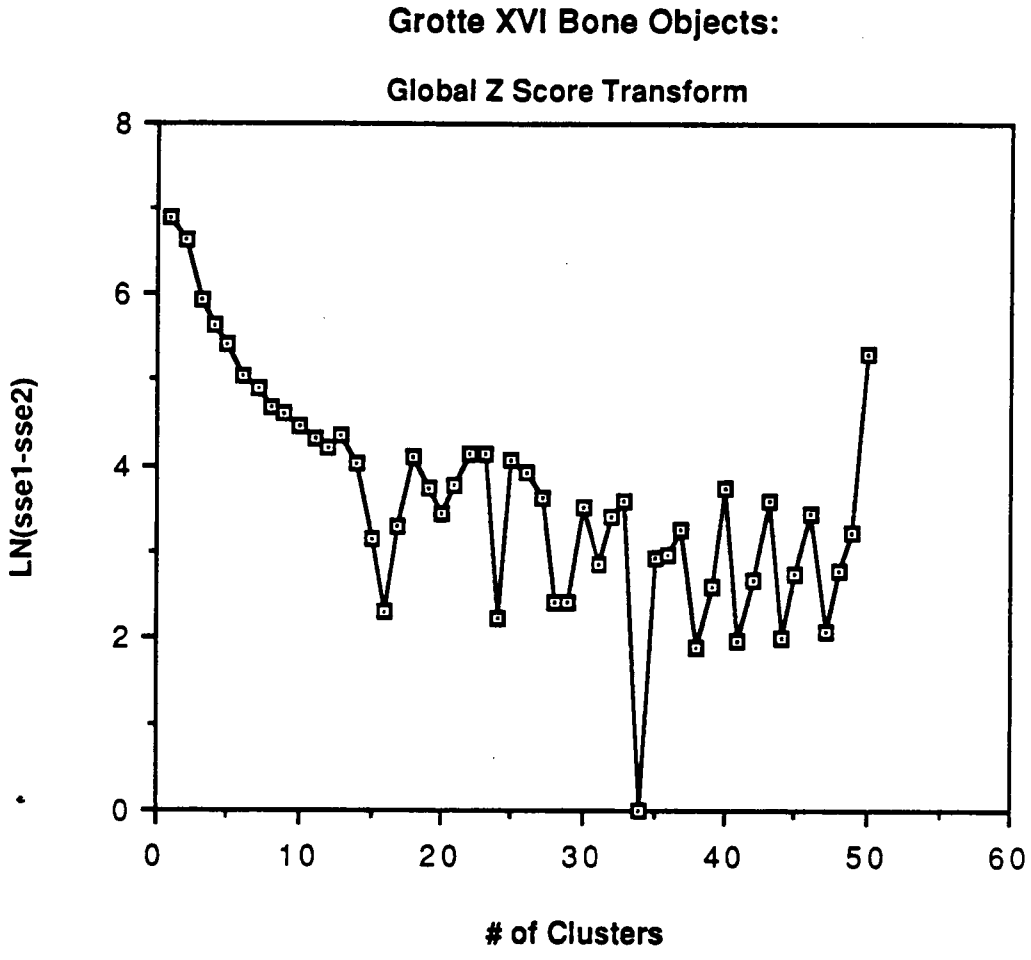


Figure 5.12 Grotte XVI bone assemblage, LN((sse1-sse2)*1000) using the global z-score transformation. Optimal solutions indicated at the 14, 19, 23, 34, 38, 41, 44, and 47 cluster solutions.

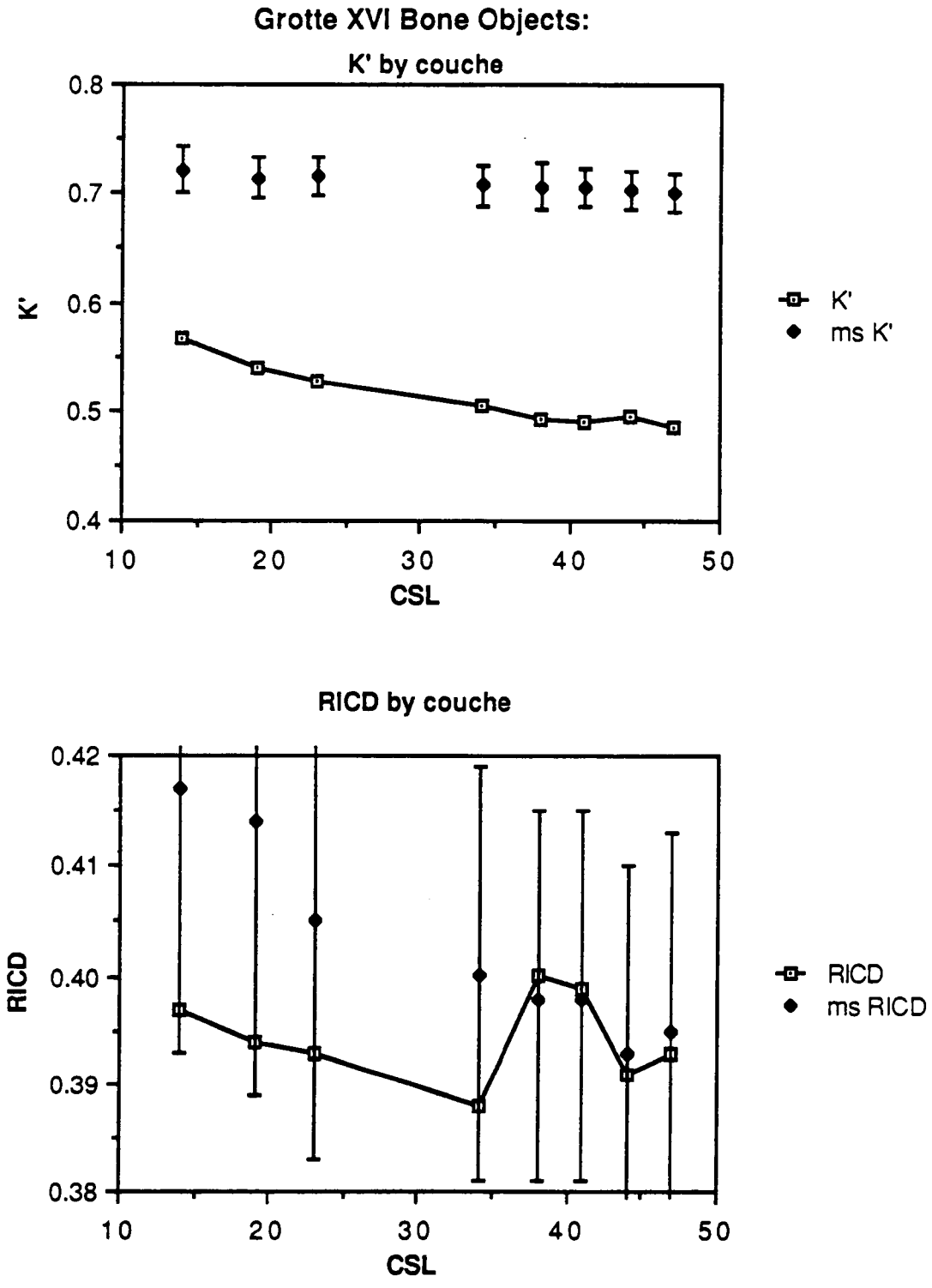


Figure 5.13 Grotte XVI bone assemblage, global K' and mean RICD by couche using the global z-score transformation.

low boundary of the 95% CI. Again, while K' values clearly separate the two cluster analyses, mean RICD values do so only on the basis of their relationship with the mean simulated values.

Couche Discrimination Error

Table 5.3 confirms the interpretations of the K' and RICD values made above. Error rates for the global z-score transformation are comparatively high (#miss between 32 and 36% of the total number of objects), while the error for the within-cluster standard deviation transformation is generally quite low (#miss typically between 3 and 4% of the total). Both transformations show a trend towards decreasing error with increasing numbers of clusters, although in this instance it is the global z-score transformation that shows variability, rather than the within-cluster standard deviation transformation. Using the global z-score transformation, all solutions are similar, but under the within-cluster standard deviation transformation, the ten cluster solution is strongly distinct from all subsequent solutions. Even though a relatively low percentage of the 10 clusters are mixed, this solution contains 3 times as many misassigned objects as any other.

Table 5.3 Various level discrimination error measures for the Grotte XVI Bone assemblage: by transformation and optimal cluster solutions.

CSL	#mix	#miss	#miss Cluster	#miss Total	(#miss/cluster) Total
10	4	260	65	12.2	3.0
19	10	86	8.6	4.0	.4
22	10	86	8.6	4.0	.4
27	10	81	8.1	3.8	.3
36	9	79	8.7	3.7	.4
47	11	79	7.1	3.7	.3
Global Z-score Transformation and Z-axis Expansion of 5					
14	14	772	55.1	36.2	1.7
19	17	756	44.4	35.5	2.1
23	21	743	35.5	34.8	1.6
34	31	727	23.4	34.1	1.0
38	35	700	20.0	32.8	.9
41	38	723	19.0	33.9	.8
44	41	713	17.3	33.4	.8
47	44	697	15.8	32.7	.7

Homogeneity by Fragmentation Class

Fragmentation classes were available for the bone objects from the Grotte XVI. Table 5.4 defines these classes. The bone assemblage from Grotte XVI represents a wide variety of species from a number of distinct time periods. In order to compare across the couches, species and the variable processes that accompany or are inherent in this as a category were deliberately ignored. Figures 5.14-5.15 show the K' and mean RICD values for the cluster solutions using both the within-cluster standard deviation transformation and global z-score transformation. K' values for these two distinct situations are extremely similar. Both are moderate and nearly identical in absolute magnitude, and both are consistently above and similar in slope compared to their corresponding mean simulated values. Observed mean RICD values behave somewhat differently, although both sets are generally similar in magnitude, slope, and distance below their mean simulated values. RICD values for the within-cluster standard deviation transformation however, are initially within the 95 % CI around their mean simulated values, and only later decline below these. In contrast RICD values for the global z-score transformation begin well below their mean simulated values.

In general these indices suggest that bone fragmentation classes are very evenly spread throughout

Table 5.4 Fragment class definitions for bone objects at the Grotte XVI.

Class	Contents
1	Long Bone Diaphysis Fragments
2	Long Bone Epiphysis fragments
3	Splinters
4	Anterior/Proximal/Superior/Interior
5	Posterior/Distal/Inferior/Exterior
6	Unknown/Unrecorded/Unclassifiable
7	Vertebral Body fragments
8	Complete Bones
9	Miscellaneous *

* This category includes objects which are currently coded inconsistently with the other categories, "tooth frag" or "burned" for example.

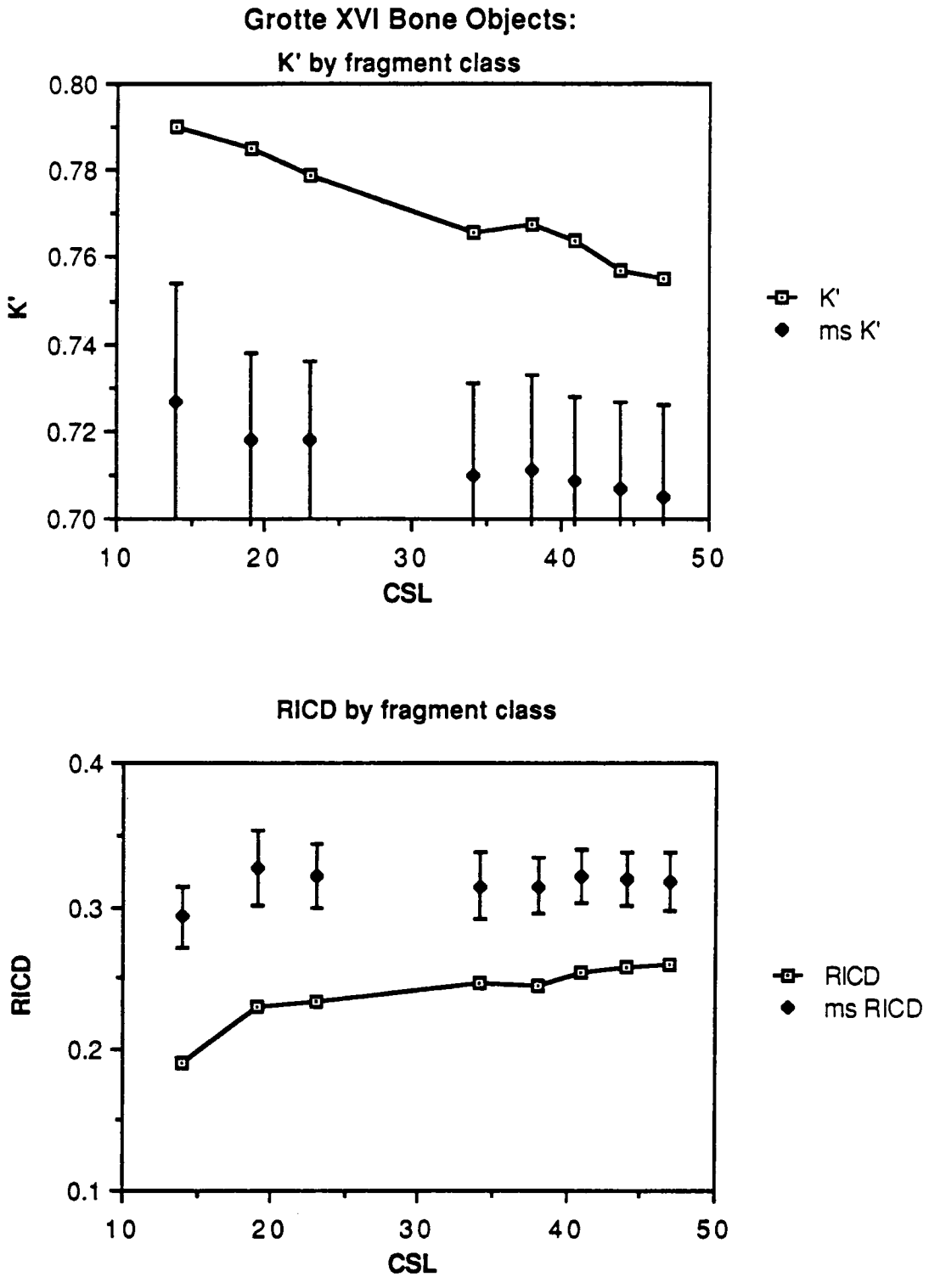


Figure 5.14 Grotte XVI bone assemblage, global K' and mean RICD by fragment class using the global z-score transformation.

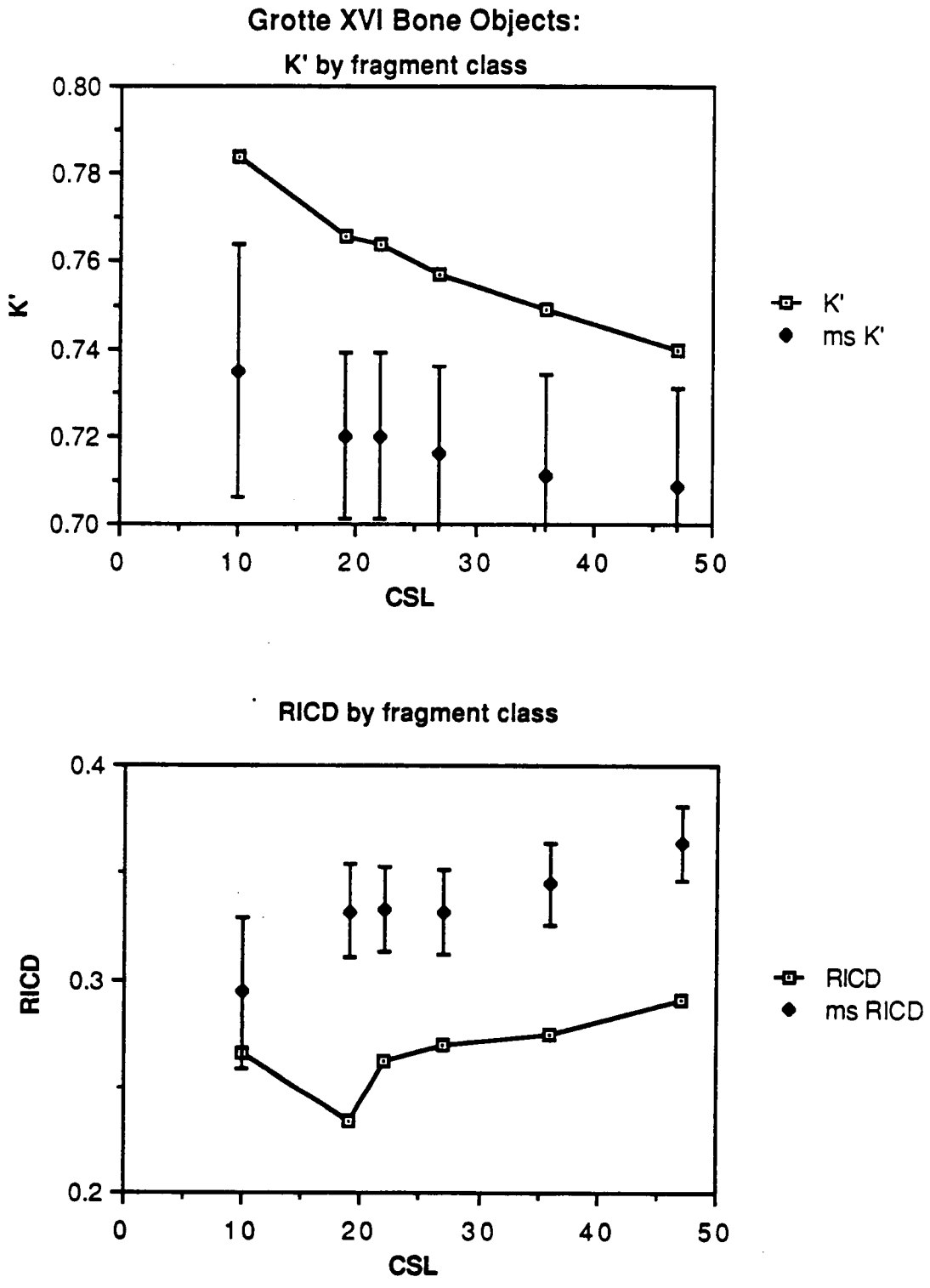


Figure 5.15 Grotte XVI bone assemblage, global K' and mean RICD by fragment class using the within-couche standard deviation transformation.

this portion of the site, and surprisingly, this situation changes only minimally when clusters change from containing mostly objects from a single couche, to more frequently containing objects from 2 or more couches, i.e. the pattern is similar under either transformation. Homogeneity by bone fragmentation class remains high then, independently of couche. Cluster similarity, while not extremely high is consistently strong throughout the site, suggesting that most clusters are dominated by a few classes. Unfortunately, unlike the classes used in the Le Flageolet II analyses, these classes may not directly reflect bone fragmentation in a mechanical sense. Classes 1 (epiphyseal fragments), 2 (diaphysial fragments) and 8 (indeterminant) are numerically dominant, and while there are many more fragments than complete bones it is not easy to suggest a common mechanical cause. These classes may not be able to resolve any very detailed patterning. The results do suggest however, that similar processes acted to fragment bone or pattern already fragmented bone (as resolved by these categories at least) regardless of spatial patterning within distinct couches, time, species, and cultural attribution. The nature of such an agent or agents obviously needs to be examined in more detail. Those that come to mind immediately: human activity, animal gnawing, and rock fall or other postdepositional geologic effects can all probably be distinguished by

careful examination of the bones themselves. At this level of analysis, however, it can only be said that extreme similarity is indicated for this portion of the site.

Flint Objects

Homogeneity by Couche

There are some 1933 flint objects in this portion of the Grotte XVI. When clustered out to 50 clusters using the within-cluster standard deviation transformation, optimal solutions were identified at 14, 17, 23, 30, and 47 clusters (Figure 5.16). When calculated with couche assignment used as classes, observed K' values for these solutions are all below .1, very low and similarly sloped compared to the mean simulated values and the 95% CI around them (Figure 5.17). This suggests that very few of these clusters contain objects from more than one couche. Observed mean RICD values are moderate in strength and always above the mean simulated values and the 95% CI around them.

In contrast, when clustered using the global z-score transformation, optimal solutions were found at the 19, 28, 32, 38, and 46 cluster solutions (Figure 5.18). Observed K' values in this situation, are all moderate in strength and substantially lower than either the

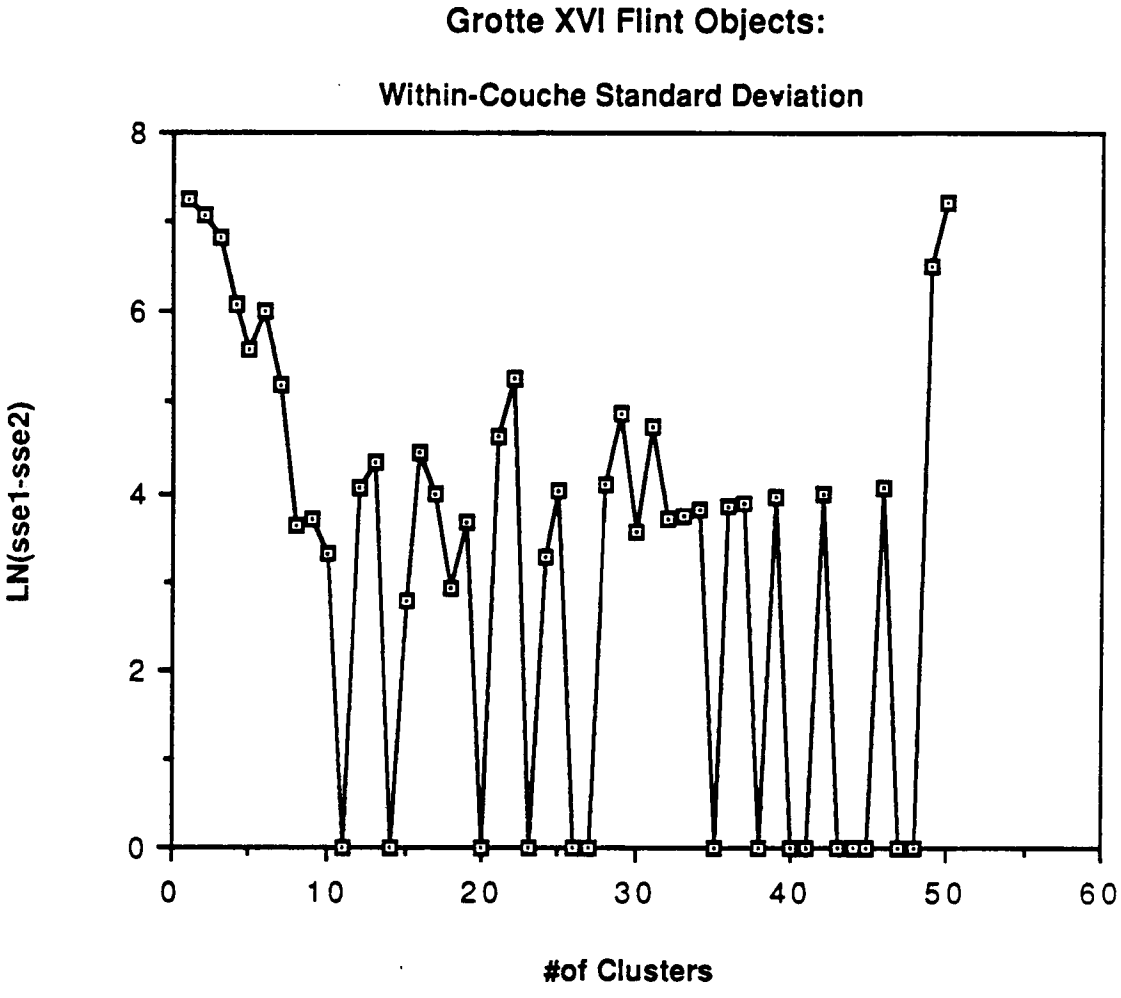


Figure 5.16 Grotte XVI flint assemblage, LN((sse1-sse2)*1000) using the within-couche standard deviation transformation. Optimal solutions indicated at the 14, 17, 23, 30, and 47 cluster solutions.

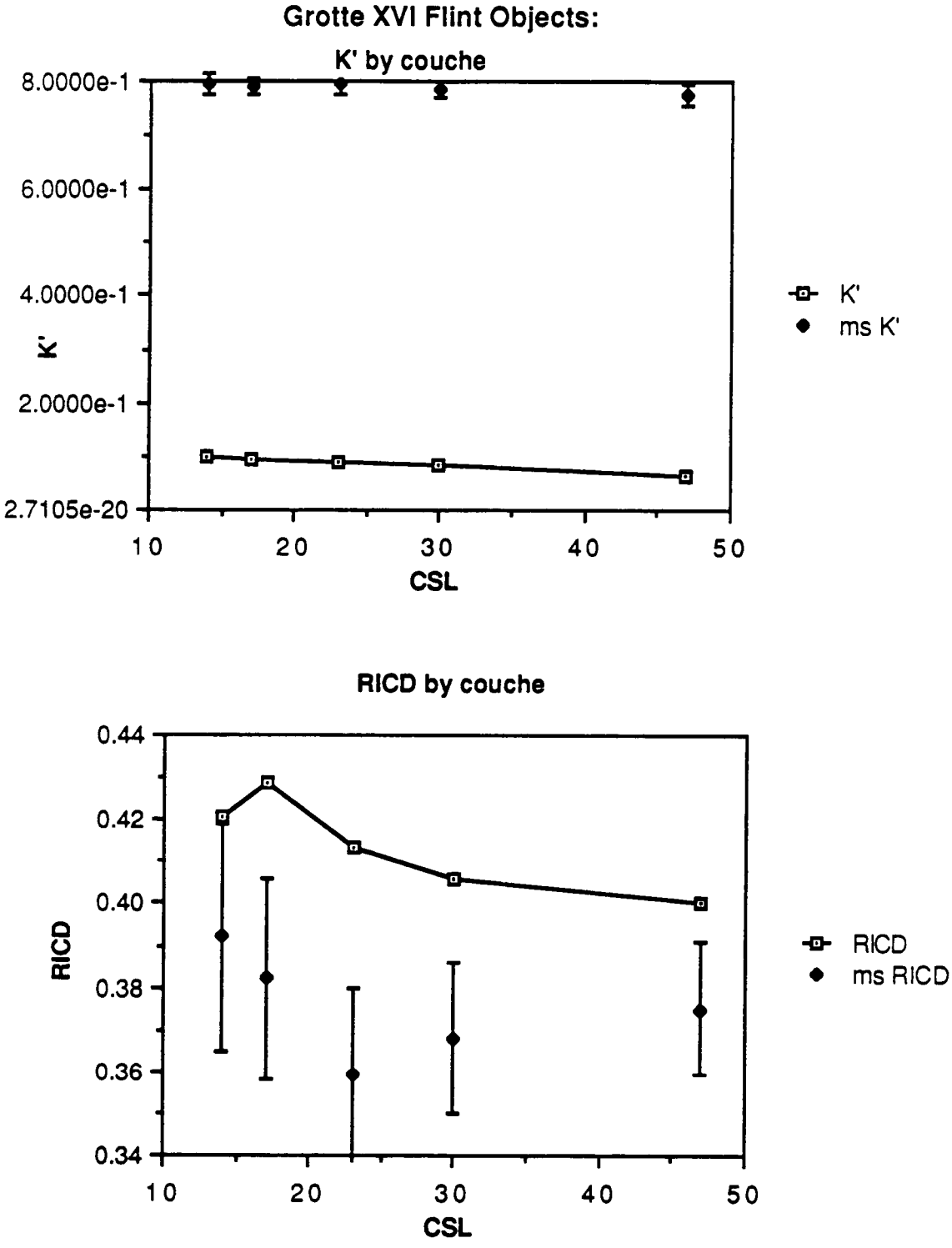


Figure 5.17 Grotte XVI flint assemblage, global K' and mean RICD by couche using the within-couche standard deviation transformation.

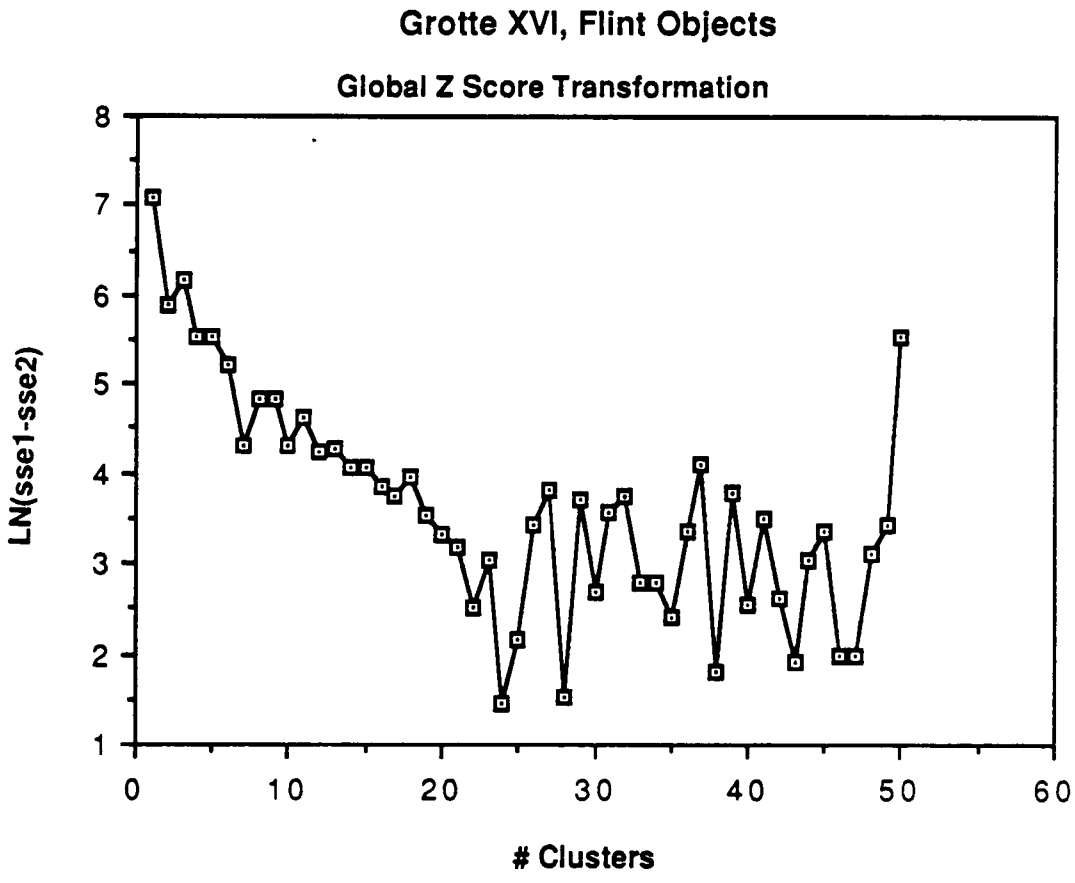


Figure 5.18 Grotte XVI flint assemblage, LN((sse1-sse2)*1000) using the global z-score transformation. Optimal solutions indicated at the 19, 28, 32, 38, and 46 cluster solutions.

corresponding mean simulated values or the 95% CI around them, although not anywhere near as low as those obtained from the within-cluster standard deviation transformation (Figure 5.19). This suggests that many clusters contain objects from more than two couches. RICD values are moderate and, with one exception, always above the mean simulated values and the 95% CI around them. Clearly, while the K' values again separate the solutions generated by these two transformation techniques, RICD values and their relationship with the mean simulated values are nearly identical.

Couche Discrimination Error

Table 5.5 confirms the impression given by the observed and mean simulated K' values. Discrimination error rates differ sharply between the two analyses: those for the within-cluster standard deviation transformation are always much lower than the global z-score transformation error rates. Although #miss clearly tends to decline with increasing numbers of clusters in both cases, when using the global z-score transformation #miss fluctuates, while with the within-cluster standard deviation transformation the decline is smoothly monotonic.

Table 5.5 Various level discrimination error measures for the Grotte XVI Flint assemblage: by transformation and optimal cluster solutions.

CSL	#mix	#miss	#miss Cluster	#miss Total	(#miss/cluster) Total
Within-Couche Standard Deviation Transformation					
14	8	121	15.1	6.2	.7
17	10	120	12.0	6.2	.6
23	10	111	11.1	5.7	.5
30	11	109	9.9	5.6	.5
47	14	87	6.2	4.5	.3
Global z-score Transformation and Z-axis Expansion of 5					
19	19	620	32.6	32.0	1.6
28	22	598	27.1	30.9	1.4
32	27	622	23.0	32.1	1.1
38	33	585	17.7	30.2	.9
46	39	558	14.3	28.8	.7

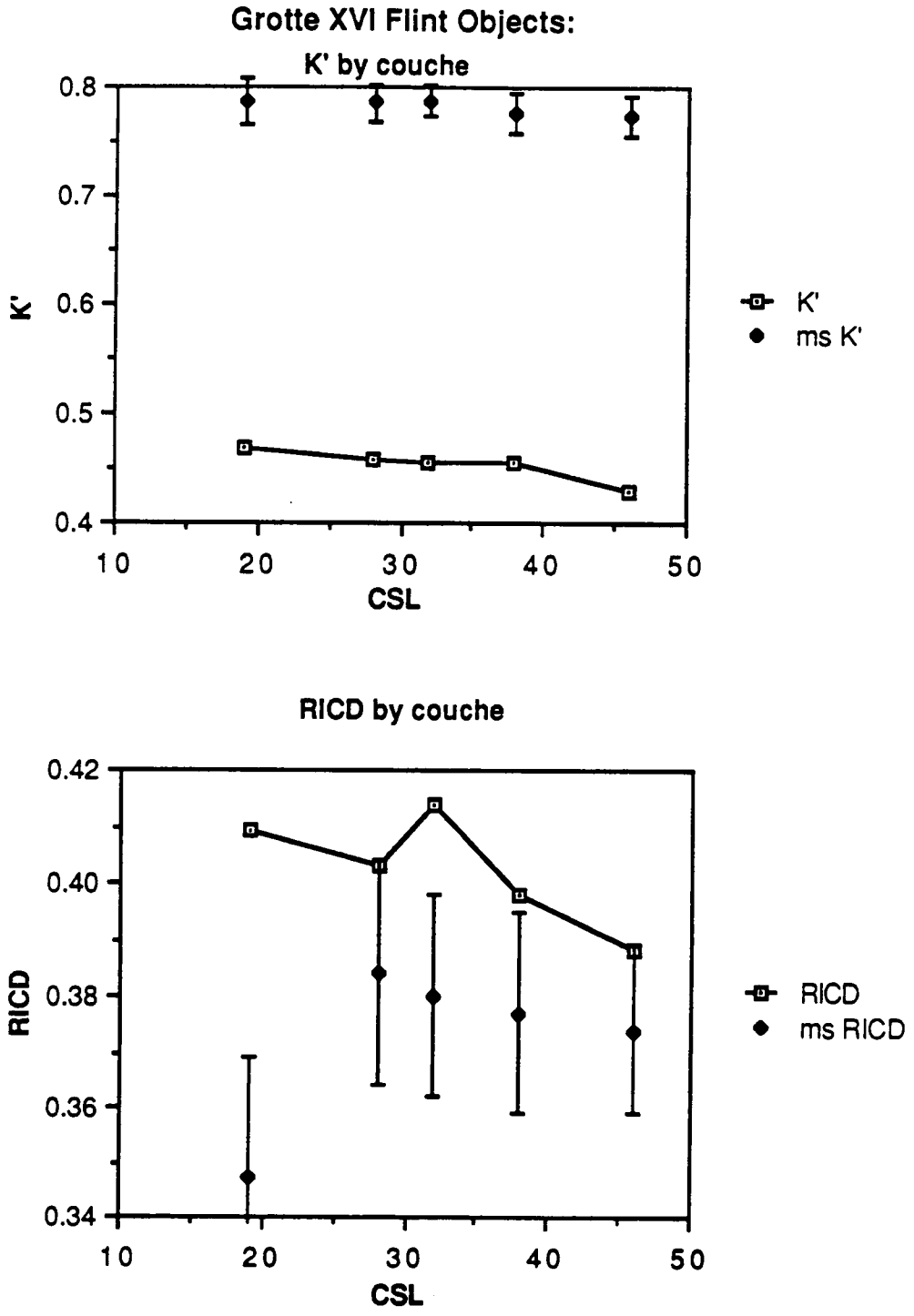


Figure 5.19 Grotte XVI flint assemblage, global K' and mean RICD by couche using the global z-score transformation.

Homogeneity by Fragmentation Class

As was the case with the bone objects, lithic materials at the Grotte XVI may also be classed by their degree of fragmentation. Table 5.6 defines fragmentation classes for the Grotte XVI flint materials. Note that there is no division of the lithic material into blade and flake categories. This is for continuity across the middle to upper Paleolithic industrial traditions, both of which are present here. Figures 5.20-5.21 show the observed K' and mean RICD values for lithics when calculated with fragmentation classes resulting from the cluster solutions using both within-cluster standard deviation transformation and global z-score transformation. Observed K' values are both of similar magnitude and both fall within the 95% CI around their respective mean simulated values; yet, there are potentially important differences. In the case of the within-cluster standard deviation transformation, observed K' values are initially at the extreme upper boundary of the 95% CI around their mean simulated values. As the number of clusters increases however, they drop closer to the mean and then fall below it. Their slope is clearly different from that of the mean simulated values. This is not the case with the global z-score transformation. In this case, the observed values are

Table 5.6 Fragmentation or technological class definitions for the Grotte XVI lithic objects.

Class	Definition
1	Complete objects
2	Proximal Fragment
3	Mesial Fragment
4	Distal Fragment
5	Central Fragment
6	Lateral Fragment
7	Ridged Fragment
8	Indeterminate

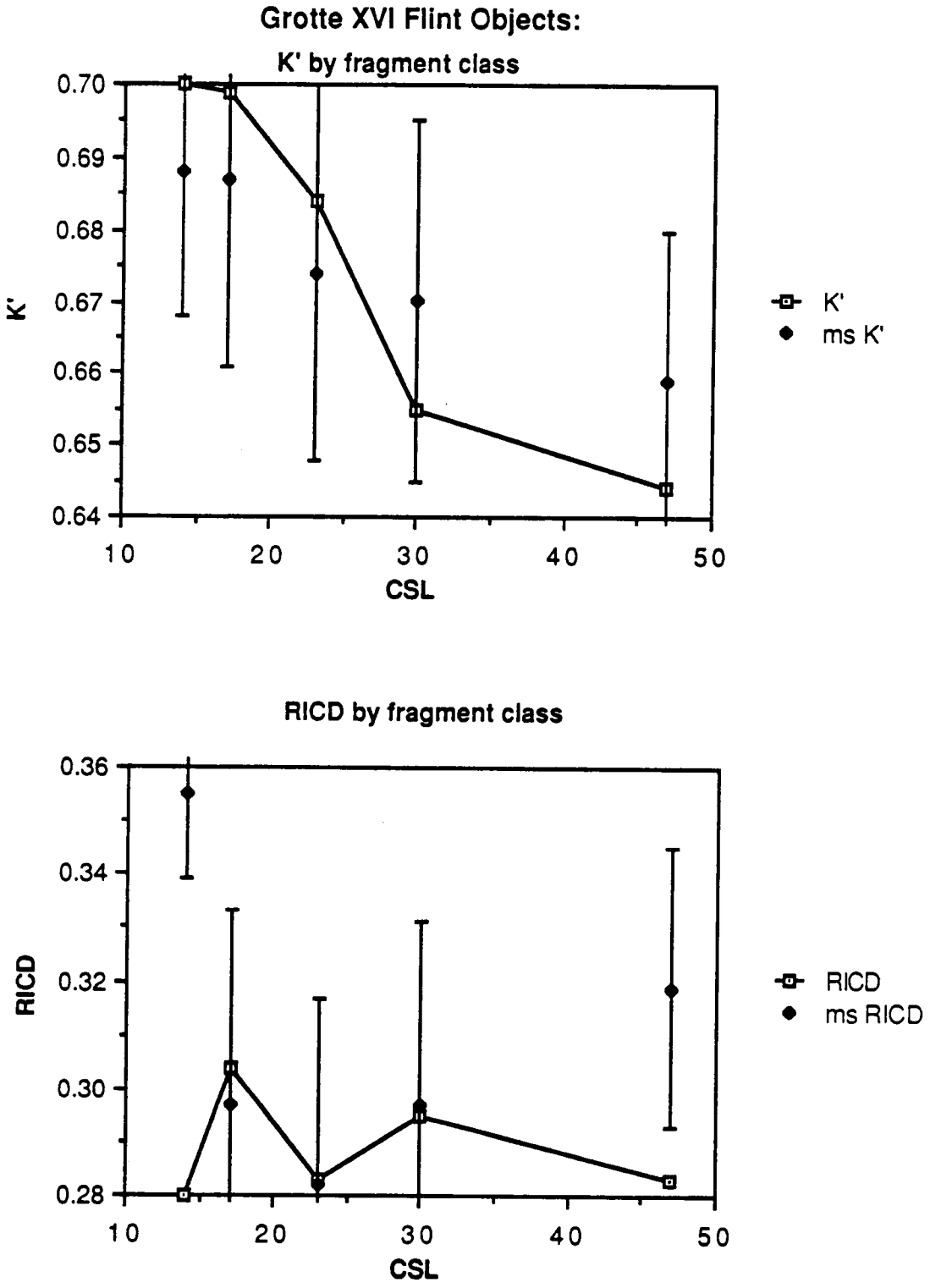


Figure 5.20 Grotte XVI flint assemblage, global K' and mean RICD by fragment class using the within-couche standard deviation transformation.

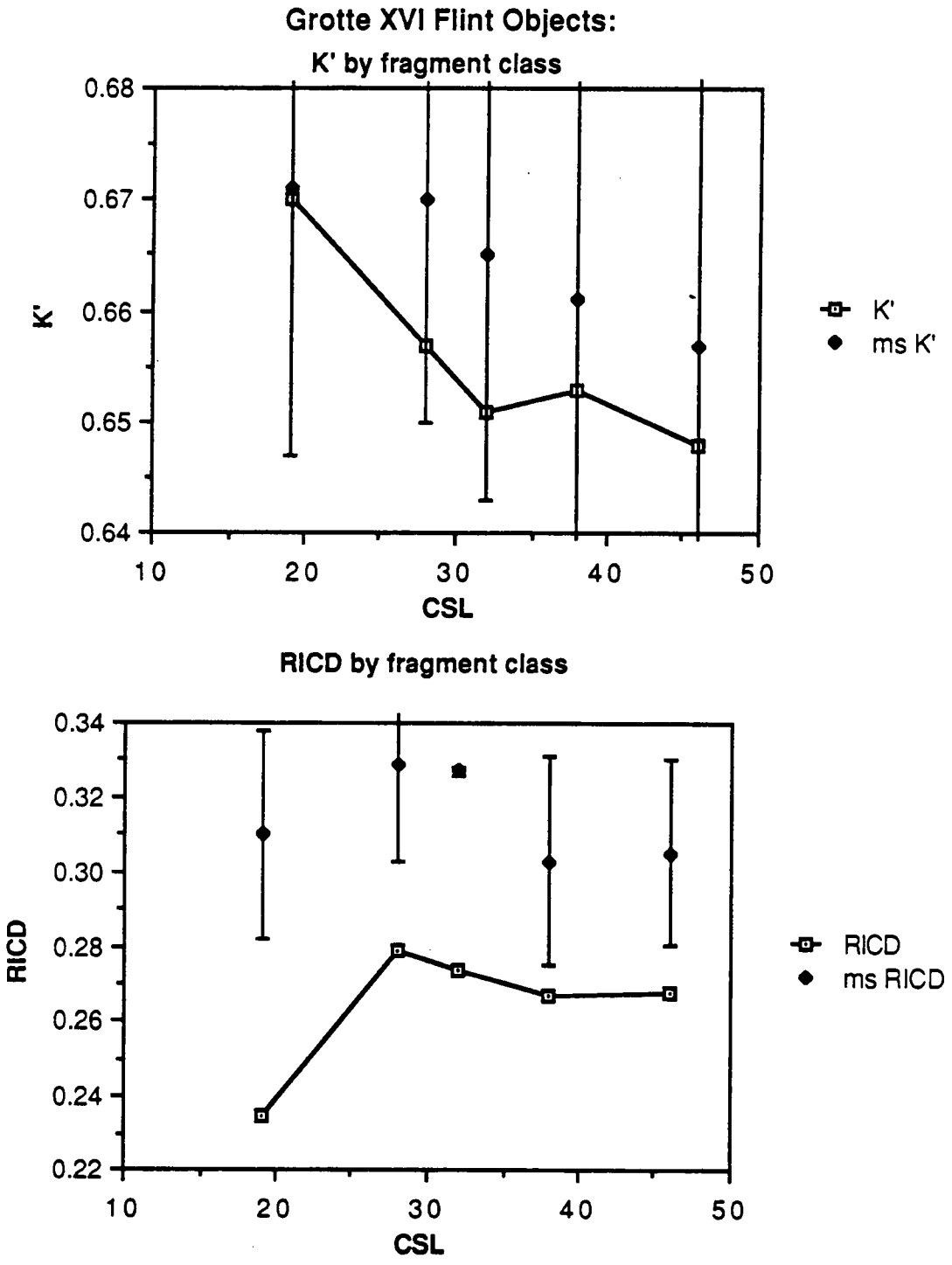


Figure 5.21 Grotte XVI flint assemblage, global K' and mean RICD by fragment class using the global z-score transformation.

always below the mean simulated values, and have a very similar slope.

Observed Mean RICD values for these two cases are also quite distinct from one another, although here the differences are more pronounced. Observed mean RICD for the within-cluster standard deviation transformation solutions begins and ends below the 95 % CI around the mean simulated values, but the middle solutions are solidly within this range. In the global z-score transformation case, only one value is within the 95% CI, the rest are substantially below these values.

Homogeneity by fragmentation class suggests that there is essentially no difference between the observed values and random occurrence. It is possible that the slight difference in slope between the observed and mean simulated values obtained for the within-cluster standard deviation transformation solutions indicates somewhat more decrease than expected under random assumptions. However, the values are all well within the 95% CI around the mean simulated values, and so this is a questionable conclusion. Observed Mean RICD values, while telling a similar tale, show that cluster similarity is often higher than would be expected, especially in the global z-score transformation case. This particular result suggests that most clusters tend to be dominated by the same group of couches.

Z-Axis Expansion Factor Experiments

Because many of the couches at the Grotte XVI can be distinguished by the number, type, raw material, and technological attributes of the flint tools they contain, the couche attributions assigned to these objects is somewhat more reliable at this stage of the investigation. Consequently these objects were chosen for a series of investigations into the effects of increasing the Z-axis expansion factor. All lithic or chipped stone objects were clustered from 1 to 50 clusters using expansion factors varying by 2 between 1 and 26. In no case were error rates lower at all solution levels than those attained with a expansion factor of 5. Individual solutions within a particular sequence were sometimes as low or lower than those from the same or similar solutions with a expansion factor of 5, but never consistently across the analysis as a whole.

In general each expansion factor resulted in a unique set of optimal solutions, although these were typically very similar. A expansion factor of ten, for example resulted in optimal solutions at the 19, 29, 34, 38 and 46 cluster solutions. Differing only slightly from those found with a expansion factor of five. The range of expansion factors between 3 and 6 resulted in error rates very similar to those found with a expansion factor of 5, but once expansion factors become greater than 6,

error rates increase (from their already high levels), sometimes dramatically. Clearly then a expansion factor of 5 was the best choice, at least in the sense of resulting in the lowest overall error rates when using this transformation technique. In somewhat more than half of these experimental cases, #miss declined smoothly with increasing numbers of clusters; in the others, greater variability was evident, although typically only one or two cluster solutions deviated from a strictly monotonic decline. Presence or absence of a smooth decline does not mark those solutions with either low, moderate or high overall error rates (no significant Chi square at $P < .10$).

Comparison

Homogeneity by Couche

Observed K' values are nearly identical across all cases when using a particular transformation. Distinctions among the K' patterns between the transformations are very clear, both in absolute magnitude, and in comparison to their mean simulated values. With or without mean simulated values, K' provides a excellent means for distinguishing the relative success of particular transformations in recovering predefined levels. Mean RICD values are less useful,

although in general moderate values falling within the 95% CI around their mean simulated values seem indicative of poorer couche discrimination, in the case of flint tools however, this pattern did not appear. In this case, both transformations produced solutions with nearly identical mean RICD values in situations that obviously differed greatly in their relative success. Neither observed K' nor mean RICD correlate significantly with #miss or #mix within a particular transformation.

Discrimination Error Rates

Overall trends in discrimination error, as measured by the number of misassigned objects are common to both types of transformation used here. The number of misassigned objects tends to decline with an increasing number of clusters. Somewhat surprisingly, this decline is often not smooth, and perhaps even more interesting is the fact that there is no particular pattern to this variability. Neither transformation produces a uniformly smooth decline in error as number of clusters increases. Both flint and bone, for example show smooth error decreases with the within-cluster standard deviation transformation, while the global z-score transformation error rates fluctuate. For the complete assemblage however, the opposite is true. These patterns probably

relate more to the unique spatial patterning within each sub-assemblage, than to the transformation technique.

Homogeneity by Fragmentation Class

These curves show some interesting trends. In general, despite the differences in cluster formation due to the transformation methods employed, homogeneity patterns for a particular material class were similar. This is particularly true of the bone objects, but perhaps less so for the lithics. This suggests that very basic aspects of the patterning in both bone and lithics remains similar throughout the site. Within a particular cluster solution, the only major deviations from the general range of the K' values occurs when very small clusters are defined, often containing less than ten objects and frequently peripheral to the main distribution. Given the long time span included this is a somewhat surprising result. It is possible that, further refinement of the classifications used, and continued excavation will change these patterns.

In contrast to the K' values, mean RICD is more variable. There is some similarity with curves for the bone objects regardless of transformation technique, as only one solution level differs substantially from the rest. Lithics, on the other hand, show no such general pattern, despite their nearly identical K' curves. In

general, mean RICD values are lower than their mean simulated values, suggesting that the mean cluster similarity is higher than would be expected. There is a particularly odd pattern in the case of the lithic clusters formed using the global z-score transformation, which show K' values well within the 95% CI around their mean simulated values but mean RICD values typically below their mean simulated values. This suggests that while homogeneity relationships conform to those expected under random models, the clusters are actually more alike in proportional frequency than expected. This is not easy to explain, and is not the case with the lithic clusters produced using the within-cluster standard deviation transformation.

V.3 Cluster Analysis

There are a number of ways in which the cluster results can be used to help in the process of further excavation and couche definition. Plotting the individual clusters in frontal and sagittal projections can be used determine the types of error that goes into producing a mixed cluster. Examining the mixed clusters produced with the within-cluster standard deviation transformation, for example, shows two clear patterns. In one, a cluster containing a large number of objects from a single couche also includes a relatively small number from a

neighboring couche. In all of these cases, little or no actual mixing is evident, different couches are always positioned distinctly within a single cluster, are usually grouped rather tightly, and are easily separated visually (Figures 5.22-5.23). In the other pattern, a single, relatively small cluster contains a number of widely spread objects from several different couches, although again, no clear mixing is evident and different couches are easily separated visually (Figures 5.24-5.25). Both of these patterns, which are consistent across the material classes and cluster solutions used here, seem to be effects of the transformation and clustering processes. Even though the within-cluster standard deviation transformation produced relatively low discrimination error rates, examining those mixed clusters seems to provide little or no help in either discovering or sorting out confusing or stratigraphically difficult portions of the site. Discrimination between the couches in this case may be too perfect to be of further value, errors in discrimination are produced as a result of the transformation process, rather than the configuration of objects in space.

Clusters produced through use of the global z-score transformation, on the other hand, do not show

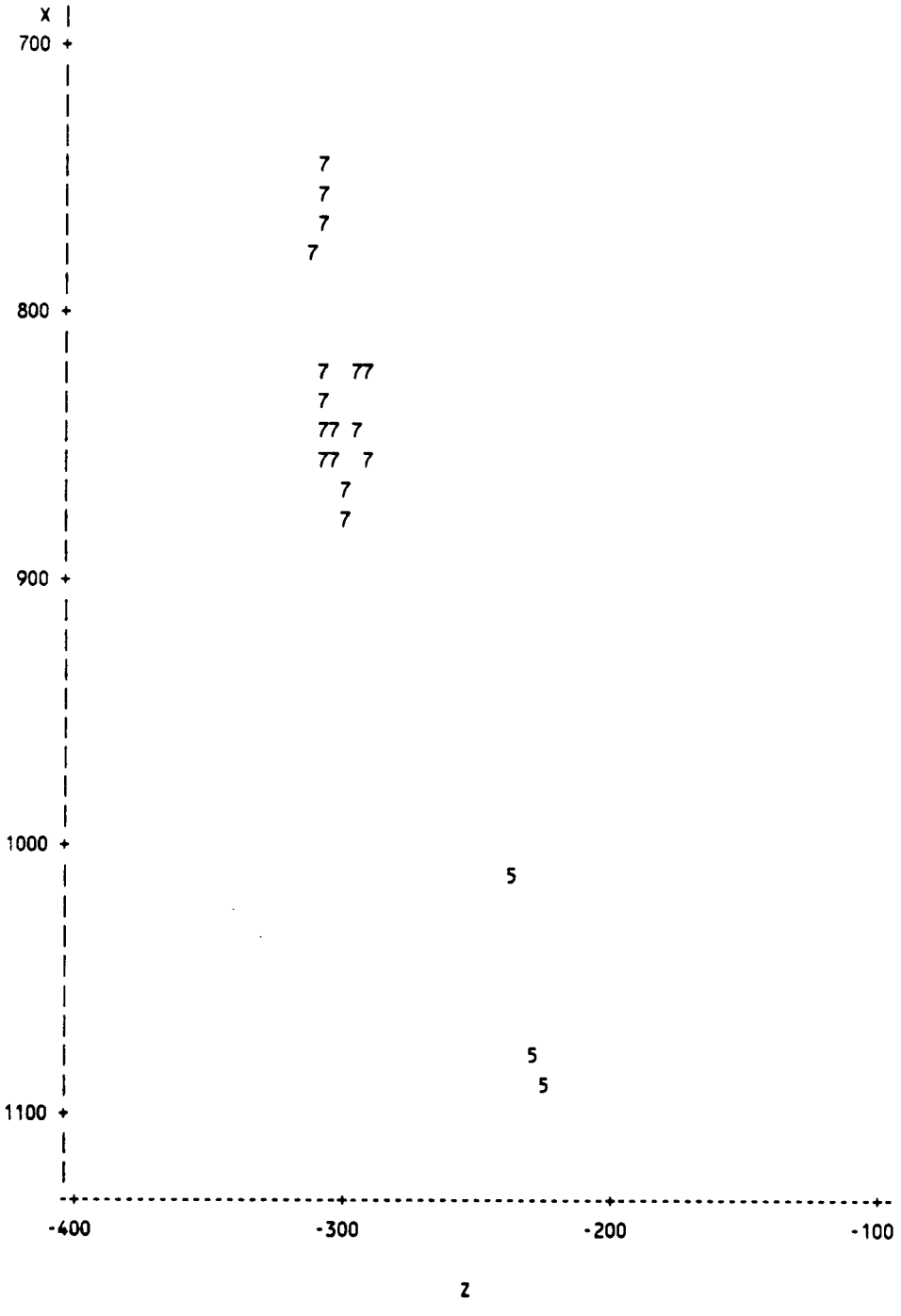


Figure 5.22 Grotte XVI within-couche standard deviation transformation, sagittal cluster projection showing a type 1 pattern: two couches, each easily separable visually.

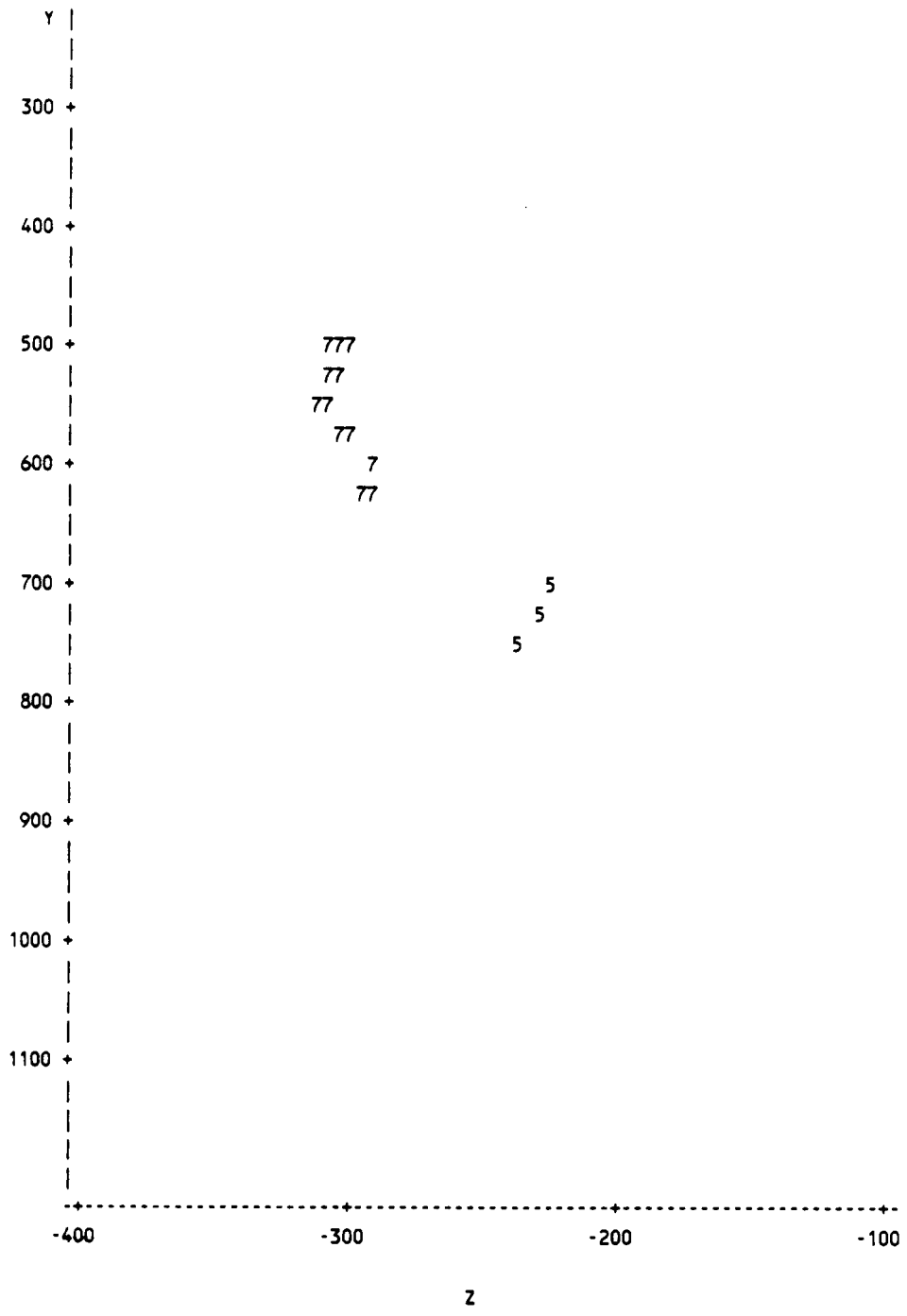


Figure 5.23 Grotte XVI within-couche standard deviation transformation, frontal cluster projection showing a type 1 pattern: two couches, each easily separable visually.

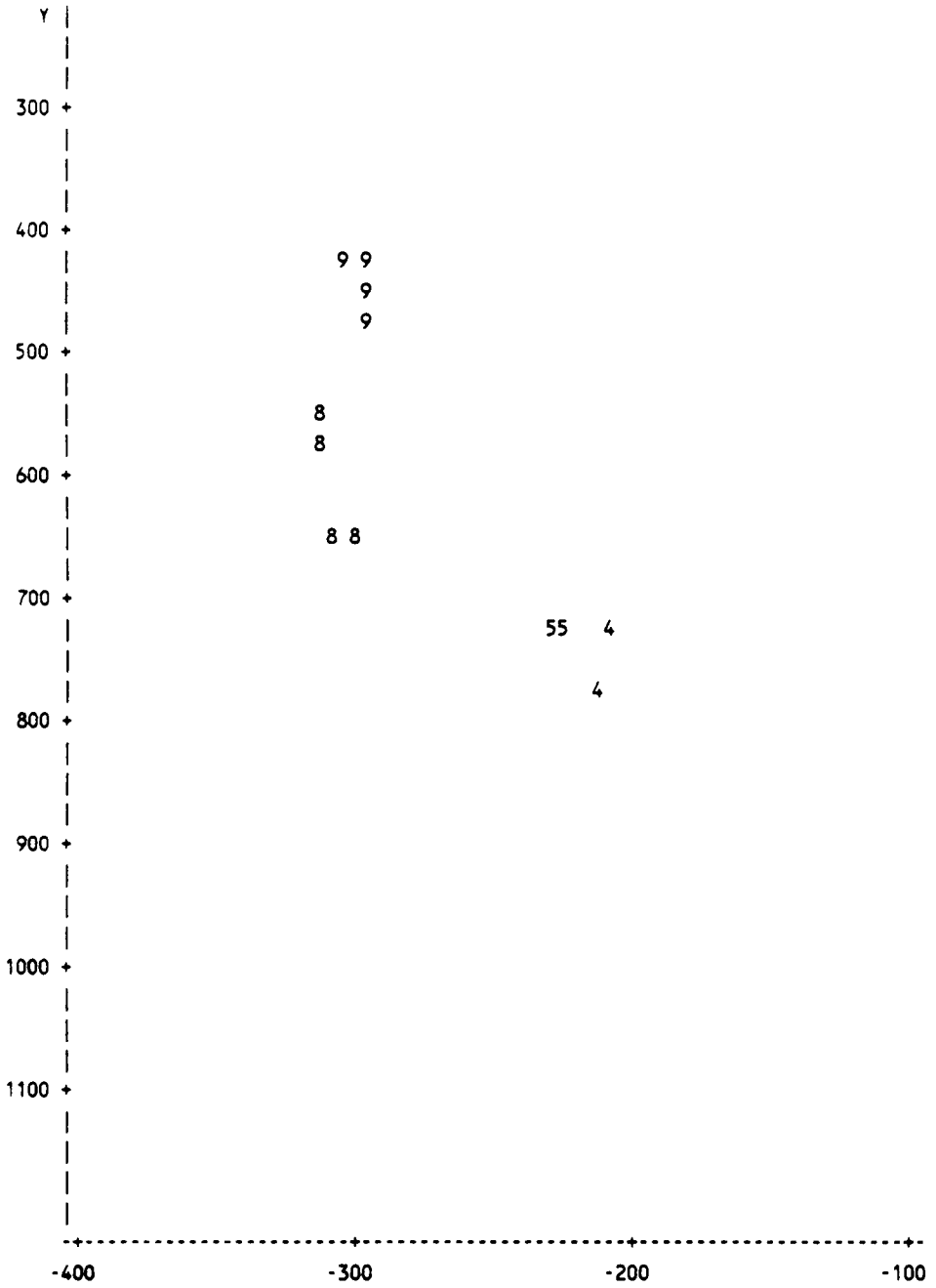


Figure 5.24 Grotte XVI within-couche standard deviation transformation, sagittal cluster projection showing a type 2 pattern: several well dispersed couches.

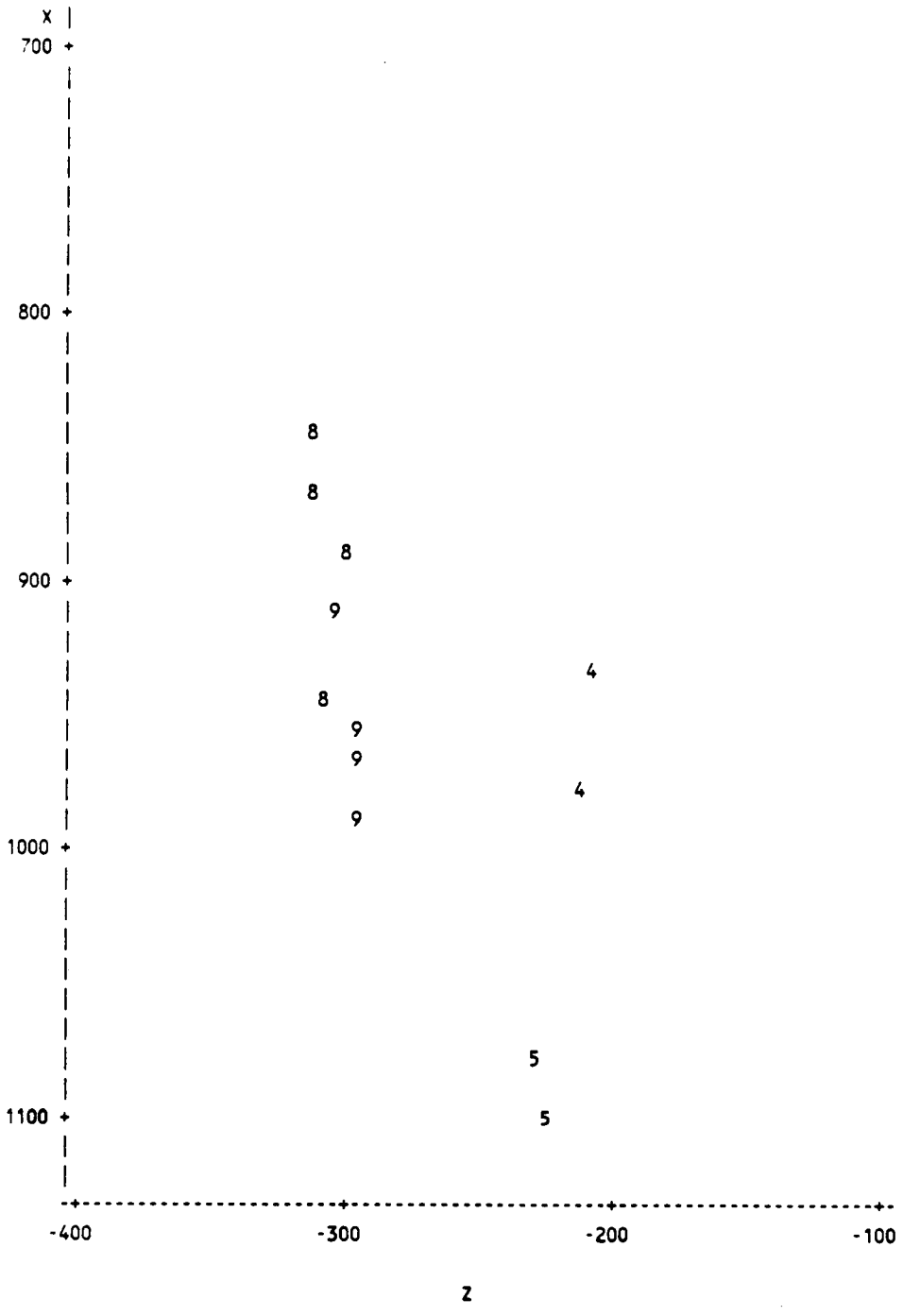


Figure 5.25 Grotte XVI within-couche standard deviation transformation, frontal cluster projection showing a type 2 pattern: several well dispersed couches.

either of the two patterns so evident in the clusters produced by the within-cluster standard deviation transformation. Instead, these clusters show clearly intermixed objects from different couches (Figures 5.26-5.27). There appears to be no unique patterning in these clusters, beyond their mixed nature.

The main differences between these two types of cluster should be clear. The within-cluster standard deviation transformation results in a unique center and range for each subdivision, and mixed clusters result when these overlap in the analytic space. When mapped back into their true space however, distinctions between the overlapping groups may become obvious, as was the case here. Although there were no exceptions to this in these cases, other results are possible. This type of patterning is useful for distinguishing those subdivisions with similar ranges of variation (as measured by standard deviations) and may provide insight as to changes in general spatial patterning when comparing two or more different levels, especially those with very dissimilar object counts. So, at this site for example, comparisons between Aurignacian and Solutrean spatial patterns are possible with a measurable amount of error. This is a somewhat tedious method to obtain results that might be more easily produced by directly focusing on spatial patterning within individual couches however. Yet as a

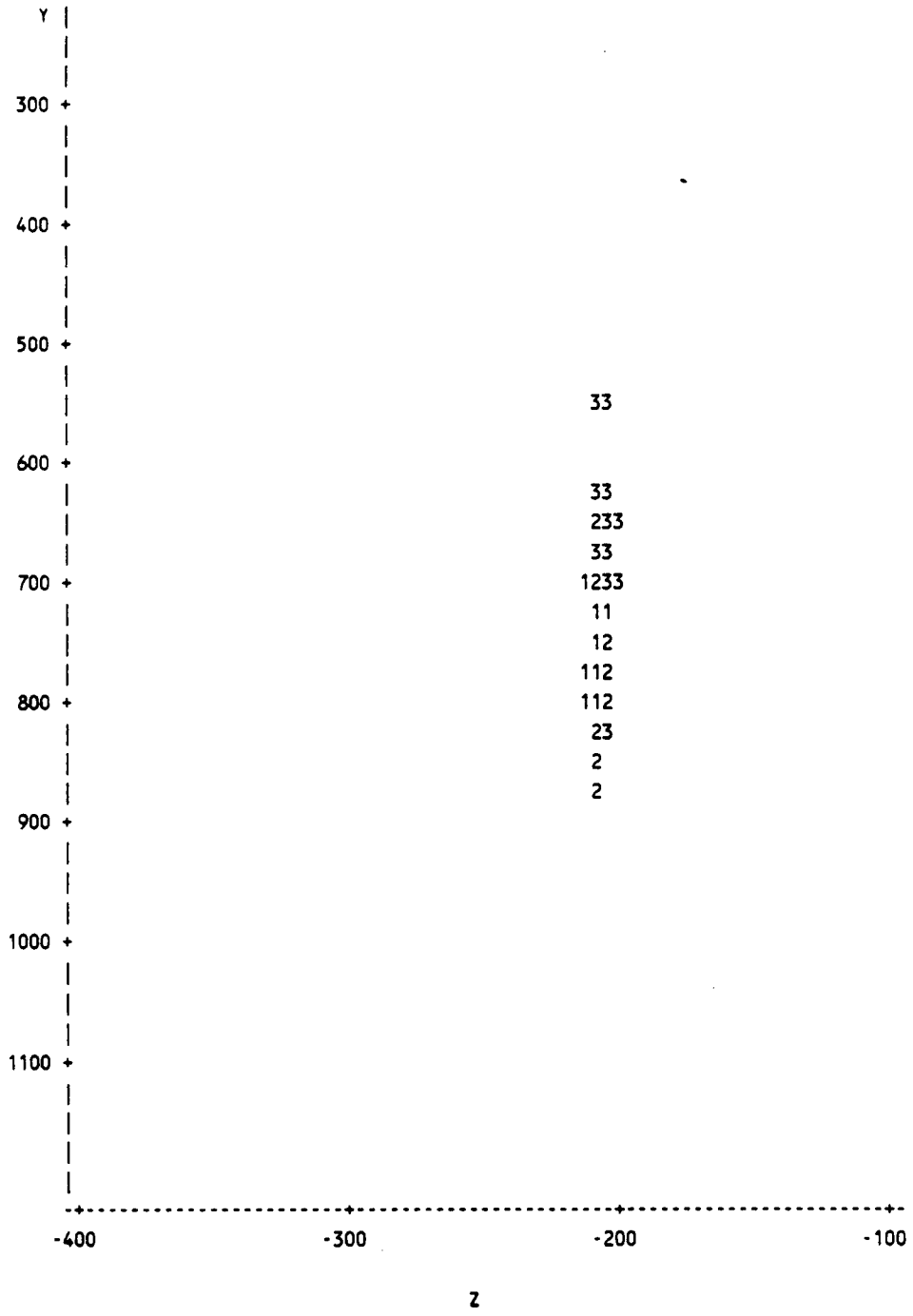


Figure 5.26 Grotte XVI global z-score transformation, sagittal cluster projection showing a typical pattern.

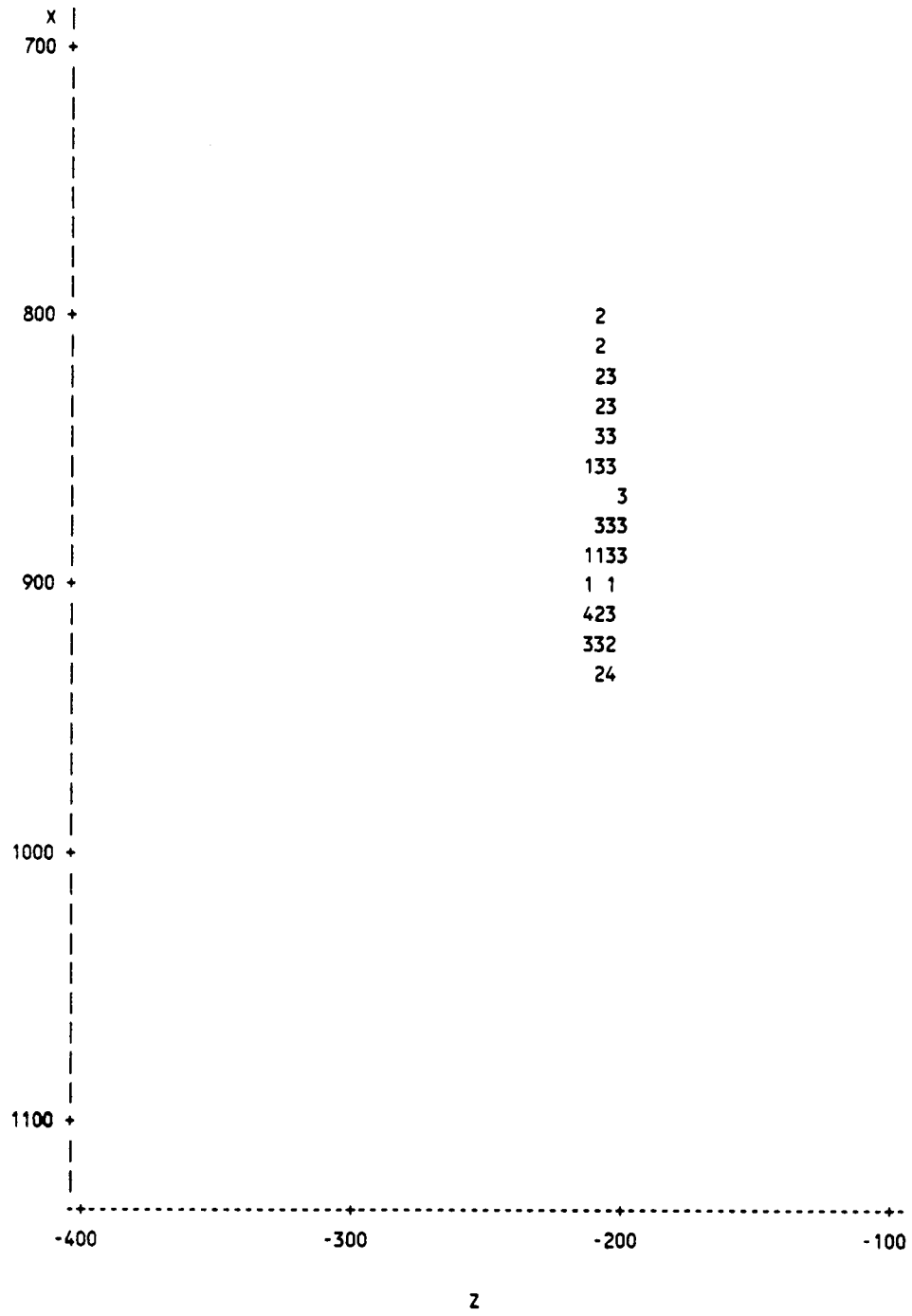


Figure 5.27 Grotte XVI global z-score transformation, frontal cluster projection showing a typical pattern.

global approach, interesting homogeneity and attribute correlation patterns were produced, especially in comparison to those obtained through different clustering procedures.

Within a single couche, use of the within-couche standard deviation transformation might provide interesting results if it was used on distinctive material types, bone and stone for example. This might show clear patterning differences between the two sets of objects, and might be combined with a variety of statistical measures to generate a good picture of the association of the two groups in space, particularly the degree to which the distributions of each material type might overlap.

The global z-score transformation tends to produce clusters with a restricted vertical range, and this tendency becomes even more pronounced as Z-axis expansion factors are increased. This seems to result in clusters that are more representative of the actual situation than was the case when using the within-cluster standard deviation transformation. Examination of clusters produced through this transformation process can show areas of intermixing clearly. This information can be used to objectively highlight potentially suspect or inconsistent couche assignments, as well as to clarify complex interstratification. At this level of analysis, the primary advantage of this technique may be its data

reduction characteristics. A significant aspect of this is its independence from constraints imposed by the grid recording system. The more traditional backplots and projections etc. used to examine three dimensional patterning are often most conveniently produced parallel to grid axes etc. Clustering produces patterning that is largely independent of these constraints and may be more appropriate to a complex depositional situation. In effect the data may speak, if not for themselves, then perhaps at least more clearly through an interpreter.

V.4 Summary and Suggestions for Continuing Excavation

The basic abilities of three dimensional clustering to produce useful data reduction, to provide clarification of complexly stratified areas, and to provide the basis for broad measures of spatial association between object classes are well established. Results of the analyses in this chapter point toward three distinct suggestions for further excavation at the Grotte XVI. First, projections of clusters produced in confusing or complexly stratified sub-volumes of the site should be available to be consulted in the field when provisional couche labeling is taking place. These projections might be more valuable than the standard projections made parallel to grid axes in many instances. Second, clusters produced at a global level that reflect patterning in problematic volumes can

be separated and clustered again as distinct units for even more detailed examination of particularly difficult relationships. Third, this information, organized by cluster, should be combined with feature and rockfall location, refit information, and other attribute patterning to provide a more complete explanatory framework for the patterning and stratigraphic relationships in particular subvolumes. It is possible to achieve such a (nearly) complete consideration of selected volumes in the field and use it to guide continuing excavation given appropriate organization and interaction between the data, microcomputer based analytic techniques, and technical analyses.

CHAPTER VI

DISCUSSION AND CONCLUSIONS

VI.1 Introduction

At the beginning of this dissertation, I set out to investigate the utility of a variety of techniques for the consideration of spatial patterning in three dimensions. In this effort, two very different situations were examined. The first was couche IX from the site Le Flageolet II, a very dense, comparatively thick Magdalenian level in the upper portion of a rockshelter behind the drip zone. The second was a restricted portion of the larger excavations at the Grotte XVI, a multicomponent site also from the Dordogne region of SW France, which is still being excavated. The goals of each of these analyses differed considerably. With the Le Flageolet II material, I strove to understand and portray the spatial patterning of sites like this, and the methods, if any, that would be useful in their characterization and further analysis. At the Grotte XVI, on the other hand, because of the continuing excavation, I wished to find methods for looking at the site's structure in ways that would contribute towards the resolution of difficult stratigraphic relationships, and in particular towards guiding further excavation of these subvolumes. In general I believe that I was reasonably successful in

both of these endeavors. Clearly however there is room for improvement, and several obvious directions to pursue in future work.

VI.2 Le Flageolet II

The excavated portion of this site is found behind the dripline of the cliff face, and the deposits making up couche IX show no substantial slope. Consequently, assuming that any discretely deposited archaeological levels and the materials that make them up within this couche were largely horizontally oriented was within reason. No spatial transformation of the deposit as a whole was necessary to create an appropriately horizontal analytic space. The objects recovered from couche IX appear to have only rarely been found in anything but a horizontally oriented position, increasing the confidence of this assumption. Moreover, because of the substantially intact features, there seems to be little or no reason to suspect any major degree of post-depositional disturbance aside from a single large pot hunters hole. For these reasons the methods developed in chapter III seemed appropriate. There were no visually obvious microstratigraphic breaks found either during my preliminary investigation using vertical projections, or during the actual excavation of the couche itself. Thus there are not any "suspected" levels, and no way to

reasonably estimate case specific errors in the level discrimination or creation process. This led me to examine an extensive series of simulated assemblages and attempt to quantify error rates empirically. Because under assumptions similar to those made for the couche IX materials, these error rates were insignificant, no attempt was made to "correct" for them in the subsequent analyses.

VI.3 The Grotte XVI

Although the goal in analyzing this site was very different from that involved in the Le Flageolet II investigation, many of the methods were similar if not identical. Several portions of this site show (at this point in the excavation) stratigraphic unconformities that are difficult to assess through traditional means. I had hoped that by examining "natural" clusters of objects these areas would become somewhat more understandable. When using the within-cluster standard deviation transformation, this was not the case. While this transformation produced much more "pure" clusters (i.e. very low couche discrimination errors), in terms of their couche components, they are nearly useless for either bringing out areas of potential difficulty, or clarifying situations known to be confusing. Clearly the transformation process eliminated all or most of the more

interesting stratigraphic relationships. Using the global z-score transformation, on the other hand, results in many more mixed clusters and preserves the spatial relationships sufficiently for the problematic areas to be visible.

Cluster solutions with large numbers of clusters (i.e. greater resolution), in particular bring out volumes within the site where couche assignment is strongly mixed. These areas are immediately obvious when the clusters are viewed in projection. There are many potential causes for such areas, solifluction, true but sudden changes in the sediments, sloppy excavation, mislabeling etc. This method alone does not allow determination of these causes, it merely brings out those volumes where they might be operating. Once the clusters are produced, many characteristics of the objects beyond their couche label also become interesting, weight distribution, horizontal vs vertical positioning, etc., especially when compared against these characteristic when examined by couche.

Clearly this type of analysis can be valuable in the correct circumstances, and the relative ease with which it is accomplished suggests that the capacity to perform these techniques be added to the other field analyses already available at the Grotte XVI project. Because most of these techniques already are, or can easily become

microcomputer based, their combination with information from refitting and other technological studies, sedimentology, and the placement of major roof fall blocks and features, can lead to very detailed understanding of difficult areas during excavation. At this point the only thing preventing this is the lack of a set of coordinated analytic and display computer programs.

VI.4 General Conclusions and Suggestions for Further Research

As is true of most "advanced" statistical methods, a cluster analysis will always produce clusters, and in these cases clusters were indeed produced. This clustering was significant compared to the same data with the coordinate associations randomized, so there is a good basis for the conclusion that they represent true "natural", or "most economic" groupings of the objects in space. There is nothing to prove that these clusters (or groupings of them into levels) are in fact coincident with behaviorally created depositional patterns, nor probably, will there ever be. These clusters are, however, the best quantitatively based, and replicable estimate of the spatial patterning that can be made at the moment. Alternative methods for creating these types of divisions are usually based on "eyeballing" the distribution, producing very subjectively defined groups

that have similar or identical problems. Little is to be gained by testing the clustering process against such procedures, except in the more extreme (and obvious) cases, beyond reasonable confidence that the solutions match.

Comparable quantitative analyses of three dimensional patterning do not exist, so no suggestions are to be gained from that direction. Even given a number of comparable analyses however, the general situation (i.e. three dimensional spatial patterning) is likely to be very complex and should certainly not be expected to show simple patterning. One of the main problems here is simply that very little is known about what to expect of a three dimensional distribution. Beyond the very general notion that vertical variation should be restricted, little or nothing can reliably be said. In fact, even what constitutes a reasonable expectation of two dimensional patterning (in often ideal "ethnoarchaeological" circumstances) is hotly contested, witness the debate over the "Pompeii Premise" (Binford 1981), or whether the concept of an activity area is useful in particular circumstances (Binford 1987; Simek 1987), or what evidence for a "home base" might consist of.

This situation led me to develop (in Chapter II) at least the outlines of a model of deposition that would be

useful for thinking about deposition, and especially behaviorally "caused" deposition in three dimensions. The implications of this model drove most of the Le Flageolet II analysis, at least so far as they could be directly addressed. Although I was not able to deal with all aspects of this model, I was able to find several new techniques (or new modifications to previously existing techniques), that allowed some of the model's major elements to be addressed. There is no doubt, for example, that the four material type classes at Le Flageolet II (tools, non-tool blades, non-tool flakes, and bones) exhibit largely distinct spatial patterning. This is consistent with the notion that each major kind of object played a different role in the tool creation, subsistence and social systems in place at that time. Further, these patterns change with depth through the couche, suggesting changes in the nature of the occupation through time, probably towards greater permanency, intensity or at least duration. This is also suggested by changes in the type of feature present, although there appear to be no clear cut coincident changes in tool type frequencies, faunal species, or objects per unit volume. This does not rule out structural changes in the use of the site however.

A number of refinements to the techniques used in this case are immediately possible. First, similar but separate analyses could be conducted for the different

material types divided by size or density. Objects greater or lesser than 2 cm in length, for example could be clustered separately within each material class. This would allow separate evaluation of sets of objects that may commonly have very different depositional histories. In couche IX from Le Flageolet II, for example, many of the bones were smaller than 2 cm. Bones in this size range were often found together, either as obvious parts of a single bone that had been broken in place (or more infrequently in excavation), or as a group of fragments from very obviously different sources that had seemingly been deposited together. The highly fragmented nature of the bones at this site has been extensively discussed (Riguad and Delpech 1974). In any case, the depositional and subsequent movement histories of the larger and smaller bone objects might reflect very different processes. This was addressed through length, width, and density correlations, most of which gave some indication of differences in spatial patterning, although somewhat less accurately than actually examining the spatial patterns of each class separately.

Changes in density, weight, length etc. with depth and cluster could also be addressed (within a single material class) through the use of homogeneity measures on categories made up of these variables. Preliminary (and unreported) investigation along these lines shows some

interesting trends, similar to those found in the attribute correlation analysis for Le Flageolet II.

Second, either independently, or in combination with division by material types, the site might be divided vertically. Although this may make total volumetric comparisons more difficult, it could be incorporated as second level analysis. Initial clustering could be used to divide the site into 2 or more subvolumes, especially if these also corresponded to patterning among the features, and these new divisions analyzed separately. The process of defining subvolumes itself might be instructive if carried out separately for size or density divisions within each material class. Coincidence of the subvolumes defined for the smaller objects within each material class might be a more sensitive indicator of some types of post depositional disturbance or human induced patterning, (e.g. Binford's drop and toss zones), should they exist, might be more clearly visible through this type of analysis.

Third, initial clustering might be used to eliminate "outliers", or groups that separate very early on in the clustering process and remain unchanged for a substantial number of clustering steps. Used intelligently, this kind of filtering (cf. Bricker 1987) might eliminate some problems involving clusters from areas that are relatively sparse. If, for example, a relatively small, isolated

area containing a few widely scattered objects is included, areas with larger numbers of more densely packed objects may be subdivided before the more sparse areas. This happens because using a global SSE clustering criteria means that many small variations could easily equal or exceed a few larger ones in terms of the total SSE. Given the correct distance relationships, and an arbitrary limit to the number of clusters produced, visually obvious divisions of the sparse areas may not ever be reflected in the clustering process. Although this appears to be a minor problem, it can create higher level discrimination error than would otherwise occur. There is no question that this occurred in a small number of the experimental situations reported in chapter III, and when using the within-cluster standard deviation at the Grotte XVI. These effects tended to disappear with increasing Z-axis expansion factors when they were applied.

Although none of the sites analyzed here provided appropriate situations, it should be apparent that even complexly sloped or shaped deposits can be analyzed using these techniques if their shapes can be adequately characterized. For example, relatively complex three dimensional shapes can be fully characterized through trend surface analysis. Transformation into a horizontal analytic space could then be accomplished by using the

residual distance between each object and the analytically defined trend surface to plot their positions with respect to a horizontal plane. Appropriate standardization and Z-axis expansion transformations could then be carried out on this new data set without violating the horizontality requirements. It should be possible through use of this technique to analyze even such grossly deformed sites as La Croix-de-Fer, in the Isle Valley (Fig. 6.1)(Gaussen 1980:231-250).

Perhaps one of the more interesting directions in which to proceed would be to investigate other clustering techniques that are not so dependant upon the use of equal variance criteria. Especially now that at least one site has been examined in detail, comparisons between this analysis and the same data via different techniques cannot help but be interesting. Spath (1980, 1985) for example, presents several clustering techniques that might be appropriate for the investigation of variously shaped and sloped point clouds in three dimensional space. Although their characteristics have yet to be investigated in detail, several of his techniques appear to be well suited to the recovery of clusters that are not constrained by the assumptions of horizontality required when using the K-means technique on untransformed data.

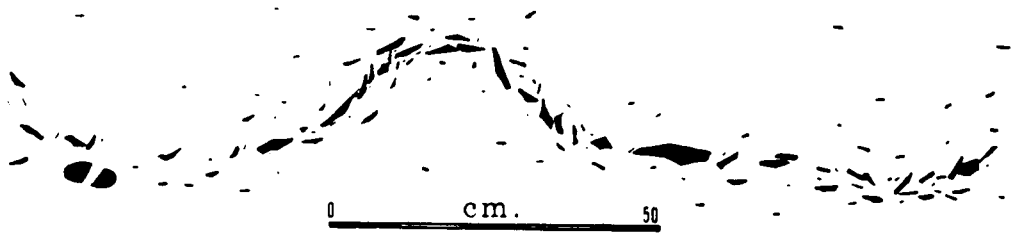


Figure 6.1 Stratigraphic profile through a portion of the site La Croix-De-Fer (Dordogne, France), showing extreme distortion caused by solifluction. Reproduced from Gaussen (1980), figure 120, with permission.

In sum, although this analysis has perhaps led to as many questions as answers, and there are any number of directions in which subsequent work could be taken, I have tried to take a few of the basic steps in considering three dimensional spatial patterning, the road continues onward. Spatial patterning can be profitably examined in three dimensions in otherwise seemingly intractable situations, can help to extend the sample of human spatial behavior that can be investigated from the Paleolithic, and can provide answers to some questions, even at this very early stage in its development and understanding.

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