AN INTEGRATIVE STRATEGY FOR THE DEFINITION OF BEHAVIORALLY MEANINGFUL
ARCHAEOLOGICAL UNITS

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1. INTRODUCTION

The partitioning of artifact loci into meaningful behavioral units and the merging of these behavioral units into socio-cultural models (i.e., as settlements, communities, bands, etc.) is probably the most crucial aspect of archaeological research. Such units form the foundation for both the analysis of culture history and for the study of cultural processes. In this paper, we will present a review of the various theoretical orientations with which this problem has been approached, explore some of the ramifications of these orientations as applied to North American and European Stone Age research, and then, by using examples from our recent investigations in the interior of Alaska, suggest a unified research strategy. While not pretending to reconcile current debates over archaeological theory and practice, we hope that both “traditional” and “new” paradigms might be served by these suggestions. The strategy which we advocate can be used for the definition of components (in a normative approach) as well as for the definition of activity areas (in a behavioral approach), thus serving the several paradigms under which archaeological research is being conducted.

2. BACKGROUND

In the past, attempts to execute a research paradigm (in Alaska and for the Stone Age of the northwestern European Plain) based on postulated models of settlements and components (in the sense of McKern 1939; Hester, Heizer and Graham 1976: Ch. 11) have been fraught with the following problems:

1. Sites are usually surface scatters of artifacts, with few “features” and little evidence for structures or vertical stratification.

2. Independent dating techniques are often inappropriate or imprecise (Campbell 1965). Natural fires preclude the uncritical use of radiocarbon dating and have more often than not been the source of “bad” dates (Waterbolk 1971; e.g., Bohmers and Wouters 1956; Vogel and Waterbolk 1972). Obsidian hydration and related techniques are not yet sufficiently reliable (Michels 1967, 1973; e.g., Holmes 1974).

3. Artifact samples are generally small (low N), often containing insufficient “diagnostic” artifacts suitable for a traditional “type-fossil” approach to comparisons (e.g., Mathiassen 1937; Clark 1972; Anderson 1972).

4. Due to the field techniques practiced, precise field data on artifact distributions are unavailable or poorly depicted, thus blurring evidence for possible horizontal stratification (e.g., Campbell 1962a, 1962b; Shinkwin 1964; Bohmers and Wouters 1956; Schwadeissen 1944; Clark 1954; Wymer 1962; Higgs 1959; Rust 1958; Althin 1954).

5. Using a normative approach, archaeologists have sought to identify the norms or mental templates that lie behind artifacts. The aggregate of such norms shared by the prehistoric inhabitants of a particular area during a particular time period was culture. This approach has led to definitions of culture in terms of “typical artifacts”, “typical artifact assemblages”, and “typical sites”. The questions which archaeologists could then ask were basically comparative and static questions about the relative distributions of different trait complexes (inferentially, cultures). This approach also led to the creation of whole cultures on the basis of the assumed total “representative nature” of the artifactual contents of a single site (Waterbolk 1974). There is no basis for charging that formal explanations and interpretations were of no concern to these traditional archaeologists. Rather, they tended to assume that the appropriate point for processual concerns came after space-time issues had been resolved. The problem with such a position is that the kinds of data one collects and the ways in which one collects those data in pursuit of space-time concerns do not necessarily permit one to answer processual questions (Dekin 1975; Paddayya 1971). The older perspectives assumed that data were data and that we all knew how to collect them. But we have increasingly realized that the ways in which we collect the data more than any other aspect of our work constrain the interpretations and explanations that we will be able to offer. Moreover, it is this aspect of the conduct of archaeology over which we can exercise the most control, thus field tactics and techniques must suit the widest possible range of potential anal-
An integrative strategy

5es (Binford 1964).
6. Greater attention was directed toward the artifacts themselves or at "artifact types" with lesser attention directed toward their functional or systemic significance. In effect, the refinement and perfections of the lithic tool and traditional pottery typologies tended to transcend the level of an analytical technique. Typology became an end in itself (Newell 1971, 1973; e.g., Rozoy 1968; G.E.M. 1969).
7. Potential settlement locations and alternate land-use patterns may be limited to environmental constraints, leading to the re-use of suitable site locations through time (e.g., Dixon 1973; Clark 1972; Wymer 1962).
8. Until recently, research has been conducted in an academic framework constrained by academic needs unrelated to the conduct of empirical research (theses had to be presented, comparisons had to be made on collections of insufficient size for the problems approached, reports had to contain "significant" contributions to knowledge, etc.) (e.g., Holmes 1974; Dixon 1972).

Alexander’s comments on his difficulty in comparing the data from surface sites in the Brooks Range exemplify some of these problems.

Much of the data that has (sic) been used for understanding the prehistory of the Central Brooks Range has come from surface sites. Data from this type of site leads (sic) to numerous problems of interpretation. In the absence of stratified sites any conclusions about a sequence of events are probably derived from typological comparisons with data from other areas, or through the use of absolute dates for each component of the surface sites. Unfortunately such data are not always available. It should also be kept in mind that when dealing with surf sites (unvegetated and unstratified) the discovery or description of how many components are present is often a matter of guess work. Once components are described, however, there is a means of analysis that can provide an internal cross-check on the validity of the components. This is through the analysis of settlement patterns. If the assumption that different cultures respond to the environment in differing ways is correct, then the differences should be reflected in the settlement patterns. The differences will not show unless the prior description of components and their groupings into related complexes is valid (emphasis added, Alexander 1969: 71-72).

These problems led to a confused mixture of implicit inductive and deductive logic. There were no clear statements of the postulates on which decisions to create analytic units were made. Virtually by default, geographic (or geological) features with artifacts became the accepted analytic unit (Newell 1973). Collections were lumped together, based on the implicit postulate that artifacts from contiguous or nearby excavation units were relatively coeval or represented the same behavioral unit (settlement or component). It was only in those rare and unusual circumstances, when artifact differences in contiguous squares were very great, that this assumption has not held (Campbell 1961a, 1962b; Shinkwin 1964). The increase in precise archaeological field data from the Arctic and Western Europe in the last several years leads us to conclude that it is no longer appropriate to operate from such a postulate (Dekin 1971; Cook et al. 1971; Plaskett 1976; Leroi-Gourhan and Brezillon 1966, 1972; Freeman and Butzer 1966; de Lumley et al. 1969; Hesse 1971; Bosinski 1969; Boulinier 1972).

In terms of research strategy, statements on within-site behaviors and relations are better made as hypotheses, because they may then be tested and either demonstrated or refuted, using appropriate field and analytic strategies. By stating such hypotheses explicitly, we focus attention where reliable inferences have previously been impossible, and attack the problem of the definition of within-site behaviors with a combination of field and analytic strategies.

However, it is also important to see this issue as part of a larger paradigmatic shift presently occurring in contemporary archaeology. Increased attention to the study of artifacts as the products of human adaptive systems has resulted in the increased emphasis on the study of technological systems. Inasmuch as the concept ‘‘system’’ refers to ‘‘a series of entities, together with the relations among those entities’’ (following Hall and Fagen 1956), it is apparent that one by-product of systemic thinking in archaeology is the increased attention being paid to the artifacts as entities in relation to other associated artifacts. It is just this latter dimension of the data on which we focus when we examine the within-site variety in archaeological data.

The most recent studies of settlement patterns in the Arctic have been by Campbell (1968), Alexander (1969) and Shinkwin (1973). They drew conceptually on the work of Willey (1956), Sears (1956) and Chang (1958, 1962, 1967, and 1968 ed.). In general, these ideas partitioned land-use studies into three dimensions:
1. the comparison of dwellings and other structures at a site;
2. the comparison of the setting of such sites on the landscape; and
3. the comparison of the patterns of such site-locations characteristic of a society.

Thus, Campbell (following Chang 1962:29) defined his unit of study, the settlement, as follows:

a settlement is any place occupied by one or more individuals for one or more nights, for any purpose that falls within the ordinary, expected and predictable round of activities of the society in question (1968:15).

His typology of six settlement types was derived inductively from the study of modern Tuluqmiut Eskimo behaviors, with a time depth limited by the informant's capacity for recollection. His typology is restricted to those land-use patterns which involved at least an over-night stay, and thus represents a model of a rather limited portion of Tuluqmiut behaviors on the natural landscape.

Alexander did not fully utilize Chang's conceptual framework because he found difficulty in studying the within-site variability in the data (i.e., the study of community patterns – Chang 1962:28-29).

In this paper I have used Chang's definitions of settlement and settlement patterns. I would like to use the definitions of community and community patterns as well. The reluctance is not based on any theoretical argument but the rather practical matter that the information is not found at the sites (emphasis added).

Chang's working definition of settlement is "any form of human occupation of any size over a particular locale for any length of time with the purpose of dwelling or ecological exploitation" (Chang 1962:29). I have tried in my field work reported in this paper to make all site designations conform to the above definition but restricting "occupation" to a single, continuing or uninterrupted event (Alexander 1969:71).

General methods for the analysis of community patterning (specifically, the study of variations in archaeological data within sites) include the inductive study of such variegation (MacDonald 1968; Fitting 1965; Wilmsen 1970) and the application of models derived from ethnographic and ethnoarchaeological studies (Binford 1976; Bonnichsen 1973; Campbell 1968; Oswalt 1972; Salwen 1973; Deetz 1967).

However, the question of the appropriateness of models derived from the study of contemporary spatial distributions of behavior, even in "magical" hunting and gathering societies, for the explanation of the spatial variegation on sites of presumed hunters and gatherers in antiquity has not been satisfactorily approached (see Leach 1973:770; Lee and DeVore 1968). The hunters and gatherers in which we are interested differ significantly in terms of their technology and artifacts from those societies studied in the derivation of the above models. These differences are most observable in the nature and location of facilities (in the sense of Oswalt 1972) and structures which affect the spatial distribution of their activities.

Bonnichsen, for example, defined loci for several activities which involved the presence of facilities produced by western industrial economies and purchased as capital investments (1973). The possible presence of storage facilities for accumulated capital goods and the permanent location of facilities such as chopping blocks, chain falls, and saw horses may have no analogue in the prehistoric period. Other structures and facilities (such as drying racks, skin scraping and stretching areas, and smudge fireplaces) may have prehistoric analogues, but these may or may not have had permanent locations.

Thus, the structure of the use of space in any prehistoric community may not be simplistically modeled by studies of contemporary communities, even though they may be "functionally comparable" in the sense of being loci of hunting activities, etc. Before any such models may be fruitfully applied to data from prehistoric hunting and gathering societies, an extensive set of precisely formulated linking arguments and postulates must be generated in order to demonstrate the applicability of the model to the data being considered. Fig. 1 presents a generalized inductive strategy for the analysis, interpretation and integration of the prehistoric remains as occupation loci so that they may be tested against other settlement models. Quite clearly, the success of this strategy will be strongly dependent upon both preservational and behavioral factors (Corbin 1976). At best, that which is preserved and recovered from an archaeological site is but some part of that which was originally extant. Once the constituent habitation units have been defined, they may then be articulated into a larger scale analysis of prehistoric land-use patterns. These abstract models may become consid-
AN INDUCTIVE RESEARCH STRATEGY

GOAL
Discover and Define Mesolithic Adaptive Processes and Life-Ways

SYNTHESIS
Reconstruction of Settlement as a Functional Habitation Unit where Adaptive Strategy is executed by a Specific Social Unit

Define Activity Areas
Define External Borders and Internal Organization of Settlement
Analysis of Horizontal Distribution and Clustering of Features
Define Classes of Features

SYNTHESIS
Reconstruction of the Ecological System in which Inhabitants of the Settlement had to integrate. Define Exploitative Potential of Site Catchment Area as Conditioning Context of Habitation

Define Activity Areas
Define External Borders and Internal Organization of Settlement
Analysis of Horizontal Distribution and Clustering of Features
Define Range of Material Culture as the Means of executing Adaptive Strategy

II. ARTIFACT ANALYSIS

Palaeobotanical
Seeds and Nuts
C14
Red Ochre

Archaeozoological
Gastroliths and Bones

Mechanical
Chipped Flint Industry

Chemical
Metamorphic Stone Industry

Morphological
Structural Stones
Hammerstones

III. ECOLOGICAL ANALYSIS

Palaeobotanical Analysis
Seeds and Nuts
Charcoal Identification
Surface Pollen
Pollen Cores

Archaeozoological Analysis
Gastroliths and Bones

Pedological

Hydrographical

Fig. 1

after Newell (1975)
General Strategy for the Analysis of Prehistoric Patterns of Land Use

changes, and through comparative methods, the statistical significance of the behavioral basis of the distinctions is assessed. Finally, the initially distinctive analytic units are merged into behaviorally meaningful units for further comparison and model building at any appropriate level of abstraction. It is essential that the logical and theoretical underpinnings of each decision made in the analytic process be assessed and made explicit, so that the contribution which the archaeologist makes to the variance in the data depiction and interpretation can be readily assessed.

The solution which we would suggest for the possible resolution of these problems rests upon
the premise that settlement sites contain artifacts produced and/or abandoned as a result of specific human behaviors. Unless disturbed by post-depositional movement, these behaviors are not distributed randomly in space, but occur at loci whose location and extent are reflected by the distributions of said artifacts. These loci may be discrete or they may overlap; they may be dispersed or they may cluster. We also realize that these behaviors are only a part of the total pattern of occupation. That which was curated and taken away to the next site is also the result of a behavioral pattern. In order to identify the loci reliably, we have increased our archaeological interest in statistical data manipulations and increased our concern for sampling, sample bias and normally-distributed variables (Mueller 1975; Redman 1974). We have increased our understanding of the cultural and natural processes which influence artifact deposition (Crabtree 1968; Binford 1972, 1973, 1976; Schiffer 1972); we have considered the natural and cultural post-depositional processes which influence the archaeological record (Ascher 1968; Newell and Vroomans 1972; Schiffer 1973; Dekin 1975); and we have renewed our interest in the effects of field and analytic strategies as sources of bias (non-representativeness) in the data available for study (Daniels 1972; Newell and Vroomans 1972; Dekin, 1975; Newell n.d.).

It is crucial to the proper interpretation of a site (in an inductive approach) or to the framing of appropriate test conditions (in a hypothetical-deductive approach) to evaluate the sources of bias which affected the sample. This must be done on a case-by-case basis. While some non-normal variables may be transformed to conform to the basic requirements for some statistical manipulations (White and Thomas 1972: 290), unfortunately nothing can be done to remove the effects of sources of bias after the sample has been drawn. That is why we have increased our concern for methodological and technical rigor in field and analytic processes (Newell and Vroomans 1972; Daniels 1972; Dekin 1975, etc.) and why we recommend the following strategy. These techniques proceed from the premise that artifacts co-occurring in horizontal space and distributed in that space as continuous contagious distributions will probably represent significant associations. Dependent upon the strength of the association, one may infer a unity of behavior. In its original state, this artifact distribution may have approximated the normal on at least one horizontal axis. However, natural and cultural-physiographic constraints, such as a cave wall, rock wall, steep slope, body of water, human facilities and structures, etc., may be expected to skew one or both tails of the observed distributions, when present. In general, the sampling error inherent in the imposition of a grid upon this distribution will probably account for a large measure of any deviation from the normal by the observed grid frequencies of artifacts.

4. PROCEDURES

The following strategy was designed specifically for the analysis of lithic artifact distribution, but is also applicable to other variables: ceramics, faunal remains, paleo-ethno-botanical remains, architectural remains, archaeological features, etc. Our strategy is based upon a grid structure of contiguous blocks. Additional strategies and/or methods better suited to alternative data bases, e.g. point-provenience data, are center-of-gravity analysis (Andersen 1972), Venn diagrams (Haggett 1965; Litvak King and Garcia Moll 1972), and nearest neighbor analysis (Clark and Evans 1954; Whallon 1973; Price n.d.b; Clark 1973; Scarry 1976). As our data base is largely restricted to the former structure, only those methods relative to data partitioned into equal grid units will be discussed in this paper.

The method proposed continuously divides the site into tentative behavioral units (preliminary analytic units of artifact concentration) and tests the null hypothesis that specific variables within that unit are homogeneously scattered and may therefore be used to characterize the entire unit. If the null hypothesis is rejected (by an explicit set of decision criteria), then more narrowly distributed sub-units of the proposed larger analytic unit are defined and their relevant variables examined in a similar manner. The strategy includes a set of statistical techniques for testing these hypotheses.

Generally, the following analytic examples ask these questions:

1. Are there discrete clusters of artifacts (described in terms of size, shape and orientation, as well as
2. Do these clusters result from different behavioral processes (different in time, activity, cultural system, etc.)?

Analytical techniques involve the plotting and inspection of raw distributional data for relevant artifactual variables, the testing of significance and correlations of these variables, and the depiction of within/among cluster variations. We will use maps with frequency distribution and contouring, tables of statistical manipulations, histograms, etc.

4.1. Analytic Units

A preliminary analytic unit (PAU) may be defined as all the material contiguously contained within the area described by the one artifact per-grid-unit contour (in other words, the maximum area of dispersion of artifacts contained within horizontally contiguous grid units). This contour connects points (or grid units) of one artifact per-grid-unit density. Contour techniques regard artifact frequencies per-grid-unit as data points located in the center of the respective grid units. These points are treated as if their interrelationships were measured on a linear scale. The one artifact per-grid-unit contour is located between the data points, in proportion to the measured disparity between the data points (Hsu and Robinson 1970).

A PAU is originally postulated to result from similar behaviors at one location. The nature of these behaviors must be determined from the analysis of the artifactual contents and of the variables’ spatial distribution within the PAU. If a variable (or set of variables) is homogeneously distributed within the PAU, then it may be reasonable to infer that it resulted from a homogeneous set of behaviors which produced these artifacts. If homogeneity of artifact composition can be demonstrated by analysis, the PAU then constitutes the basic analytic unit (BAU).

The contouring proceeds from the one artifact per-grid-unit line to higher interval contour lines. If subsequent (incremented) lines are isometric and roughly symmetrical, the concentration will probably prove to be homogeneous, i.e. incremented lines follow the form and orientation of the one artifact per-grid-unit line. If the incremented contour lines are not symmetrical and do not follow the form and orientation of the one artifact contour line, subsequent isopleth(s) most probably either represent separate entities or discriminate peripheral, tangential BAU’s.

After the excavated area has been contoured into one (or more) preliminary analytic units, these are then analyzed separately at the next level of analysis. If a variable is not homogeneously distributed within the PAU, then it reasonably may be inferred that two or more secondary analytic units exist. Contouring of the eccentric variable(s) at the one item per-grid-unit level should initiate the analysis of these new PAU’s. The eccentric variables can be identified in different ways: inspection of the chi-square coefficients of the executed statistical tests or cross-tabulating the block variables into series of attribute variables and subsequently testing for significance. Variables which co-vary will show no significance of difference. This process is repeated with the same variables in smaller and smaller units until spatial homogeneity and co-occurrence of one or a number of constituent variables is found. When this has been achieved, the basic analytic units (BAU) have been defined.

Throughout the above analysis, it has not been specified whether the defined BAU’s have temporal significance (chronological units/components), functional significance (activity areas/functional division of space), or a combination of both. The algorithm suggested here is based on the proposition that all three possible sources of variation in the observed data have an equal probability of explaining the origin of the nature of a BAU. The purpose of this paper is to provide an objective and replicable strategy whereby the basic analytic units, or origins of variations in the data, can be identified and defined. How these building blocks are used for the further hypothesis testing and interpretation of the site is beyond the scope of this paper and forms, in fact, the subject matter of a broader range of archaeological literature. That these successive attempts at interpretation and synthesis have not proven equally successful is in part due to their inability to partition the data into basic analytic units which reliably reflect the sources of primary human behavior.

Once the BAU has been identified and defined as to constituent variables and spatial distribution, the frequencies of the horizontal distribution
should be tested for uniformity or the existence of contiguous clusters. The single-sample chi-square test is perhaps the most suitable method for this step (Siegel 1956). It is this Basic Analytic Unit which we seek and which forms the behavioral basis from which the subsequent process of archaeological analysis, whatever one’s questions or orientations, may proceed.

5. TACTICS

Having established the preliminary analytic units, the next step is the determination of optimum block size and the identification of the nature and scale of patterning of the artifact(s) distribution within those blocks. This step structures the context in which the analysis for internal homogeneity of each preliminary analytic unit is to take place. The original excavation units may not be the optimal units of measure. This is because an excavation grid is imposed upon the site and may or may not reflect the real (prehistoric) or field (archaeological) parameters of the site. Also, the imposed grid units all too often yield frequencies too small for valid statistical manipulation and/or too variable for reliable approximation to existing statistical models (e.g., the normal curve). Some form of amalgamation may be needed. Grid units may be consolidated by the archaeologist until he attains frequencies which make his analysis convenient, but this seems too subjective. A more replicable alternative is the objective measurement of the area of significant clustering and the intensity of that clustering.

For nominal data (Siegel 1956), e.g., flake counts, artifact counts, bone counts, etc., a number of techniques have been developed for the identification of the nature of the variable’s distribution and the determination of the optimum block size and scale of patterning. In the recent archaeological literature (Whallon 1973a; 1973b; 1974; Price et al., 1974; and Price n.d.a, n.d.b) some of these methods have been attempted for the discrimination of floral and faunal assemblages or of “tool-kits” of formal types of retouched tools based upon spatial co-occurrence and correlations. However, instead of proceeding directly to this level of integration, it is apparent that some of the same techniques could be used at a more basic level to resolve our more fundamental problem and to place such integrative analyses on a firm empirical foundation.

The variance/mean ratio (V/\(\bar{X}\)), first published by Greig-Smith in 1952, uses the incremented block structure for measuring the relative degree of randomness or clustering. Its use is based upon the premise that the measure of aggregation varies with grid unit size, providing information on patterning (Pielou 1969). If the ratio is 1.0 (variance = mean), the pattern of distribution is random, whereas, if the ratio is greater than 1, the pattern of distribution is non-random and contagious. The level of intensity of clustering is determined visually from a graph of the variance or mean square plotted against block size. In the past, this method has suffered from a lack of satisfactory statistical tests of significance. At first the F test was suggested, but later Bartlett (cited in Greig-Smith 1964) has shown this to be statistically invalid. Thompson (1958) has cogently argued that the chi-square Index of Dispersion is a reliable test. Whallon (1973a), on the other hand, argues that this test ignores the influence of larger scales of clustering which may be expected to exist. Instead, he has suggested an improvement in the original statistic in the form of a corrected mean square which should more reliably measure the variance and the departure from a random distribution at each block size. For a significance test of this index, he uses confidence limits on the mean. This last method presupposes a close approximation to a normal (or at least symmetrical) distribution but where the sample N is small, the confidence limits may be embarrassingly skewed. Pielou (1969) criticizes the application of the V/\(\bar{X}\) ratio as a test statistic on theoretical grounds. She contends that it is often unreasonable to postulate that the population is random and therefore this ratio should not be regarded as a test but rather as a sample descriptive statistic.

Alternatively, Morisita (1959 and 1962) has suggested an approach to the analysis of pattern which, while similar to the V/\(\bar{X}\) ratio, would be unaffected by quadrant size. His index measures the departure from randomness based upon Simpson’s (1949) measure of diversity rather than directly upon a Poisson distribution. This statistic is based upon the premise that the population under study is a mosaic of large patches (relative to the original grid units) within which the pattern is random. At each
incremented block size, Morisita's index will have a value of 1 for a random distribution, or will have a value of < 1 for a regular distribution or will have a value > 1 for an aggregated distribution.

Because block size (gridunit) intervals break up a continuous variable and may mask intermediate unit sizes at which aggregation is the strongest, we compare Morisita's index of dispersion (IΩ) at each pair of adjacent block sizes in the series 1, 2, 4, 8, etc. The pair having the highest value for the ratio IΩ (b)/IΩ (a) will indicate the block size interval (5-25) at which the tendency for the specific variable to aggregate is the strongest.

As Whallon (1973a) states, some variation in the chosen index values may be expected, depending upon the corner from which the block incrementation is begun. In the course of the larger work (Newell and Wiersum 1977), from which the examples below were drawn, this variation was also observed, but it was not so great as to alter the determination of optimum block sizes. However, for the purposes of replication, the point of departure for the incrementation should be explicitly stated. In the examples below, we proceeded from the south-west corner of the largest rectangle of grid units necessary to enclose the one artifact per meter square contour.

This method has a number of theoretical and practical advantages. In the first instance, the significance of values indicative of non-random distributions can be reliably tested by Snedecor's F test. Secondly, the test values are not dependent upon block size (Greig-Smith 1964). Furthermore, as Price (n.d.a.) has remarked, the test statistic is easily calculated and the results readily applicable for interpretation. Also, the results are said to be indicative of a smaller optimum block size for significant concentrations, e.g., significant concentrations represent smaller surface areas. Finally, eventual secondary clusters at different block sizes are thought to be more readily displayed.

A third approach is that proposed by Dacey (1973). Using original grid counts he advocates first testing for randomness with the V/X ratio and the chi-square test of that ratio's significance. He then tests for absence of spatial association using 2 × 2 contingency tables and contiguity ratios. While the method is an interesting departure from the above, we would suggest that the original grid counts are subject to the bias of the imposition of an artificial grid upon the site and may not reflect the clusters of scale of patterning inherent in the living-floor. As such, it is probably not the optimum point of departure for the definition of behavioral units.

Alternatively, when dealing with continuous data, one should first test for normality; and if successful, do parametric descriptive statistics in order to define the area of dispersal by the standard parameters of dispersion (e.g., standard deviation). If linear normality cannot be demonstrated at a predetermined significance level, the data may be transformed and reassessed, but subsequent manipulation must be on the data as transformed (Snedecor and Cochran 1967; White and Thomas 1972).

Where it is possible to use parametric statistics and standard measures of dispersion about the mean for the definition of the parameters of the site, such a procedure is certainly to be preferred above that of the choice of arbitrary and untestable density contour intervals for the definition of the interval parameters of a site (Clark 1954; Higgs 1959; Rankine and Dimbleby 1960; Radley and Mellars 1964) or even hierarchical block sizes and V/X ratios, however corrected (see Pielou 1969:104-106). In many, if not most cases, the small sizes of the sites relative to the size of the excavation grid units will make the latter procedure statistically invalid.

In any case, the determination of the optimum block size and the measurement of randomness or aggregation are made in order to determine the scale of patterning which allows the reorganization of the original grid count data, with all its inherent sources of variation and error, into a format which best reflects the concentration of artifact types on the ground. In other words, this optimum block size is, in fact, the optimum level of amalgamation for the analysis of the homogeneity or heterogeneity of the analytical unit. It is the scale of patterning at which the sampling error inherent in the imposition of the basic grid is reduced to a minimum.

Once this has been achieved, the testing and measuring of the parameters of horizontal distribution of the variables measured on a nominal, ordinal, interval, or index scale may commence. Eligible variables could include flake counts of different raw materials, primary metric attributes of
artifacts, indices of those measurements, artifact densities or interval frequencies.

In all cases, the internal homogeneity of the analytical unit(s) (both preliminary and basic) must be demonstrated. For the nominal data, the simplest technique is the contouring of frequencies to determine symmetry and co-occurrence of “natural contour intervals”.3 Natural contour intervals are preferred above uniform or systematic intervals because the use of the latter assumes a unimodal continuous contiguous distribution, and, in some cases, a normal distribution.

Where the frequency distribution is not unimodal, the arbitrary selection of uniform intervals may mask significant discontinuities in the grid frequency data. If we are, in fact, dealing with a single set of behaviors, this may be a fair hypothesis, but it must be tested. If the analytical unit is characterized by a multimodal or discontinuous distribution, this phenomenon may be lost or disguised by the use of inappropriate uniform or systematic intervals. The consequence might be the loss of recognition of superimposed multiple occupations and/or functional (behavioral) concentrations. However, at the descriptive level, the co-occurrence or homogeneity of the variables contoured in space cannot be objectively appraised. In the past, this question has been approached through the visual inspection of back plot and contour density maps (Leroi-Gourhan and Breziliion 1966; Hesse 1971; and others) and their interpretations have been impressionistic at best, and impossible to verify.

In order to objectify the decision making and measure of co-occurrence, we would suggest that the analysis of differential distributions is a two-step process. Firstly, we would concur with Greig-Smith (1964) that the possibility of a significant departure from a null hypothesis of identical distributions of the variables in their block size cell-structure must be tested with an $N \times K$ chi-square test, or, where the respective frequencies make this test invalid, a Fisher exact probability test (Siegel 1956), or, by means of Ghent’s $2 \times N$ or $N \times K$ contingency tables, based upon binomial coefficients (Ghent 1972). Secondly, the strength or intensity of the relationship must be measured using a correlation coefficient. In the recent literature (Whallon 1973a, 1973b; Price et al. 1974; an/ Price n.d.a, n.d.b), Pearson’s product-moment-correlation-coefficient has been used as a measure of the degree of co-occurrence or association between two artifact classes. Then by means of a sorted correlation matrix, intercorrelated classes of items have been interpreted as behaviorally significant floral and faunal assemblages or “tool kits”, by means of visual inspection for “significant” patterning of frequency histograms of the resulting coefficients. The degree of similarity of patterns observed for two or more types has been likewise decided by observation and subjective estimation. The choice of the Pearson’s $r$ coefficient is, at best, open to question. Snedecor and Cochran (1967) and Siegel (1956) all state that the use of Pearson’s $r$ is based on the assumption that both populations have a normal distribution and that measurement is in the sense of at least an interval scale.

“For a test of the null hypothesis that there is no correlation, $r$ may be used provided that one of the variables is normal. When neither variable seems normal, the best-known procedure is that in which $X_1$ and $X_2$ are both rankings” (Snedecor and Cochran 1967:191-199).

The choice of correlation coefficient and specifically the underlying assumptions and constraints of the Pearson product-moment-correlation-coefficient has received considerable attention in the literature (Ferguson 1959; Steel and Torrie 1960; Carroll 1961; Guilford and Fruchter 1973; Hays 1974). The discussion revolves around the following three points:

1. The necessity of bivariate normal distributions for both populations relative to the interpretation and significance of the coefficient (Ferguson 1959; Hays 1974);
2. The various standardizing procedures used to approximate normality (Ferguson 1959; Steel and Torrie 1960; Guilford and Fruchter 1973);
3. The nature of the data to which Pearson’s $r$, in whatever form, may be applied (Ferguson 1959; Guilford and Fruchter 1973).

In terms of the first point, only Guilford and Fruchter suggest that the distributions do not have to be normal. However, they do stress that a linear relationship between the variables must be established and that both distributions must be unimodal and “fairly symmetrical”. The difficulties and ambiguities of subjectively assessing what is “fairly symmetrical” when dealing with ar-
archaeological materials has been presented excellent by Speth and Johnson (1976). Further statistical reasoning against this dubious approach is to be found in Carroll (1961).

The scaling, standardizing, and normalizing of scores advocated by Ferguson (1959) and Guilford and Fruchter (1973) have been criticized severely by Carroll (1961) and shown by Speth and Johnson (1976) to introduce an additional source of variance which may increase the problem of suitability rather than eliminate it. In fact, we cannot escape from the feeling that many of those additional problems, and steps in the analytical procedure, could be eliminated by adhering to the original constraints of the coefficient. Finally, Steel and Torrie (1960) do not discuss the nature of the data, while Hays (1974) implies the use of continuous variables. Guilford and Fruchter (1973) mention that the variables must be continuous but warn against the dangers inherent in the use of ordinal data. Carroll (1961) states that the variables must be scaled in equal intervals but adds that tetrachoric \( r \) may be used for ordinal data. However, it “does involve reference to underlying normal bivariate surfaces with linear regressions” (p. 362). Ferguson (1959) is most specific in his agreement with Snedecor and Cochran (1967) and Siegel (1956) when he writes of Pearson’s \( r \):

“This measure is used where the variables are quantitative, that is, of the interval or ratio type. Other varieties of correlation have been developed for use with nominal and ordinal variables. One measure commonly used to describe the relationship between two nominal variables is the contingency coefficient.” (p. 87).

Surprisingly, in their treatise on the use of correlation coefficients, and particularly Pearson’s \( r \), for the identification and measurement of relations for the spatial correlations of tools, etc., Speth and Johnson (1976) do not address this critical aspect of the question.

In the literature cited above, and in the samples presented below, the original data are measured on a nominal scale and do not achieve the interval scale requisite for the valid application of Pearson’s \( r \). As the original data are not presented in two of the sources cited above (Whallon 1973a, 1973b) surely the onus of proof of normality is on the author. Secondly, a check of both the original frequencies and, when given, the frequencies of the optimum block size of the other works cited above (Price et al. 1974; Price n.d.a) were run. In no case was a normal distribution found. As Doran and Hodson (1975) remind us:

“The most regular and obvious departure from the normality assumption is when there are many extreme and relatively few intermediate values for an attribute. This happens regularly when counts of categories are made and where such categories are often absent from many of the samples” (p. 144).

On the strength of these empirical observations, we would suggest that a normal distribution for nominal data for archaeological sites cannot be assumed. Even when \( N \) of a specific sample is large, an implicit reliance upon what Blalock (1960:138) calls the “law of large numbers” is not a satisfactory substitute for a proof of normality. While the cited “results” gained by use of Pearson’s \( r \) may be suggestive of real relationships, they cannot be considered statistically valid or analytically conclusive. Price’s (n.d.b) suggested conversion of the artifact frequencies into indices of relative density before doing the correlation coefficients would seem to effectively eliminate the problem of the basic nature of the data. However, his subsequent work has indicated that such a data transformation still does not work well (Price, pers. comm.). In any case, it would appear that normality is better demonstrated than uncritically assumed.

Finally, by visually inspecting and impressionistically evaluating (i.e., “eyeballing”) the “cut-off” points of frequency distributions of Pearson’s \( r \) product-moment coefficients, one could be accused of being subjective. Without testing the significance of the alleged associations, we have no means of assessing how much (or even if) the correlations have any real meaning. Therefore, we would argue that first, one should test for the homogeneity; secondly, measure the relationships among the variables, using a proper coefficient and its significance test; and only then assess the results with previously stated criteria for acceptance or rejection of the hypotheses being considered.

Greig-Smith (1964:103) has suggested that Kendall’s \( \tau \) is the most appropriate measure of the degree of association or correlation. However, Siegel (1956) cogently argues that both Kendall’s
tau and Spearman’s rank correlation are equally powerful (power efficiency 91%) in rejecting the null hypothesis and that they make equivalent use of the information in the data. A larger problem arises due to the fact that the two coefficients are not mutually comparable. Furthermore, in many analytical situations, a 2 × N comparison may not be compatible with the data structure. Kendall’s tau makes no provision for this contingency. On the other hand, Kendall’s coefficient of concordance (W) is designed for an N × K table and its results are directly comparable to those obtained from a Spearman’s r, calculated on a 2 × N table.

However, when dealing with nominal data, one of these coefficients may be applied. As stated above, the interpretation of Pearson’s r requires a bivariate population with normal distributions measured on at least an interval scale. Kendall’s tau, the Spearman rank correlation coefficient, and Kendall’s coefficient of concordance all demand data measured on at least an ordinal scale (Siegel 1956; Blalock 1960; Snedecor and Cochran 1967).

The nominal scaling operating is (the) partitioning (of) a given class into a set of mutually exclusive subclasses. The only relation involved is that of equivalence. That is, the members of any one subclass must be equivalent in the property being scaled. The equivalence relation is reflexive, symmetrical and transitive. Under certain conditions, we can test hypotheses regarding the distribution of cases among categories by using the non-parametric statistical test, $\chi^2$, or by using a test based on the binomial expansion. These tests are appropriate for nominal data because they focus on frequencies in categories, i.e., on enumerative data. The most common measure of association for nominal data is the contingency coefficient, C, a non-parametric statistic (Siegel 1956:28).

On the other hand, ordinal data or ranking scale is when

“objects in one category of a (continuous) scale are not just different from the objects in other categories of that scale, but that they stand in some kind of (measured) relation to them” (Siegel 1956:24).

For a non-parametric analysis, any order-preserving transformation does not change the information contained in an ordinal scale. The scale is said to be ‘unique up to a monotonic transformation’. That is, it does not matter what numbers we give to a pair of classes or to members of these classes, just as long as we give a higher number to the members of the class which is greater...

The only assumption made by some ranking tests is that the scores we observe are drawn from an underlying continuous distribution. An underlying continuous variate is one that is not restricted to having only isolated values. A discrete variate, on the other hand, is one which can take on only a finite number of values; a continuous variate is one which can (but may not) take on a continuous infinity of values.

Frequencies (counts) of mutually exclusive classes (tool types, raw material types, etc.) of artifacts are not drawn from an underlying continuous distribution. They have isolated values which stand in a reflexive and symmetrical relation to each other. In these cases, we are dealing with enumerative data on a nominal scale. The best measure of association is the contingency coefficient.

The contingency coefficient, C, measures the degree of association between two sets of attributes or artifact categories. Unfortunately, there are strict limitations upon the applicability of the coefficient. Firstly, it cannot attain unity for perfect association and secondly it is not mutually comparable unless both coefficients have been obtained from contingency tables of the same size. A third limitation is that the statistic is subject to the same restrictions as the chi-square test. Finally, C is not compatible with most other correlation coefficients (e.g., Pearson’s r, Spearman’s $r_s$, or Kendall’s tau). However, the contingency coefficient is a valid measure of association between two categories of counts of variables measured on the nominal scale.

When dealing with nominal data whose structure is too weak to meet the constraints of chi-square and whose significance has been tested by Ghent’s contingency tables based upon binomial coefficients, the validity of C cannot be established. An alternative measure of association is Pearson’s Index of Mean Square Contingency (phi-squared) (Hays 1974). This coefficient has the advantage that it is readily comparable to the coefficient of contiguity, C, mentioned above. Finally, in addition to arguments of compatibility and ease of calculation, non-parametric statistics are, perhaps, inherently more suitable to the questions and data structures with which we are dealing (Bradley 1972).

Upon completion of these analytical procedures, the decision for acceptance or rejection of the null hypothesis (that the preliminary analytic unit (PAU) is homogeneous and therefore constitutes the basic analytic unit (BAU) in both behavioral (real) and archaeological (analytical) terms) is de-
ependent upon the outcome of the chi-square test of significance for variables’ co-occurrence in space. Only the strength of that association may be measured by the appropriate correlation coefficient.

These hypotheses deal explicitly with discontinuities in the data. Considering the possible sources of error in field sampling, artifact retrieval, artifact retention, data depiction and analysis, it is apparent that these errors (especially cumulative) are directional, rather than random, with regard to artifact continuity/discontinuity. They are more likely to result in discontinuities in the data than in false continuities.

When dealing with hypothesized discontinuity in these data, as our strategy requires, our statistical manipulations are more fraught with the dangers of perpetrating a Type I error (the acceptance of the proposed hypothesis “H₁” when in fact it is false) than of committing a Type II error (the rejection of the proposed hypothesis “H₁” when in fact it is true). Therefore, we would suggest that a decision criterion at the 1% level be the minimum acceptable level of significance, while higher levels (2%-5%) will probably be highly suggestive.

Upon completion of a large series of analyses, we might anticipate that the values of the correlations would dichotomize in their distributions, dependent upon the above results, and prove to be a reliable indicator of homogeneity. However, experiments have shown that the correlation coefficients of nominal variables (attribute sets), tested for significance of difference, while higher levels (2%-5%) will probably be highly suggestive.

Upon completion of a large series of analyses, we might anticipate that the values of the correlations would dichotomize in their distributions, dependent upon the above results, and prove to be a reliable indicator of homogeneity. However, experiments have shown that the correlation coefficients of nominal variables (attribute sets), tested for significance of difference, while higher levels (2%-5%) will probably be highly suggestive.

6. EXAMPLES

Having presented the theory, procedure and methods of our research strategy, it now remains to apply them to some real data as an illustrative example.

In the first instance, the spatial homogeneity of bivariate nominal data (counts of lithic raw material of flakes) will be demonstrated for a preliminary analytic unit. The equivalence of the PAU with a basic analytic unit (BAU) will be established. Secondly, the spatial heterogeneity of similar multi-variate data for another PAU will be presented. Finally, through the exercise of the “do-loop” concept, we will show how the data from the PAU dichotomizes into two, spatially overlapping but compositionally discrete, BAUs.

For the nominal data, two concentrations from the Fish Creek site, GUL-065, Paxson, Alaska, will be used. This site lies on a lateral moraine of Wisconsin date, measuring ca 580m x 250m, and which is 518m east of the proglacial remnant, Summit Lake. Originally discovered by Dr. John Cook and Robert Gal, it was excavated in the summer of 1975 by a field crew varying between 5 and 19 graduate students under the direction of field foreman Curtis Wilson. The excavation methods consisted of careful side-trowelling through the moss and scrub vegetation mat to the B horizon of the culture-bearing active soil. Unavoidable constraints such as the nature of the soil matrix, time, and the absence of an available water supply precluded wet or dry sieving of the backdirt. The excava-
Fig. 3

FLOW CHART

Objectives
- Identify PAU(s)

Strategies
- Select Data
  - Plot data points in grid units
  - Plot contour intervals from grid frequencies
  - Contour at one artifact per grid unit level

Tests
- Are there two or more separable clusters of artifacts (by inspection)?
  - yes
  - no

Delineate PAU(s)

Select a PAU for analysis

- Identify BAU(s)

Determine variables for PAU

- Determine block sizes, Morisita's Index
  - yes
  - no

Establish optimum block size

Combining frequencies of variables at optimum block size

- Test variables for cluster and association
  - yes
  - no

Homogeneous

Measure strength of association of variables (Contingency Coefficient)

Establish PAU as BAU

Define BAU

- Are there other PAU(s) to evaluate?
  - yes
  - no

Compare BAUs

Next Level of Analysis
vation and subsequent analysis have transpired as part of the Alyeska Archaeological Project, University of Alaska, under direction of Dr. John Cook. Full and complete amplification of the data used here can be found in the final report (Dekin 1977) and (Newell and Wiersum 1977). Both authors...
would like to express their appreciation to the Project Director and the contractor, Alyeska Pipeline Service Company, for their gracious permission to make use of these data in another format, prior to publication of the final report.

The site is characterized by a well developed Arctic miniature podzol soil of weathered till mixed with aeolian silt (Prof. Dr. F. Ugolini, personal comm. 1975). In some restricted areas, cryoturbation has convoluted and/or broken the profile, while in others, solifluction and/or surface erosion has denuded one or two horizons. In neither of the following examples could these secondary processes be shown to have significantly altered the original depositional or pedological situation. The artifacts were all located in a single, thin, and compact band commencing immediately below the surface vegetation mat in the very thin A1 and distinctive A2 horizon. The vertical dispersion varied from 2 cm to 7 cm below the surface. Also, no evidence of vertical sorting of the artifacts by surface area or weight could be discerned. In conclusion, the culture-bearing zone has been interpreted as an in situ occupation layer clearly related to the top-most horizons of the presently pedologically active soil. Also, as no more significant deviations from the original condition than those attributed to oxidation and elluviation have been found, the site has been interpreted as reliably reflecting the situation and condition of the prehistoric settlement(s) at the time of its abandonment. As such, the site is suitable for subsequent spatial analysis.

6.1. Concentration D1

The most northerly excavation area at the Fish Creek site has been designated Area D. Forty 2 × 2 meter squares were excavated, which contained 90 unretouched flakes. As in the other parts of the site, the soil was an Arctic miniature podzol with a very thin A1 horizon. In some parts of the area, the A1 horizon was discontinuous or lacking, possibly the result of surface erosion. As this could conceivably bias the archaeological sample as originally deposited, the affected areas have been shaded in Map 1. Also, cryoturbation was reported from squares 722-724/130-132, 722-724/134-136, 724-726/126-128, and 728-730/126-128. As will be demonstrated below, some of these natural phenomena may have influenced the archaeological sample. The frequency of raw materials is as follows:

<table>
<thead>
<tr>
<th>Manufacture and Waste Products</th>
<th>Total</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type of Raw Material</td>
<td></td>
<td></td>
</tr>
<tr>
<td>gray chert</td>
<td>28</td>
<td>31.11%</td>
</tr>
<tr>
<td>basalt</td>
<td>58</td>
<td>64.44%</td>
</tr>
<tr>
<td>obsidian</td>
<td>3</td>
<td>3.33%</td>
</tr>
<tr>
<td>brown chert</td>
<td>1</td>
<td>1.11%</td>
</tr>
<tr>
<td>T = 90</td>
<td>99.99%</td>
<td></td>
</tr>
</tbody>
</table>

As Map 2 indicates, 84 of the 90 flakes were clustered in a small area in the middle of Area D. Their raw material composition is as follows:

<table>
<thead>
<tr>
<th>Manufacture and Waste Products</th>
<th>Total</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type of Raw Material</td>
<td></td>
<td></td>
</tr>
<tr>
<td>gray chert</td>
<td>25</td>
<td>29.76%</td>
</tr>
<tr>
<td>basalt</td>
<td>58</td>
<td>69.05%</td>
</tr>
<tr>
<td>brown chert</td>
<td>1</td>
<td>1.19%</td>
</tr>
<tr>
<td>T = 84</td>
<td>100.00%</td>
<td></td>
</tr>
</tbody>
</table>

The frequencies of the 84 flakes from the contiguous 16 quadrants were plotted onto frequency distribution graphs in order to determine the pattern of their distribution and the possible presence of natural breaks for the purpose of defining frequency contour intervals (Fig. 4). By plotting a histogram of frequencies of grid units (y axis) containing N number of artifacts against X number of artifacts per-grid-unit (x axis), the analyst can readily see whether the distribution of frequencies is continuous and unimodal, multimodal, or whether the distribution is discontinuous. The variables were found to group into several natural intervals which were used for the isopleths in Map 1 (Fig. 4). The interval homogeneity of these intervals has been confirmed by a series of single-sample chi-square tests (Appendix I).
Proceeding from the maximum horizontal dispersion, the one flake per m² contour, the flake material is distributed in an irregular, broad ellipse 6 m long and 3.5 m wide, at the widest point, and 1 m wide at the narrowest. This concentration, designated D1, is 14.6-15 m² in area and has an ave-
The question of whether the material from D1 represents a single or multiple component occupation has been approached through an analysis of the horizontal distribution and clustering of the flakes and their constituent raw material. Visual inspection indicates that both gray chert and the gray basalt closely coincide with the spatial parameters of the concentration. Gray basalt shows the greater dispersion and gray chert is entirely contained within the area of maximum dispersion of the gray basalt. At the incremented block sizes, the counts of flakes gave the following results (Table 1). These indices demonstrate a maximum clustering between the 8 and 16 quadrant block size and that a tendency toward randomization begins at block size 16, when Morisita’s Index approaches 1.0.

As the areas described by these blocks represent the configurations of maximum significant aggregation, they will be used for the analysis of the co-occurrence and association of the various types of raw material. Firstly, the co-occurrence of the gray basalt and the gray chert was tested using the Fisher exact test and Ghent’s $2 \times 3$ contingency table at block sizes 8 and 16. The results were as follows:

\[
\begin{array}{c|c|c|c|c}
\text{Block} & A & B & C & D \\
\hline
\text{Grid Squares} & 719-723/126-130 & 723-727/126-130 & 723-727/130-134 & 719-723/130-134 \\
\hline
\text{gray chert} & 11 & 13 & 1 & \\
\text{basalt} & 3 & 25 & 24 & 6 \\
\text{brown chert} & 1 & & & \\
\end{array}
\]

\[
\begin{array}{c|c|c|c|c}
\text{Block} & A & B & C & D \\
\hline
A & & & & \\
B & & & & \\
C & & & & \\
D & & & & \\
\end{array}
\]

\[
\begin{array}{c|c|c|c|c}
 & A & B & C & D \\
\hline
p & .359 & & & \\
\hline
p & .296 & p > .80 & & \\
\hline
p & .700 & p = .274 & p = .217 & \\
\end{array}
\]
At block sizes 8 and 16, there were no significant differences in the occurrence of all three materials.

Visual inspection of the contour map (Map 1) indicates that the isopleth of the next higher interval is fairly symmetric in form and orientation to the basal one flake per m² line. Both the second and third natural intervals appear to indicate a certain spatial bimodality on the E-W axis. As this is independent of the frequencies of the respective raw materials, the explanation may be sought in terms of natural processes or in terms of past human behavior and activities. It has been mentioned above that square 722-724/130-132 had been affected by frost-heaving and cryoturbation. At that square, and especially the westerly quadrants parallel to the E-W fall line, a more probable explanation for the observed “clusters” is to be sought in the natural processes affecting the site after its occupation.

Concentration D1 yielded no chipped-stone re-touched tools nor faunal remains. Furthermore, no features in the form of hearths, fire pits, or charcoal horizons were identified so that further tests of the homogeneity of additional nominal variables are impossible. The results of all the above tests would indicate that horizontal dispersion of the raw materials in Concentration D1 is homogeneous and probably represents the remains of a single occupation rather than multiple components.

In conclusion, the data and the above analyses clearly substantiates the acceptance of the excavation unit Concentration D1 as a basic analytic unit characterized by the homogeneous spatial distribution of the constituent nominal variables. This unit is then characterized by the homogeneous distribution of 84 unretouched flakes of gray chert, basalt, and brown chert in an irregular, broad elliptical pattern, measuring 6 m x 3.5 m at the widest point and 1 m at the narrowest. Having an area which varies from 14.6-15 m², BAU D1 is oriented E-W on its long axis and has an average density from 5.71 to 5.60 flakes per m². Having identified and defined the composition of the BAU, these, and other, attributes may be used for comparison with those of other BAU’s for the purpose of proceeding to the next level of analysis, the definition of settlement type.

6.2. Area A Concentration A-14

Proceeding from the natural contour intervals (Fig. 5) of the frequency contour map of Σ Flakes by quadrant (Map 3), Concentration A-14 is defined by a discrete, slightly plump cruciform outline at the basal contour of one flake per m². As in the previous example, the non-uniform nature of the distribution of frequencies has been confirmed by single-sample chi-square tests (Appendix II). The contouring indicates that the cluster measures 9.8 m long by 5 m maximum width and 2.2 m minimum width. The minimum area is 18.44 m² while the maximum area is 20 m². The long axis of Concentration A-14 is oriented NW-SE.

TABLE 1

<table>
<thead>
<tr>
<th>Fish Creek Site GUL-065</th>
<th>Concentration D1</th>
<th>Σ</th>
<th>Flakes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Block Size</td>
<td>Morisita's Index</td>
<td>F Test</td>
<td>N1</td>
</tr>
<tr>
<td>-------------</td>
<td>----------------</td>
<td>--------</td>
<td>----</td>
</tr>
<tr>
<td>1</td>
<td>8.133</td>
<td>9.235</td>
<td>63</td>
</tr>
<tr>
<td>4</td>
<td>5.443</td>
<td>22.988</td>
<td>15</td>
</tr>
<tr>
<td>8</td>
<td>3.045</td>
<td>21.095</td>
<td>7</td>
</tr>
<tr>
<td>16</td>
<td>1.523</td>
<td>10.595</td>
<td>3</td>
</tr>
<tr>
<td>32</td>
<td>1.539</td>
<td>21.881</td>
<td>1</td>
</tr>
<tr>
<td>64</td>
<td>1.000</td>
<td>-1</td>
<td>0</td>
</tr>
</tbody>
</table>
The material from Concentration A-14 consists of:

**Manufacture and Waste Products**

<table>
<thead>
<tr>
<th>Type of Raw Material</th>
<th>Total</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>gray chert</td>
<td>64</td>
<td>61.54%</td>
</tr>
<tr>
<td>black chert</td>
<td>10</td>
<td>9.62%</td>
</tr>
<tr>
<td>red banded chert</td>
<td>30</td>
<td>28.86%</td>
</tr>
</tbody>
</table>

**Utilized and Retouched Artifacts**

<table>
<thead>
<tr>
<th>Artifacts</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>biface fragment</td>
<td>1</td>
</tr>
<tr>
<td>blade</td>
<td>1</td>
</tr>
<tr>
<td>end scraper</td>
<td>1</td>
</tr>
<tr>
<td>core fragment</td>
<td>1</td>
</tr>
<tr>
<td>utilized blade</td>
<td>2</td>
</tr>
</tbody>
</table>

**Total Lithic Artifacts** Σ = 110

As in the former example, the shape, size, and orientation of this concentration are largely determined by the horizontal distribution of the gray chert. The red banded chert, while less numerous, appears to nearly duplicate the gray chert dispersal while the black chert is more restricted in its distribution (Map 4). Before this apparent variation may be analyzed, the scale of patterning and degree of randomness must be determined. The data from the same range of tests and indices which have been applied above are presented in Table 2.

Both Morisita’s index and the mean square index of the dimensional analysis of variance indicate a maximum clustering of flakes between block size 4 and 8. At the former block size, the raw materials of the flakes are distributed as follows:

<table>
<thead>
<tr>
<th>Block</th>
<th>Grid Squares</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
<th>VI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>494-496</td>
<td>494-496</td>
<td>494-496</td>
<td>494-496</td>
<td>494-496</td>
<td>490-492</td>
<td></td>
</tr>
<tr>
<td>gray chert</td>
<td>8</td>
<td>5</td>
<td>25</td>
<td>3</td>
<td>13</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>black chert</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>red banded chert</td>
<td>21</td>
<td>5</td>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
TABLE 2

Fish Creek Site GUL-065
Area A
Concentration A14
∑ Flakes

<table>
<thead>
<tr>
<th>Block Size</th>
<th>Morisita’s Index</th>
<th>F Test N1</th>
<th>1δ15/1δ25</th>
<th>D.A.V. df</th>
<th>Mean Square V/X</th>
<th>G-S</th>
<th>I.D.</th>
<th>df</th>
<th>Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.332</td>
<td>9.276</td>
<td>47</td>
<td>sig.</td>
<td>1.2</td>
<td>1294</td>
<td>24</td>
<td>10.417</td>
<td>5.942</td>
</tr>
<tr>
<td>4</td>
<td>3.170</td>
<td>18.545</td>
<td>11</td>
<td>sig.</td>
<td>1.843</td>
<td>733.5</td>
<td>6</td>
<td>56.167</td>
<td>10.878</td>
</tr>
<tr>
<td>32</td>
<td>1.243</td>
<td>12.000</td>
<td>1</td>
<td>sig.</td>
<td>1.243</td>
<td>211.250</td>
<td>0.75</td>
<td>13.000</td>
<td>26.000</td>
</tr>
<tr>
<td>64</td>
<td>1.000</td>
<td>-1.000</td>
<td>0</td>
<td>n.s.</td>
<td>1.243</td>
<td>225.333</td>
<td>0.375</td>
<td>-18.777</td>
<td>-</td>
</tr>
</tbody>
</table>

As the frequencies in many cases are too small for an N × K chi-square test, the homogeneity of the respective blocks was tested by pairs using either a 2 × N chi-square, the Fisher exact probability test, or Ghent’s 2 × N contingency tables. The results are as presented in Table 3.

Proceeding from the stated 1% significance level, it is quite obvious that the raw materials are not homogeneously distributed through the concentration. Blocks I, IV, V, and VI show no mutually significant differences between their raw materials. Block III differs only from Block I of the former list while Block II is significantly different from all the rest. Clearly, this is no surprise as Block II is the only block which contains black chert.

At block size 8, the raw materials of the flakes are distributed as follows:

TABLE 3

<table>
<thead>
<tr>
<th>Block / Block</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td></td>
<td>.003</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>II</td>
<td>.013</td>
<td></td>
<td>.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>III</td>
<td>.000</td>
<td>.069</td>
<td></td>
<td>.178</td>
<td></td>
</tr>
<tr>
<td>IV</td>
<td>.130</td>
<td>.033</td>
<td>.010</td>
<td></td>
<td>.421</td>
</tr>
<tr>
<td>V</td>
<td>.137</td>
<td>.145</td>
<td>.030</td>
<td>.201</td>
<td>.421</td>
</tr>
</tbody>
</table>

Again, many of the frequencies are too small for an N × K chi-square test so the homogeneity was tested by pairs. The results are as indicated in Table 4.

At this block size, the discrimination of the block containing the black chert is even stronger, while the spatial homogeneity of the gray chert and the red banded chert is confirmed.

As a result of these tests, it would seem that Concentration A-14 consists of two basic analytic units: 1) the distribution of the gray chert and red banded chert, and 2) the distribution of the black
chert. This is perhaps confirmed by an inspection of the contour and density maps (Maps 3 and 4) where we observe fairly consistent frequencies in contiguous quadrants except those occupied by the black chert.

Finally, an attempt was made to measure the scale of patterning and nature of the horizontal dispersal of the five retouched tools. In Table 5 the disappointing results are presented. They clearly demonstrate a uniform distribution with no significant indication toward clustering. While it is not statistically significant, there is a slight increase in Morisita’s index and the mean-square index of the dimensional analysis of variance which reflects the group of three tools in the northwest corner of the concentration. The fact that these tools are made of black chert and co-occur with the black chert flake block discriminated earlier may indicate a cluster which can not be statistically defined. In any case, the exercise does demonstrate the lower limit of resolution inherent in our methodological approach.

In conclusion, Concentration A-14 consists of two compositionally discrete basic analytic units. BAU A14-I is a homogeneous scatter of 94 unretouched flakes of gray chert, red banded chert, and two retouched tools distributed in a slightly plump cruciform pattern, measuring 9.8 m long by 5 m maximum width and 2.2 m minimum width. The minimum area is 18.44 m² while the maximum area is 20 m². The average flake density varies from 4.70 to 5.10 flakes per m² while the retouched tool density varies from 0.10 to 0.11 tools per m². The total lithic density varies from 4.80 to 5.21 per m². The long axis of BAU A14-I is oriented NW-SE. The second BAU is A14-II. It consists of a small scatter of ten black chert flakes and three black chert tools within two contiguous square meter quadrants. While the scale of the grid, relative to the scatter of

<table>
<thead>
<tr>
<th>Block</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>p = 0.200 × 10⁻³</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>p = 0.178</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>p = 0.215</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>p = 0.152</td>
<td>p = 1.30 × 10⁻³</td>
<td>p = 0.421</td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>p = 0.206</td>
<td>p = 0.358 × 10⁻³</td>
<td>p = 0.421</td>
<td>p = 0.306</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Block</th>
<th>Morisita's Index</th>
<th>F Test</th>
<th>N1</th>
<th>Signif. at 1% Level</th>
<th>I₁δ₁/₁δ₂</th>
<th>D.A.V.</th>
<th>df</th>
<th>Mean Square</th>
<th>G-S</th>
<th>V/X</th>
<th>I.D.</th>
<th>Signif. at 1% Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.8</td>
<td>0.295</td>
<td>47</td>
<td>n.s.</td>
<td>7</td>
<td>24</td>
<td></td>
<td>0.146</td>
<td>0.15</td>
<td>0.6</td>
<td>3</td>
<td>n.s.</td>
</tr>
<tr>
<td>2</td>
<td>2.4</td>
<td>0.192</td>
<td>23</td>
<td>n.s.</td>
<td>2</td>
<td>3.5</td>
<td>12</td>
<td>0.146</td>
<td>0.15</td>
<td>0.6</td>
<td>3</td>
<td>n.s.</td>
</tr>
<tr>
<td>4</td>
<td>1.2</td>
<td>-0.017</td>
<td>11</td>
<td>n.s.</td>
<td>0.667</td>
<td>1.75</td>
<td>6</td>
<td>0.063</td>
<td>0.15</td>
<td>0.6</td>
<td>3</td>
<td>n.s.</td>
</tr>
<tr>
<td>8</td>
<td>1.8</td>
<td>0.375</td>
<td>5</td>
<td>n.s.</td>
<td>1.125</td>
<td>1.375</td>
<td>3</td>
<td>0.187</td>
<td>0.533</td>
<td>1.6</td>
<td>2</td>
<td>n.s.</td>
</tr>
<tr>
<td>16</td>
<td>1.6</td>
<td>0.350</td>
<td>3</td>
<td>n.s.</td>
<td>2</td>
<td>0.813</td>
<td>1.5</td>
<td>0.271</td>
<td>0.1</td>
<td>0.2</td>
<td>1</td>
<td>n.s.</td>
</tr>
<tr>
<td>32</td>
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<td>1</td>
<td>n.s.</td>
<td>0.406</td>
<td>0.75</td>
<td>0.02</td>
<td>0.1</td>
<td>0.2</td>
<td>1</td>
<td>n.s.</td>
<td></td>
</tr>
<tr>
<td>64</td>
<td>1.0</td>
<td>-1</td>
<td>0</td>
<td>n.s.</td>
<td>0.391</td>
<td>0.375</td>
<td></td>
<td>0.02</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

As an integrative strategy
artifacts, is too large for a precise description of size and shape, the one flake per m² contour line would indicate an oval form occupying some 3.0 m² in area (Map 5) with the long axis oriented E-W. The average flake density is 3.33 per m² while the retouched tool density is one per m². The average total lithic density is 4.33 per m².

7. CONCLUSIONS

In the sections above, we have presented the theory and reviewed the methods presently available for the assessment of homogeneity and spatial patterning within the constraints of gridded data. While our approach has been largely critical, we have attempted to present an integrated strategy consisting of the best of the various alternatives. In terms of a comparative assessment of the indices of clustering, Morisita’s index vs. dimensional analysis of variance, the examples included in this paper would indicate an agreement with Brose and Scarry (1976) in that both indices are equally powerful in the
approximation and recognition of spatial patterns. However, in the larger work from which these examples were drawn (Newell and Wiersum 1977), the use of Morisita’s index led to the recognition of significant clustering at an earlier stage in the block size incrementation than did dimensional analysis of variance in a number of instances. This apparent greater sensitivity clearly lends support to Price’s (n.d.a) claim that Morisita’s index is the better of the two techniques. Nevertheless, inherent problems in the application of this and similar inductive strategies still remain. Many of these have been recognized and corrected by other authors (Pielou 1969; Whallon 1973a; Price n.d.a; Schiffer 1974; Riley 1974; Clay 1975), and in some cases we have been able to indicate corrections and/or suggest alternatives. Other problems, such as the accommodation of features and the relation of artifacts to features, still remain unsolved.

The final resolution may be in the application of even more stringent field techniques so that we are no longer restricted by the limitations of gridded
data partitioning, but rather may use point-provenience data and the methods better suited to that data structure (Clark and Evans 1954; Whallon 1974; Price n.d.b; Clark 1975; Scarry 1976). However, in their applications of the various techniques of nearest neighbor analysis to archaeological sites, Clark (1975) and Brose and Scarry (1976) have demonstrated that even those methods are subject to problems of sample size and the interpretation of the size and location of clusters. After experimentation, the best alternative may prove to be a strategy in which point-provenience data are collected for all the artifacts in the field and then automatically combined and partitioned into small grid units for the identification and location of the basic analytic units as well as some aspects of artifact class patterning and that the point-provenience techniques then be used to complete and confirm the analysis.

Instead of or perhaps in conjunction with the suggested further refinement of the above inductive approach, we could also pursue Dekin’s (1976b)
alternative use of heuristic models for the initial structuring and partitioning of our archaeological data. Through the application of an elliptical model, he has been able to,

...test hypotheses on the nature and design of the structure itself, the division of its activity areas, and on the definition of activities and possible divisions of labor and tool use. (p. 86)

In the effect, he has accomplished the same goal to which Speth and Johnson (1976) strived when they wrote,

...if natural provenience units, such as huts, pits, and hearths, can be identified on an occupation horizon, partitioning the archaeological material into reasonable subpopulations prior to analysis may be possible. (p. 57).

...In order for multivariate groupings adequately to reflect underlying patterning in the data, the archaeological material should be divided, whenever possible, into its component subpopulations. (p. 57).

In fact, testing for the best-fit heuristic model should lead to the identification and location of the constituent provenience units or component subpopulations in the form of activity areas and discrete spatial divisions of labor and tool use. As the effectiveness of this technique has already been demonstrated (Dekin 1976b) it would seem that this line of approach could be expected to better answer the questions posed above and attacked by means of the inductive approach. Quite clearly some further experimentation with the basis for the selection of the shape of the model and its constituent analytic units needs to be undertaken, e.g., the use of polar coordinates, concentric circles, and other spatial partitions as well as models derived directly from ethnographic sources (Boas 1888; Geudon 1971; Briggs 1970; Clark and Clark 1974, etc.). In this way, the optimum case-specific models will be generated and by means of comparison, some wider generalizations may be found to be consistent. One direct advantage to this approach is the facility with which features and the relationship of features to artifacts may be accommodated in the analysis. In any case, we find the heuristic approach sufficiently encouraging to expand upon it and make use of it in our future research, which will be reported in due course (Newell and Dekin n.d.).

8. ACKNOWLEDGEMENTS

In the course of the preparation and publication of this paper, we have had the good fortune to have profited from the full interest, cooperation, and good advice of a larger number of people than we can remember. Most important of these are the project director, Dr. John P. Cook, and our Alyeska Archaeology Project colleagues, R. Gal, M. Kunz, G. Lothson, D. Slaughter, R. Stern, W. Wiersum, and M. Yarborough. The Alyeska Pipeline Service Company, and especially Mr. R. Fisher, are to be thanked for their permission to make use of pipeline data and publish same separate from the full project report. Invaluable help in the computer programming and execution was provided by K. Kokjer of the Institute of Arctic Biology and T. Fulham of the University of Alaska Computer Center. Discussions with and/or critical remarks by the following archaeologists have added to our perceptions of the problems incurred and hopefully increased the clarity with which our solutions or suggestions have been presented: S. H. Andersen, R. Bedaux, R. Borofsky, J. Brown, G. Clark, Ruth Dekin, A. McCartney, J. E. Musch, G. Odell, T. D. Price, R. Reanier, S. Scholz, J. D. v.d. Waals, and C. Wilson. Messers L. Th. van der Weele and T. Wierstra of the Rekencentrum of the State University of Groningen are to be thanked for their critical and always helpful guidance of the exact statistical formulations and arguments. D. Borchert of the Institute of Arctic Biology, University of Alaska kindly prepared the original drawings while Barbara White, the project secretary, patiently and helpfully suffered through innumerable redrafts, in conjunction with her normal work load. Sandra Smith got it all together for the final draft. Mr. J. Dijkema drafted the final line drawings. To all these people, our debt is great.
**APPENDIX I**

### Artifact Frequency Per Quadrant P.A.U. DI

<table>
<thead>
<tr>
<th>number</th>
<th>expected</th>
<th>$x^2$ Coefficient</th>
<th>number</th>
<th>expected</th>
<th>$x^2$ Coefficient</th>
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<tr>
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<td>4.654</td>
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<tr>
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<td>4.654</td>
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</tr>
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<td>.346</td>
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</table>

$\sum x^2 = 100.762$

$df = 15$

$p < .001$

### Artifact Frequency Per Quadrant P.A.U. A-14

<table>
<thead>
<tr>
<th>number</th>
<th>expected</th>
<th>$x^2$ Coefficient</th>
<th>number</th>
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<th>$x^2$ Coefficient</th>
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<td></td>
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</table>

$\sum x^2 = 95.072$

$df = 15$

$p < .001$

### Decision

- $p < .001$
- $0.05 > p > .02$
- $0.20 > p > .10$
- $0.50 > p > .30$

1-4

7-13

22
### 11. APPENDIX III

#### ARTIFACT FREQUENCY PER QUADRANT B.A.U. A-14-I

<table>
<thead>
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$\Sigma x^2 = 107.872$

$df = 15$

$p < .001$

#### ARTIFACT FREQUENCY PER QUADRANT B.A.U. A-14-II

<table>
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</tr>
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<td>0.20</td>
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<tr>
<td>4</td>
<td></td>
<td>0.20</td>
</tr>
</tbody>
</table>

$\Sigma x^2 = .40$

$df = 1$

$.70 > p > .50$

**decision**

4-6

---

2. Block size is a hierarchical scale of incremented grid units beginning with minimal units of the individual grid quadrant and incrementing in size by doubling the area of the block until all the site is contained within one block (i.e., blocks of 1, 2, 4, 8, 16...N excavation units).

3. “Natural contour intervals” are those intervals which reflect the real distribution (dispersion or clustering) of observed frequencies along a continuous scale. Such intervals are determined by visual inspection of consistent gaps and clusters at varying interval scales as recommended by Speth and Johnson (1976), and then tested for homogeneity with the single-sample chi-square test (Siegel 1956).

---

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An integrative strategy

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logisch-Archeologisch Institut Groningen.


