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The Use of Point Pattern Analysis in Archaeology: Some Methods and Applications

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THE USE OF POINT PATTERN ANALYSIS IN ARCHAEOLOGY:
SOME METHODS AND APPLICATIONS

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by

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Abstract

This study explores a field of spatial statistics known as Point Pattern Analysis (PPA) and its application in archaeology. The overall goal is to provide a resource which will guide and assist the reader in the proper application of PPA. Past archaeological applications are combined with more recent geographical and statistical mathematics to create a more inter-disciplinary, synthesized approach. Included are a discussion of analytical methods and two detailed case studies/applications.

The study begins with an overview of PPA approaches in archaeology, starting with a general introduction and several commonly understood concepts such as first and second order effects and simple and labeled point patterns. It also describes options for calculating statistical significance and their appropriate uses which depend on the analysis being performed --something which is not well articulated in the literature. It goes on to describe appropriate techniques for analysis introducing another new concept called *resolution focus,* which facilitates comparison of various statistics in the analysis of first order effects. Finally, it provides logical structured approaches to conducting a PPA and selecting appropriate statistics for various kinds of analysis including some refined and new routines. A series of PPA statistics developed in R are provided.

The first case study analyzes the distribution of surface material in the 1.9 ha Davidson Archaic site in Ontario. An analysis of first and second order effects of the distribution of lithic debitage using multiple statistics leads to the conclusion that the Broad Point occupation represents an aggregation site with a series of similar clusters representing socially distinct groups of people. A second order analysis of the distribution of more formal artifacts shows a more complex deposition than the flake clusters.

The second case study examines the distribution of discrete genetic traits in the Kellis-2 cemetery in Egypt evaluating the hypothesis that the cemetery was organized on a kinship basis and that male kin ties governed grave placement. In addition, it is shown that a lower than expected number of males in the cemetery is not spatially random but tends to occur more frequently in some of the kin-based groupings.

Keywords

Spatial statistics, point pattern analysis, bioarchaeology, unconstrained clustering, discrete genetic traits, artifact distributions, R statistics, labeled point patterns

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Secondly, I would like to thank my co-supervisor, Dr. El Molto for is work helping me through the analysis of the Kellis-2 material. In fact I think the first discussion on the back of a napkin in the grad club happened before I actually started the program at a chance encounter back in 2008. His encouragement of my interest in statistics in general and spatial stats in particular over the past few years has been enlightening and useful. Finally the data from Kellis-2 provided an opportunity to push the analysis of spatial data beyond anything I would have imagined. Indeed it could be taken further by integrating genetics into the analysis.

Next I would like to thank the PhD examination board, Dr. James Conolly, Dr. Jacek Malczewski, Dr. Jean-Francois Millaire, and Dr. Andrew Nelson for the time they spent reading this and all of the helpful comments (and penetrating questions) at the defence. Their comments improved the overall dissertation and will provide a great first step in revisions on the road to publication.

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Table of Contents

List of Tables

List of Figures

List of Appendices

Chapter 1

1   Introduction and Background

1.1   Background

All human behaviour, past and present, occurs in a real time spatial context. In reality, most of our behaviours cannot be traced in terms of material data. This is a real challenge for archaeology since its defining role is the reconstruction of past human behaviours. The reconstruction of past spatial environments offers a potential means of addressing the reconstruction of a portion of past human behaviour. It is the purpose of this study to examine the distribution of archaeological material utilizing spatial statistics. Specifically, I use an analytical technique called Point Pattern Analysis (PPA) (Bailey and Gatrell 1995). The specific goals of this study are to develop new, and refine existing, spatial statistical methods and to demonstrate their utility through their application to two archaeological data sets; a) the artifactual data recovered through surface collections from the Davidson Late Archaic site in Ontario (ca. 2500-800 BC); and b) the biological/skeletal data recovered from the Kellis-2 Christian cemetery in Egypt (ca. 100- 400 AD). Since, as noted, all archaeological material has a spatial context, in my opinion, there is a great deal of information to be obtained through the analysis of spatial distributions of various artifacts and other data sets. The same is certainly true for the distributions of archaeological sites across the landscape but, for purposes here, I will concentrate on the distribution of artifacts/biological traits within a single site context.

Archaeologists have had a controversial relationship with statistics over time. During 1960/70s with the advent of the "New Archaeology" statistical applications were in vogue, such that *American Antiquity* looked more like the *Journal of the Royal Statistical Society* with many pages of mathematical notation. The post-processual movement in the 1980s reversed this trend, as statistics, and indeed, the scientific method, became passé, especially in Europe. At the turn of this century, a balance returned to the application of

theory in archaeology within a growing trend that Trigger (2006) calls "pragmatic synthesis". This synthesis included spatial analyses.

The term "spatial" is used to distinguish this type of statistical analysis from classical statistics. The first question emerging is what are "spatial statistics" and how do they differ from the classical statistics that were conventionally taught in postsecondary education? Basically, spatial statistics involves the application of specific techniques using the actual location in geographic space to make inferences about various phenomena. As a hypothetical example, a confidence interval that states that 34% +/- 2.5%, 19 times out of 20, of Canadians would vote NDP if an election were called today takes no notice of the location of various voters. Each voter is located in a single riding, but the actual location of the voter is ignored. Indeed, to be accurate, the sample must be randomly selected from the set of all Canadian voters. The polling industry may give regional breakdowns, and sometimes will be separated by provinces, but this separation does not qualify this analysis as spatial statistics. In order to be a spatial statistic, the mathematical calculation of the statistic needs to make use of the exact spatial location of each variate, for example, in archaeology, exact coordinates for each artifact relative to a datum point as plotted in a controlled surface pickup (CSP).

A fundamental difference between spatial and classical statistics is that the latter assumes that data are independent of each other. For example, in sampling, any data item is as equally likely to occur as another. In fact, lack of independence effectively negates or at least complicates the application of classical statistical methods. When it comes to application of statistical methods to human activity in space, the least likely thing that we could expect to find is to have the events randomly distributed in space, a condition called *Complete Spatial Randomness* (CSR). In geography, a concept called Tobler's First Law of Geography (Tobler 1970) states that all things are related in geographic space and nearby things are more related than distant things, in effect, the closer the geographical proximity, the more similar the data. An example of this is elevation points on a landscape where, barring the occasional precipice, your next step is very likely to be approximately the same elevation as your previous one. In human activity, nearby sites of the same time period are expected to yield similar styles of artifacts, with the reverse

occurring with more distant sites. In spatial statistics this factor is known as *spatial autocorrelation* and it almost always occurs in human activity. Fortunately, spatial autocorrelation does not negate the application of spatial statistics as it would have in classical statistics. It is the nature of these relationships in space that has the most potential for better understanding past human activity. Interestingly, the recognition of this problem within anthropology started when Francis Galton critiqued a paper by E.B Tylor in 1889 --his critique has subsequently been recognized as statistical in nature and become known as Galton's Problem (Stocking 1968; Naroll 1961, 1965).

Spatial data has two primary components. Like data in classical statistics, it has one or more values or attributes which describe the nature of the specific phenomena for each data element being considered. For example, this characteristic could be the projectile point type, the raw material, measurements of the artifact, etc. In addition, the second type of component defines the location of this data element in geographical space. This spatial component of data can be represented in three ways: a point, a line or an area object. A *point* has the Cartesian coordinates (x,y) of each particular item of interest, such as the east and north components of a position coordinate of a number of sites or artifact finds on the landscape. A *line* is exemplified by a road on a map but this form of spatial data is not used in this study. An *area unit* is a subsection of a site or region and can be any shape. For example, it could be as small as a 50cm square or as large as a Borden unit, county or province. The key difference is that with the point data each instance has its own specific (x,y) coordinates, whereas an area unit can be defined with many different shapes, although each unit describes a unique, non-overlapping block of space. Of course, it is possible to convert from one to the other especially from point to area data, but the reverse is problematic and should generally be avoided. Point data could be summarized into an area unit by counting the number of instances of a point pattern within a unit (e.g. the number of flakes in a five metre square). Problems with this conversion are described in more detail below. It is important to emphasize that each of these classes of data have their own set of appropriate statistical techniques, including interpretive problems.

Further, in selecting a specific technique, it is necessary to consider the nature of the data to be analyzed (e.g. nominal, ordinal, interval, and ratio). For example, one set of data might have the size of each site in hectares and a second set of data might have the particular site type: the first is ratio data and the second is clearly nominal. As with classical statistics, some statistical processes are appropriate for nominal data and some are appropriate for ratio data. For example, applying a technique called Moran's I to nominal data such as a set of locations encoded with 0 meaning absent and 1 meaning present is invalid, though results can be obtained. These specific data types (nominal/ratio) apply to both of our two main classes of data (point or area unit).

In this study I will concentrate primarily on point pattern data as such data is very common in archaeology. Obviously analytical techniques for both types are important but, for our purposes, the main focus will be on point pattern analysis since, in my opinion, point pattern analysis of archaeological materials in the past has been weak. It should be noted that archaeological data and geographical data are often different. Geographers often deal with data that are summarized by areal unit whereas archaeologists deal more often with point pattern data; hence the emphasis herein. However, both fields have to be cognizant of the strengths and weaknesses of the statistical methods. In this regard Bailey and Gatrell (1995) and/or O'Sullivan and Unwin (2003) provide excellent discussions of the application of spatial statistics.

To further illustrate questions that arise within point pattern data, consider Feature 1 at the Crowfield site in southwestern Ontario (Deller et al. 2009). This feature is a pit containing an apparent cache of heat-fractured early Paleoindian stone artifacts (ca. 11,500 BC). The spatial data are represented by piece-plotted artifacts in a two metre square so that each fragment has an associated (x,y) coordinate (and z coordinate for that matter). The database consists of the location of each fragment as well as the type of the original tool, if known. The question arising is whether the fluted points/weapon tips, or any other Paleoindian artifact type, are distributed differently than the other artifact types in the feature. In more general terms, we need to identify a sub-cluster, the distribution of which can be shown to be spatially clustered with statistical significance with respect to the structure of the overall cluster. Figure 1-1 shows a plot within a two metre square of all piece-plotted artifacts from Feature 1 at the Crowfield site with the location of all

fluted point fragments identified in colour. Visually, the distribution of these points appears non-random, but is this distribution random or not? A non-random spatial distribution may have some culturally significant information. What matters is not whether the fluted point fragments are clustered within the 2 m square (almost all archaeological material is clustered at some spatial scale) but whether they are

Figure 1-1: Fluted Point Fragments in Feature 1, Crowfield Site
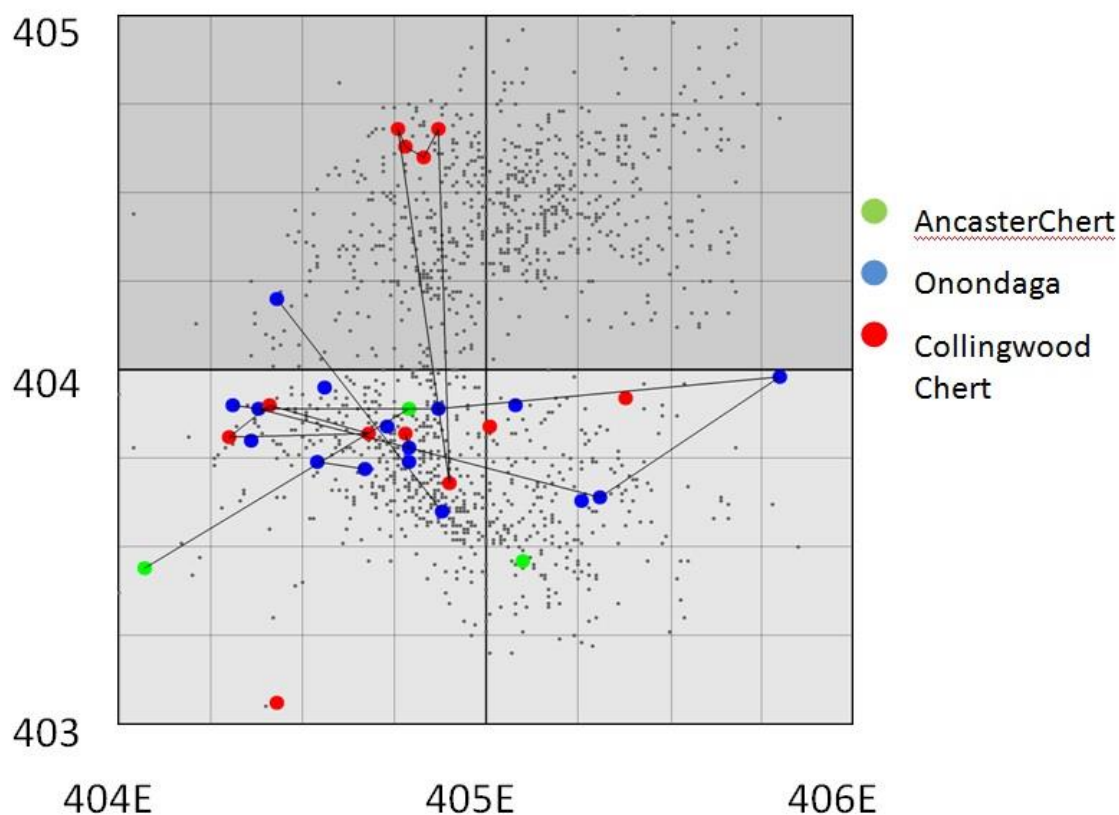
clustered with respect to the distribution of all the other tool fragments in the feature. The implications and interpretations vary depending on the answer to this question. Deller and Ellis (1984) interpreted this feature as the deliberate burning of the tool kit of a single individual, very likely in a ceremonial context, while Kelly (1996:236) has claimed that the Crowfield Feature 1 represents simply refuse or garbage disposal. Ignoring the other contextual arguments, Kelly's (1996) assertion could be considered as a viable hypothesis with which to explain the data. Using this to form the null hypothesis, one would expect a refuse disposal to be fairly randomly distributed. Thus, being able to demonstrate that

overall artifact types are clustered within the feature to a greater degree than would be expected by random chance, can be used to reject the null hypothesis (H_0) as it suggests a more careful and organized placement in the feature. But it must be emphasized that the clustering is with respect to all the other artifact locations; not whether they are randomly distributed in the two metre square.

Applying spatial statistics to archaeological patterns in an organized matter accomplishes two significant interpretive tasks. First, it confirms (or denies) those patterns we can detect visually. In the Crowfield Feature 1 example, significant patterning of the tool fragments was evident with the first set of plots. However, the question still remaining was the statistical significance of the pattern. Secondly, it allows the detections of spatial patterning where, owing to large numbers of points or more complex patterns, the clustering of the archaeological entities is not visually evident. In general, appropriately applied spatial statistics ameliorates us from the natural human tendency to create non-existent patterns and to recognize patterns which are not visually evident. To quote Wheatley and Gillings (2002:125):

> In essence, we see formal spatial analysis not as a means of producing complete archaeological interpretations but as an extension of our observational equipment. Although the human mind is a fine interpretative tool, if it is presented with a series of random dots it does have a tendency to suggest patterns even if none exist.

Much archaeological data presents a pattern of dots leading to interpretive arguments that may not reflect archaeological real time. For example, Seeman and Branch (2006) discuss the distributions of Adena and Hopewell burial mounds in Ohio in a landscape archaeological analysis, but the entire analysis rests on visual interpretation of the dot pattern. While they may be correct in their observations of the pattern, I would argue that in a number of situations, statistical demonstration of non-randomness would be a better test for interpreting patterns. While some patterns may seem obvious, many others are not, and in these cases, quantitative methods are the only reasonable approach to detect the patterns.

1.2   Spatial Statistics and Archaeology

The application of spatial statistics in archaeology has proliferated since the 1970s. The initial research borrowed heavily from other disciplines, particularly from ecology. In the broader academy, spatial statistics has a history extending back over sixty years, spanning several intellectual disciplines herein termed traditions. Prominent people in each of the traditions are listed along with some of their publications frequently referenced in the archaeological literature. The central tradition is the field of mathematical statistics, which included scholars such as P.A.P. Moran (1950), M. Morsita (1959), J.K. Ord (Cliff and Ord 1973), P.J. Diggle (1983) and R.D. Ripley (1988). From this tradition recent texts on spatial analysis include Schabenberger and Gotway (2005) and Gelfand et al. (2010). The second intellectual tradition developed in the field of ecology and this tradition strongly influenced early archaeological practitioners. Examples here include P. Grieg-Smith (1952), the heavily cited within archaeology E.C. Pielou (1959, 1960, 1964, 1969, 1977), and Getis (1984). The third tradition developed in the early 1970s as geographers adopted quantitative and statistical processes in what was referred to at the time as "The New Geography". This tradition has continued to be active in subsequent years. Collaboration between geographers and statisticians has been normal and can be seen in the classic spatial statistics text by Bailey and Gatrell (1995). Other recent texts from this tradition include Fotheringham et al. (2000) and O'Sullivan and Unwin (2003). Indeed, this has been the primary tradition influencing archaeology in this century.

In archaeology, spatial patterning of archaeological materials has been a traditional focus, with description of observed patterns documented in many site and synthetic reports. For most of the previous century, visual review of mapped points of interest was practiced (e.g. Kroll and Issac 1984). In the 1960s, classical statistical methods were first applied to the spatial distribution, primarily across household units to quantify the observed patterns (e.g. Longacre 1964; Hill 1968, 1970; and Whallon 1968). This process was similar to the earlier example of voters by province. In the 1970s, there was increased interest in spatial statistics, with at least two textbook syntheses of methods (Hodder and Orton 1976; Clarke 1977), as well as a number of journal papers (e.g. Riley 1974; Hietala and Stevens 1977).

In archaeology, RobertWhallon (1973) is generally regarded as a pioneer in techniques which would now be called point pattern analysis (Wandsnider 1996) as he attempted to define the degree of spatial correlation of a pair of artifact types. His research utilized a technique called Dimensional Analysis of Variance (DAV) based on the work of Greig-Smith and Pielou from the ecological tradition. The same year a geographer, Dacey (1973), published an article in *American Antiquity* that was also based on the ecological tradition. In 1974, Whallon (1974) advocated the use of the Nearest Neighbour Clustering statistic that he suggested was superior to DAV. The research in the 1970s helped define the key problems that can be addressed by special statistics and paved the way for expansion of techniques during the next decade. Many methods were borrowed from other disciplines and some were developed specifically for archaeology, particularly with regard to expanding variants of nearest neighbor analysis. Hodder and Orton (1976) introduced Pielou's S coefficient, as well as a contingency table/chi-squared method. Hodder and Okell (1978) defined the A-Statistic, which measures the degree of spatial association between two artifact classes. Further variants on the Nearest Neighbour distance measure were added by Graham (1980), who calculated the Nearest Neighbour distance by taking the distance from each point of one type to the nearest neighbour of a second type. The result is what was then called Class Constrained Nearest Neighbour. Later, Hietala (1984) published his volume of edited papers on spatial analysis. This volume introduced another set of statistics, namely a Permutation Test (Berry et al. 1984), Local Density Analysis (Johnson 1984) and Unconstrained Clustering (Whallon 1984). Also in 1984, Christopher Carr introduced his Polythetic Association method (Carr 1984).

With the plethora of new techniques applied to archaeological sites in the 1980s, conflicting interpretations resulted in numerous critiques of spatial statistics. This result was not unexpected as often techniques were erroneously applied to the data. The nature of the critiques focused on the application to archaeological theory and on inherent assumptions of the spatial methods.

In terms of theory, the primary focus of the analyses was almost exclusively on identifying activity areas and households through the identification of tool kits and occupations units (see Carr 1984). This narrow focus was generally called the "functional

approach". A key assumption was that correlation between different artifact types in space would define an activity area. However, this assumes a "Pompeii-effect", where the tools were discarded at the actual activity area or place of last use. In reality, many other activities, such as artifact curation and site cleaning, obscure the simplistic definition of activity areas by co-resident tool kits. Another confounding variable requiring control is post-depositional site formation effects. The influence of depositional and post-depositional events was discussed in detail by Hivernal and Hodder (1984). As a result of this critique, the analysis shifted to depositional events instead of activity areas, which in my opinion, is an equally narrow focus. Throughout the mid to late 1980s and early 1990s critiques of spatial statistics were in vogue, with the intent of refining and improving the interface between spatial method and theory (see Hietala1984; Carr1984, 1985; Kent 1987; Kroll and Price 1991).

The second set of critiques was directed at the nature of the methodological assumptions in terms of archaeological data and the inherent limitations in the methods. Principal among these was the hypothesized mismatch between assumptions of the methods and the nature of the archaeological record as noted by Christopher Carr (1984), who essentially provided the first synthetic analysis of all then current archaeological spatial statistics. He noted that

> the techniques of spatial analysis currently available to the archaeologist do not have assumptions that are logically consistent with: (1) the organization of archaeological remains, and (2) the patterns of human behaviour and the archaeological formation processes responsible for that organization (Carr1984:133).

Another critique was the problem of methodological borrowing from other disciplines. Orton (1992) noted, with specific reference to borrowing methods from the ecological tradition, that artifacts were not plants and did not behave like plants. A common methodological problem with most spatial ecological methods is that they assume all of the points constitute a single contemporaneous set. This assumption is invalid with archaeological data in that they are usually a palimpsest of items through time, both within a single occupation and between succeeding occupations. Moreover, variations in depositional processes, like site cleaning, and in post-depositional site formation effects,

like rodent burrows, tree roots or erosion, can impact the patterning of the archaeological record. The patterning observed variously combines both human activity and post-depositional disturbance.

Another methodological criticism involves the nature of archaeological recovery techniques. Source data for these various analytical methods are usually in one of two forms, either counts by grid square or point patterns (x,y coordinates) and most frequently any given site will have data recorded in both forms. Furthermore, this material is usually size graded where the larger objects are piece-plotted and everything else that is large enough to be caught in a screen is only recorded by grid square and level. Many analytical techniques require point pattern data, which is not available for the artifacts that have only been recorded by square. A recommendation following these critiques that is relevant today is that spatial techniques must be developed specifically for archaeology (e.g. Whallon 1984; Kantner 2008).

Given the amount of criticism of spatial statistics applied to archaeology, it is not surprising that by the mid-1990s these applications were in decline. Most publications were summary discussions of spatial analysis (e.g. Kintigh 1990) or briefer discussions in the context of quantitative methods in archaeology (e.g. Ammerman 1992; Aldenderfer 1998). This waning was not only the result of the above factors but also resulted from a theoretical position known as post-processualism and the introduction of Geographic Information Systems (GIS). The extreme post-processual critique suggests that quantitative methods were invalid. It associated these methods with the enlightenment, science, processualism, Euro-American hegemonies, and environmental determinism (e.g. Whitridge 2004), rejection of which took spatial statistics out of the analytical tool kit for most archaeologists of the post-processual persuasion. Also, the introduction of GIS software attracted many people with a spatial interest in archaeology. For example, Kenneth Kvamme was initially involved with spatial statistics (e.g. Berry et al. 1984) but subsequently became involved and has published a number of articles on GIS and archaeology (e.g. Kvamme, 1993, 1998). Kantner (2008) notes that the older spatial methods are being replaced by use of GIS. However, the introduction of GIS, which was borrowed from geography, posed similar problems and challenges as did the earlier

archaeological statistical methods. The main post processual challenge is that the use of GIS leads to environmental determinism; see the summary by Witcher 1999) as it privileges environmental factors over social factors. Exceptions to this trend include Keith Kintigh (2015), who developed and has kept current software implementing a number of the older archaeologically developed methods that are still in use. Also, Clive Orton has remained active (e.g. Orton 2005).

Another interesting use of point pattern analysis (PPA) in archaeology deserves mention here, although it is not widely applicable. This use involves measurement of spatial autocorrelation (SA). Despite being described by Hodder and Orton (1976), who drew heavily on Cliff and Ord (1973), SA has not seen much application in archaeology (Premo 2004). The primary exception is a series of articles using Moran's I (Cliff and Ord 1973) to examine the Mayan collapse via spatial patterning in the latest long count date at each classic period site (Whitely and Clark 1985; Kvamme 1990; Williams 1993; Premo 2004).This discussion was executed more as a test of the potential use of Moran's I in archaeology as opposed to an open research question.

While measures such as Moran's I provide a single global statistic that quantifies the degree of SA in the study area along with significance tests, what it does not do is identify clusters within the data. In archaeology, this identification was explored by Gladfelter and Tiedeman (1985), who developed what they called a contiguity-anomaly method. That method examined individual contributions to the value of Moran's I, thus identifying local anomalies in the values which might be meaningful for archaeological explanation. Anselin (1995) subsequently developed a similar procedure called Local Indicators of Spatial Autocorrelation (LISA), which Premo (2004) used to examine the last Mayan long count dates by site. Moran's I and LISA can be used on either point pattern or areal data (Kvamme 1990) but it should be noted that they require interval data as a minimum, whereas the point patterns of different artifacts types are most definitely nominal. However, other techniques were described by Hodder and Orton (1976) to deal with nominal data.

The last decade has witnessed a partial revitalization of spatial statistics in archaeology, (e.g. Bevan and Conolly 2009; Crema et al.2009; Hill et al. 2011). In Britain, spatial statistics are reemerging once again, borrowing methods from outside the discipline, this time from the geographic tradition such as Bailey and Gatrell (1995), as well as integrating with GIS (e.g. Wheatley and Gillings 2002; Conolly and Lake 2006) as recent GIS systems start to include modules with spatial statistics. Recently, Andrew Bevan (2010) is now running grad courses in spatial statistics at University College London, using the open source GIS, GRASS, and the R statistical language. Also being explored are solutions to problems that occur due to the nature of the archaeological record (Bevan and Conolly 2009). As well, interest is reappearing in North America where spatial statistics were used in a recent *American Antiquity* paper (Hill et al. 2011) looking at clustering of artifact types in a Paleoindian site in Nebraska. Unfortunately, it only looked at the distribution of each type while a comparison could have been easily made using the same tools looking at the relative distributions of different types.

While some of the same problems are extant, there is a much greater awareness of both the potential and limitations of spatial statistics. New statistical approaches and programming languages such as R, together with expansion of computer technology which can deal with the enormous amount of information generated by spatial analyses, are, in part, responsible for this trend.

1.3   Purpose of This Study

The previous section has described the history of the application of spatial statistics in archaeology. While much interesting work has been done, there is not a coherent body of spatial statistics that provides a tool box of approaches to spatial analysis for archaeologists. Bevan and Conolly (2009) illustrate this by noting that the most recent text on spatial statistics in archaeology is forty years old (i.e., Hodder and Orton 1976). While this study is not designed to completely fill this void, the hope is that by restricting the scope to a subset of spatial statistics, namely point pattern analysis, that I can make a reasonable contribution to spatial statistics in archaeology. The selection of this subset of spatial statistics is defendable, since much of our archaeological data are recorded in this fashion, varying from piece-plotted artifacts within a two metre square (Deller et al.

2009) to sites across a major portion of the continent (e.g. Sassaman 2010). Further, despite the fact that many of the archaeological statistics developed 30 years ago are analyzing point patterns, point pattern analysis (PPA) per se, as defined in the geographic texts, is reasonably novel to archaeological research. One reason for this is that PPA does not seem to be emphasized within geography and the text book examples provided have been somewhat elementary (see examples in Bailey and Gatrell 1995; O'Sullivan and Unwin 2003).

As noted earlier, this study includes two detailed case studies. More importantly, it details a description of the logic developed to approach the analysis of archaeological material, including options for determining statistical significance and the introduction of a concept which I have called "resolution focus" when dealing with clusters of points. A suite of point pattern statistical routines that can be integrated into ArcGIS is also provided. Finally, for the student of spatial statistics in archaeology, I note this work is not intended to be a standalone document, but more intended as a supplement to geographic texts such as O'Sullivan and Unwin (2003) and Bailey and Gatrell (1995). The reader is specifically referred to the first of these as the better introductory text.

1.4   Dissertation Organization

The remainder of this dissertation has five chapters. Chapter 2 provides an introduction to PPA and a background into its associated analytical methods, including the two main subsets, quadrat analysis and distance based methods. It discusses commonly understood concepts such as first and second order effects, the modifiable area unit problem, complete spatial randomness, edge effects, etc. There is also discussion of concepts that have not been well articulated in the past, especially as it relates to archaeology, such as options for determining statistical significance of distributions and another, termed here "bandwidth", which relates to analysis of clustering.

Chapter 3 includes a description of all the statistical methods used in this dissertation. Some of these are commonly understood statistics such as Hodder and Okell's A-statistic, some are new variations on other common statistics such as Nearest Neighbour, and some are completely new statistics, such as Proximity Count. Others, such as Whallon's

Unconstrained Clustering, which is implemented with Kintigh's Tools For a Quantitative Archaeology (TFQA), are described elsewhere (Whallon 1984; Kintigh1990, 2015). The descriptions provided here give a general overview of the statistic and then add an important description not available anywhere as to how to run Unconstrained Clustering in TFQA.

Chapter 4 provides the case study examining the surface distribution of over 1000 artifacts on the Late Archaic Davidson site near Parkhill, Ontario. This site was occupied for over 1500 years, during which artifact styles changed dramatically and site usage varied significantly.

Chapter 5 presents the second case study on the distribution of discrete genetic traits in the Kellis 2 cemetery in Egypt. In this case study, the spatial distributions of a set of 38 discrete cranial traits, as well as the individual's sex, are examined to better understand burial practices, such as whether or not family members are buried in close proximity to each other.

Finally, Chapter 6 summarizes what has been learned about applying Point Pattern Analysis to archaeological materials, including an evaluation of the strengths and weaknesses of the various methods and strategies for approaching spatial analysis of archaeological materials.

Chapter 2

2   Introduction to Point Pattern Analysis

2.1   Introduction

The starting point for any application of point pattern analysis (PPA) is a set of data where each instance in the set has coordinates representing the specific point location where that item is located. Recording the location in space is typically done with Cartesian coordinates, which take the form (x,y) representing the location in geographic space, with x representing an easting coordinate and y the northing coordinate. Other forms are possible and were common in archaeology prior to the development of computer based mapping systems. One of these is known as polar coordinates, where a distance and direction are used, such as would be recorded with an older transit. The direction and distance would then be used directly to construct a map by hand.

Maps of point patterns are abundant in archaeology, with many different scales, ranging from sites in a province or region through a map of the surface finds on a specific site down to the previously discussed example shown in Figure 1-1 that represents four square metres. One thing that must be recognized, though, is that in archaeology we are never dealing with a true point in the mathematical sense. Everything we deal with is an area object at some scale. For example, a map of sites in southern Ontario may be shown as a point pattern but, if we could zoom in on the map, every site would cover some area regardless of how small. Similarly, a stone point on the surface of a site occupies some small area rather than being a true point. This scale effect, however, does not create a stumbling block in treating the distribution as a point pattern. However, in most cases, if the scale is large enough, even 2ha villages can be treated as a point pattern. In fact, looking ahead to the Chapter 5 case study of the Kellis cemetery in Egypt, at the scale being used, each grave is an area object. Yet, the analysis proceeds using point pattern analysis with the centre of the grave as the (x,y) location of the trait. In this case we are using cranial traits, which would only occur in one small area of the event. So rather than try to locate each cranium, the centre of the event is used instead.

In PPA, the specific points are usually called *events* and this is the terminology that will be used in this study. These events represent the specific locations of occurrences of some phenomena.

2.2   PPA Methods

PPA methods are broken into three primary classes of methods: quadrat methods, density estimation and distance based methods. With *quadrat methods* the study area is broken up into regular sized units, usually four sided (hence, quadrats, although other options are possible), where a summary statistic such as the number of sites or average site size is recorded for each quadrat. It should be noted, though, that the starting data set going into this analysis is always a set of events, each of which has its own Cartesian coordinates. The specific events within each quadrat are combined and summarized for that quadrat. Quadrat methods suffer from a number of short comings. First and foremost, they represent a summary of the data. For instance, if the data represents the number of archaeological sites in a specific Borden number, any specific patterning within that unit is lost. Thus, if all of the Late Archaic sites in one region occur in one specific river valley and we choose quadrat analysis as an analytical tool and then summarize by one kilometre squares identified from a topographic map, we might see three adjacent one kilometre squares, each with a count of sites such as 10, 18, and 2. In doing so, we would completely miss the particular pattern, which might have been detected had we had access to the specific latitude/longitude of each site and plotted them accordingly on a map with regional topography.

Another problem which occurs with quadrat analysis is the *Modifiable Area Unit Problem* (MAUP) (Goodchild 1996). The choice of the size and positioning of the unit is entirely arbitrary and different size units and/or different origins for the grid can give different results. For example, in a site excavation we could summarize the data by 1, 2, 5 or 10m square units. Second, if we select one of these, say a five metre square unit, it is also necessary to determine the origin of the grid. Normally one chooses a point value such as (0,0) for the origin of a grid of 5 m squares, but could as easily choose a value for the origin such as (2.5,2.5). In the first case, the square to the northeast of the grid origin would start at (5,5) and in the second, it would start at (7.5,7.5). The point is that the patterning of the data within the grids might well appear different, depending on the choice of origin and the size of the grid. In fact, assignment of the original (0,0) for the site excavation is, in most cases,

entirely arbitrary. The MAUP can occur with both of these choices. Thus, for quadrat analysis, careful consideration of the unit size and position of the origin is critical. The other and most significant problem with quadrat analysis is the creation of quadrats essentially summarizes the data and we lose the fine detail that might have been seen in a plot of all of the (x,y) coordinates. An excellent example of this can be found in the case study in Chapter 4 (e.g. compare Figure 4-17 with Figure 4-21).

On the positive side, in archaeology much of our data consists of a summary by grid unit, so Quadrat methods have a great deal of utility. The standard CRM excavation report, which shows the number of artifacts in each one metre excavation unit, is an elementary example. Given the limitations of quadrat analysis, generally it should be avoided if specific Cartesian coordinates are available for study or at least used to supplement other statistical approaches, such as those used in this study. However, if we can be reasonably sure we are avoiding or minimizing the aforementioned problems, summary counts by unit change nominal data to ratio data. In one sense this summarization by quadrats effectively converts point data into area data and has the strength that it enables a number of statistical techniques not applicable to point patterns. An example of this procedure will be presented in Chapter 4.

The second category of PPA methods is called *density estimation*. This category is likely familiar to most archaeologists, as we have created density patterns of archaeological deposits for many years. Basically, these are all fairly simple models. The density of each point on the output map is calculated by determining the density of events within a specified radius of each point on the map. It should be noted that there are options for calculating the density. The main option is the radius, but there are various methods for calculating a density value that can be as simple as the naïve density (count/area, where $area = \pi r^2$) to more complex weighting methods known as Kernel Density, where events closer to the point being calculated are weighted heavier than points close to extremity of the radius. An example of this procedure can be found in the Davidson case study below.

The third category of Point Pattern methods is called *distance methods,* which operate on data consisting of a series of points with coordinates in two dimensional Cartesian space. Certainly three dimensional analytics are possible and are being considered (see Baddeley 2010b) but they are not well developed at this time and not widely applied. Regardless, with archaeologically excavated material, three dimensional analyses would have a great deal of

utility. All forms of analysis in this study are two dimensional. There are a number of distance based methods both in point pattern analysis as explained in the geographic texts and in previous archaeological work. In fact, much of the archaeological specific methods developed 30 years ago are essentially distance based methods. What all distance based methods have in common is that they calculate the distance between two events using the Pythagorean Theorem. Indeed, in developing the set of R programs used here, the very first 'function" developed was one to calculate the distance between two points.

One of the more common problems with distance methods is known as *edge effects*. Edge effects occur with some distance based measures in cases where the distribution extends beyond the edge of the study area. The Nearest Neighbour (NN) statistic is a good example of a statistic that is susceptible to this problem as hinted above. In cases where edge effect occurs, the NN statistic can be distorted because distances from points close to the boundary must be computed to other points within the study area, when there could be closer points just outside that study area. Thus, the statistic being developed might be distorted by lack of access to data beyond the boundary of the study area. One technique of dealing with this problem is to define a buffer area around the edge of the study area, effectively reducing it in size but leading to the calculation of a more accurate statistic. Another technique would be to evaluate statistical significance with a Monte Carlo technique. A good example where edge effects could exist is the Kellis 2 cemetery discussed in Chapter 5, where unexcavated graves are found to the west, north and east of the excavated portion.

2.3   First and Second Order Effects

Many different processes can influence the position of events on the landscape, individually or operating together. In discussing these processes, a useful distinction to make is between first and second order effects. The critical difference between the two is that first order effects operate such that each event in located independently of other events, while with second order events the location of one event is influenced by the locations of other events; essentially there is an interaction between events which influence their locations. One form of first order effect occurs where event location is influenced by specific topographic features on the landscape. Are events randomly

distributed over the landscape or are certain subsets of the landscape preferred? How do soil types, forest cover, mountain passes, rivers etc. impact the location of events? One example can be found in the Ontario Iroquoian Tradition, where Early Ontario Iroquoian sites seem to be found on sandy soils while Late Ontario Iroquoian sites are found on clay soils (Pearce 1996). Similarly, large expanses of swampy land might be almost devoid of site location while higher ground around the swamp would seem to be a preferred location. Another first order effect, which can impact the distribution of events, is the presence of navigable waterways used as transport routes. Hodder and Orton (1976) illustrate an analysis where the patterning could not be reasonably understood until the occurrence of rivers as transportation routes was considered. The critical hallmark of first order effects is that the apparent variation can be largely explained by reference to the landscape over which the events are distributed. Another useful example of the concept of first order effects occurs in epidemiology, where one could be examining the occurrence of instances of a specific disease. One could easily plot the incidences on a map and look for clusters, but a problem occurs when the at-risk population is not randomly distributed over the landscape but tends to clump together in cities, towns and villages. The apparent clusters from the plotting of the disease might just be reflecting the distribution of the at-risk population. In this case, the distribution of the population over the landscape would be considered as a first order effect. Analogous situations present themselves frequently in archaeology. Examples discussed in later chapters are the distribution of artifacts over a site or graves in a cemetery.

In contrast, second order effects are characterized by the interaction between two events. Essentially the occurrence of one event in space influences the positioning of other events in space. A good example here would be the spread of infectious disease. In 17th century Huronia, for example, once small pox had been introduced to a village, there was a high probability that many other cases would occur there as well. In examining the distribution of various artifact types on an archaeological site, we might notice that not all types are randomly distributed over the site. Projectile points, preforms and flakes of bifacial reduction might tend to occur together, whereas scrapers may be located separately and pottery might be located differently from the others. The tendency for certain types to cluster with each other and potentially with other artifact types is a second order effect.

Archaeological analysis along these lines informed the basis of much of the application of spatial statistics towards determining activity areas in the 1980s, despite the fact that the first/second order effects terminology was not used at that time.

In archaeology the majority of the material with which we deal is clustered. A site is most frequently a cluster of artifacts occurring somewhere on the landscape, surrounded by adjacent areas with no artifacts or, at least, significantly reduced numbers of artifacts. Thus, at one level of analysis, the cluster of artifacts representing a site can be considered a second order effect since, once the site location is selected, the occurrence of artifact locations will always be near other artifact locations. At a different level of analysis, when it comes to analyzing the relative distribution of various artifact types on a site, it is better to treat the overall distribution of all artifacts as the first order effect and the relative positioning of various types within that as a second order effect. However, while the site selection itself on the landscape based on specific preferred topographical features would be a first order effect, site selection based on close spatial proximity to other closely related human groups would be a second order effect.

So far we have discussed the interaction of second order effects as an attractive process leading to clustering of events. However, O'Sullivan and Unwin (2003:65) use the example of 19th century supply towns across the Canadian Prairies as an illustration of a second order effect, where one event precludes the presence of others nearby. Here the positioning of one town effectively suppressed occurrences of other towns in close proximity, leading to an overall pattern where the towns tend to be evenly spaced over the landscape with the distance between them related to the economics of travel time to get to a town. Of course, such an effect is at the centre of many classic geographic models, such as those that employ Central Place Theory (e.g. Christaller 1972).

From the preceding discussion, the boundary between first and second order effects can be somewhat fluid, especially in archaeology. For example, site selection might be a first or second order effect or possibly both. In the case studies that are included in this dissertation, a collection of material from the surface of an Ontario Late Archaic site and an ancient Egyptian cemetery, the analyses treat the actual distribution of events over the

site as a first order effect but focuses on the relationship between the events, which is truly a second order effect. In any event, the distinction is a useful one to make, even if somewhat arbitrary.

Another aspect of the analysis of second order effects is that they occur over a distance less than the size of the study area. There is an upper limit to the distances to be considered and this distance should be small in relation to the overall size of the study area. While this was observed in practice, it also seems logical since we are looking for second order effects that should occur at distances well under the overall size of the study area. Larger distances thus become meaningless. The specific distance most likely varies with the nature of the second order effects being examined. With the Kellis-2 cemetery, it was found that 3, 5 and 7 m were practical sizes, 10 m was problematic and 15 m and over seemed to be meaningless. In order to quantify this result, a value of 10 m is just over 20% of the square root of the site area. Whether this result would hold in other cases is unclear.

For further discussion of first and second order effects the reader is referred to O'Sullivan and Unwin (2003). There is also a description in Bailey and Gatrell (1995). However, it is somewhat confusing and I question whether the example used properly describes the various effects and how they differ.

2.4   Simple Events and Labeled Point Patterns

There are two primary classes of point patterns, each of which have their own unique statistical methods. They are *simple point patterns* with no attributes other than the location in space and *labeled point patterns* where the points may have one or more associated attributes attached to them, each of which may have several different values.

With simple point patterns we have nothing more than the Cartesian coordinates of specific events, all of which represent the same phenomena and might conceivably pose questions of such events such as whether they are clustered, randomly distributed or evenly spaced throughout the specific study area. If the points are clustered, we might be interested in describing the nature of the clustering. While almost all sites are clusters of artifacts at some scale, we might be interested in examining the internal site structure by looking at

relative clustering within the overall site. An example of this concern can be found in Chapter 4 where the distribution of coarse-grained metasediment flaking debris is examined within the Davidson site. Normally when dealing with a simple point pattern we would be examining the first order effects that led to their creation.

When events have specific attributes attached to them, for example a Controlled Surface Pickup where we might have a specific artifact type (scraper, projectile point etc.), and maybe source material (Onondaga chert, Kettle point chert, etc.), then they are referred to as labeled point patterns.   Unfortunately, the terminology varies between authors. For example, Bailey and Gatrell (1995) refer to this characteristic as a labeled point pattern while Baddeley (2010a) calls it a "marked point pattern". Here I will use the former term.

When dealing with a labeled point pattern, analysis gets more complex. First, all of the questions that might be asked of a simple point pattern apply if the labels are simply ignored. When considering the value of the labels, we could examine the simple distribution of all events of type A, B, etc. individually, each on its own merit. But a number of interesting questions arise when we consider the relative distribution of various types of labels compared to each other.   How are events of Type A distributed with respect to events of Type B? Do they occur together, are they segregated or are they randomly distributed with respect to each other? These kinds of analyses form the basis of much of the archaeological analysis done 30 years ago and inform most of the archaeological statistics developed at that time. In almost all cases, when events are compared to each other, we are dealing with second order effects.

2.5   Global and Local Statistics

Another terminology that is used to describe various techniques is whether the statistic is global or local. A *global statistic* is one where a single numeric statistic is calculated on the entire study area (e.g. Nearest Neighbour, Hodder and Okell's A). Thus, variation in the distribution inside the study area is reduced to a single number. A slight variation on this is where a statistic is calculated at specific distances, such as K function or Proximity Count. While several statistics are produced at differing distances, the derived function is still a global statistic.   In contrast, a *local statistic* will vary over the study area and can

be either mapped showing areas where similar values tend to cluster (Kernel Density) or graphed. A good example would be functions within the spatial statistics extension of ArcGIS, such as LISA or Geti-Ord Gi*.

2.6 Determining Statistical Significance

One of the complicating factors in spatial statistics, which is rarely discussed, is the determination and meaning of statistical significance. This issue is not a concern in classical statistical theory as statistical significance is well-developed from a mathematical perspective and these methods are embedded in statistical packages. For example, a confidence interval based on a sample is well-defined from a mathematical perspective. Where this concern becomes an issue in spatial statistics is when you ask the question "random with respect to what"? For example the K function (see below) has a mathematical determination of the statistical significance of the resulting function. However, this significance test is a test against an assumption of Complete Surface Randomness (CSR). As Unwin and O'Sullivan (2003) note, and as was recognized long ago in archaeology (e.g. Graham 1980), in the field of human activity, CSR is not a particularly useful model against which to test significance of a pattern. They argue that what we really should be testing is whether or not the outcome that we observe is the result of some hypothesized process, and test against that.

One example of this issue is seen in the Kellis 2 case study in Chapter 5 where the grave shafts are all discrete and do not overlap. Thus, CSR could never result in a pattern of graves such as occurs at Kellis 2, since the centres of two graves can never be closer than 1-2 metres. The only utility of CSR here is in demonstrating what we can already see, namely that the graves tend to be more evenly spaced than one would expect from a truly random process. Another way of looking at this problem is that the presence of a grave exerts a second order effect which keeps other graves no closer than a minimum distance. Another example of this problem comes from epidemiology. Gatrell et al. (1996) were trying to determine if apparent clusters of larynx cancer were the result of some local pollution factor, as had been claimed. Here testing against CSR is nonsensical since the background at-risk population is not evenly distributed across the landscape but occurs with greater concentrations of people in urban as opposed to rural areas. A test against

CSR would indicate that the cancer cases are clustered when, in fact, they may be randomly distributed in a population that is not randomly distributed over the landscape. Instead of CSR, the testing needs to be against the distribution of the background population. Unwin and O'Sullivan (2003) argue that when it comes to significance testing of spatial patterns, we would be better off testing against almost any hypothesized pattern other than CSR. With a hypothesized pattern defined, statistical significance then can be tested using computer simulation or a Monte Carlo technique.

When we are examining second order effects in a labeled point pattern, statistical significance is better tested against something called random labeling where the event locations, considered to be first order effects, are held constant and the locations of the second order effects are randomized over them. For example, if we have a data set with 20 instances of Type A and 130 of Type B. The significance of potential clustering of Type A within the first order effect of the distribution of all types is determined by randomly selecting 20 of the total 150 locations a number of times and then recalculating the statistic. The actual statistic is then compared to the results of the randomizations and significance determined by where the actual result falls within the distribution of the randomized results. This computation could be done by calculating a standard error for the randomized results, but this procedure is not feasible with a skewed distribution such as Hodder and Okell's (1978) A-statistic. In this case another technique used here is counting the number of random runs which are either greater or lesser than the actual statistic. For example, if an A-statistic of .78 occurs for the actual data and after running 999 randomizations of this we find that only 40 randomizations were less than that value, we can calculate that the result is significant at the .04 level. In this case, it is a one-tailed test but results for a two-tailed test could also be easily calculated if that was the appropriate approach.

In conducting the analysis of the Kellis-2 cemetery, I initially ran several executions of a function in Baddeley's (2015) Spatstat called Kcross -- an implementation of the K function which uses CSR for determination of statistical significance. In comparing the results of Kcross with the results of the Proximity Count statistic over a number of runs on separate traits, KCross was found to generate type 2 errors where the null hypothesis should be

rejected but is not. Whether this would be the case in general though is an open question. It may just apply in the cemetery context.

In any event, the selection of a specific process against which to test statistical significance is a choice that must be made within the context of the problem being investigated. In most cases considered in this study, the preferred method is against random labeling. An example of the difference between CSR and random labeling is shown in the next section using the average Nearest Neighbour distance.

2.7   Nearest Neighbour as an Explanatory Device

In order to illustrate how all the above concepts interact, the Nearest Neighbour (NN) statistic and a variant of it will be used, since it is conceptually easy to understand and has a long history in archaeology going back to the 1970s (e.g. Whallon 1974). NN is a distance based method of point pattern analysis that simply calculates the distance from each point to its nearest neighbour and then calculates the average NN distance. In its simplest form, this statistic is also called the Evans and Clark R statistic. But that form has a number of problems and is not very useful in archaeology unless you are trying to demonstrate that a set of events is evenly distributed in the study area. However, variations on it are more useful and understanding the basics of this technique is useful to understanding how distance based statistics work and the options for determining statistical significance.

In this simplest form, we are dealing with a set of events in a study area that are not labeled. The events are all identical and have no associated information other than the specific Cartesian coordinates. Consequently, we are using this version of the statistic to understand only the distribution of points, not differences between points that arise from labeling. The processes creating the events might be either first or second order effects but in either case the calculations are identical.

There are two different components to the R statistic, one being the average Nearest Neighbour distance, which is simply the average distance from each point to its Nearest Neighbour, $(\overline{d}_{min})$.

Given a set S of n events

$$\overline{d}_{min} = \sum_{i=1}^{n} \frac{d_{min}(s_i)}{n}$$

Where $d_{min}(s_i)$ is the distance from event s_i to the nearest member of set S.

For the R statistic, this measure is calculated by dividing $\overline{d}_{min}$ by a mathematically determined average NN distance that would occur with an assumption of CSR over the study area. This expected distance $E(d)$ is given by the formula

$$E(d) = \frac{1}{2\sqrt{\lambda}} \quad \text{where } \lambda \text{ is the intensity of the process calculated by} \quad \lambda = \frac{n}{a}$$

Thus $\quad R = \dfrac{\overline{d}_{min}}{1/2\sqrt{\lambda}}$

If the value of the resulting statistic is less than one, then the events being examined are clustered within the study area and if the value is greater than one, then they tend to be evenly spaced in the study area. A value of one means that the events are randomly distributed in the study area and that they are identical to what would be expected with CSR. At this stage though, there is no way of determining the statistical significance of the resulting R statistic. Thus, the R statistic is a simple global statistic, which tells you nothing more than whether a spatially distributed set of points is clustered, random or evenly spaced.

A problem with the R statistic is that it is susceptible to distortion because of the edge effect, as described above. Another issue is that the size of the study area can seriously distort the statistic, particularly if we are dealing with an entire archaeological site that has adjacent areas with no artifactual material. The same point pattern will look and give an R statistic that appears to be more clustered when a bigger study area is used that extends beyond the actual artifactual material distribution.

One way to minimize the impact of edge effect is by calculating the expected value using a Monte Carlo technique. That technique generates multiple instances of the statistic and one can then take the average, rather than using the mathematically determined expected NN Distance (O'Sullivan and Unwin 2003). This procedure works, since the edge effect is

constant in both the observed pattern and in all the randomizations of it. It also has the advantage that it allows an assessment of how unusual the observed NN distance is and in turn, leads to determination of statistical significance.

It is here where spatial statistics deviate from classical statistics. With classical statistics we are dealing with data that are assumed to be or nearly homogeneous and normally distributed, with significance determined by a rigorously proved mathematical process or theorem. With spatial statistics, building a Monte Carlo technique, there is a decision that must be made concerning what the "expected" pattern should be. So far we have only been discussing CSR, but as discussed in the previous section, it is only one of a number of possible expectations that we might place on the data. If we wished to demonstrate that a particular set of points is clustered, random or evenly spaced in the study area, then CSR is a good choice for the underlying process. But as most archaeological material is clustered at some level, having a way of proving that clustering is present is not particularly useful. The other option used regularly in this study is random labeling, which is applicable when dealing with a labeled point pattern. Given a labeled point pattern, the approach used here when looking for significance is to use the process of random labeling. This procedure requires a minimum of two different labels in the study area, such as say Type A and Type B. The calculation of statistical significance is done with a Monte Carlo technique, which takes the set of all possible locations for both Type A and Type B. It then chooses a number of events without replacement that matches the number of instances of the particular label in which we are interested. If this was Type A, and there were 20 instances of it, then we would choose 20 locations without replacement from the set of both Type A and Type B. The NN Distance is then calculated again and the result saved. This iteration is repeated a number of times, and the distribution analyzed with respect to the actual data.

Before exploring the differences between CSR and random labeling, there are some variants on NN that have been used in archaeology that should be outlined. These involve calculating the average NN between differently labeled points. Graham (1980) calculates what he calls Class Constrained NN by taking the distance from each point of one type to the Nearest Neighbour of a second type. This same approach is also called Between Types Nearest Neighbour (Kintigh 1990). Kintigh (1990) suggests another approach using NN statistics to compare the distribution of various artifact classes. It involves using the ratio of the NN

statistic for one artifact class and dividing it by the NN statistic of a second artifact class, giving a relative ratio which resolves the boundary and edge effect problems, since they are constant for each class.

The differences between CSR and random labeling are explored in the following example using the Between Types Nearest Neighbour statistic. The data used in this example are the locations of male and female individuals in the Kellis 2 Egyptian cemetery, which is discussed in more detail in Chapter 5. The question explored is how the location of graves is influenced by the sex of the interred individuals. Do the males tend to cluster together separately from the females or do the two sexes tend to be intermixed? In this case we are exploring the second order effects of sex on the distribution of the graves. The distribution of graves here would be best considered a first order effect. Given this scenario, the better choice in selecting the calculation of significance would be random labeling but, for demonstration purposes, both CSR and random labeling will be calculated.

Keith Kintigh's (2015) Tools for a Quantitative Archeology (TFQA) provides a program to calculate the "Between Type Nearest Neighbour". Instead of calculating the Nearest Neighbour of each point as in the R statistic, it assumes events have different labels and calculates the Nearest Neighbour distance between each possible combination of labels. In our case there are two labels, male and female. It calculates the Nearest Neighbour of each pair of combinations. Male to Male and Female to Female are simply the R statistic if we were to separate the sexes and do the calculations. For Male to Female, it calculates the average Nearest Neighbour from each male to the nearest female. Female to Male is just the reverse of this procedure. The expected Nearest Neighbour, though, is calculated against a model of CSR giving the results as shown in Table 2-1. "Observed NN Distance" is the results derived from the actual data, "Expected NN Distance" is the average of all the randomizations, "Ratio" is calculated as Observed divided by Expected. "Prob" is the statistical significance.

One of the observations here is that in all cases where the Ratio is greater than 1 there is a tendency towards even spacing of the all combinations of Male and Female and in two cases the results are statistically significant. This result is not surprising, given the non-

overlapping nature of the graves in the cemetery. In a modern cemetery, the plots are evenly distributed in the extreme.

Table 2-1: Nearest Neighbour Between Types – CSR - TFQA

Table 2-1				
	Observed NN Dist	Expected NN Dist	Ratio	Prob
Female to Female	2.03	1.83	1.11	p<.05
Male to Female	2.16	1.82	1.19	
Female to Male	2.45	2.2	1.12	p<.05
Male to Male	2.28	2.21	1.03	

As an alternative, these statistics were calculated in R but the expected value and significance are determined by a Monte Carlo technique, which randomly distributes the 98 males and 142 females over the existing grave locations. The results are shown in Table 2-2.

Table 2-2: Nearest Neighbour Between Types Random Labeling

Table 2-2				
	Observed NN Dist	Expected NN Dist	Ratio	Prob
Female to Female	2.03	1.98	1.03	.23
Male to Female	2.16	1.97	1.10	.05
Female to Male	2.45	2.38	1.03	.28
Male to Male	2.28	2.39	.95	.18

As can be seen, the observed NN distances are the same in both Table 2-1 and Table 2-2 (as should be expected). However, the expected distances are all higher by a similar amount when holding the grave locations constant and then randomly distributing the males and females over the fixed locations. With CSR, there will be a number of graves that would be closer than physically possible. More importantly, the results of the

calculation of statistical significance are very different in each of these cases. As can be seen, the results of these two analyses differ both in the values of the ratio and in the calculated significance. Clearly the choice of CSR or random labeling is a critical decision that must be made during the analytical process.

2.8   First Order Analysis of Clusters

Within the traditional field of point pattern analysis as defined by Bailey and Gattrell (1995) and O'Sullivan and Unwin (2003), there are a number of techniques for mathematically characterizing clusters, such as Nearest Neighbour, and the F, G, and K functions. In archaeology I have never found any of these particularly useful functions, possibly excepting the K Function. This lack of utility may be because of an unstated assumption that the study area which we are trying to characterize is a subset of a much larger, frequently ecological, niche. For example, many of the discussions in Baddeley's (2015) Spatstat library of R routines are related to the distribution of plants within a subset of a much larger ecological niche. The difference in archaeology is that we are almost invariably dealing with something that is most definitely a cluster on the landscape and we are frequently looking at the entire cluster, so trying to prove it is a cluster is just mathematically demonstrating the obvious.

However, what is of significant interest in archaeology is whether or not there is structure within the overall cluster that might provide insight into the habits of the people who occupied it. For example, the Bullbrook Paleoindian site (ca. 11,000 BC) is composed of a series of discrete clusters, each of which are interpreted as being smaller scale individual social units within a larger aggregation site (Robinson et al. 2009). In these cases, a simplistic characterization of the overall site cluster does not shed any light on the really important issues. The analysis of the coarse-grained flake tool-making debris distribution at Davidson included in Chapter 4 is a good example of the analysis of structuring within the overall site cluster. In this case, the use of Kintigh's Pure Locational Clustering and the ArcGIS functions of Kernel Density and a Hot Spot Analysis of a quadrat summary proved much more useful than the global statistics like the F, G and K functions.

In conducting the analysis of Davidson it became clear that there were some decisions required that at first seemed somewhat arbitrary. The selection of some of the options tended to give an interpretation of that data that fit my expectations, so these results were preferred.

But why is this particular result better than that one? Is it because it fits my preconceptions? Obviously, it is not a good thing to begin with that presumption. This problem led to a definition which I have not seen articulated elsewhere and which I call *resolution focus*. One standard point pattern analytical technique is called *density estimation;* one implementation of this in ArcGIS is called *Kernel Density*. This function calculates the relative density of each point on the map and constructs density contours, but points closer to the centre of the circle are weighted higher than points further away. The main parameter entered is the density radius. Different values here tend to give what initially appear to be very different results; for example, see Figures 2.1, 2.2 and 2.3.

Figure 2-1: KD Radius at 50 m
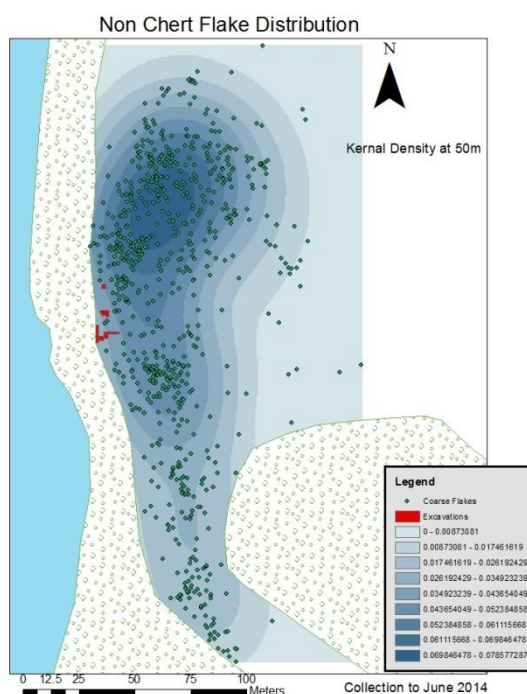
The obvious question presenting itself here is which radius is "right"? In the literature of density estimation, the concept of resolution focus has been thoroughly discussed, where it is referred to as "bandwidth selection" (Bailey and Gatrell 1995; O'Sullivan and Unwin 2003). As can be seen, these texts contain diagrams not unlike these three figures. There are also general rules around selection of bandwidth, which generally take the form "not too generalized (like Figure 2-1) and not too localized (like Figure 2-3)". This conclusion is true in general. For instance, the density map with a bandwidth of 50 m is not particularly useful, especially at the south end where 50 m takes in a lot of offsite area. The result is that a lower density is reported than if the area considered was restricted to the site boundaries and edge effects were controlled. Similarly, a bandwidth of one metre would produce a map that would simply put a one metre circle around each artifact with a few showing two or three adjacent artifacts. This would not show anything that could not be seen with the simple plot of artifacts. However, I would argue that

in the middle ranges of bandwidth, different features might be better isolated at different bandwidths. Such is the case, as will be discussed, with the Davidson study.

Figure 2-2: KD Radius at 12 m
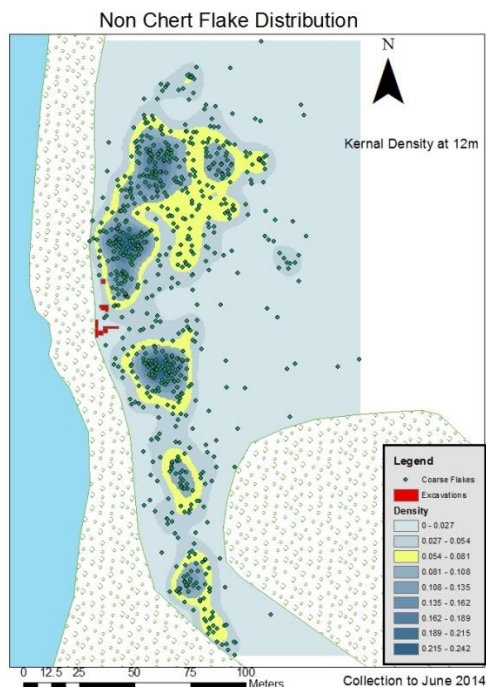
If density estimation were all that mattered, there would be no need to introduce the new term *resolution focus*. However, in the Davidson case study two other techniques were used, Kintigh's (2015) Pure Locational Clustering and high/low clustering (Getis-Ord Gi*) of a quadrat summary. In both these cases, a similar concept applies but is not articulated. Within Pure Locational Clustering, you can request various numbers of clusters to be isolated from your point pattern by entering a number that defines the number of clusters that you want to produce. As with bandwidth specification in density estimation, a fewer number of cluster gives results consistent with a large bandwidth and a request for many clusters gives results similar to narrow bandwidth specification. Thus, the request for the number of clusters in TFQA actually functions as a resolution focus variable. In fact, as was found in the Davidson case study through a process of trial and error, the results of density estimation and Pure Locational Clustering produce similar results when the resolution focus matches.

The other technique with similar considerations is the application of high/low clustering to a quadrat summary of the point pattern. Here the variable that influences the resolution focus is the size of the quadrats. Larger quadrats give results that look similar to Figure 2-1 and smaller quadrats yield results that are consistent with Figure 2-3.

When it comes to selection of the resolution focus such as occurred in the Davidson case study, I as yet do not have any hard and fast rules as to how to go about making decisions. The best approach seems to be trial and error and comparison of the results of all three methods.

Figure 2-3: KD Radius at 6 m
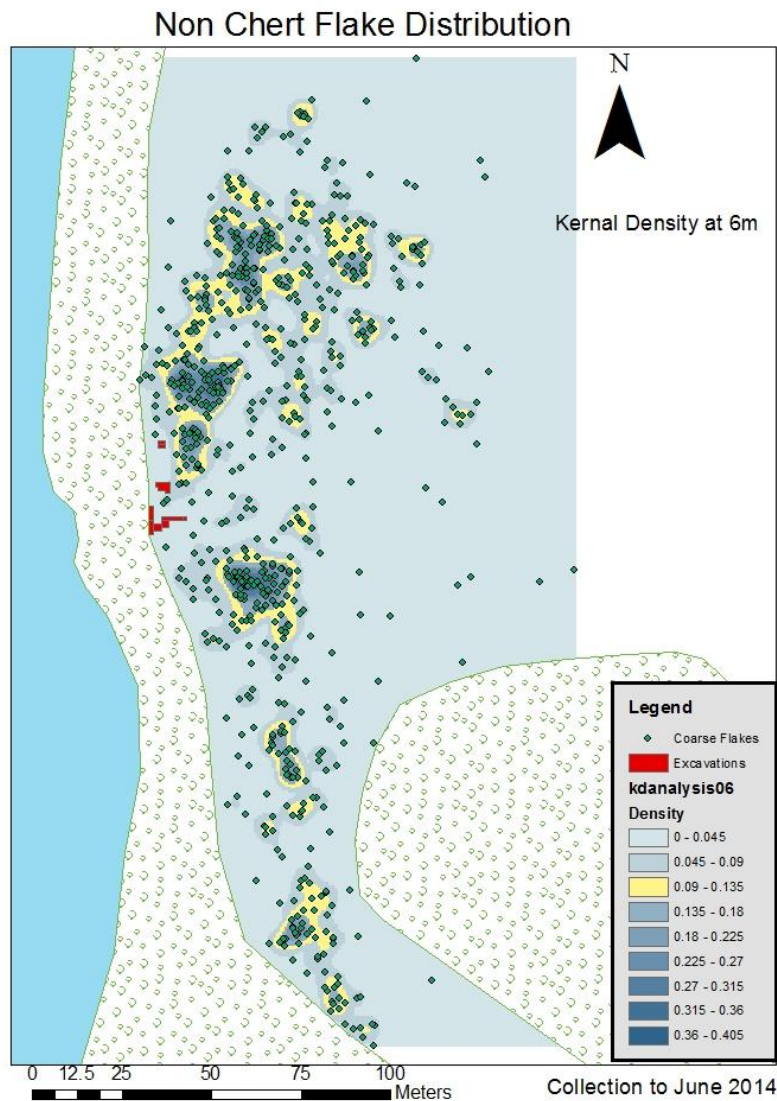
One final comment here relates to my initial question of which one is right? Barring the obvious extremes, I do not think there is a right answer. In reality, multiple scales of analysis

may show you different things about the site, as will be shown in the Davidson case study. While it would be preferable to have a mathematical technique that shows exactly what's happening on a site, the reality is that it is ultimately the interpretation of the archaeologist doing the analysis that determines the "right" answer.

2.9 Cluster Within a cluster – Second Order Effects

Frequently in archaeology we are dealing with the analysis of a labeled point pattern, where a Controlled Surface Pickup (CSP) is the classic example. Each point is the location of one surface find and it will normally have several attributes such as tool type, raw material, completeness, etc. Here the classic archaeological question is whether or not the projectile points, for example, are distributed differently from the scrapers. In this area, classic point pattern analysis is not well-developed, with the Gatrell et al. (1996) paper in epidemiology being the usual example employed. This problem is one with which archaeologists have been dealing for the last forty years, with a number of archaeological methods developed such as Hodder and Okell's (1978) A-statistic. The problem to be resolved here is not simple clustering, randomness or regular dispersal but whether the specific types of events are clustered or segregated from each other with statistical significance within the overall structure of the point pattern.

When considering the relative distribution of different event labels, there are two classes of statistical routines. The first and simplest class is the comparison of a single set of labeled points of one type with either all other types or some other specific type. For example, referring the Crowfield Feature 1 distribution of artifacts noted in Chapter 1 (Deller et al. 2009; Deller and Ellis 2011: 113; see Figure 1-1), are the fluted bifaces clustered in one part of the feature or randomly distributed throughout versus the other artifacts, and is this apparent clustering statistically significant?

The second class of solutions to be developed is more complex and involves simultaneously considering several types/attributes for the purpose of demonstrating whether various groups of traits co-occur, separate spatially or are independent of each other. At this point, at least three different approaches have been developed within archaeology. These include Whallon's (1984) Unconstrained Clustering, Carr's (1984)

Polythetic Sets, and Merrill and Read's (2010) unnamed method using graph and lattice theory. Herein, I will only use Whallon's Unconstrained Clustering.

Regardless of the method selected to question a given distribution, it must be noted that this analysis is entirely focused on second order effects and, in determining statistical significance, the correct choice is random labeling and not CSR.

2.10 Structure of Analysis

In order to bring some structure to the preceding discussion, it is necessary to provide a general discussion on how to approach a point pattern analysis. Obviously, there needs to be a starting dataset for analysis, which would typically have an identifying number (e.g. catalog number), the (x,y) coordinates of the event and a series of attributes describing the nature of the event.

The first step in analysis is to explore the data and the simplest way to do this is to import it into ArcGIS. In the following case studies the import happens in two ways. In the Davidson Site case study it is a simple AddXY (note that a second Export step is required to create a selectable layer). With the Kellis case study, where we already have a digitized shapefile (a file format in ArcGIS), it was accomplished by simply "joining" the data table to the shapefile using the grave number. With either of these in place, it is simple to use the "Select by Attributes" function and highlight the events meeting the criteria. Optionally, another layer can be created with the selected events. Here there are no rules as to how to proceed. It is a case of selecting data until some patterns in the data start to emerge. I cannot stress enough the importance of having a deep visual understanding of the various distributions. The analyst really must have a deeply ingrained mental image of the data.

One also needs to consider the nature of the questions being asked and selecting the right tool(s) to test the question. Depending on the nature of the particular data set, there may be some basic confounding factors that should be dealt with first. A good example occurs in the following Kellis case study where the nature of the imbalance in numbers of males and females has to be considered before proceeding to the spatial analysis of the discrete cranial traits.

In order to assist the analyst with selection of appropriate statistical techniques, Tables 2.3 and 2.4 are provided. These tables contains all of the techniques used or referenced in this study and structures most of the concepts discussed in this chapter, such as point/area classes, first/second order effects, quadrat/distance measures, local/global statistic, etc. It also specifies the data type (nominal, interval, ratio) which is appropriate for the specific technique, which should hopefully help to avoid the problem where techniques such as Moran's I are run on nominal data coded with numerical values. The other critical column is the appropriate choice for determining statistical significance, either against CSR or against random labeling. In broad general terms, testing against CSR is appropriate when first order effects are being considered, and random labeling is appropriate when second order effects are being analyzed. Note too that some statistics can be used with both first order effects and second order effects, but the choice of significance testing is different. Nearest Neighbour or K function are good examples of this. There are also a couple of redirections in the table -- for instance, when (x,y) data is converted to quadrats. However, it should be stressed again that the data types (nominal, ratio, etc.) must be observed in selection of the appropriate techniques. An example occurs in the Davidson Case study: by counting the nominal events in each quadrat the result is ratio data, so application of Getis-Ord Gi* is appropriate.

Table 2-3: Area Data Statistics

Tool Class	Statistic	Data Type	Stat Level	Stat Sign	Computer Tool
Area Data	Moran's I	Interval/Ratio	Global	yes	ArcGIS or Geoda
	LISA	Interval/Ratio	Local	yes	ArcGIS or Geoda
	Getis-Ord Gi*	Interval/Ratio	Local	yes	ArcGIS

Hopefully this table provides a good conceptual structuring of the various routines used or referenced in this study.

One final point that should be made is that most statistical techniques, especially global statistics on second order effects, seem to have a number of limitations in what they can "see". Thus, it is strongly advised that multiple techniques be run, as can be seen in the Kellis case study. Not all of them can detect a pattern, as they vary depending on the exact nature of the pattern.

Table 2-4: Point Pattern Statistics

Tool Class	Sub Class	Technique	Data Type	Level	Stat Sign	Technique	Data Type	Level	Stat Sign	Computer Tool
			First Order Effects				Second Order Effects			
Point Pattern	Quadrat	Colour grade and print	Go to area data techniques							ArcGIS
	Density Estimation	Simple Density	(x,y)	Local	n/a					ArcGIS
		Kernel density	(x,y)	Local	n/a					ArcGIS
		Pure location clustering	(x,y)	Local	n/a					TFQA
		Convert to Quadrat	Go to Quadrat Techniques							
	Distance	Nearest Neighbour	Nominal	Global	CSR	Nearest Neighbour	Nominal	Global	Rand Label	R
		F, G	Nominal	Global	CSR	Nearest neighbour by Sex	Nominal	Global	Rand Label	R
		K Function	Nominal	Global	CSR	NN between types	Nominal	Global	Rand Label	TFQA/R
						Proximty Count	Nominal	Global	Rand Label	R
						A- Statistic	Nominal	Global	Rand Label	TFQA/R
						Proximity Probability by sex	Nominal	Global	Rand Label	R
						LDA	Nominal	Global	n/a	TFQA
						Unconstrained Clustering	Nominal	Local	Rand Label	TFQA
						K Function	Nominal	Global	Rand Label	R

2.11 Computer Software for Spatial Statistics

First, in order to actually apply the methods to data, for practical concerns, what is required is a workable, supported set of computer based tools that can execute the required analysis. Luann Wandsnider reported that Christopher Carr in 1995 had remarked to her that while other and better methods had been published (including his own), the use of Kintigh's K-Means clustering algorithm by archaeologists was due to the fact that "it is available in a user-friendly and well-supported form in Keith Kintigh's (2015) Tools for Quantitative Archaeology "Wandsnider (1996:337). As a more recent example, Hill (2004) uses Kintigh's software.

There are a significant number of standalone software packages that perform the required calculations but then, of course, the problem becomes one of database design so that data is either imported into both the GIS and the spatial stats program or possibly exported from the GIS into the statistical program. Some statistics can be accommodated with spreadsheets, either through built-in functions or through calculations, but most are too complex for the spreadsheet paradigm, so the availability or the programming of spatial statistical algorithms is required.

In an ideal world, spatial statistics and GIS should be tightly integrated. In 1995 Bailey and Gatrell noted that, at that time, the ability of GIS to perform spatial statistics was very limited and that it had best be done outside of GIS for anything but the most basic analysis. Today ArcGIS has two modules namely, Spatial Analyst and Spatial Statistics, available with the product. However, they are still limited as far as archaeological data is concerned. Spatial Analyst enables map algebra, which allows manipulation of raster maps with a number of arithmetic and logical operations, and one archaeological paper recently implemented Unconstrained Clustering with map algebra (Craig et al.2006). The other module, "Spatial Statistics", automates several of the more common spatial statistics, like Nearest Neighbor, Getis-Ord G-* and Ripley's K but, as noted above, these statistics on their own only allow you to measure clustering. Furthermore, with these methods examination of statistical significance is permitted but statistical significance is assessed against CSR. As we saw, CSR is of limited applicability for the analysis of second order effects in archaeology. Moran's I is an exception, but archaeological data is typically point pattern and nominal, unsuitable for Moran's I, which requires interval or ratio data.

ArcGIS does, however, allow the implementation of various extensions which can act upon the data stored in the GIS. So the ideal solution to the absence of appropriate statistical procedures in ArcGIS is to develop the required calculations so that they can be implemented as an ArcGIS extension. The original plan was to use the JAVA programming language but, once I was introduced to the R statistical language, JAVA was quickly dropped. ArcGIS allows both of these development platforms to be implemented as an extension. But R is just as flexible as JAVA from a calculation perspective and yet, is much more powerful with respect to statistics. The ideal situation, then, would be to deliver a set of ArcGIS extensions that could be used especially in archaeology to analyze the various point patterns that we encounter. However, we do not live in an ideal world and with the exigencies of completing the program, I backed away from this alternative and ended up running the R routines developed as a standalone system and even in some cases avoiding redevelopment in R where an existing system such as TFQA had a program to run Unconstrained Clustering. It just did not make sense to spend time redeveloping several programs in R and then implement these and others that were developed in R as an ArcGIS extension. However, this remains the ultimate goal and this will be pursued after completion of this study. Consequently, while this study uses some functions within ArcGIS, some in native R and some in TFQA, the ultimate goal is to build all of these in R and implement as an ArcGIS extension.

2.12 Other Software Tools with Spatial Statistics

GeoDa is available from the the GeoDa Center for Geospatial Analysis and Computation and includes a number of options for exploratory data analysis, spatial regression, Moran's I, and LISA as well as multivariate versions of Moran's I and LISA. Web site as of May 2015 - http://geodacenter.asu.edu/

PASSaGE: at first glance Passage appears to be a software package growing out of the ecology intellectual tradition in spatial analysis. It also contains a number of methodologies for point pattern analysis as well as spatial autocorrelation such as Moran's I and Geary's C. Web Site as of May 2015 - http://www.passagesoftware.net/

Another potential tool, called *CrimeStat* (Levine 2009), was developed to analyze spatial patterns with respect to crime statistics in cities. However, this tool is essentially point pattern analysis. It contains a number of statistics discussed above, such as Nearest Neighbour, Moran's I and Ripley's K. At this point, I have not taken a closer look at it. Web Site as of May 2015 - http://www.icpsr.umich.edu/CrimeStat/

Orton (2005) reports use of a module of a package called *ADE-4* (Ecological Data Analysis) called ADS (Spatial Data Analysis) from the University of Lyons, France for teaching at University College London. This contains a section called Ripley, which calculates K and L functions.

INFO-MAP is a program provided with the Bailey and Gattrel (1995) text. The problem with it is that it was written for the MS-DOS system and will only work in native MS-DOS. Orton (2005) reports an attempt to use that failed due to both students unfamiliar with DOS and problems with the software when it exceeds 640K memory requirements. It would be best ignored unless one was familiar with DOS and wished to use it only as a learning aid to working through their text. I managed to load an old computer with DOS 6 and load INFO_MAP but could not find an appropriate mouse driver; INFO-MAP works best with a mouse.

2.13 Summary

This concludes the description of the concepts of point pattern analysis as applied to archaeological material. In Chapters 4 and 5, I present two major case studies of the analysis of archaeological material, which should broaden the understanding of the reader.

Chapter 3

3   Statistics Used

This chapter has one section for each of the various statistical routines used in this study. Detail varies depending on whether or not the statistic is new or different. For completely new (e.g. Proximity Count) and variations on other statistical routines (Cross Nearest Neighbour by Sex), an exact definition of the calculations involved is provided. Where an existing routine is used (e.g. Kernel Density) a brief description with reference to any issues encountered is provided, with references cited where one can find the more detailed definition.

3.1   Nearest Neighbour – Random Labeling

The definition of this routine, and how it varies from the Evans and Clark R statistic, has already been discussed in Chapter 2. With this statistic we are exploring the second order effects of the distribution of a labeled point process. There are two labels which, in the Kellis Case Study, are the presence or absence of a discrete genetic trait on an individual. In most cases we are looking at the presence of the trait, although absence would be just as valid. In this implementation the average Nearest Neighbour distance is calculated as usual and appears in the output table under the heading ActualAvgNN. The expected distance and significance are calculated with a Monte Carlo technique, which implements random labeling. Statistical significance is evaluated against a spatial process, where the event locations are held constant and a number of locations equating to the number of traits in the original calculation is randomly distributed over them and the statistic recalculated. This value appears in the table column labeled RandAvgNN. NNR, which is analogous to the Evans and Clark R Statistic, is calculated by dividing the actual distance by the randomized average distance. The evaluation of the resulting statistic is similar to the classic NN Statistic. Values lower than unity indicate clustering, values above unity indicates even spacing and values at and close to unity indicate random intermixing of the two traits. The significance of NNR is calculated using a Monte Carlo technique with 999 randomizations. Significance is not a true two-tailed test but could

perhaps be better described as a double one-tailed test. If the resulting ratio is less than one, significance is determined by counting the number of instances of randomization less than the observed ratio. If the ratio is greater than one, significance is determined by counting the number of cases greater than the observed ratio.

3.2   Cross Nearest Neighbour by Sex –Random Labeling

This statistic is similar to what is called in archaeology the Between Types Nearest Neighbour (Kintigh 1990). Again we are exploring second order effects of the distribution of labels over a point pattern. The actual locations of all the events are assumed to be a first order effect that should be held constant. Consequently the process against which the distribution is tested for significance is random labeling. This calculation differs from the normal Between Types Nearest Neighbour in that the data points have two independent labels. In the Kellis case study one of these is the presence or absence of a discrete genetic trait and the other is sex. All events in the pattern must have clear indication of both of these characterizations. For instance, an individual for whom it is impossible to tell if the trait is present or absent must be eliminated from the calculations. What we are interested in is how the discrete genetic trait is distributed by sex. Male to Male calculates the statistic only considering males with the trait. Female to Female considers only females with the trait. These two are the same as if the samples were separated and the Nearest Neighbour – Random Labeling was run. Male to Female calculates a between types Nearest Neighbour considering only individuals with the trait and calculates the distance of nearest female neighbour from each male. Female to Male is the same but in reverse. In effect, it would be a true between types Nearest Neighbour if we were considering only individuals with the trait. However, with the use of random labeling as a means to determine statistical significance, all of the individuals without the trait are used in the randomization routine but the sex is held constant (i.e., males are randomized only to males and vice versa). Interpretation of the resulting ratio is the same as Nearest Neighbour – Random Labeling.

It would be possible to generalize this routine to use any two labels, but at this point this has not been done, so the statistic as currently coded is only applicable in analysis of

cemetery population. One of the labels needs to be sex with "Male" and "Female" being the only valid labels. Execution of the routine produces a table similar to Table 2-2.

3.3   Hodder and Okell's A-Statistic

Hodder and Okell (1978) developed this statistic as a means to measure the degree of segregation between two discrete types of events (artifacts within a site or site types across the landscape). It is investigating a labeled point pattern, but the statistic is limited to using only two types at a time. It takes the average distance between all points of Class A ($\overline{r}_{AA}$), multiplies it by the average distance between all points of class B ($\overline{r}_{BB}$), and divides that by the square of the average distance of the between class distances ($\overline{r}_{AB}$). A value of one indicates complete cluster overlap and a value significantly less than one indicates segregation. As Kintigh (1990) notes, values greater than one are rare. In the original definition of the A-Statistic, Hodder and Okell (1978) developed a rough approximation of statistical significance by modeling various scenarios. However, a better way to accomplish this end is the application championed above of a Monte Carlo technique, which is essentially a random labeling process. Kintigh's (2015) TFQA, as purchased, calculates a Standard Error for the distribution, but the distribution is highly skewed, making application of the SE to determine significance problematic. In discussions of this problem with Keith Kintigh (personal communication 2012) he pointed out that probability of the particular distribution could be better calculated by counting the number of random events that created a lower statistic than the actual set of data. Thus, 50 events creating a lower A-statistic out of 1000 randomizations would yield a probability of $p = .05$. He subsequently programmed this change into HOA and sent me a copy. This statistic was also built in R but it runs much slower than in TFQA. This is a global statistic and, since it uses all points, is not susceptible to the edge effects. For the sake of brevity, the rest of this study will refer to Hodder and Okells A-statistic simply as the A-statistic.

3.4   Proximity Count

This technique is one that is defined here for the first time. It developed out of ideas on the clustering of discrete genetic traits in the Kellis-2 cemetery and the potential efficacy

of removing the first order effects by collapsing the distribution of graves to a simple 30x30 matrix. How this might be accomplished was explored, but it quickly became quite complex, as it involved a number of subjective decisions as to what was required to place two graves adjacent to each other and especially as it related to some of the internal gaps in the cemetery (see Figure 5-3 below). In order to remove the subjectivity, it was necessary to define a specific distance required for adjacency. At this point it became evident that the entire effort of removing the first order effects was unnecessary since it would be possible to simply count the number of pairs of graves within the specified radius that shared the same discrete genetic trait. While it was initially developed in the context of the Kellis 2 analysis, it has wider application. In the subsequent discussion the term grave has been generalized to event. The actual count developed is a count of pairs of events, not the total number of events with the trait which are found within the specified radius. Thus, two events within the specified radius would be a count of one, three events all within the radius would be a count of three and four would be a count of six, etc. In a highly clustered set of events with the trait, the count developed can exceed the number of events with the trait or even in the cemetery. The routine works through the list of events with the given trait one at a time counting how many other events with the trait can be found within the specified distance. Any given pair though is only counted once (i.e., A to B adds one to the total but B to A does not.)

This is defined mathematically as follows.

Given a set of n events $s_1 \ldots s_n$

$$PC(d) = \frac{\sum_1^n no.\,[S \in C(s_i, d)]]}{2}$$

Where $C(s_i, d)$ is a circle centred at event s_i of radius d

And $no.\,[S \in C(s_i, d)]]$ is the number of events within radius d of event s_i

As defined this is a continuous function but in practice it is usually calculated for a small number (5-10) values of radius d.

The significance is calculated against an assumption of random labeling using a Monte Carlo routine across the set of events that display either the presence or absence of the

trait. It does not include other events, the condition of which makes it impossible to determine presence or absence of the specific trait. The Monte Carlo routine randomly selects a number of events without replacement which matches the count of events displaying the discrete trait. This selection calculates the Proximity Count and then repeats a specified number of times. The number of counts greater than the actual count is totaled and divided by the number of randomizations to obtain the probability of the actual count. This procedure is effectively a one-tailed test.

In using the original single run statistic it became evident that the actual distances yielding significant results can vary from trait to trait, with significant clustering occurring at different distances. For example, in one case there was significant clustering at 3 m and in another significant clustering occurred at 7 m. Consequently the R routine was modified to do several runs with different user defined distances, with statistical significance calculated at each distance. In the Kellis 2 case this was set to 3, 5, 7 and 10 m. This is a global statistic and, with the addition of multiple runs at multiple distances, could be described as a function similar to the F G and K functions as defined in Bailey and Gatrell (1995).

While the Proximity Count was originally created to define clustering, in practice some sets of data created low counts that were smaller than the vast bulk of the randomizations, creating p values such as .95. In other words, only 5% of the randomizations created lower than the real count (e.g. Frontal Grooves at 7 m; see Figure B.7). This result is the opposite tail of the distribution and essentially implies that the trait is more evenly spaced than would be expected at that distance. Note that in this example Nearest Neighbour-Random Labeling also shows even spacing, but not with significance. At this point in time, since a count of events has been calculated, no attempt has been made to define differences between the two tails of the distribution and work that into the statistic. It would require something like "a count of 18 at 5 m, clustering with $p = .05$". Currently high p values can be taken to mean even spacing.

The statistic was originally defined in the context of the Kellis 2 cemetery analysis in Chapter 5. However, as currently coded, it is applicable to other cases where we are

looking at the relative distributions of two types of events such as occurred in the Chapter 4 Davidson site analyses.

The routine was implemented using the R Statistical programming language.

3.5   Cross Proximity Count by Sex

This routine builds on the Proximity Count described above. However, it allows consideration of the co-occurrence or not of two traits. As it stands at this writing, this routine has not been generalized to use any two traits, so one of these must be the sex of the individual. It again counts pairs of individuals within a user specified distance of each other. Four different statistics are produced:

1. The number of pairs of events with a specific trait looking only at male data.
2. The number of pairs of events with a trait counting females near males.
3. The number of pairs of events with traits looking at females only.
4. The number of pairs events with a trait counting males near females.

Numbers 1 and 3 are identical to a Proximity Count that could be obtained if only data from one specific sex was selected. Numbers 2 and 4 are the actual cross comparison. Each starts with the set of all individuals of one sex with the trait present and then counts all the individuals of the opposite sex or with the trait present. For 2 and 4 the count will be identical but the probabilities can be different. Statistical significance is determined using a random labeling approach by selecting a series of random samples without replacement from the set of all the target sex and calculating the statistic repeating the process a number of times (999 is recommended). The number selected is identical to the number of individuals with the trait present in the target sex.

3.6   K Function

This statistic has not been used in this study but has been referenced several times, so a brief discussion is warranted. An implementation of the K Function is included with the spatial statistics extension of ArcGIS and can be also be found in Spatstat (Baddeley 2015). A description of the function can be found in O'Sullivan and Unwin (2003) and Bailey and Gatrell (1995). Basically, the statistic counts the number of events from each

event in the study area within a distance of a series of increasing radii and divides each by the average intensity of events within the study area.

3.7   Unconstrained Clustering

Unconstrained Clustering is a technique proposed by Robert Whallon (1984) as a methodology to determine activity areas by considering the spatial location of a number of different artifact types found on living floors. While this might seem a rather narrow focus, in the 1980s the entire purpose of spatial statistics in archaeology in North America seems to have been focused on that specific objective. In his 1984 paper, Whallon critiques the then current methods of spatial analysis, noting that all are in various ways constrained in their capabilities. For example, his Nearest Neighbour analysis (Whallon, 1974) has an implicit constraint that fails to handle clusters of varying density. The Nearest Neighbour distances will be lower in the denser cluster even though the clusters might be compositionally identical. As an example, consider two knapping stations where only one biface tool was produced at one, while several were produced at the other. In contrast, Unconstrained Clustering was designed to minimize the number of constraints that might come into play. For a more detailed description of Unconstrained Clustering see Whallon (1984) or Kintigh (1990).

As envisioned by Whallon (1984:244) the technique has a seven step process which proceeds first, by creating smoothed density contours for each artifact type. The smoothed values are then taken at each point (artifact location) and are combined into a vector of values for that point. These vectors are then used to create proportional densities for each point, thus removing variable artifact density from the process. Cluster analysis is then used to combine data points into reasonably homogeneous clusters, which can then be plotted and examined for spatial integrity. If this integrity is demonstrated, then description of the clusters and their interpretations can proceed. Keith Kintigh (1990:192) proposed a variant to this procedure, which he considers to be "more direct and, I believe, theoretically preferable to Whallon's proposed procedure." This methodology substitutes local density calculations (Johnston 1984) for the smoothed density and proportional vectors used by Whallon's procedure. Further, Kintigh (2015)

went on to provide a software product (TFQA) that can be used to perform Unconstrained Clustering

The analysis conducted in this study was with the TFQA which is well-documented and the documentation is available on the WWW (Kintigh 2015). With Unconstrained Clustering, TFQA requires the execution of three different programs and while each of these is well documented on its own, the actual process to conduct Unconstrained Clustering is not well defined with respect to how the three programs interact. The remaining portion of this section describes what was learned about conducting Unconstrained Clustering in TFQA through a series of questions to Kintigh, as well as trial and error.

In Kintigh's procedure, the first step is to run a Local Density Analysis on all the types in the study area. Local Density Analysis is a procedure developed by Johnson (1984) that measures the local density of one artifact type around a second artifact type and divides this result by the density of the first artifact type as if it was randomly distributed over the study area. The size of the area around the second point is a user specified variable. This creates a statistic where a value of one indicates that the two artifact types are not associated, a value lower than 1 indicates that they are segregated, and a value greater than one indicates a greater degree of association. If multiple types are present, Kintigh's software calculates a pair-wise matrix measuring the local density coefficient of each pair of types in the original data. This spatial statistic is a reasonable one on its own but Kintigh's software includes the option to create a file which can be used for Unconstrained Clustering. The program in TFQA which performs this operation is LDEN. At this stage in running Unconstrained Clustering, the key variable parameter that is entered is the radius of the area for which local density is calculated. This parameter is critical since different radii can give better or worse results for the analysis. There are no rules for selecting this radius so the only approach is to try different numbers and run the entire Unconstrained Clustering process and compare the results. In the Kellis 2 example in Chapter 5, several different radii were selected specifically 5, 7.5, 10, 15 and 20 m. Comparing the results, 5 m and 7.5 m were consistently worse than all others so were discarded.

The next stage in the analysis in TFQA is the program KMEANS, which performs the cluster analysis. One of the key user inputs into this program is the number of clusters expected. In this case Kintigh's (personal communication 2014) recommendation is to start with twice the number of clusters that you are expecting. The program then goes through an iterative procedure dividing the input points into more and more clusters.

In order to measure the goodness of fit for both the local density radius and number of clusters, a statistic called the Sum Squared Error (SSE) is created, which essentially measures misfits in cluster assignment. Smaller values of the SSE represent a better fit to the data. The SSE is very high for one cluster and gradually reduces as more clusters are split off. After some number of clusters is reached, the decrease in the SSE becomes negligible and division into more clusters produces only a slight reduction in SSE. Thus, the number of clusters can be fairly simply determined from a single run by examining the resulting SSE values and locating the number of clusters beyond which only marginal improvement in the SSE is seen. This number is essentially the "knee of the curve" in non-mathematical parlance. To find the best local density radius it is necessary to run a series of Unconstrained Clusterings and track how the density radius impacts the SSE values. When comparing multiple Unconstrained Clustering runs, the best form of SSE to track is the %SSE, which shows the SSE at the nth cluster as a percentage of the SSE with one cluster.

While minimizing the SSE does represent a better fit to the data, it does not indicate if the SSE is statistically significant or not. The program also provides the option of conducting a series of randomizations on the input data, which can then be used to plot significance envelopes. If the SSE of the real data is outside these randomizations, then the results are statistically significant, but the program does not calculate a P-value. In Figure 3-1, the narrow lower line is the actual %SSE. Clearly, as more clusters are created, the value decreases with the knee of the curve occurring around 15 clusters. The thicker line higher in the graph represents the results of the randomizations such that the slope envelopes would be represented by the top and bottom of the thick line. Unfortunately, no p value is given. However, simple examination of Figure 3-1 shows that the results of Unconstrained Clustering are highly significant.

The results of Unconstrained Clustering are then plotted with the program KMPLT. This program can plot both the SSE actual versus random values for various degrees of clustering and an actual map of the clusters with a cluster number assigned to each point in the original data. The down side of the plot program (and to some extent all of TFQA) is that it was designed to run under DOS with a command line user interface. While this procedure is acceptable in running the calculations, the plot is not really up to modern standards of publication quality. Further, the KMPLT program does not run in the current Windows Command Prompt interface and thus, requires a third party software tool called DOSBOX software to even run. At this point, you must capture the resulting graph with a Print Screen. However, the values are all available and can be used as input to modern graphics programs.

Figure 3-1 is a plot of the %SSE and the associated slope envelopes from one of the runs with the Kellis 2 data. Figure 3-2 shows the plot of various clusters from this run.

Figure 3-1: SSE Plot from Unconstrained Clustering
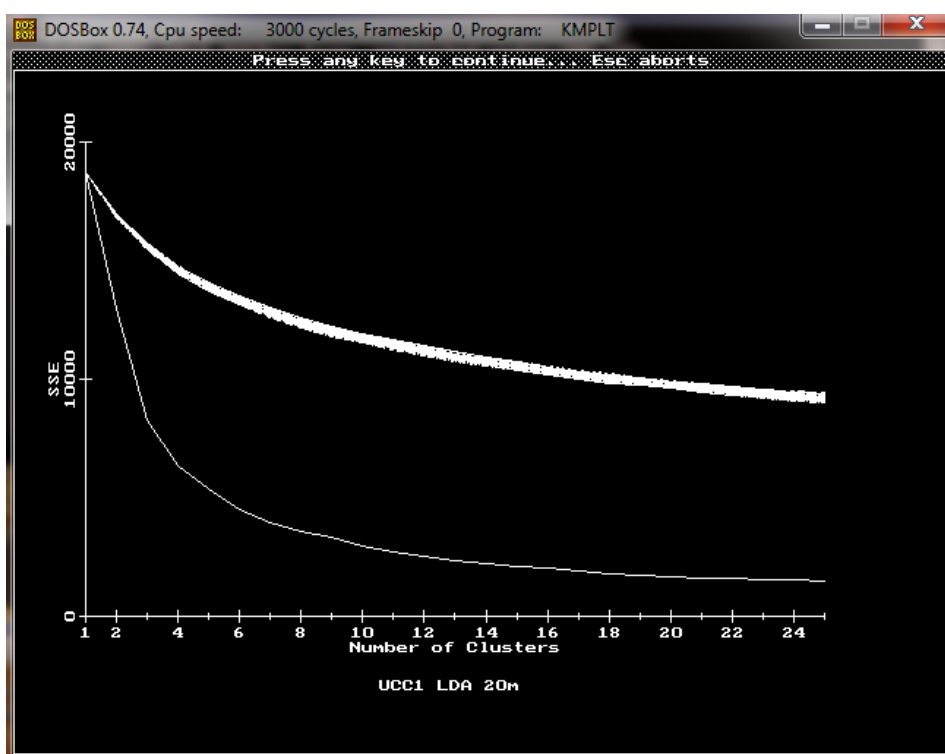
Figure 3-2: TFQA Plot of Unconstrained Clustering
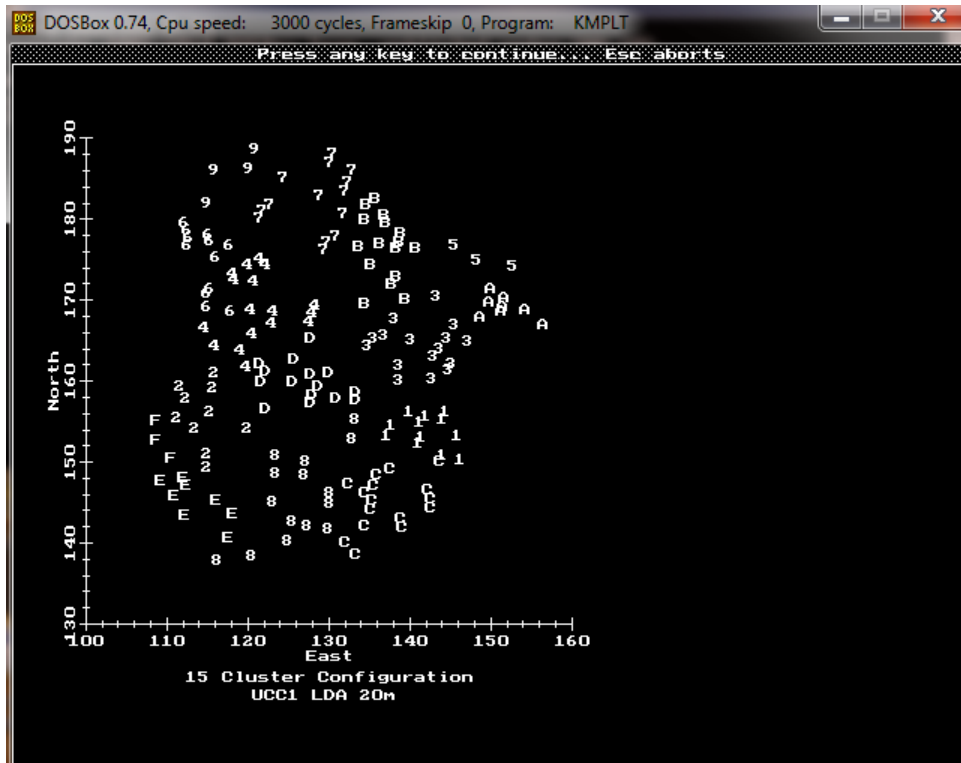
3.8   Local Density Analysis

Another statistic, proposed by Johnson (1984), is methodologically similar to the K function and Proximity Count described above. This procedure also calculates a global statistic by measuring the density of class B points within a set radius of each class A point and dividing it by the overall density of Class B points across the study area. A value of one indicates that the two classes are randomly distributed, a value greater than one indicates spatial association, and a value of less than one indicates spatial segregation. One advantage of this method for archaeological data is that it can use totals by grid square as input. As Kintigh (1990) notes, in this case, this statistic is subject to the boundary problem and, as it uses quadrats, is also subject to the MAUP. The TFQA implementation can also run against point pattern data and has been used as such in this study. Further, as implemented in TFQA, it does not have a means of determining if the resulting statistics are significant, although Kintigh (personal communication 2013) notes that that would be possible. The

implementation in TFQA can do multiple calculations with a series of radii given a set of values that behaves like a function. It is a global statistic.

3.9   Kernel Density

Kernel Density is easily carried out using the ArcGIS Density function found in the Spatial Analysis extension. It allows you to measure the relative density of points within a defined radius. The density is measured from all points on the map, not from specific artifacts such as occurs with the Proximity Count or Local Density Analysis. However, as with both those methods, it becomes a judgment call in picking the radius. Basically, the larger the radius the more smoothed the result becomes, to the extent that smaller patterning is obscured. The issue of selecting a proper radius has been described above in the section on Resolution focus in Chapter 2. In general, there are a number of options that can be used in calculating the density, varying from a simple count divided by the area to various forms where closer points are weighted heavier than further points within the specified radius. Kernel density in ArcGIS implements the latter.

3.10 Pure Locational Clustering

This routine is implemented within TFQA in the K-Means program. One of the options in this program is called Pure Locational Clustering. This function takes the x-y coordinates of all the points in the study area and the user's expectation of the number of clusters in the group and then proceeds mathematically by carving out clusters one at a time by minimizing the sum of the squared distances from each point assigned to a cluster to the centre of that cluster. So again, there is a judgment factor applied in assigning the estimated number of clusters. Kintigh's advice here (personal communication 2012) is to aim higher than you might expect. The program then generates all possible numbers of clusters up to the specified limit. While the program provides a graphical picture of the cluster assignment, it is basically an old DOS program with less than ideal graphics and a major problem printing under recent versions of Windows. However, the printed listing gives you the centre of each cluster and the RMS value, which is the radius of a circle around the centre. The RMS value is calculated by taking the square root of mean squared distances from each point in a cluster to the cluster centre. A circle around the

centre of the cluster with the radius equal to the RMS value is useful for display purposes. Selection of the number of clusters to be used in the analysis is a judgment call, but some generality here can be gained by treating the number of clusters as a resolution focus issue as discussed in Chapter 2.

3.11 ArcGIS Hot Spot Analysis (Getis-Ord Gi*)

In the spatial statistics extension, ArcGIS provides a routine called Hot Spot Analysis, which makes use of the Getis-Ord Gi* statistic. This routine expects area data and, when dealing with a point pattern, this expectation means summarizing the point pattern into quadrats, which is simply done with ArcGIS after creating a Fishnet. The method of calculating is adequately described in the ArcGIS documentation. Basically, the routine calculates Getis-Ord Gi* for each area unit in the analysis and then looks for a collection of adjacent areas with either high values or low values. If the values exceed statistical significance, then the collection is flagged as a hot spot (high values) or a cold spot (low values). Various levels of statistical significance are given, usually at 90, 95 and 99% confidence. This routine is not a point pattern statistic, but when measuring clustering is useful for calculating statistical significance.

Chapter 4

4   Davidson Site Case Study

This chapter presents a spatial analysis of the artifacts recovered as surface finds from the Davidson Site (AhHk-54) located in southern Ontario. As an Archaic site in Ontario, it is abnormally large covering approximately 1.9 ha. The site contains two primary components from the Broad Point and Small Point Archaic, the former of which covers the entire 1.9 ha area. The Small Point component is restricted to the northern portion of the site but is still quite extensive. The questions addressed here through spatial analyses are why is the Broad Point component so large? -- does it represent repeated occupations by small groups or does it represent a larger occupying group (e.g. an aggregation site) or combination thereof? In addition, is there evidence that the use of the site shifted over time from the Broad Point to Small Point occupation?

4.1   Introduction and Site Setting

The Davidson Site (AhHk-54) located southwestern Ontario (Figure 4-1) on the Ausable River where it enters the Thedford Marsh. The material recovered from the site dates predominantly to the Late Archaic and represent what have been called the Broad Point (ca. 4000-3400 BP) and Small Point (ca. 3400-2800 BP)[1] Archaic after a characteristic of the predominant forms of stone weapon tips characteristic of each development (see Ellis et al. 1990, 2009). The Broadpoints from Davidson are large stemmed forms assigned largely to types such as Genesee (Ritchie 1971a; see Figure 4-2 and 4-3) dated to ca. 3800-3400 BP, but a few examples more closely approximate a slightly earlier type (ca. 4000 BP) called Adder Orchard (see Figure 4-4; Fisher 1997; Kenyon 1983). Small Points are by definition, smaller, and tend to be expanding stemmed or notched forms that are assigned to various types/styles such as Crawford Knoll, Innes/Ace of Spades or Hind (Kenyon 1989; Figure 4-5). The Smallpoint varieties are generally believed to be

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[1]Following convention, the terms Broad Point and Small Point will be used throughout to designate each development while Broadpoint and Smallpoint are used to refer to examples of the points themselves (Eastuagh et al. 2013).

measuring changes in point form over time, with Crawford Knoll the earliest and Hind the latest (Ellis et al. 2009).

Figure 4-1: The Davidson Site in Southern Ontario
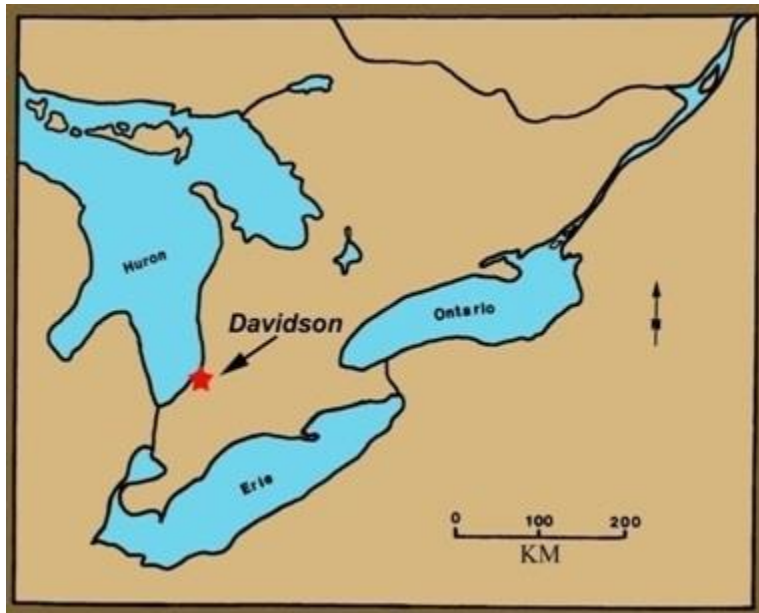
Figure 4-2: Genesee Points on Onondaga from Davidson

Figure 4-3: Genesee-like Points on Subgreywacke from Davidson

Figure 4-4: Adder Orchard Points from the Adder Orchard Site
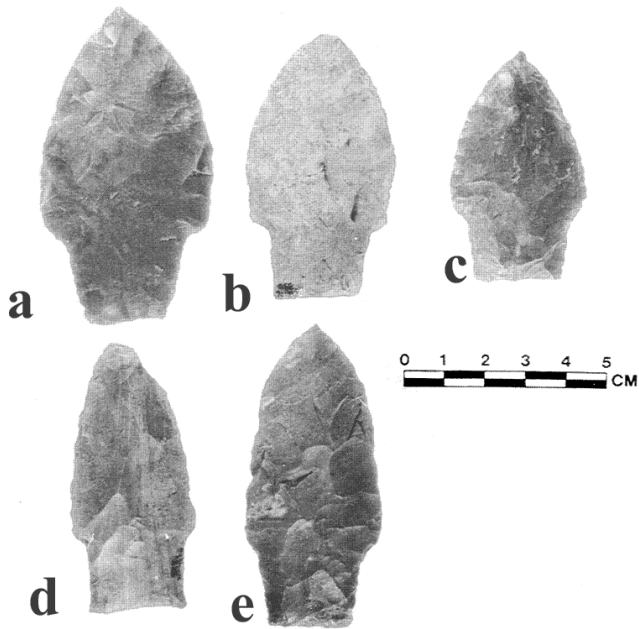
Figure 4-5: Smallpoints from Davidson

Top row Hind points, Bottom left, Innes point, bottom four right Crawford Knoll

The Davidson site is located about 12 km inland from the modern Lake Huron shore on the east bank of the Ausable River (Figure 4-6). It is situated just below the old shoreline of the Nipissing Phase, a high water level that existed from about 5000 BP to 4500 BP in the Lake Huron Basin (see Karrow 1980; Figure 4-6). Thus, the site occupation has to postdate that Nipissing high water mark and this interpretation is consistent with the age of known site components. The area to the immediate north of the site represents the flat bottom of a large embayment of that early lake phase and, prior to drainage in recent times for agricultural purposes, much of the area was a large marsh containing two small lakes. The Thedford Marsh extended north almost to Lake Huron. To the south of the site, the Ausable River carves through hilly terrain and eventually cuts a deep river valley through the Wyoming Moraine, which represents the terminal point of the last major glacial ice advance in the area.

Figure 4-6: The Davidson Site Local Topography
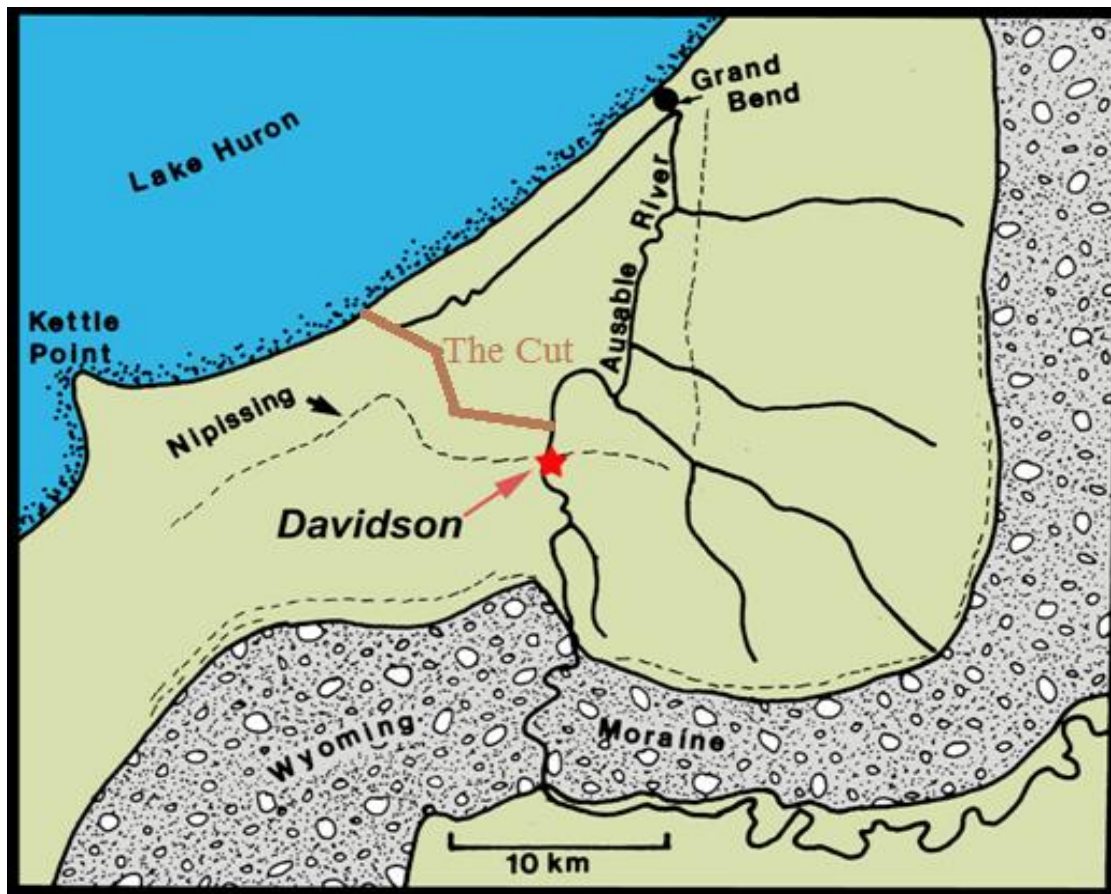
Research to date (Ellis 2010, 2014) indicates the Davidson site covers a total of about 1.9 ha (Figure 4-7). By Archaic standards this site is abnormally large and there are suggestions that comparable large Archaic sites of at least Broad Point age occur at other locations in the lower Ausable River area (Chris Ellis, personal communication, 2006). The current owner reports that the site was only brought into cultivation in the 1940s and so would have been largely intact up to that point (Rick Davidson, personal communication to Chris Ellis, 2006). From then until the early 1980s only the north end of the site and a small area to the south end was cultivated, as revealed by air photos (Figure 4-8, 1978 air photo for comparison). Notably, as is still the case, there was a strip of unploughed, wooded vegetation separating the ploughed field from the river all along the west site margin, as well as bordering a fence-line/ hedge row across the centre of the site extending from the river area to an unploughed wooded swale area on the site's east-southeast central margin (outlined in red in Figure 4-8). In the early 1980s, this hedge

row was removed and the cleared land cultivated, as was a portion of the interior swale north of the current wooded area and along the east side of the site.

Almost since the land was first ploughed, the site has been known to relic collectors and areas accessible in the ploughed field of the time were combed for artifacts (Brian Deller, personal communication to Chris Ellis, 2005). Based on the testimony of an older informant who visited the site during our fieldwork, a favoured site for the earliest surface collections and artifact finds, notably including Broad Point Archaic tools made on coarse-grained rocks, was just over the central fence line/ hedge row that existed at that time. However, Davidson was first discovered and reported to the professional archaeological community by Ian Kenyon (1978, 1979, 1980a, 1980b) who found the site while conducting a canoe survey down along the Ausable River in 1977. A major erosional event along the river bank that year had removed a large bite out of the Ausable river bank in the site centre that extended through the wooded area bordering the river and out into the south end of the ploughed field of the time (Figure 4-9). Kenyon discovered a paleosol in the eroded river bank approximately one metre below the then current surface that contained several Broad Point Archaic features. The immediate area along the river, where erosion was occurring, was subjected to limited salvage excavations in 1977 and, due to continued erosion, again in 1978 (Kenyon 1978, 1979). The bank was subsequently stabilized by the landowner by covering it with stone slabs. Figure 4-9 shows Kenyon's (1979) map of his 1978 excavations (in black) superimposed on the 1978 air photo, along with the location of some recent excavations shown in red.

Kenyon (1978, 1979) posited that the buried paleosol was the old ground surface prior to European intrusion in the area and that the overlying sterile deposits were deposited in flood events initiated by extensive agricultural land clearing and damming of the river downstream during European times, an interpretation supported by more recent site work. At the time, Kenyon (1979) mentioned that, back from the river, artifacts could be found on the surface of the ploughed area in two distinct areas. One is over the central fence-line/hedge row wooded area that transected the site at the time and corresponds to the informant testimony of the location of surface materials mentioned above. However, in

Figure 4-7: Davidson Site Extent - Current Air Photo

The Davidson Site Extent

Legend
- 2014 Surface Events
- Excavations

0 25 50 100 150 200 Meters

Collection to June 2014
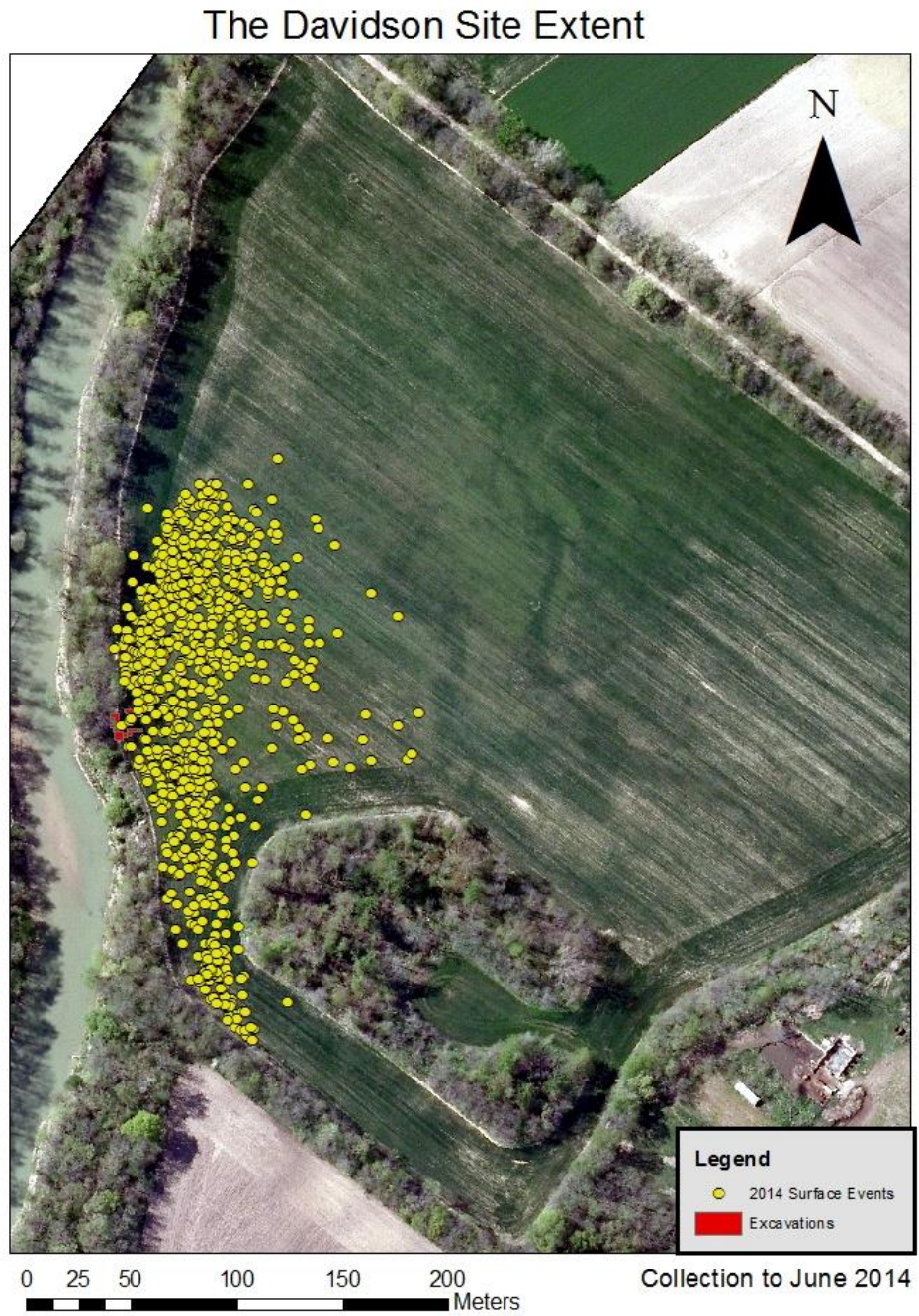
Figure 4-8: Davidson Site Extent - 1978 Air Photo

The Davidson Site Extent
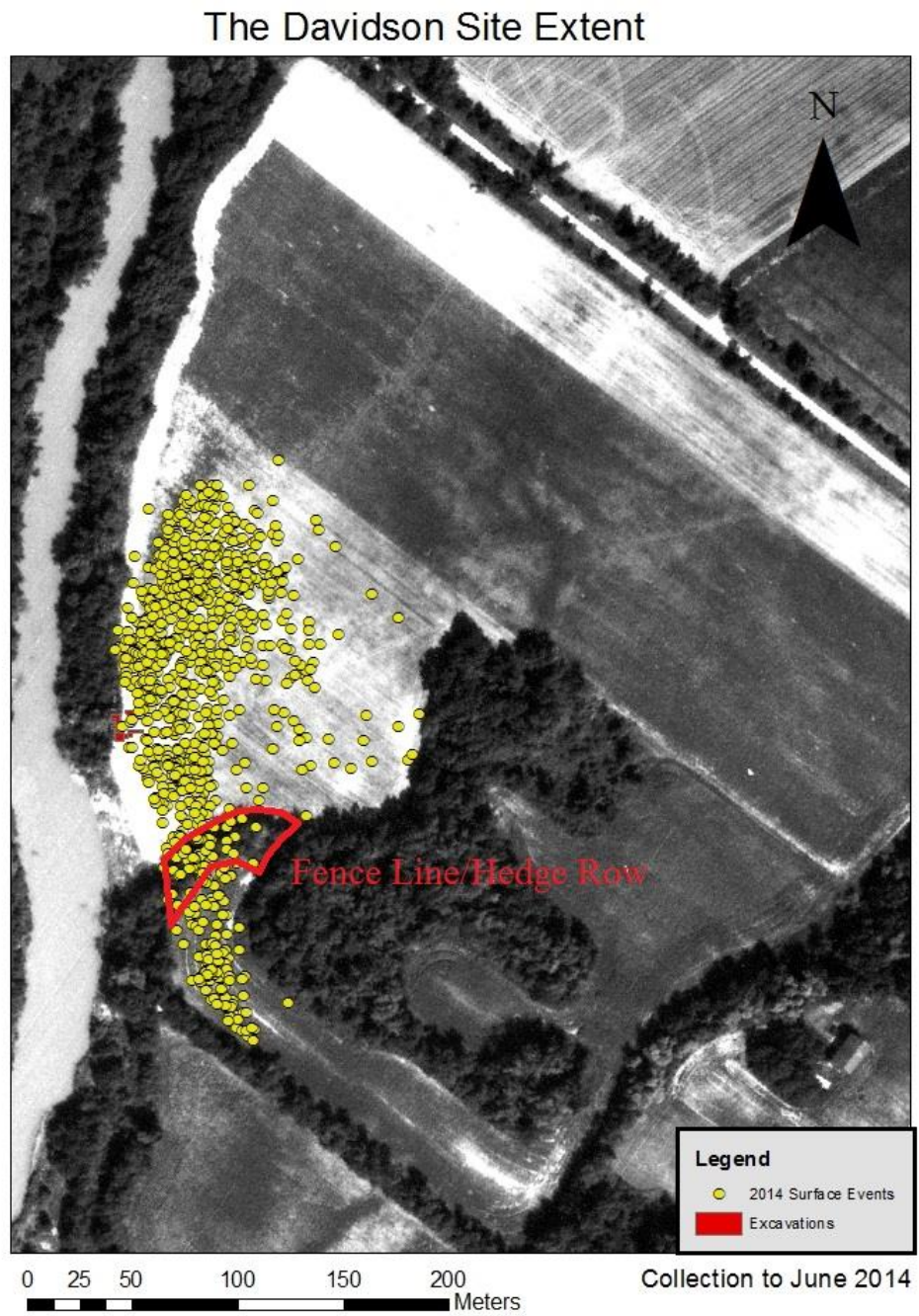
Figure 4-9: Kenyon's Map on 1978 Air Photo

The Davidson Site 1978 with Kenyon Map
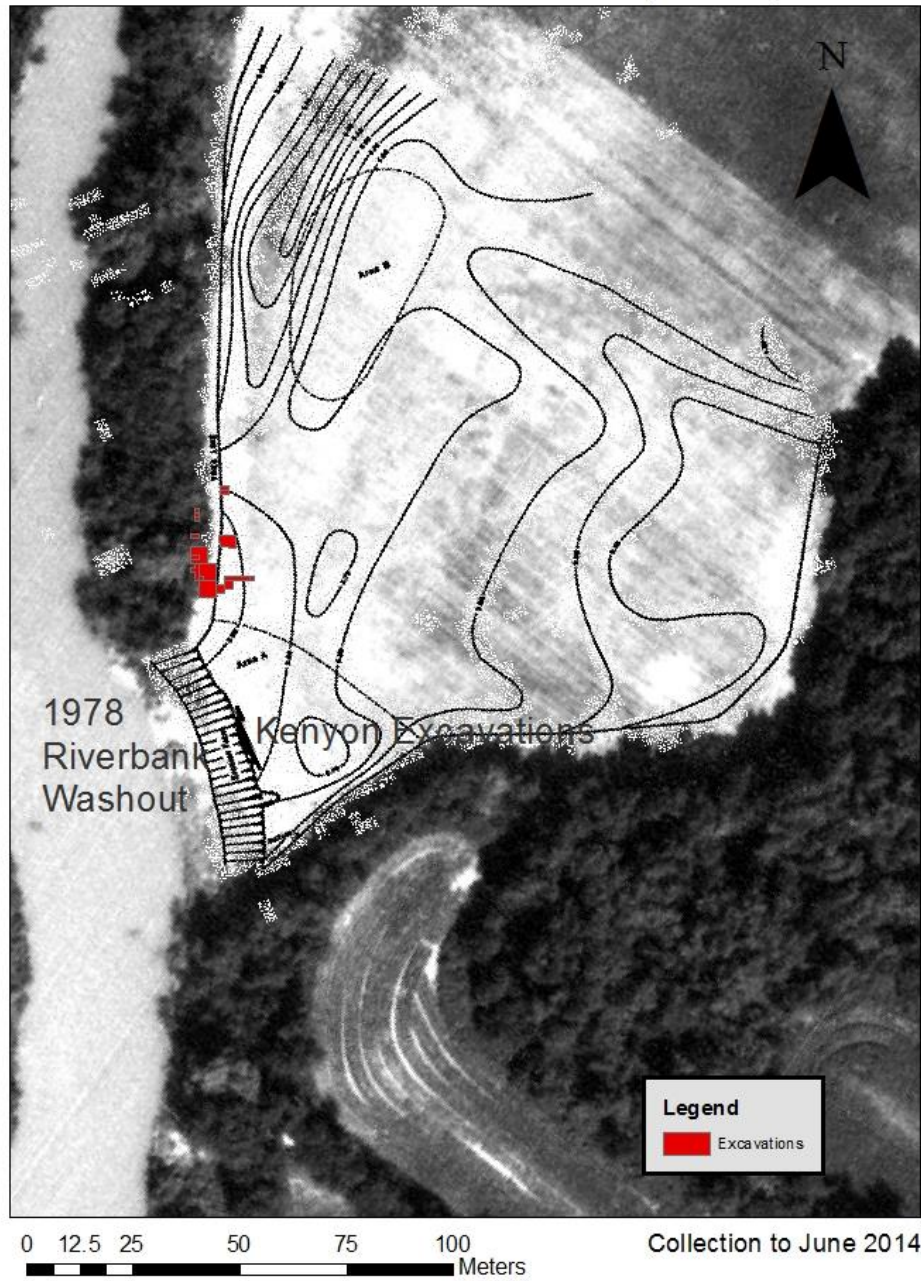
contrast to informant testimony about substantial tool recoveries, Kenyon (1979:1) reports it is "nothing more than a thin scatter of undiagnostic debitage". Kenyon's other area was to the northeast of his excavation work bordering the east edge of a "swale-like depression" (Kenyon 1979:1). This area, which he called Area B on his map (Kenyon 1979; see Figure 4-9), was estimated to cover only ca .16 ha and was said to have yielded unspecified Archaic and Woodland artifacts.

Current investigations are under the direction of Dr. C.J Ellis of the University of Western Ontario (e.g. Eastaugh et al.2013; Ellis et al. 2015). The earlier work of Kenyon, along with a brief surface reconnaissance in 2005, suggested that there may be a considerable area of undisturbed material in a paleosol buried well beneath the plough zone beside the river. That paleosol was speculated to slope up to the east away from the river until it was eventually encompassed in the ploughed field where the surface finds occurred. In order to evaluate that hypothesis, excavations began in 2006 with five test pits dug just to the north of Kenyon's (1978, 1979) excavations and the old eroded bank (see Figure 4-10). All of these units revealed thick cultural layers buried under the superimposed layer of historic flood deposits. Moreover, all units contained diagnostic Broad Point artifacts similar to what Kenyon had recovered. The primary excavations took place in 2008-2010 and additional test excavations of limited areas further to the south were conducted in 2014 (Ellis 2010, 2011a, 2011b, 2015). In the main excavated area, the work uncovered a large number of overlapping features, which range from hearth to small pits to specialized refuse disposal areas ("middens") in old erosional channels, to house structures (see Ellis et al. 2015). These features include ones assignable to both the Broad Point and Small Point Archaic. Both occupations were on the same occupation surface and the later dating features of the Small Point Archaic often cut through the pre-existing Broad Point ones. Within the small area excavated, the AMS radiocarbon dates obtained to date suggest three periods of site use (see Figure 4-11). The two earliest clusters, including one calibrated to around 2500-2200 BC and another with three dates from one spatially limited excavated site area centered around 1700-1800 BC, are associated with the Broad Point occupation. The last cluster, dated to around 1400-1100 BC, is related to the Small Point component. Whether the gaps in these dates are

Figure 4-10: 2006 Test Pits Relative to Kenyon's Work

The Davidson Site 2006 Test Pits
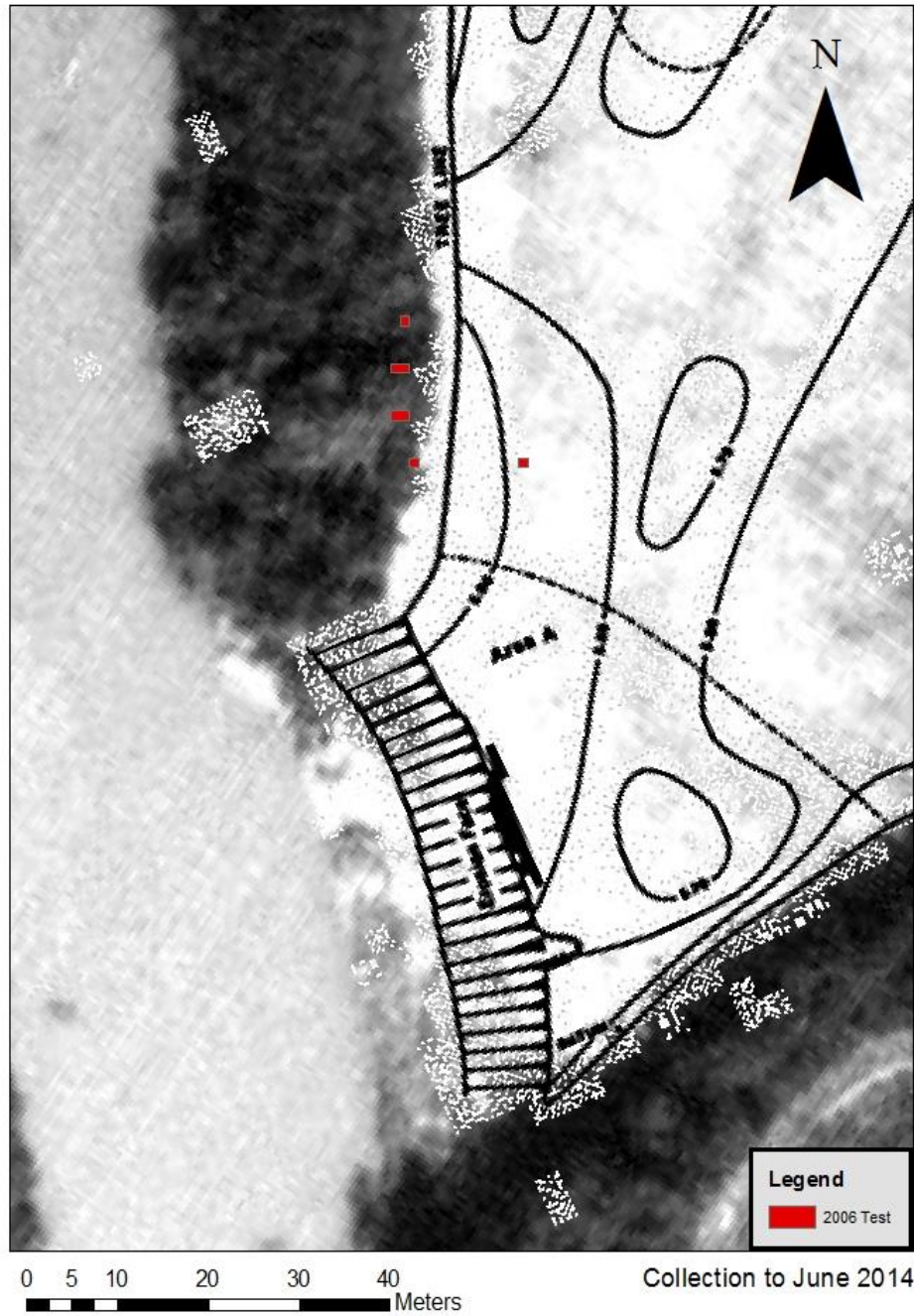
real or representative of all use of the site is not clear. The only date from beyond the area excavated in 2008-2010 is from Kenyon's (1980a) work just south of our excavations which dates to the Broad Point component there (3760+/-90BP) and corresponds to the 2500-2200 BC cluster of the current work.

Figure 4-11: Calibrated C14 Dates Jan 2015 – Dark One Sigma, Light Two Sigma
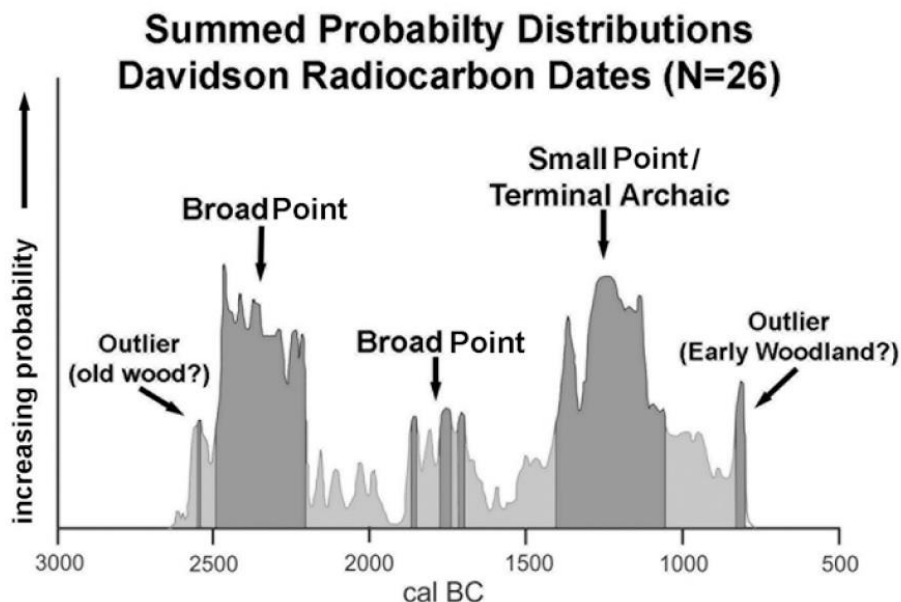
Between 2007 and 2014 we conducted eleven Controlled Surface Pickups (CSP), recovering 1046 artifacts from the surface. The results of these surface collections form the basis of this case study and are shown in Figure 4-12, which also shows the area surveyed. Since the field is literally covered with thousands of artifacts, including fire-cracked rocks and much debris from making stone tools, we have only, to date, collected and mapped what are believed to be either temporal diagnostics or tools. The diagnostics include tools such as finished and unfinished stone weapon tips but we have also plotted flaking debris on metasediments and other coarser-grained rocks, notably sub-greywacke. For reasons I will detail below (see section 4.2), these flakes on coarse-grained rocks are primarily associated with the Broad Point use of the site.

As in the case in the excavated areas, most of the surface finds, represent the two main Late Archaic components. Among the surface collections only 7 of the 1046 artifacts fall

outside these two components: one untyped archaic projectile point, three Early Woodland Meadowood points, one Middle Woodland projectile point, one Late Woodland scraper and one potsherd of undetermined cultural affiliation. On the northern half of the site, the area of surface extends beyond the area Kenyon (1979) shows as his Area B (compare Figures 4.8 and 4.9).

During the recent project, the site area has also been subjected to geophysical investigations. Between 2008 and 2013, the site area within was surveyed with a gradiometer/magnetometer and in 2013 a magnetic susceptibility survey was also carried out (Eastaugh et al. 2013; Ellis 2008, 2013, 2014; Ellis and Eastaugh 2014). The magnetometer survey (Figure 4-13) revealed a dense, linear band of magnetic anomalies extending from the area just north of Kenyon's (1978, 1979) earlier work northeast into the area of surface finds noted above, referred to on his Map as Area B. This dense anomaly band maintains a relatively constant width of ca. 20-25 m wide that overall covers some 4600 m^2. The anomalies excavated to date shows they all represent major cultural features, such as the pit clusters and houses mentioned above (Eastaugh et al. 2013). Notably, the northwest margin of the dense anomaly band corresponds to a drop off in surface finds in a linear southwest to northeast direction that Kenyon (1979) referred to as the swale-like depression. All indications are that this area represents the river course at the time of the site occupations and the adjacent dense band of anomalies/features show that the people tended to camp closer to the river bank. Beyond the dense anomaly band and notably extending to the extreme southern site margin of the site, as determined by the current fieldwork project, anomalies are present but these are rare. Nonetheless, 2014 test excavations in the more southern areas that targeted some of these anomalies show they also correspond to more isolated features such as pits and hearths that contain materials suggesting a Broad Point association (Ellis 2015).

Figure 4-12: Davidson Surface Collection by Time Period
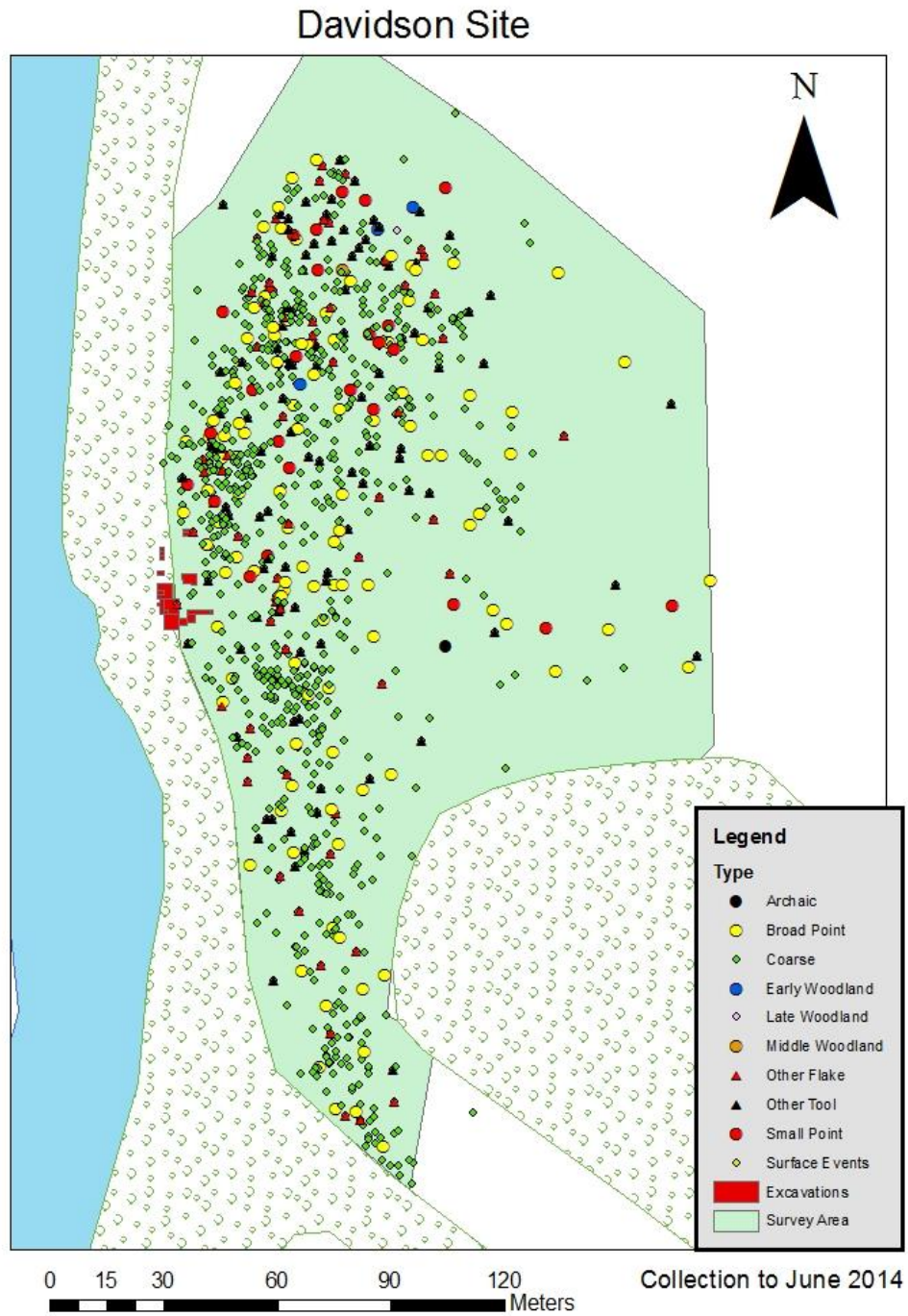
Davidson Site

Figure 4-13: Davidson Site Geophysical Investigations

The Davidson Site Geophysical Investigations
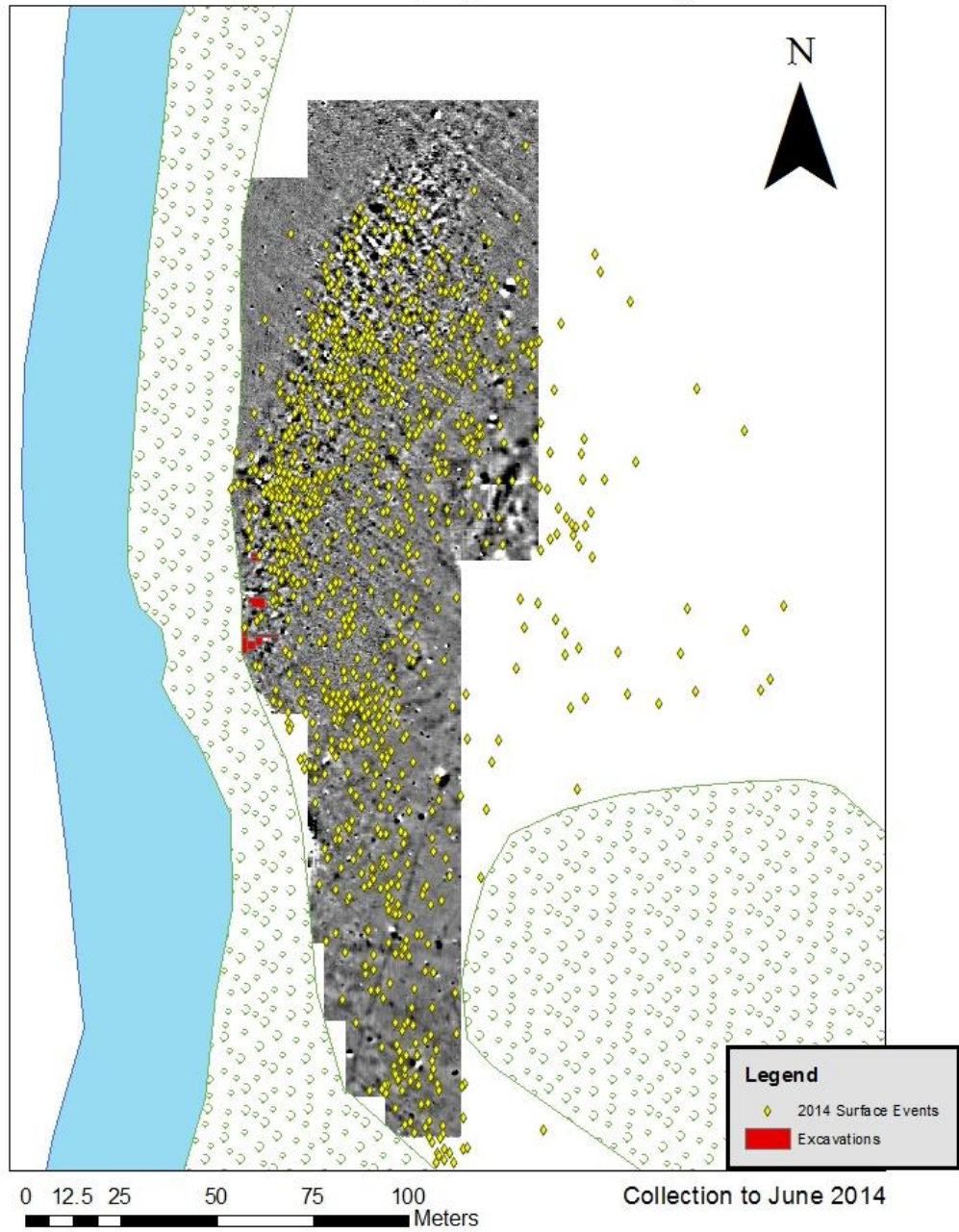
The magnetic susceptibility meter survey does not provide the detailed precise anomaly recognition revealed by the gradiometer work but nonetheless, the results (Figure 4-14) show a major area of intense susceptibility that corresponds to the same location as the large gradiometer anomaly band on the northwest site margin (Eastaugh, Hodgetts, and Ellis, unpublished data). Moreover, that survey revealed deposits with a different susceptibility, the margins and extent of which are indicated by the yellow area on Figure 4-14. These deposits actually represent the extent of the deposits left by the European age flooding of the current riverbank area.

To summarize, results of the recent excavations and the surface collections confirm that the site occupations predominantly represent Late Archaic Broad Point and Small Point components. As measured with the GIS, and taking into account the buried areas revealed by test pitting excavations and coring, as noted above, the site covers at least 1.9ha, extending from just north of Kenyon's (1979) Area B to the current wooded field boundary much to the south. Of that total area, some 3600 square metres closer to the river in the central site area consists of either a completely buried paleosol or an area where the paleosol is partially intact at the base of the plough zone, having been protected by the subsequent European age flood deposits (Eastaugh et al. 2013). Overall, it is obvious that the site has been or may have been subjected to various post-occupational formation processes that can affect the representativeness of the surface sample. These include natural formation processes such as river meandering and overbank flooding, as well as cultural formation processes such as differences in the areas that were cleared for agricultural purposes and hence, differential access of surface finds to relic collectors. Such factors and their effects on the sample must be and are considered in the analyses and they are detailed in the next section.

Figure 4-14: Magnetic Susceptibility Survey
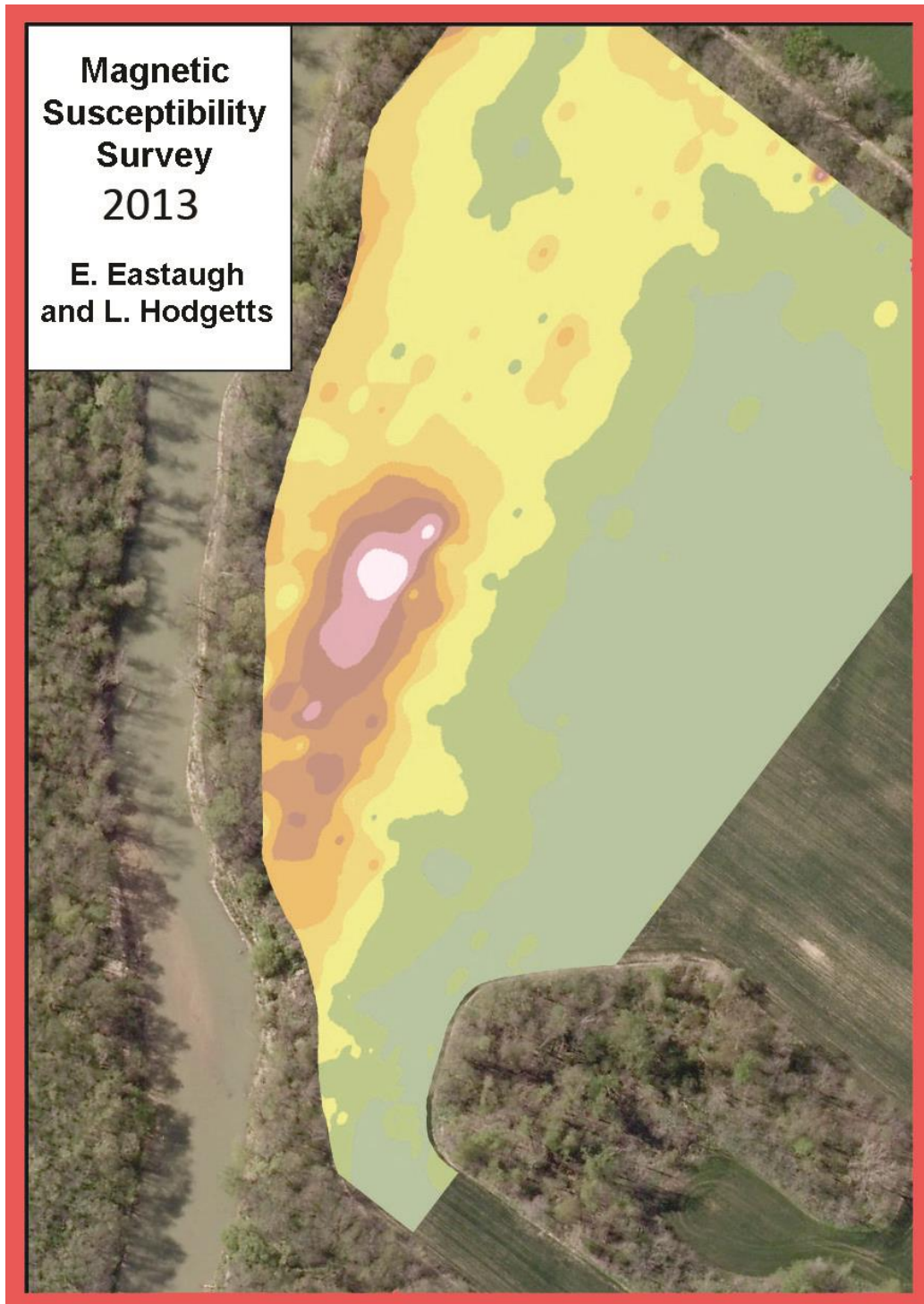
4.1.1   Representativeness of the Surface Collections

Since this site has been heavily ploughed as well as impacted by artifact collectors, it is necessary to address a number of factors that affect the representativeness of the surface collection of the entire site occupation. These include site formation processes, both natural and cultural (e.g. modern agricultural processes and the depredations of artifact collectors).

First, given that the site has buried deposits and is clearly multi-component with two primary occupations during the Broad Point and Small Point Archaic, the first factor to be considered is whether the surface material exposed by the plough are equally representative of both occupation periods. For example, if much of the Broad Point occupation is buried by the later strata of the Small Point occupation, the Broad Point material could be under represented. Excavations have shown that there is clearly some stratigraphic separation in the deposits, for example as in multiple layers in a Broad Point midden located in an erosional gully (Ellis 2013). Further, in some locations later Small Point pithouses and other features cut through earlier Broad Point features. However, in all excavated areas for the most part, the land surface during both these occupations was essentially the same, with the notable exception of potential changes in the course of the river (see below). What was happening with few exceptions was that the later Small Point groups were digging through earlier Broad Point material and essentially mixing the two occupations, as opposed to the earlier occupation being more deeply buried and hence obscured. Another indication that there is no differential representation of the two components is that the subsurface artifact assemblage recovered during excavations is similar to the surface collections just to the north of those excavations. All major point types and artifact types are duplicated. Any stratigraphic layering that may have formed was undoubtedly shallower than the impact of modern ploughing of the site and would have been obliterated by it. With the mixing created by ploughing, both occupations should be reasonably equally represented in surface material where the paleosol is high enough to be encompassed within the ploughed zone. Thus, a reasonable hypothesis is that the depositional history has not made the surface collection unrepresentative of one site component versus another.

A second natural factor impacting site formation is the changes in the river course over time. The initial discovery of the site goes back to the riverbank erosion (see Figure 4-9) just south of the more recent excavations. Thus, to some extent post-occupational changes in the river course have removed portions of the site from any possible consideration. As noted, at the northwest end of the site the distribution of artifacts moves away from the modern day river bank suggesting that at some point in the past the river bank was immediately adjacent to the band of artifacts. The deposits underlying the paleosol/occupation layer itself represent laterally accreted riverbank deposits based on GPR work (Roger Phillips, personal communication to Chris Ellis 2009), suggesting that the river course has consistently moved predominantly west over time. In the 19th century a channelization called "the cut" routed the Ausable River just north of the site directly to Port Franks (Figure 4-6 shows the location of "The Cut"), and most likely deepened the modern river channel adjacent to the site. Prior to this, the river course would have been shallower as it flowed in its "grand bend" to Lake Huron (Stewart et al. 2009) and perhaps more subject to meandering. It is difficult to interpret the dense band of cultural features of a constant width paralleling the linear depression as anything other than an old, and relatively stable river course during much of the course of the Archaic occupations. It is possible that the river bank placement shifted slightly east during the occupation of the site. Alternatively, it may have eroded a portion of the site by moving east slightly for a short period subsequent to the occupation. However, as noted, the consistent width of the anomaly band and the dense artifact finds in the same area suggest such effects were minor. It is also possible that the river bank position actually moved from a position more easterly to the west *during the site occupation*. As will be detailed below, there are substantial numbers of artifacts of both Broad Point and Small Point artifacts in the river bank/anomaly band area, which does suggest, if such a river course shift occurred, it would have to have been in Broad Point times. However, given the number of early Broad Point radiocarbon dates (Figure 4-11) in the excavated southern portion in the band area, a course shift during that occupation seems unlikely. Regardless, while river bank erosion may have removed some minimal portion of the site, what remained further out in the field, as indicated by our current surface collection (Figure 4-12), can be considered to be unaffected by these process. The worst case would be that

any conclusions developed, while being appropriate for the remaining portion of the site, might still be skewed by the removal of the portion along the riverbank.

A third natural site formation process of note is the accumulation of a layer of alluvial silt from flooding along the river bank after the onset of European agricultural processes. Clearly this event has made occupations closer to the modern river inaccessible for surface collection. Beyond this problem, as noted, the layer of silt is deepest closer to the river and thins out moving back from the modern bank. The excavation of the east-west trench, which can be seen in the map in Figure 4-15 running grid east from the primary excavations, was to examine how the silt thickness varied moving back from the river bank. Closer to the river the layer of silt may be close to a metre in depth, but it generally grows thinner moving away from the river bank and was largely absent by the end of the East-West trench, giving a reasonable expectation that only the 10-15 metres closest to the modern river bank would be obscured by this layer of silt. Another way to view the impact of the historic silting process is the yellow area in the magnetic susceptibility study, as shown in Figure 4-14. Similar to the discussion of riverbank erosion, this factor has only made a small portion of the site inaccessible and again, the remaining portion beyond this narrow band should not be impacted.

However, this discussion brings us to another or fourth factor that may impact site surface interpretations. As noted, the east-west trench work and other excavations confirmed that the general trend was for a shallower burial of the old paleosol as one moved back from the river. Yet, it was not a consistent rise in elevation as, at one point, the paleosol completely disappeared into the ploughzone only to reappear, albeit relatively shallowly, at the very base of the ploughzone farther out into the field. Similarly, a series of Oakfield soil probes was taken in a linear array transecting diagonally (e.g. south to north) across the dense gradiometer anomaly band area near the northern end of the site. On both sides of the anomaly band and extending out into its centre, the paleosol was present at the base of the ploughzone but it disappeared in some probe samples in the centre of the band, suggesting it had been completely encompassed in the ploughzone in that area (Ellis 2011a: Table 2). Why the paleosol has been removed in these smaller areas adjacent and apparently paralleling the river is not clear. It is

Figure 4-15: Davidson Site Main Excavations

The Davidson Site Primary Excavations

East-West Trench

N

Legend
◇ 2014 Surface Events
■ Excavations

0 2.75 5.5   11   16.5   22
Meters

Collection to June 2014
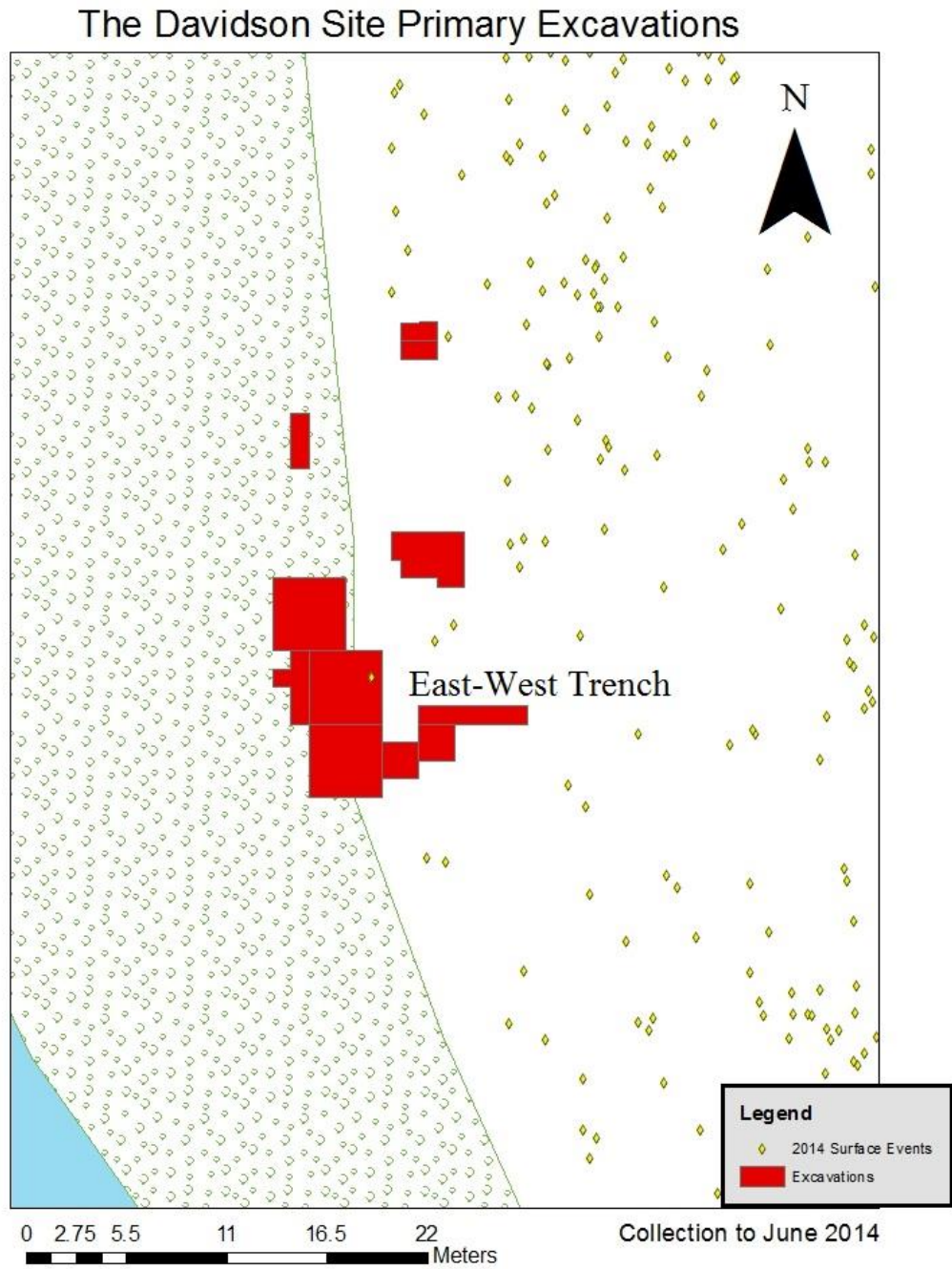
possible that overbank flooding in the past resulted in a slight elevated levee along the river. Later, the European aged floods, while predominantly represented by accumulated deposits, on occasion could have scoured and perhaps leveled out somewhat the paleosol surface and removed these more elevated deposits. Whatever the cause, there is evidence the paleosol has been removed completely in some areas but not others paralleling the old river course. It is notable that in the northern areas the spatial restricted area lacking a paleosol remnant corresponds generally to the restricted area by the "swale-like depression" where Kenyon (1979) reported surface finds on his map in a more restricted area than is evident today. It is plausible therefore, that during the time of Kenyon's 1970s work the paleosol was still largely buried in the northern site areas, only to subsequently become more exposed when subjected to continued deeper ploughing and deflation. This factor has relevance to how surface collections by relic hunters have impacted the site (see below). It has also been suggested that the recent flood events may have scoured away some of the site along the old river bank or eastern swale margin (Joe Desloges, personal communication to Chris Ellis, April 2013). Yet, as argued above, the consistent width of the dense anomaly band suggests these effects were minor.

A fifth impact of note, relates to cultural processes impacting the representativeness of the surface collections, notably the impact caused by artifact collectors over many years. Given the nature of the practice, the primary impact would be with respect to formal artifacts, particularly projectile points and large bifaces, an effect that would be amplified by ploughing, which tends to bring larger artifacts like these tools to the surface (see below). Further, there would be a preference by collectors for complete unbroken artifacts, with broken pieces frequently overlooked perhaps until more recent times. Most of the formal artifacts in our collections from the surface of the site tend to be broken. What is expected from this activity is that the number of formal artifacts in the plough zone would have been significantly depleted. Further, this depletion would have been greater in the areas of greatest concentration and less severe in areas where material is less dense, especially along the east side of the site. The net effect of this would be to reduce the density of formal artifacts in areas of highest concentration, with a much lesser impact on areas to the periphery. The activity continues to this day, as we have found footprints, especially in the spring, representing such activity and these footprints do tend

to stick to the main site area. Thus, analysis of the distribution of formal artifacts is weakened because of the activities of artifact collectors. However, few collectors retain lithic detritus, so any analysis based on this category will be much more representative.

Finally, another modern cultural practice that impacts the representativeness of the surface sample is land clearing and related agricultural practices. Over the last thirty or forty years, changes in agricultural equipment have led to deeper ploughing. Larger tractors can work the ground faster but cause soil compaction, which is typically counteracted with deeper ploughing. The result is that areas once just out of reach of the plough, and housing previously undisturbed archaeological material, are now being impacted. Several times during our surface collecting we encountered ploughed up portions of what, until the most recent planting, had previously been undisturbed features, such as hearths. Another example of this was encountered in 2014 excavations in the cultivated southern part of the site where we found obvious, recent, pristine plough marks cutting down below the former ploughzone and deeply impacting underlying cultural features (Ellis 2015). Thus, as the plough cuts deeper, previously undisturbed archaeological material is being exposed.

Of course, plough disturbance will scatter previously tighter clusters of material and spread them over larger areas with a bias toward movement in the direction of ploughing (e.g. Ellis and Deller 2002). Yet, studies of such effects to date, such as by artifact refits and experiments (e.g. Diez-Martín 2010:35; Odell and Cowan 1987; Roper 1976) indicate that general clustering of materials will still be preserved. They do reveal however, that larger artifacts such as tools do tend to be moved farther than smaller ones such as flaking debris. Also, these studies show larger artifacts are more likely to be exposed on the surface rather than smaller ones (e.g. Diez-Martín 2010; Lewarch and O'Brien 1981; Trubowitz 1978). In any case, one expects the plough is biting deeper due to the combined effects of the use of larger and more powerful agricultural implements along with the continued deflation of the original surface due to wind driven removal of fine sand particles on the exposed field surface. Since the focus here is on the horizontal distribution, the expectation is that while the elevation may be impacted by deflation, the easting and northing should remain reasonably constant or unaffected by this process.

Excavations have indicated considerable mixing of both the Broad Point and Small Point components on the northernmost part of the site, so it is unlikely that deflation would create much more confusion than already exists. In areas where earlier material had been removed by collectors, both the process of deeper ploughing and deflation into the paleosol may actually be increasing the relative density of formal artifacts or even exposing artifacts in some areas for the first time such as the birdstone that we recovered. As previously discussed, at least on the north end of the site, Kenyon's (1979) work indicates that artifacts were much more restricted on the surface with little material noted north of the old east-west fence-line that transected the site at that time, the exception being a small .16 ha area by the old river course (Figure 4-9). If so, this change may indicate that much of the paleosol north of that former fence-line lay buried and materials would not have been accessible to relic hunters until the 1980s or more recently. In contrast, the southern half of the site over the fence-line would have been more intensively collected over a longer period of time. The central unploughed fence-line/ hedge row itself would also have protected that portion of the site until its removal in the 1980s. It would have only been exposed more recently to cultivation and the activities of collectors and we might expect a greater concentration of formal artifacts to be found in the old fence line -- this inference seems to hold (see below).

Overall, in terms of representativeness of the surface collection, it is reasonable to assume that the assemblage of lithic detritus thus far collected is representative of the portion of the site not impacted by river erosion or alluvial deposits, even though it may be more spatially diffuse due to cultivation. In contrast, the distribution of formal artifacts may have been compromised to an unknown extent by the removal of items by artifact collectors, but differentially across the site as a whole due to different periods of accessibility. However, the distribution of formal artifacts that we have recovered, despite removal of many by artifact collectors, should retain some of its structure, providing some insight into the use of the site by the inhabitants.

4.1.2   The Data and Analytical Methods

The data analyzed here were recovered from the surface of the Davidson site, primarily during the eleven CSPs of the site area. There were also a few surface artifacts recovered

that were encountered during the excavations. These CSPs were not a complete surface pick up, since we mapped and retained only what we considered to be formal tools and diagnostic artifacts. Most of the retained flakes are subgreywacke or other coarse-grained metasediments. While non-Broadpoint making people made sparing use of this material, during Broad Point times it was used heavily and it is considered diagnostic of Broad Point Archaic occupations in the area (see discussion below). The count by artifact type of the surface collection is shown in Table 4-1. Some artifacts were eliminated from the analysis, one a spatial outlier and two others, which at the time of this analysis could not be located for the more detailed typological analysis.

Table 4-1: Surface Artifacts by Type

Table 4-1	
Adze	1
Anvil Stone	1
Beak	1
Biface	21
Core	14
Drill	11
Flake	785
MiscTool	17
Piece Esquillee	6
Point	60
Preform	96
Retouched Flake	15
Scraper	15
Shatter	3
Total number of finds	1046

During 2013 and 2014, a refined typological analysis was conducted by Dr. C Ellis to provide a consistent and detailed typology, which was then incorporated into this analysis. Thus the typology was conducted by a single person who is a recognized expert in lithic technology so it is internally consistent and not subject to inter observer error. Fields in the file used for this analysis include the following.

- Catalog Number.
- Location – (North, East) XY coordinates of the surface find.

- Category – Major classification of the artifact type (e.g. flake, projectile point, core etc.). This is a new column that was added to facilitate analysis here. It is a more general classification than the Description field. For example, eight different flake types are collected into the Category "Flake". Other Description types such as Biface, Drill, Point, Preform and Scraper are also summarized. There is one catchall category here labeled "MiscTool". These are formal artifacts which are only represented by one or two instances. This field was added for this analysis as it gives a higher level summation than the "Description" field.

- Description – A more detailed typological classification. For Category "Flake" there are actually eight specific flake types reflecting various stages in the reduction sequence. Similarly, the categories of "point" and "preform" are broken down into various forms. The category "MiscTools" is broken down here.

- Type – These are primarily classic projectile point types (e.g. Crawford Knoll, Genesee, Hind, etc.)

- Cultural Assignment. All artifacts which can safely be assigned to a particular time period. (e.g. Broad Point, Small Point, etc.). For example, subgreywacke flakes, Genesee points and pentagonal preforms are all clearly "Broad Point".

- Raw Material – The raw material used in manufacturing the artifact (e.g. subgreywacke, Kettle Point chert, etc.)

- Segment – Complete or broken artifacts (e.g. for broken artifacts, midsection, distal, proximal, etc.)

The data was analyzed using three separate tools. First, the surface data were imported to the GIS and appropriate tools within ArcGIS were used in the analysis. Second, the tabular data were used as input to various R routines and third, the tabular data were analyzed with Kintigh's Tools for a Quantitative Archaeology (TFQA). Specific tools are mentioned in the relevant sections which follow and are documented above in Chapter 3.

The following analysis proceeds in two parts. The first considers the distribution of the subgreywacke and other flakes on coarse-grained rocks and the second looks at the distribution of the formal artifacts/tools.

4.2   Coarse Flake Distribution Analysis

Broad Point users, especially in southwestern Ontario, used metasediments primarily for projectile point manufacture. For some reason, undoubtedly socially imposed, large projectile points are important during Broad Point times. The only local chert source in southwestern Ontario, other than cobbles in the glacial till, is Kettle Point chert which, while it is high quality, is flawed and prone to fracture into pieces too small to enable production of large projectile points (see Kenyon 1980b). Further east, especially in the Niagara region, Onondaga chert was very suitable, tough and was heavily exploited by Broad Point people with classic, large stemmed Genesee type points (see Ritchie 1971) on that chert being a hallmark of the Late Archaic. In the Fort Erie region there are workshops where Onondaga was mined and hundreds of Genesee points were manufactured (Williamson and MacDonald, 1998). Classic Genesee points made on Onondaga chert occur in southwestern Ontario but not in large numbers, especially in the extreme western part of southern Ontario. The Broad Point people in the area here resorted to metasediments to make up for the short fall because, while more difficult to flake, these materials occur as larger pieces. These peoples knapped considerable numbers of Genesee-like projectile points from this material, a situation which is without parallel in any other time period in the area. Consequently, the coarse-grained flakes in large numbers can be taken as almost certainly diagnostic of the Broad Point Archaic, affording us the chance, not normally available on multi-component sites, of being able to map activity areas from the distributions of flakes on this material.

The approach to surface collection has been to first walk the field systematically with transects spaced at 2m intervals flagging the artifacts as observed. Later, we would go back and record precisely all locations with the Total Station transit. Thus, prior to shooting in the locations, the distribution of all finds that day can be observed looking down the field seeing the patterning of the flags. One of the field observations that we have noted several times during the controlled surface collections at Davidson is the occurrence of what seemed to be several discrete clusters of flaking debris. While there are certainly outliers, in most cases the artifact locations seem to occur in several discrete clusters, particularly on the southern half of the site. This analysis focuses on examining

whether or not these observations are spurious. Are they an artifact of the combination of a human mind that likes to see patterns combined with stochastic variations in the material recovered, or are the observations real and indicative of internal structure to the site? The null hypothesis in this analysis is that there is no measurable patterning in the surface distribution of recovered artifacts and that all indications of such can be accounted for by simple stochastic variation.

4.2.1   Non-Chert Detritus

Since the typological analysis identified Broad Point artifacts, it would be possible to select all such artifacts for the spatial analysis. The inclusion of all Broad Point material would be statistically desirable since it increases the number of artifacts being compared. However, early in the analysis it was found that including the Broad Point bifaces confounded some of the spatial patterns that appeared when the density of only the coarse flakes was examined. One possibility for this may be the activities of the relic hunters who have removed tools and preforms from certain areas of the site. Also, as discussed earlier, larger objects, which are more common on ploughed surfaces, will be moved farther by ploughing and may not match as readily the distribution of smaller items. Lastly, the deposition of coarse flakes by the inhabitants probably was a much simpler process compared to that of the finished projectile points, so dealing with the coarse-grained flakes alone made sense since we would be measuring a similar and more spatially contained process. The final discard of any specific artifact type can vary between relatively simple for a flake resulting from a knapping event to complex for a projectile point. More formal bifacial artifacts can be manufactured, used, broken, resharpened, broken again, and recycled into a secondary use and potentially broken again before final discard, in a number of different locations during the use life. Consequently, the initial spatial analysis was restricted to coarse flakes.

In the typological analysis, four types of non-chert raw material were identified: subgreywacke, quartzite, slate and unidentifiable materials coded as simply "coarse-grained". These flakes were plotted and the distribution is shown in Figure 4-16. The first question examined is which of these materials were actually being used by the Broad Point people? Since we have a number of Broad Point subgreywacke projectile points

and no indication of the use of subgreywacke in other times, subgreywacke flakes undoubtedly relate primarily to that occupation. However, the question of whether or not the other three material types were used exclusively or largely by Broad Point people needs to be examined more closely before including them in the analysis. Examining Figure 4-16 visually, the quartzite flakes, with one exception, occur in a tight cluster at the north end of the site, an area where Small Point materials cluster (see later discussions) and Broadpoints *per se* are not known on that material. The slate flakes also tend to be mostly to the north, but do occur elsewhere, and Broadpoints on this material do occur. The coarse-grained flakes, visually, seem to be similarly distributed with the subgreywacke flakes.

In testing these visual observations, the A-statistic was run comparing relative distribution of each material type compared to the other three material types giving Table 4-2. This table is symmetrical so only the values in the upper right have been highlighted. The table has pairs of columns which represent the actual A-Statistic (A) plus the significance (p).

Table 4-2: A- Statistic on Non Chert Flakes

Table 4-1									
		Coarse		Subgrey		Quartzite		Slate	
	n	A	p	A	p	A	p	A	p
Coarse	49			.99	.25	.61	.04	.96	.20
Subgrey	688	.99	.25			.59	.03	.93	.11
Quartzite	6	.61	.04	.59	.03			.86	.20
Slate	16	.96	.20	.93	.11	.86	.20		

A value of the A-statistic which is close to unity indicates that the two types are randomly intermixed. Thus, we see a value for subgreywacke and coarse-grained flakes of .99 indicating almost identical distribution. Values less than unity indicate segregation and here the one exception that stands out, as it did in the visual examination, is the A-statistic for quartzite flakes as compared to both subgreywacke and coarse-grained. Both

Figure 4-16: Distribution of Non Chert Flakes

Non Chert Flake Distribution

Legend
Slate Flake
Quartzite Flake
Coarse Grained Flake
Subgreywacke Flake
Excavations

Collection to June 2014
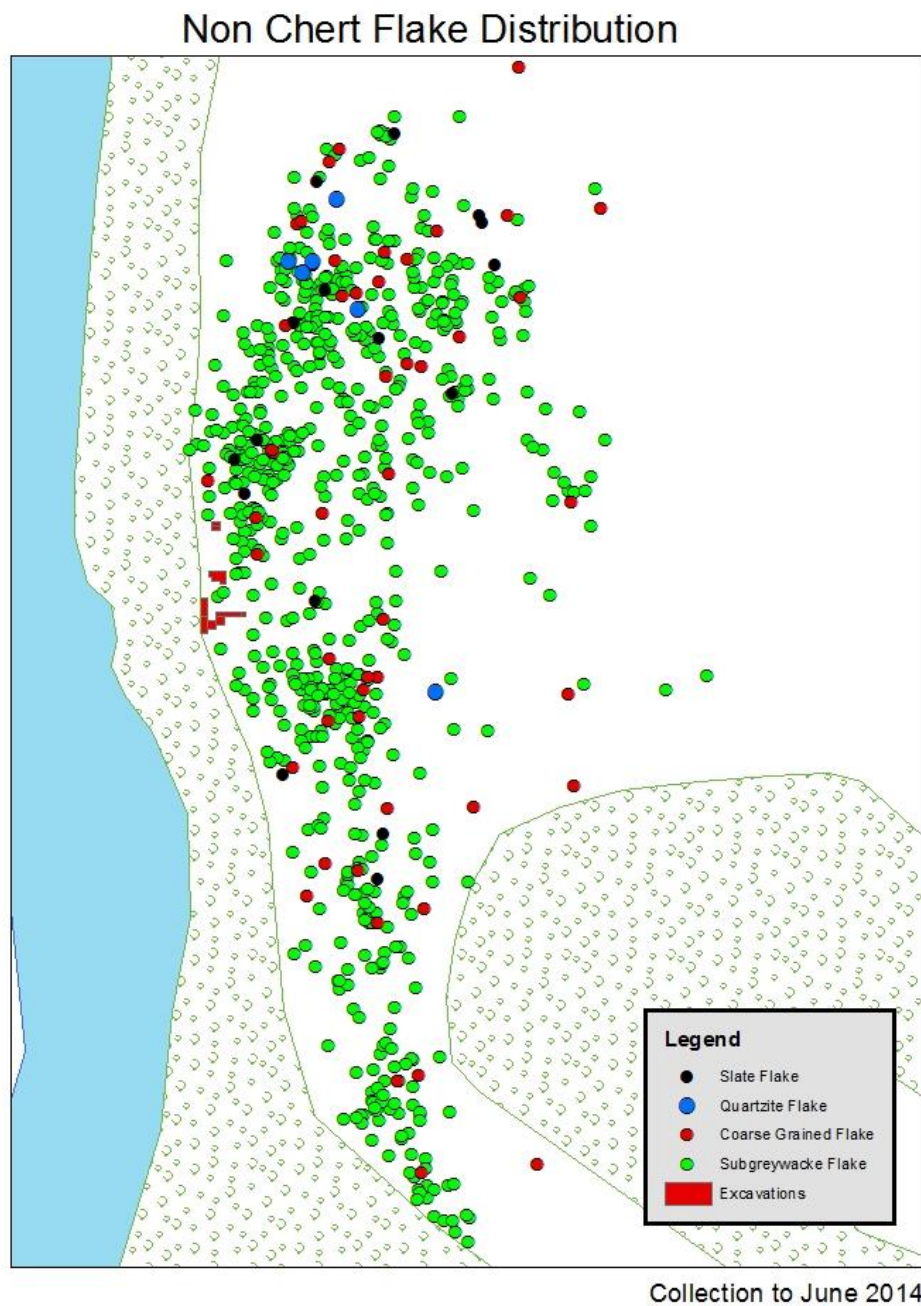
values, .61 for coarse-grained and .59 for subgreywacke, are significant at $p = .04$ and $.03$ respectively. While the A-statistic for slate flakes relative to coarse-grained and subgreywacke also indicates a lesser degree of segregation, the results are not significant although the significance of slate versus subgreywacke approaches significance.

Based on the visual observations and the statistics, coarse-grained flakes will be included with the subgreywacke flakes for the Broad Point site structure analysis. The distribution of quartzite flakes is very restricted and it may represent a single knapping event that could be either Small Point or Broad Point because, as will be detailed later, they cluster in the north end of the site where both components are present. Consequently, that material will not be included. Similarly, while the distribution of slate flakes does not show statistically significant differences in distribution, they have been excluded, since use of slate cannot be restricted to the Broad Point Archaic. Slate was widely used for ground stone tools throughout the Archaic and such tools were roughed into shape initially by flaking. Consequently, the sample for spatial analysis, presumably all Broadpoint associated, includes 688 subgreywacke flakes and 49 coarse-grained flakes. In subsequent discussion the combination of these two raw materials will be referred to as *coarse flakes*.

4.2.2   Coarse Flake Distribution Analysis

The distribution of coarse flakes (i.e. coarse-grained and subgreywacke) is shown in Figure 4-17. Visually, there seems to be three clusters towards the south end of the site and possibly two to the north. In examining the distribution mathematically, four techniques were used. Kernel Density and Pure Locational Clustering are both point pattern techniques, which unfortunately do not give an indication of statistical significance. To establish statistical significance, two other techniques are used, Anselin's local Morin's-I and Getis-Ord Gi*although only the latter is reported since results were similar. As neither of these techniques is applicable to our nominal point pattern data, the distribution is collapsed into counts by quadrats, as can easily be done with ArcGIS. As discussed above, the use of quadrats suffers from a loss of information.

Figure 4-17: Distribution of Coarse Flakes

Davidson Site Subgreywacke/Coarse Grained Clustering

Legend

• Coarse Flakes

▮ Excavations
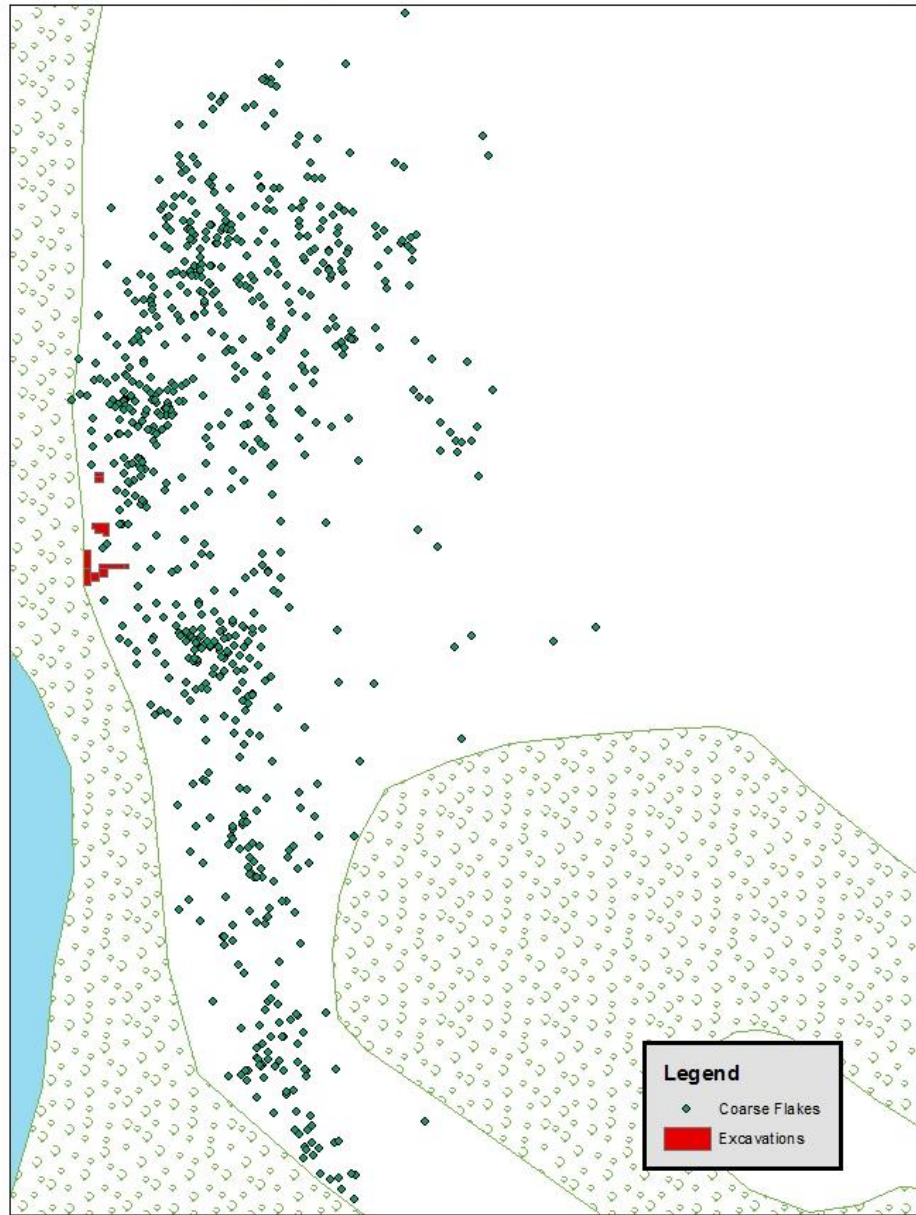
Collection to June 2014

However, this loss is entirely acceptable since it establishes the significance of the pattern found with the point pattern analysis.

One issue which applies to all of these techniques is the issue of *resolution focus* which was discussed in Chapter 2. As was shown, selection of the resolution focus can have a major impact on the results obtained. In running each of the four techniques, multiple scales of analysis were attempted to see how they impacted the results. In executing this analysis, Kernel Density and Pure Location Clustering were run at the same time, comparing the results of both in an iterative process to work out the optimal resolution focus. After this analysis was complete, the analysis shifted to determining the statistical significance of the results using the two quadrat methods.

4.2.3   Kernel Density and Pure Locational Clustering

Both techniques were repeated varying the resolution focus parameter and the results compared. As described in Chapters 2 and 3 above, Kernel Density simply calculates the density of events within a specified radius of each point on a map. This function is simply and most easily calculated using the Kernel Density function found in ArcGIS's Spatial Analyst Tools, which employs a weighted density calculation. In executing this function the resolution focus is selected with the search radius parameter. In order to evaluate the resolution focus, several runs of the function were executed varying the radius over 4, 6, 8, 10, 12, 16, 20 and 50 m and the results compared.

Pure Locational Clustering is a function available in the KMEANS program of TFQA. Since this program is not available as a function within ArcGIS, a file was created with the (X,Y) locations of all the coarse flakes and this file was input into the program. With this program, the resolution focus is selected with a parameter specifying the number of clusters the user wishes to create in the run. The program then divides the set of events into the specified number of clusters. For this analysis the choices evaluated were 7, 9, 10, 15 and 20 clusters. While the program can print a map of the resulting cluster assignment, it is a rather unappealing map as would have been generated 30 years ago with the then current computer technology, so this was bypassed. Instead, in a printed output, the program lists the centre of each cluster and the RMS value. The centres can be

easily imported into ArcGIS with the AddXY function. The RMS values were drawn as a radius around the appropriate cluster centre.

In comparing these two techniques, it was immediately obvious that the larger scales of analysis, such as were discussed and illustrated in Chapter 2, provided no useful information other than the approximate boundaries of the site as a whole. Also, it was noted that, when properly matched, variations in the resolution focus with the two techniques tended to give comparable results. Medium-grained scales compared well, as did the finer-grained scales. In considering which of these scales to accept it was evident that it was not necessary to choose between a medium-grained scale and a fine-grained scale. In fact, both of these results were valid and showed different aspects of the site structure.

Figure 4-18 shows both Kernel Density at 12 m and Pure Locational Clustering with 9 clusters. Densities in the .054 to .081 range are coloured yellow to better outline the clusters. The centres of the clusters derived from Pure Locational Clustering are shown as large red dots with the RMS values shown as a radius around seven of them. Two of the clusters do not have the RMS radius drawn around them as both of these are small outlier clusters. Also evident is their concordance with the Kernel Density areas of concentration.

What these two analyses show is a series of equally sized equally spaced clusters of coarse flakes paralleling the river bank. There are five definite clusters adjacent to the river. These clusters are all approximately 35 m across and equidistant from each other at approximately 50 m (centre to centre). The clusters do not all have the same density. The two southern clusters have less material than the three to the north along the river. There is also another cluster at the northeast corner, which is also less dense than the three northern riverside clusters. A seventh potential cluster occurs to the southeast when looking at the four northern clusters. This cluster was visually more apparent in an earlier analysis (Keron 2012) but in this analysis with additional data, it is relatively weak. With the data now available, I do not believe that this identified cluster is

Figure 4-18: Coarse Flakes - Medium Resolution Focus
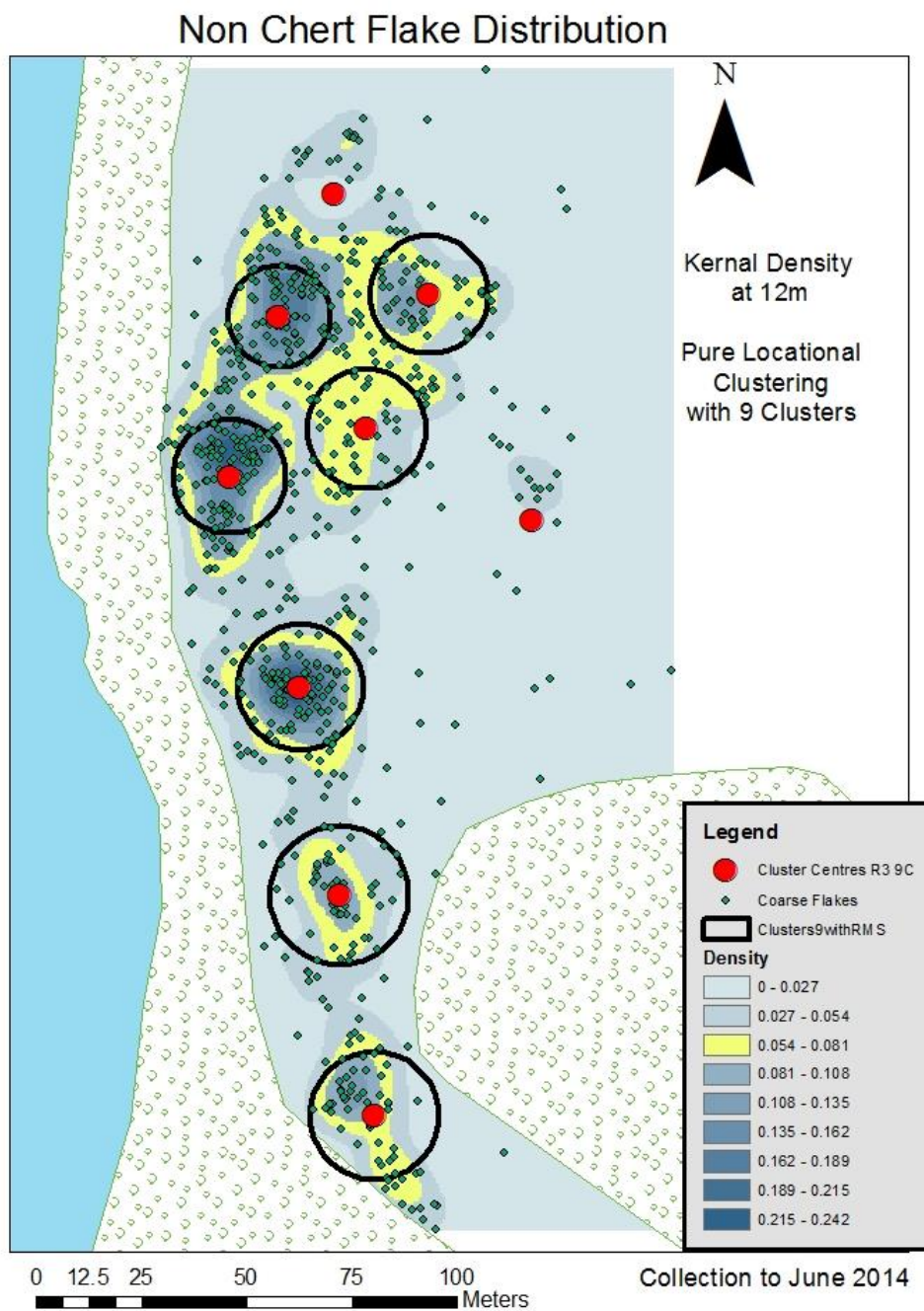
comparable to the others and it likely represents a different kind of activity. Regardless, this analysis confirms the field observations suggesting several clusters are present.

The resolution focus selected for the analysis requires some explanation. Foremost is that it shows a site structure where the clusters are spaced with regularity along the river. As noted, the four southern clusters are almost exactly 50 m apart and are all of approximately the same size. This spacing and similar size suggest a clearly planned human occupation. It suggests the site is not simply a palimpsest of varying occupations over the years where a group came back to the same general site location on a seasonal basis. That kind of organization would result in a much more random pattern. Second, it cleanly divides the site into a series of clusters which are of an appropriate size if each cluster represents a small group campsite. A circular site with a 35 m diameter provides a reasonable amount of space for a small socially distinct group of people.

Figure 4-19 shows a fine resolution focus of the site with the Kernel Density radius set to 6 m and Pure Locational Clustering set to 20 clusters. This resolution focus divides the site into more and smaller clusters, although it is concordant with the same general pattern as seen in Figure 4-18. Again, one of the Kernel Density contour bands had been coloured yellow to better define the clusters. For the run of Pure Locational Clustering only the centres of the clusters are shown. RMS values are not shown. On initial examination it looked like a different clustering pattern but, upon reflection, this resolution focus shows repeating structure within each of the major clusters from the medium resolution focus. Each of the earlier clusters breaks down into two sub-clusters with a thicker cluster to the north and a less dense cluster to the south or southeast. All six of the definite clusters from the medium resolution focus show this pattern. Notably, the extension or less dense cluster is not in the direction of ploughing of these areas (some were ploughed north to south, others east to west, etc.) nor is it in two directions from the cluster, both of which we would expect if ploughing was involved in influencing these distributions. The only cluster not showing this pattern is the problematic seventh one (southeast cluster of the northern four). This fine-grained analysis identifies a further level of site organization which was not evident looking at the pattern of subgreywacke flakes on the site. Each cluster identified with the medium resolution focus has a

consistent structure within it which, along with the similar size and equal spacing, suggests each had a similar function or saw very similar activities.

Figure 4-19: Coarse Flakes – Fine Resolution Focus
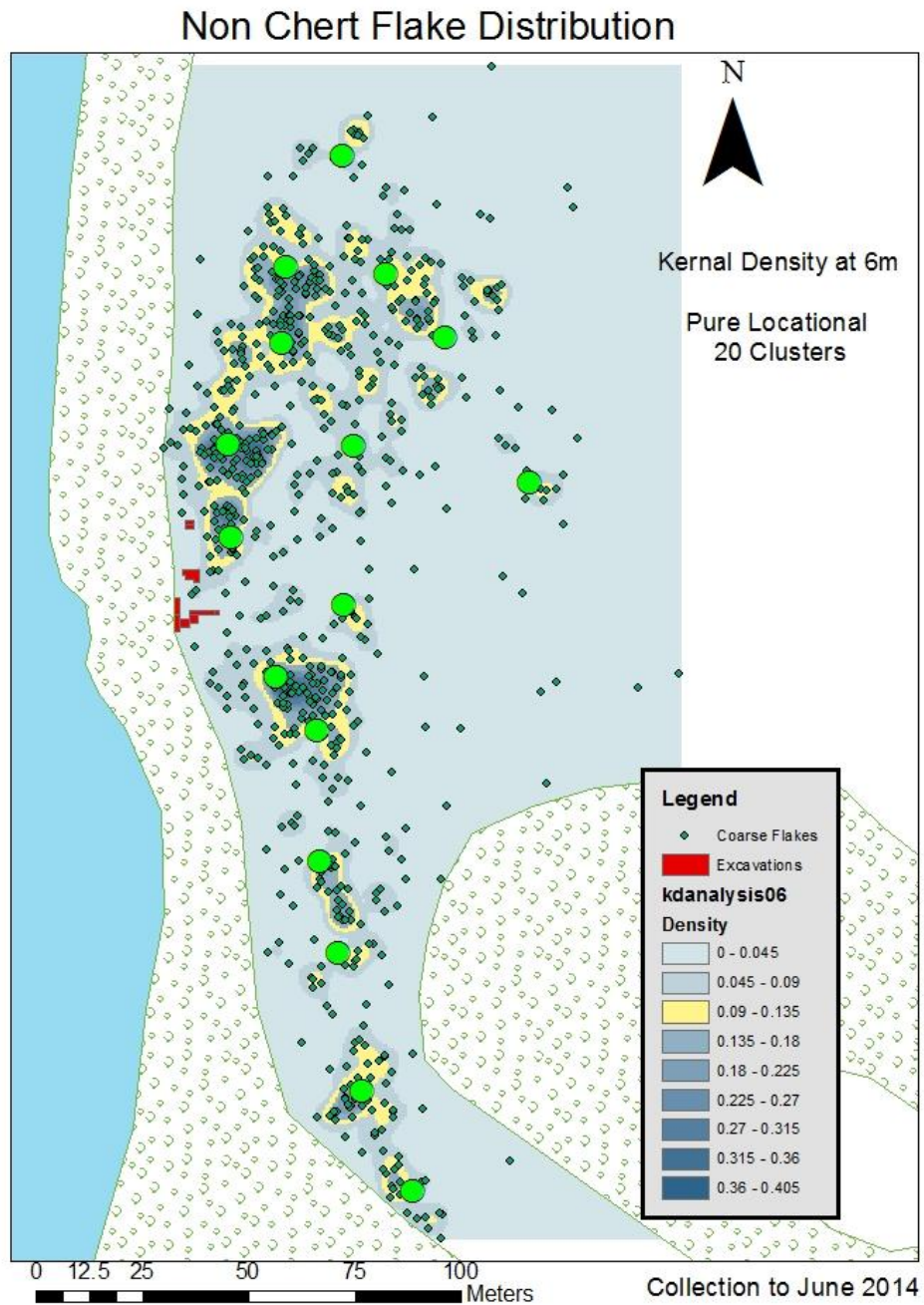
4.3   Statistical Significance

The preceding spatial analysis is relatively clear but needs further statistical refinement. To provide this, testing and tests of significance were performed using ArcGIS. ArcGIS has several powerful spatial statistics such as Anselins Local Morans-I (Cluster and Outlier Analysis) and Getis-Ord Gi* (Hot Spot Analysis). The problem however, is that these techniques require ratio or interval data to be applied and the point pattern from Davidson site is clearly nominal. Thus, to apply these techniques the data must be converted from nominal to ratio. To accomplish this analysis, a series of quadrats of various sizes was generated with ArcGIS using the fishnet function and the number of coarse flakes counted in each quadrat, in effect transforming the data from nominal to ratio. With this analysis the resolution focus must also be considered and is determined by the selection of quadrat size. As with the above analysis, the resolution focus is best determined by running the analysis with varying sized quadrats and comparing the results both with each other and the previous analysis. Both Anselin's Local Morans-I and Getis-OrdGi* were run, but only the latter is reported here as the results were largely identical. In evaluating the resolution focus it was found that the 5m Fishnet gave results similar to our medium-grained resolution focus above (Figure 4-20) and the 3 m Fishnet more closely matched the finer-grained resolution focus (Figure 4-21). Both of these analyses support the conclusions reached above for the two scales of resolution. The other factor that needs to be considered when using quadrat methods is the chance that the MAUP might be impacting results. For these two analyses this impact is not likely the case, given the scale of the units relative to both the site size and the size of the clusters being examined. Shifting the origin (0,0) of the units by a few metres in any direction would give very similar results. However, condensing the data into quadrats creates is a loss of detail. A comparison of Figures 4.17 with Figures 4.20 and 4.21 illustrates this. However, the advantage gained is that the clusters are clearly statistically significant at both scales of resolution. Also, note that the significance is established using CSR, which is appropriate given that this is an analysis of first order effect. Clearly our null hypothesis can be rejected. Spatially discrete Broad Point Archaic flake clusters exist and each has a similar internal structure.

Figure 4-20: Coarse Flakes – Getis-Ord Gi* on 5 m Fishnet

Getis-Ord - 5m Fishnet - Coarse Grain

Legend

Excavations

Clusters9withRMS

HotSpotCoarse05

Gi_Bin

Cold Spot - 99% Confidence

Cold Spot - 95% Confidence

Cold Spot - 90% Confidence

Not Significant

Hot Spot - 90% Confidence

Hot Spot - 95% Confidence

Hot Spot - 99% Confidence

0 12.5 25   50   75   100

Meters

Collection to June 2014
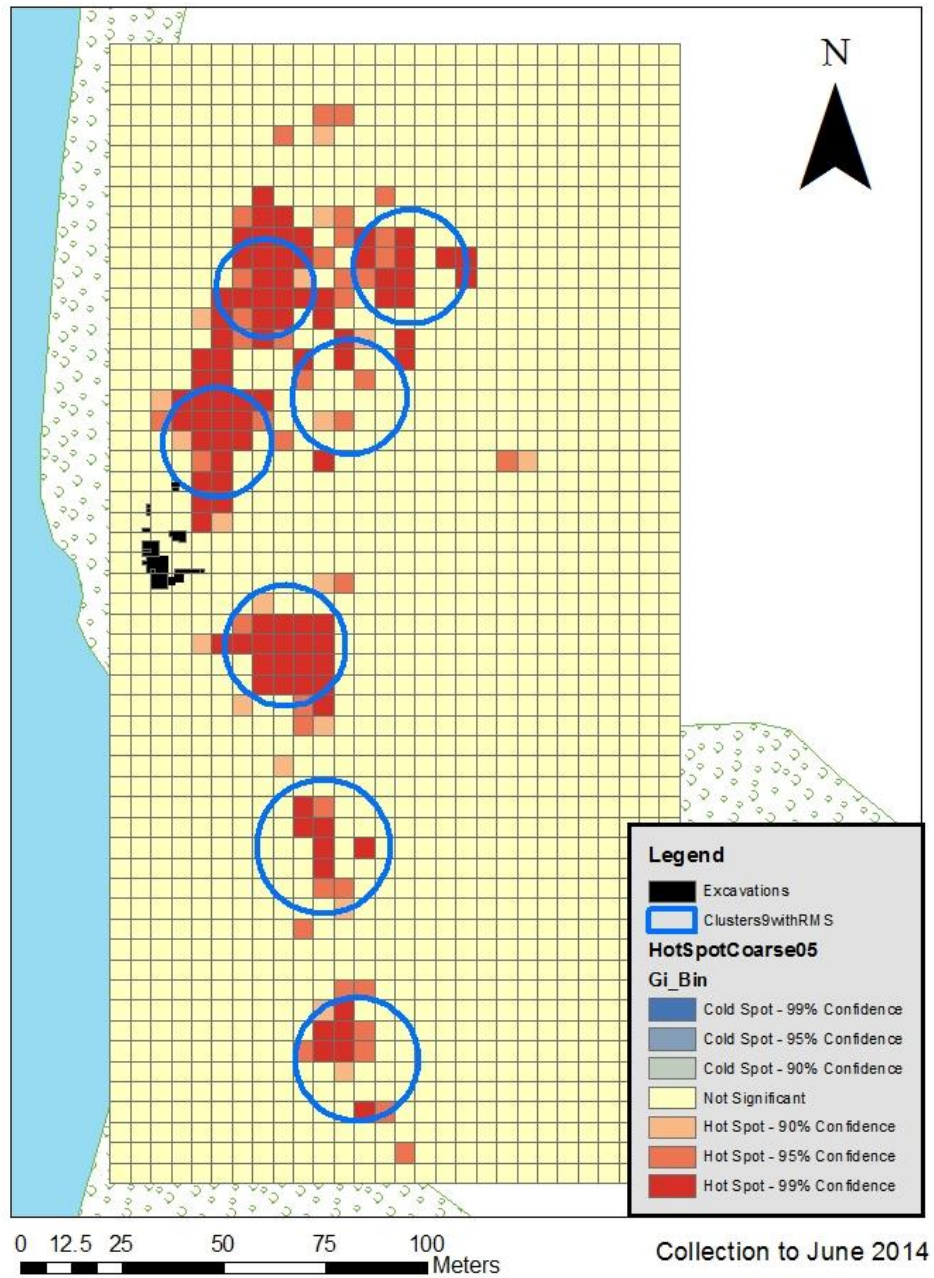
Figure 4-21: Coarse Flakes - Getis-Ord Gi* on 3 m Fishnet

Getis-Ord - 3m Fishnet - Coarse Grain

Legend

- Excavations
- Clusters9withRMS

HotSpotCoarse03

Gi_Bin

- Cold Spot - 99% Confidence
- Cold Spot - 95% Confidence
- Cold Spot - 90% Confidence
- Not Significant
- Hot Spot - 90% Confidence
- Hot Spot - 95% Confidence
- Hot Spot - 99% Confidence

0   12.5   25   50   75   100
Meters

Collection to June 2014
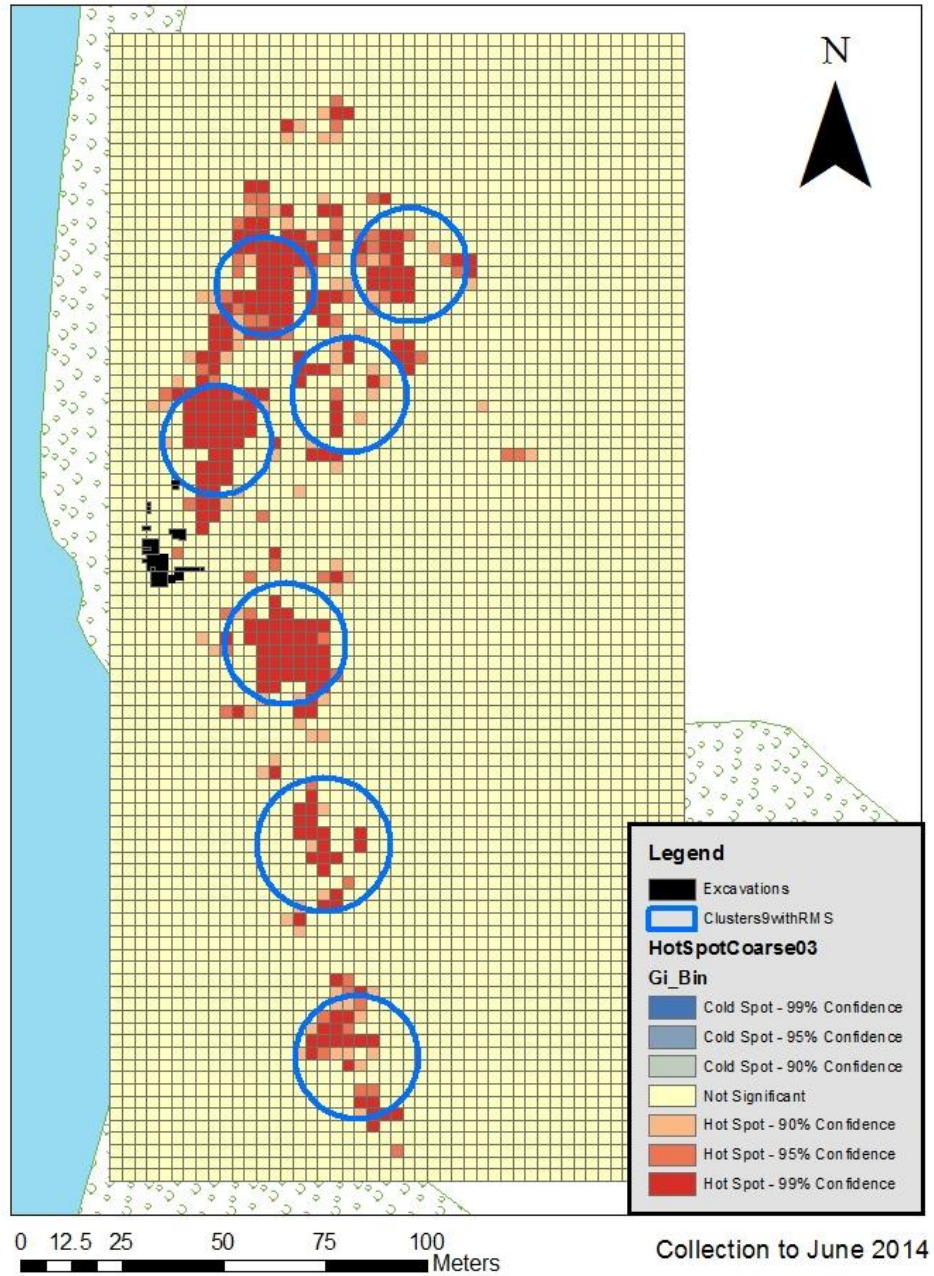
4.4   Clusters and the Reduction Sequence

The next analytical stage is to examine these clusters more closely looking for other internal patterns. To accomplish this end it is germane to clarify terminology using the word "cluster". The term "spatial cluster" will be used to refer to those clusters identified in the preceding analysis (i.e., the 35 m diameter clusters spaced along the river). The term "activity cluster" refers to areas of the site with similar ratios of flake types as identified by the following analysis. These activity clusters are presumably areas of the site where similar activities occurred. They are synonymous with the term "activity area," which was the major focus of spatial statistics in archaeology 30 years ago. Thus, each spatial cluster could conceivably have similar activity clusters within it where similar activities took place. If the hypothesis that the spatial clusters represent encampments by similar groups of people is true, then we would expect a similar range of activities to occur at each spatial cluster.

With the more detailed typological analysis of the artifacts, all flakes have been classified by a series of flake types which relate to the reduction sequence. The flake types are described in Table 4-3.

Table 4-3: Flake Typology

Reduction Sequence	Type	Striking Platform	Description
1	Primary Reduction Flake	90 deg	Dorsal surface all original cobble surface
2	Secondary Reduction Flake	90 deg	Dorsal surface part original cobble surface
3	Tertiary Reduction Flake	90 deg	Dorsal surface all flake scars
4	Biface Thinning Flake	acute	Early to middle stage flake removed to thin a biface
5	Biface Reduction Flake	acute	Small flake, earlier stage biface trimming or final edge finishing
6	Biface Reduction Error Flake	acute	Biface edge simply collapsed when struck during thinning attempts
?	Unknown Flake Fragment	missing	Distal or midsection fragment

An eighth type identified was an overshot flake but this has been dropped, as there was only one occurrence in the surface collection. The primary and secondary reduction flakes retain cortex surfaces of the original material pieces, so represent largely earlier stages of manufacture while all the other types lack these surfaces entirely and so represent predominantly later stages of reduction. Amongst these other types, some can be definitely said to be from biface/point preform reduction (reduction sequence 4 through 6). The biface thinning flakes are larger, often expanding and wider items that were removed to thin the biface by removing a large surface area, whereas the reduction flakes are smaller examples removed in trimming a biface or shaping edge outline so may represent to some later stages of reduction than the thinning flakes. Biface reduction flakes are smaller and represent the finishing stage of biface reduction. Biface Reduction Error Flakes are a type which occurs with coarse-grained flaking when, in the course of flaking a biface, the striking platform collapses leaving a semicircular bite on the edge of the biface. The flake is little more than the striking platform itself rather than a longer biface reduction flake. These could occur at a stage in the reduction sequence where either early or later stage bifaces are being produced. Unknown Flake Fragments are the distal or central portions of a flake that collapsed during removal or broke due to ploughing. The striking platform is missing. These may happen more frequently with biface thinning, but could also result during tertiary reduction of cores. As such, this category is problematic as far as the reduction sequence goes. Given that there are no formal tools from the site on coarse-grained stone other than bifaces, the various activity areas derived should be reflective of various reduction stages, starting with an unflaked cobble through to resharpening bifaces in the course of use.

This next part of the analysis focuses on whether or not these flake types are randomly distributed across the various clusters. Here the null hypothesis is that all flake types are randomly distributed across the spatial clusters. Or, phrased differently, all the spatial clusters have a similar composition with respect to the stone reduction sequence.

Examining the plot of the flake types indicates that most seem to be evenly distributed over the various clusters, but the actual patterns may be too complex for simple visualization to be effective (see Figure 4-22). What Figure 4-22 does rule out is the

possibility that the clusters are various stages in a very structured manufacturing process where primary reduction takes place in one spatial cluster and the results are passed along to the next spatial cluster for further refinement in a manufacturing process geared towards creating finished projectile points.

In order to look more closely than a simple visual plot, three forms of analysis will be conducted. First, a G-test is computed comparing the relative frequencies of flake types by spatial cluster. Second, the A-statistic is calculated comparing all the various flake types. Finally, Unconstrained Clustering is run searching for similar activity areas across the site.

The first analysis separates the flake types by spatial cluster and then applies classical (non-spatial) statistics to determine if the counts of flake types are similar across the clusters. In conducting Pure Locational Clustering each flake was assigned to one and only one cluster. This cluster assignment into one of nine requested clusters was listed as one of the outputs of the program. The cluster assignment was then matched back to the original data file, which was then imported into the GIS. The results can be seen in Figure 4-23. The assigned cluster numbers unfortunately do not reflect a simple sequence from south to north or vice versa, so there is no clear sequence in cluster numbers spatially. Pure Locational Clustering assigns every flake to a cluster, which works nicely for the six or seven main clusters. However, clusters 8 and 9 are best considered problematic. Visually some of the flakes assigned to Cluster 9 should more likely belong to Clusters 3 and 4 with the others being outliers. For Cluster 8 these are best considered as outliers, although there may be a very small cluster at the north side of cluster 8. Similarly there could be another small cluster at the north side of Cluster 9.

Figure 4-22: Coarse Flakes by Type

Coarse Flakes By Flake Type

N

Legend

Primary Reduction Flake
Secondary Reduction Flake
Tertiary Reduction Flake
Biface Reduction Flake
Biface Reduction Error Flake
Biface Thinning Flakes
Unknown Flake Fragment
Clusters9withRMS
Excavations

0   12.5   25   50   75   100

Meters

Collection to June 2014
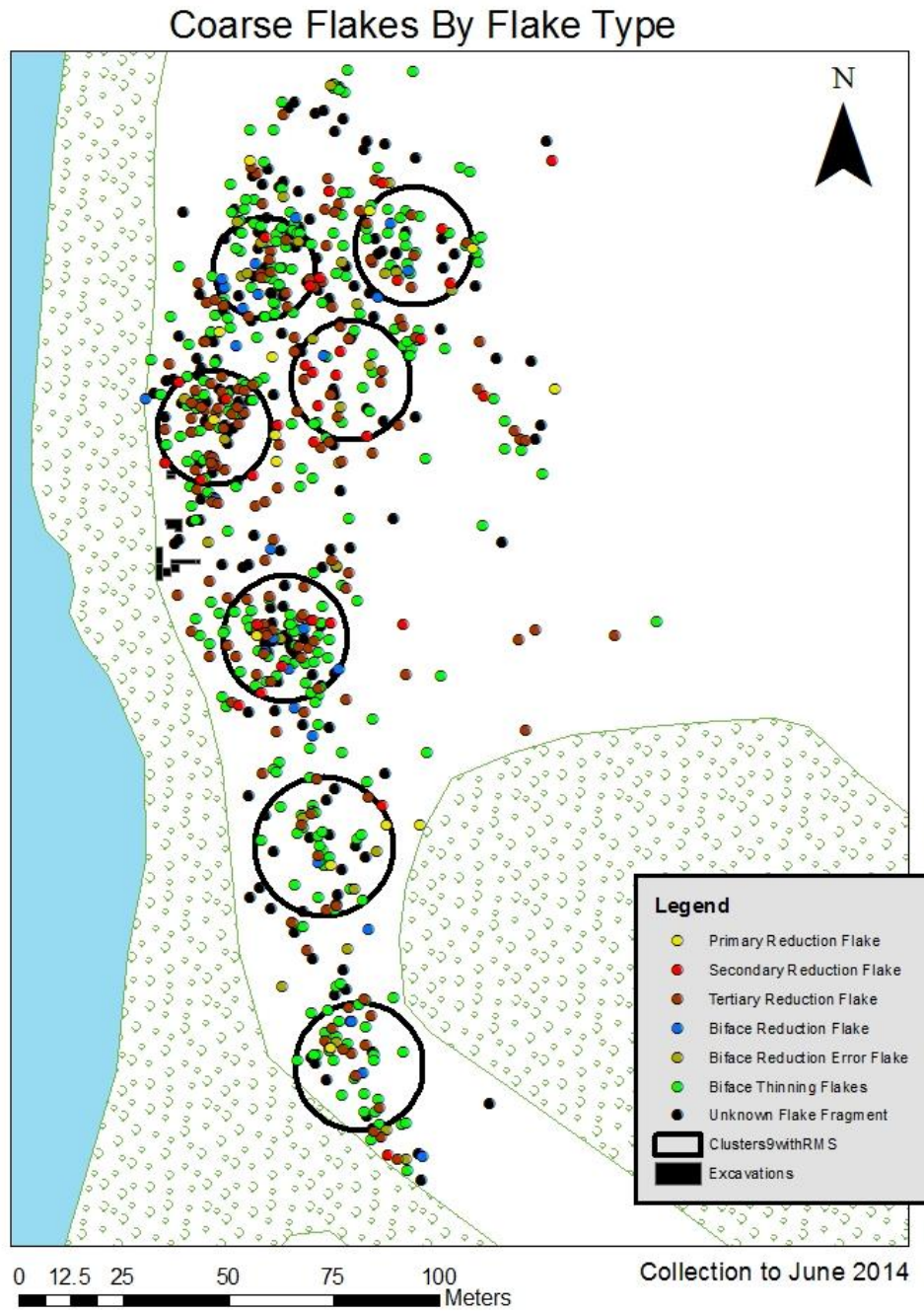
Figure 4-23: Coarse Flakes by Spatial Cluster

Coarse Flakes By Spatial Cluster

Legend
- ▲ Cluster 9
- ◆ Cluster 8
- ● Cluster 7
- ● Cluster 6
- ● Cluster 5
- ● Cluster 4
- ● Cluster 3
- ● Cluster 2
- ● Cluster 1
- ⬭ Clusters9withRMS
- ■ Excavations

0   12.5   25   50   75   100
Meters

Collection to June 2014
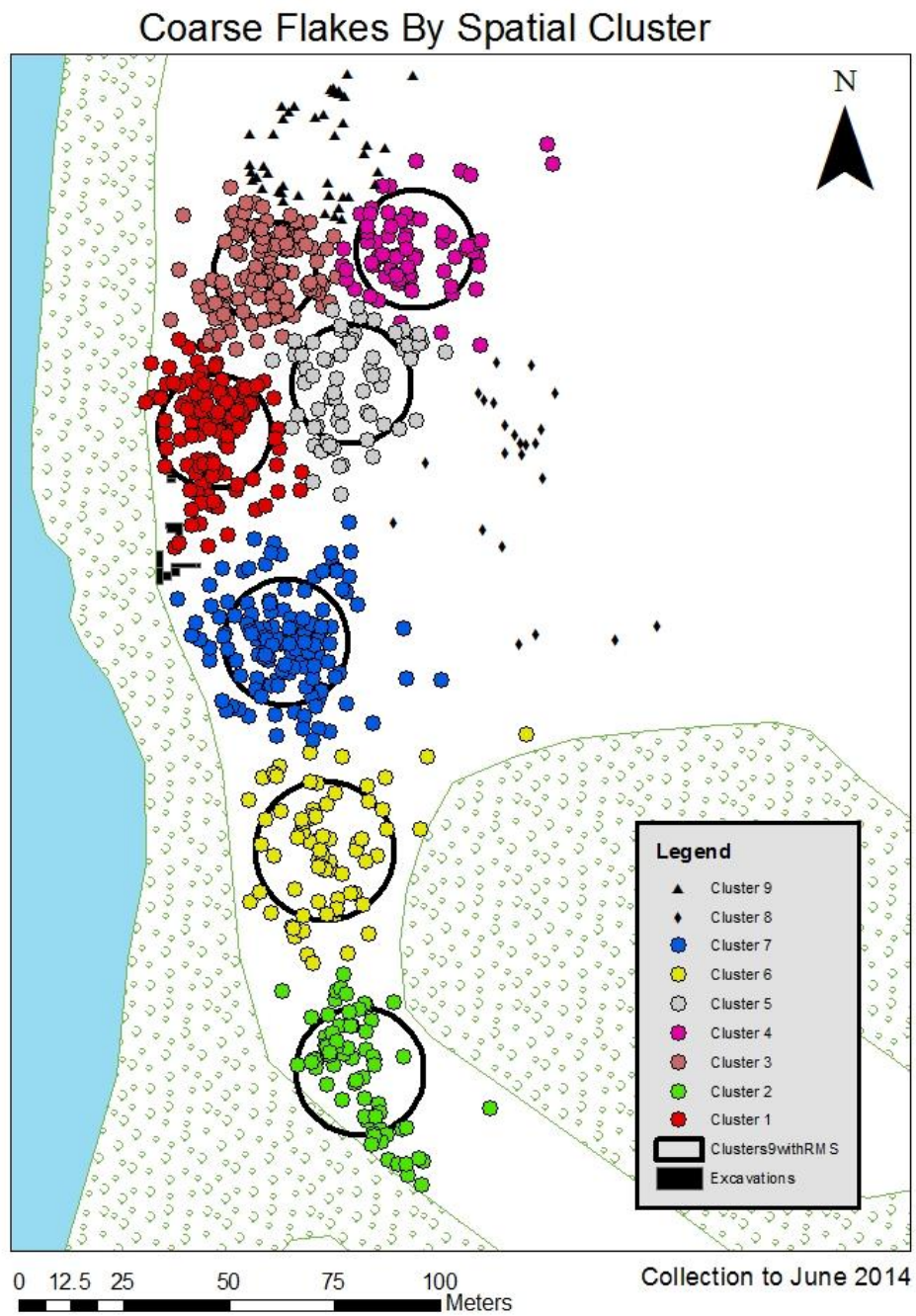
The total flakes types by cluster are shown in Table 4-4.

Table 4-4: Flake Types by Spatial Cluster

Table 4-4										
	Cluster									
Flake Type	1	2	3	4	5	6	7	8	9	Total
Primary Reduction Flake	3	1	1	2	1	3	1	1	1	14
Secondary Reduction Flake	6	1	3	5	8	1	7	1	1	33
Tertiary Reduction Flake	38	14	18	10	18	11	36	7	9	161
Biface Reduction Error Flake	5	4	5	6	5	4	2	0	3	34
Biface Reduction Flake	3	3	7	3	1	2	8	0	0	27
Biface Thinning Flake	46	32	48	26	21	32	53	8	15	281
Unknown Flake Fragment	34	13	34	16	13	20	34	6	16	186
Totals	135	68	116	68	67	73	141	23	45	736

A G-test, run using Table 4-3, was not significant ($G = 57.24$, $p = .17$, $d.f. = 48$) suggesting that there are no differences between the clusters and the null hypothesis cannot be rejected.

The second form of analysis of the distribution of flake types compares the distribution of each pair of flake types using the A-statistic to determine if any segregation occurs between different flake types. This analysis ignores the arrangement of spatial clusters. Table 4-5 shows all the pairs of flake types and the associated A-Statistic and the probabilities of each. Note that this table is symmetric along the diagonal.

The various A-statistics range from .93 to 1.06 indicating non statistically significant segregation. Only one comparison, secondary retouch flakes compared to biface thinning flakes, highlighted in Table 4-5, is significant at $p = .028$, but the $A = .93$, which indicates only weak segregation. Of course, with 21 pairs of comparisons, a significant finding can occur stochastically. This difference between biface thinning and secondary core reduction should be more closely examined. Consequently, several more runs of the A-Statistic were conducted.

Table 4-5: A-statistic Coarse Flakes by Type

Table 4-5		Biface Reduction Error Flake	Biface Reduction Flake	Biface Thinning Flake	Primary Reduction Flake	Secondary Reduction Flake	Tertiary Reduction Flake	Unknown Flake Fragment
A- Statistic	N							
Biface Reduction Error Flake	34		1	1	1.06	.97	.97	1.01
Biface Reduction Flake	27	1		1.03	1.06	.93	1.02	1.01
Biface Thinning Flake	281	1	1.03		1.05	.93	.99	.99
Primary Reduction Flake	14	1.06	1.06	1.05		1	1.04	1.04
Secondary Reduction Flake	33	.97	.93	.93	1		.97	.97
Tertiary Reduction Flake	161	.97	1.02	.99	1.04	.97		.99
Unknown Flake Fragment	186	1.01	1.01	.99	1.04	.97	.99	
Probabilities								
Biface Reduction Error Flake			.38	.38	.84	.19	.15	.65
Biface Reduction Flake		.38		.92	.84	.11	.68	.5
Biface Thinning Flake		.38	.92		.96	.03	.15	.18
Primary Reduction Flake		.84	.84	.96		.37	.81	.83
Secondary Reduction Flake		.19	.11	.03	.37		.13	.13
Tertiary Reduction Flake		.15	.68	.15	.81	.13		.18
Unknown Flake Fragment		.65	.5	.18	.83	.13	.18	

The distribution of the secondary reduction flakes was compared to the distribution of all other coarse flakes. The results were $A = .96$, $p = .061$. While this is approaching significance, a value of A at .96 indicates only very marginal segregation.

The distribution of primary reduction flakes and secondary reduction flakes was compared to the location of all other coarse flakes. The results were $A = .99$, $p = .19$. The

first two stages of core reduction are virtually identical to the distribution of the rest of the coarse flakes.

Finally, the distribution of secondary reduction flakes was compared to the distribution of tertiary reduction flakes. The results were $A = .99$, $p = .32$ indicating random mixing of the types.

With these results, the null hypothesis is accepted.

4.4.1 Unconstrained Clustering of the Flake Types

Unconstrained Clustering (See Chapters 2 and 3 for more details) is a technique that was developed for determining activity areas within a scatter of different artifact types, each with its own (x,y) coordinates (Whallon 1984). The technique determines zones in the site which have similar proportions of artifact types. These zones can then be interpreted as activity areas and the term activity cluster will be used here when referencing these zones. Each point in the input set is assigned to one of these zones. While the analysis effectively maps zones with similar ratios, the results are typically mapped and reported by flagging each artifact location with the cluster number to which it has been assigned. This assignment creates a map which reflects the total artifact distribution over the site, but the label value reflects the activity cluster number to which it was assigned.

With a well-defined flake typology, the coarse flakes at Davidson make an ideal candidate for Unconstrained Clustering. While the preceding analysis has indicated that the flake composition of the seven spatial clusters is identical, Unconstrained Clustering provides a means to investigate smaller variations within each cluster. For example, is core reduction done in one area and biface reduction done in a different area within the spatial clusters? Obviously Unconstrained Clustering works best in a single occupation, short duration site where activity areas are discrete. Interpretation becomes more complex with multi component sites or when activity areas overlap. For example, two different overlapping activity clusters could resolve to three activity areas with Unconstrained Clustering, with the area of overlap resolving to a third activity area. With Davidson, while we can clearly attribute most of the coarse flakes to the Broad Point period, they

almost certainly represent a palimpsest through time. Nonetheless, given the persistent structuring of the spatial clusters that persists through the Broad Point occupation, it seems worthwhile running Unconstrained Clustering looking for patterning inside the spatial clusters and over the entire site.

For Unconstrained Clustering the entire set of coarse flakes used in the preceding analysis was used. The set of flake types used is considered to be reflective of the reduction sequence described above in Table 4-3.

TFQA (LDEN and KMEANS) was used to conduct the analysis. As described in Chapter 3 above, there are two key parameters that impact the results. The first is the maximum number of clusters. In the all test cases 15 proved to be a good choice, with all executed runs showing a flat %SSE at around 10 clusters. The other input parameter is the local density radius, which significantly impacts the resolution focus obtained. The first problem presented was that, with 736 flakes, the plot of the activity clusters using TFQA's KMPLT was largely illegible since it plots a number indicating to which activity cluster an event was assigned. With the limited scale available in TFQA KMPLT, most of the denser areas of the site had so many points that the numbers overlaid each other to an extent which completely obscured the numbers and prevented interpretation. Keith Kintigh (personal communication 2015) pointed out that the contents of the plot file are easy to use. Examining this file, it proved to be very easy to copy and paste the results to a spreadsheet, which could then easily be plotted with ArcGIS for visualization. Runs of Unconstrained Clustering were executed with local density radii of 2.5 m, 5 m, 10 m and 20 m. All of these were examined considering the resolution focus. Both the 10 m and 20 m radius proved to be much too large, as it essentially included everything in each of the seven spatial clusters, with the result that activity clusters included the whole spatial cluster and each spatial cluster/ activity cluster was distinguished by subtle differences in the frequency of the flake types in each cluster. The 2.5 m radius proved too small, with the activity clusters proving to be overly jumbled and too influenced by a very few points located nearby. The 5 m local density radius seemed optimal, with some well-defined activity clusters emerging that seem reasonably consistent over the entire site.

The following analysis was done with a local density radius of 5 m and 15 clusters requested. Since the %SSE was essentially flat at 10 clusters (Figure 4-24) and plots of 15 clusters resulted in a number of very small activity clusters with fewer than 10 events, the following analysis is based on 10 clusters. Even here, three of the activity clusters are very small with 3, 7 and 13 points respectively. Figure 4-25 shows the plot of activity clusters assigned with this setting. Once this configuration was selected, the UCC output was joined back to the catalog and the total number of occurrences of each flake type was calculated, giving Table 4-6. Table 4-7 converts these data into percentages. Table 4-7 is critical to the following discussion.

Figure 4-24: SSE Plot LDEN = 5 m
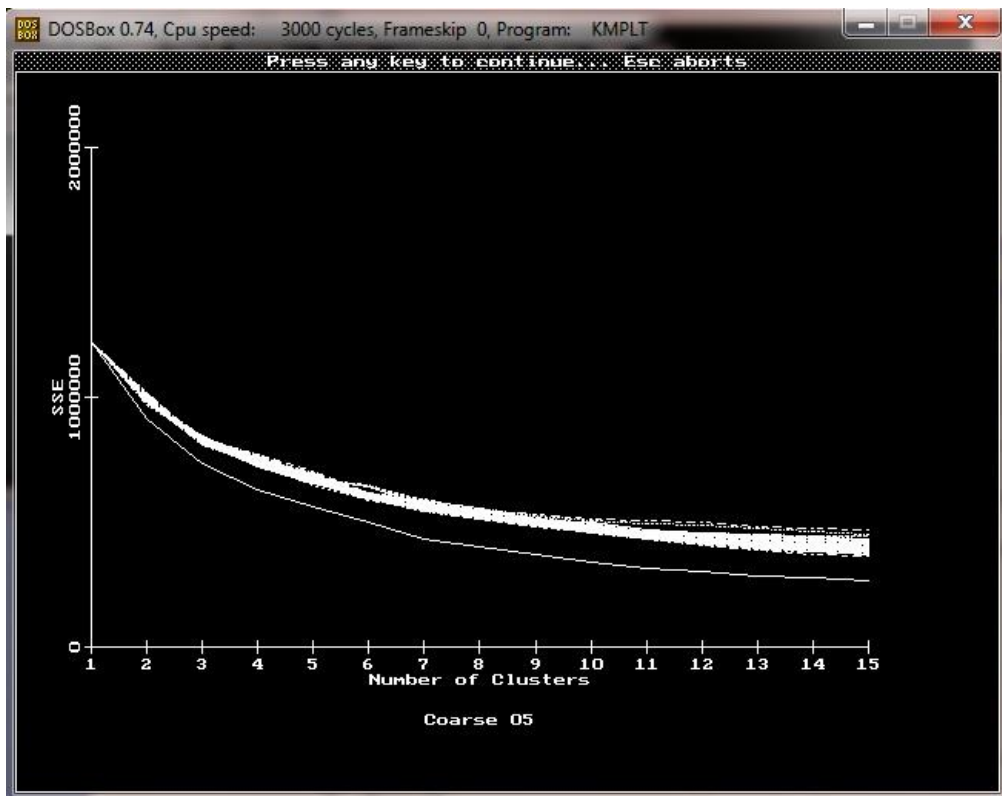
Figure 4-25: Unconstrained Clustering of Coarse Flake Types

Unconstrained Clustering of Coarse Flake Types

Local Density 5m

Display 10 Clusters

N

Legend

- UCC Cluster 1 (67)
- UCC Cluster 2 (27)
- UCC Cluster 3 (144)
- UCC Cluster 4 (173)
- UCC Cluster 5 (154)
- UCC Cluster 6 (47)
- UCC Cluster 7 (6)
- UCC Cluster 8 (3)
- UCC Cluster 9 (13)
- UCC Cluster 10 (103)
- Spatial Clusters RMS

0 12.5 25   50   75   100
Meters

Collection to June 2014
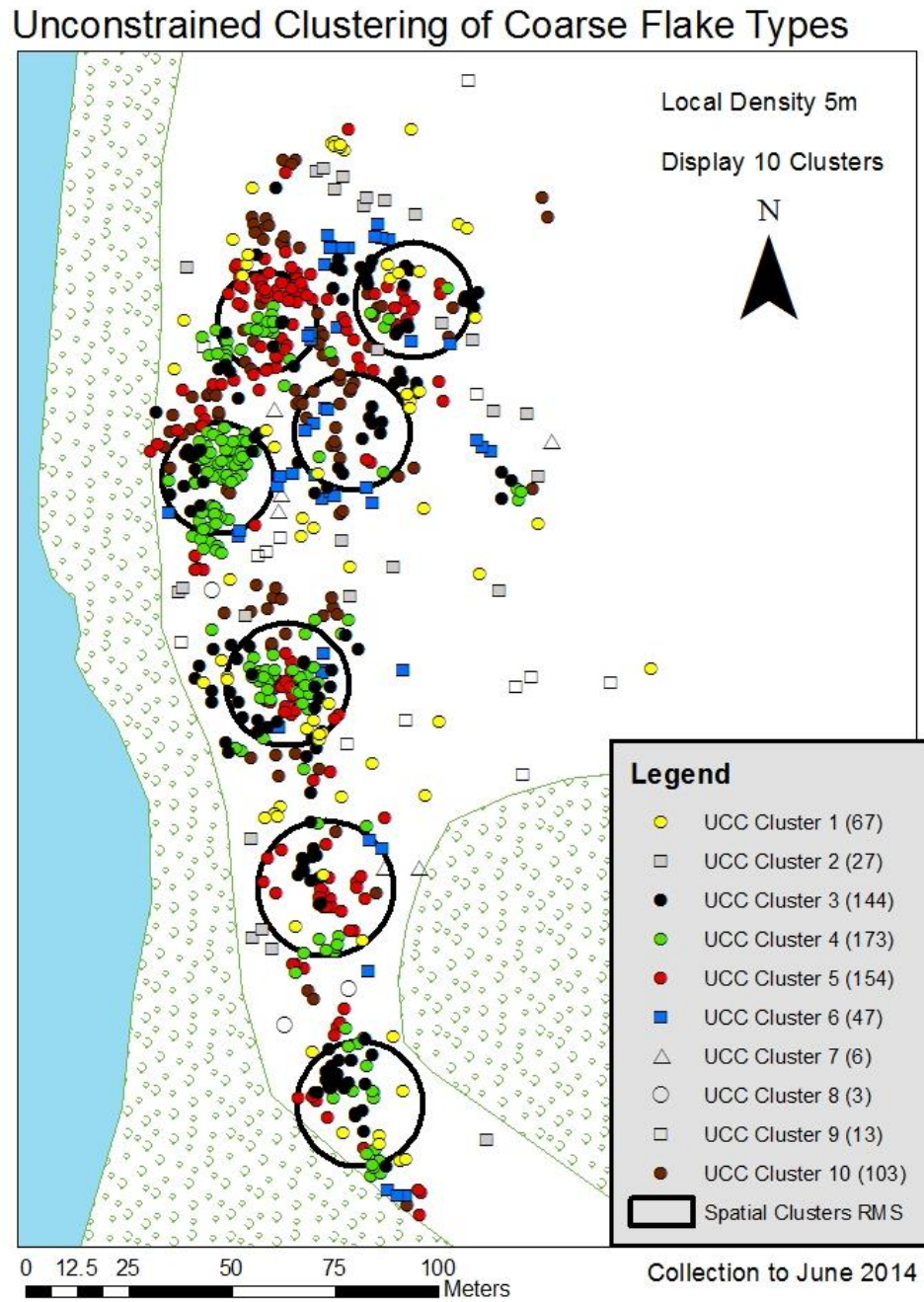
Table 4-6: Counts of Flakes by Activity Cluster

Table 4-6											
Cluster Number	1	2	3	4	5	6	7	8	9	10	Total
Primary Reduction Flake	0	0	3	2	2	1	5	0	0	1	14
Secondary Reduction Flake	1	0	3	7	4	11	0	0	0	7	33
Tertiary Reduction Flake	3	0	38	63	8	13	1	0	12	23	161
Biface Thinning Flake	58	0	80	54	63	11	0	0	0	15	281
Biface Reduction Flake	1	1	6	6	7	2	0	0	0	4	27
Biface Reduction Error Flake	1	0	6	3	9	4	0	3	0	8	34
Unknown Flake Fragment	3	26	8	38	60	5	0	0	1	45	186
Total	67	27	144	173	153	47	6	3	13	103	736

Table 4-7: Percentages of Flakes by Activity Cluster

Table 4-7										
Cluster Number	1	2	3	4	5	6	7	8	9	10
Primary Reduction Flake	0%	0%	2%	1%	1%	2%	83%	0%	0%	1%
Secondary Reduction Flake	1%	0%	2%	4%	3%	23%	0%	0%	0%	7%
Tertiary Reduction Flake	4%	0%	26%	36%	5%	28%	17%	0%	92%	22%
Biface Thinning Flake	87%	0%	56%	31%	41%	23%	0%	0%	0%	15%
Biface Reduction Flake	1%	4%	4%	3%	5%	4%	0%	0%	0%	4%
Biface Reduction Error Flake	1%	0%	4%	2%	6%	9%	0%	100%	0%	8%
Unknown Flake Fragment	4%	96%	6%	22%	39%	11%	0%	0%	8%	44%

Table 4-7 has the flake types highlighted in yellow, which dominate each activity cluster. There are five activity clusters, highlighted in grey, which are dominated by a single flake type, and five composed of multiple flake types that have not been highlighted.

For activity clusters 7, 8, and 9, in Table 4-6, the counts for these clusters are 6, 3, and 13 respectively. Figure 4-26 shows the location of these activity clusters. Given the low

Figure 4-26: Activity Clusters 7, 8 and 9

Unconstrained Clustering of Coarse Flake Types

Local Density 5m

Display 10 Clusters

N

Legend

▲ UCC Cluster 7 (6)

● UCC Cluster 8 (3)

■ UCC Cluster 9 (13)

◇ UCC Points (737)

▭ Spatial Clusters RMS

0 12.5 25 50 75 100
Meters

Collection to June 2014
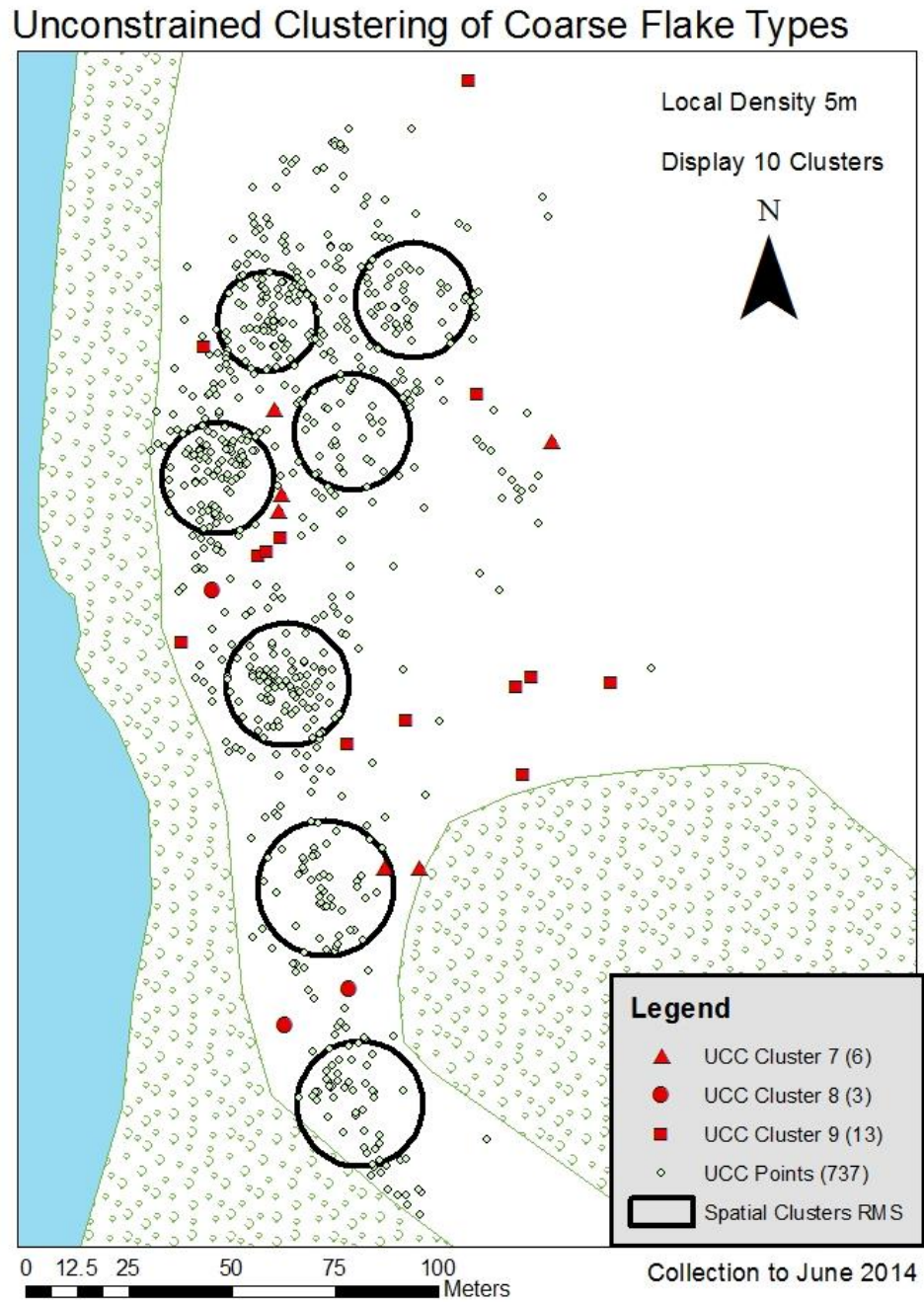
counts, these activity clusters are not useful and are mostly single flakes away from the main area of concentration. The one possible exception is the presence of 5 of the 14 primary reduction flakes outside of the RMS circles on the site. For the distribution of coarse-grained flakes only 4 of the 14 occurrences are located clearly inside the RMS circles, suggesting that primary core reduction may have taken place on the periphery of the spatial clusters although this trend could also be the result of site cleaning.

Activity clusters 1 and 2 (Figure 4-27) are also composed primarily of a single flake type, but these occur in larger numbers at 67 and 27 respectively. Activity cluster 1 is composed primarily of bifacial thinning flakes and is found predominantly outside of the spatial cluster RMS circles. While it was argued above, and is certainly the case that the deposition process for flaking detritus was much simpler than that of formal artifacts, not all flake types would have a simple deposition process. This would be especially true for bifacial thinning flakes and, to some extent, unknown flake fragments since these would be created not simply in the initial reduction process but in subsequent resharpening/reworking of damaged and used bifaces. As such, it is expected that these two types would be more widespread over the landscape and on the periphery of the site itself, similar to what we see around the more northerly spatial clusters. This patterning also occurs in the southern two spatial clusters, but these may arise because these clusters are not as dense as the ones to the north. In effect, the occurrences of activity cluster 1 in the southern two is an artifact of the less dense concentration where a bifacial thinning flake from the initial reduction process is somewhat isolated and thus, gets included with the activity cluster 1 as opposed to one of the others. Thus, these two activity clusters may be indicative of tool resharpening after damage or use.

The remaining five activity clusters have various mixes of the seven flake types. In Table 4-7 the predominant flake types by percentage are highlighted in yellow. Since the flake types are representative of various stages in the reduction sequence, it may be possible to order these activity areas as to where they fit in the reduction sequence. Examining Table 4-7, of the five activity clusters, cluster 6, with fully 53% reduction flakes, is clearly the earliest in the reduction sequence. The other end of the sequence is clearly activity cluster 5, which has only 9% core reduction and 91% various stages of biface production

Figure 4-27: Activity Clusters 1 and 2

Unconstrained Clustering of Coarse Flake Types

Local Density 5m

Display 10 Clusters

N

Legend
- UCC Cluster 1 (67)
- UCC Cluster 2 (27)
- UCC Points (737)
- Spatial Clusters RMS

0   12.5   25   50   75   100
Meters

Collection to June 2014
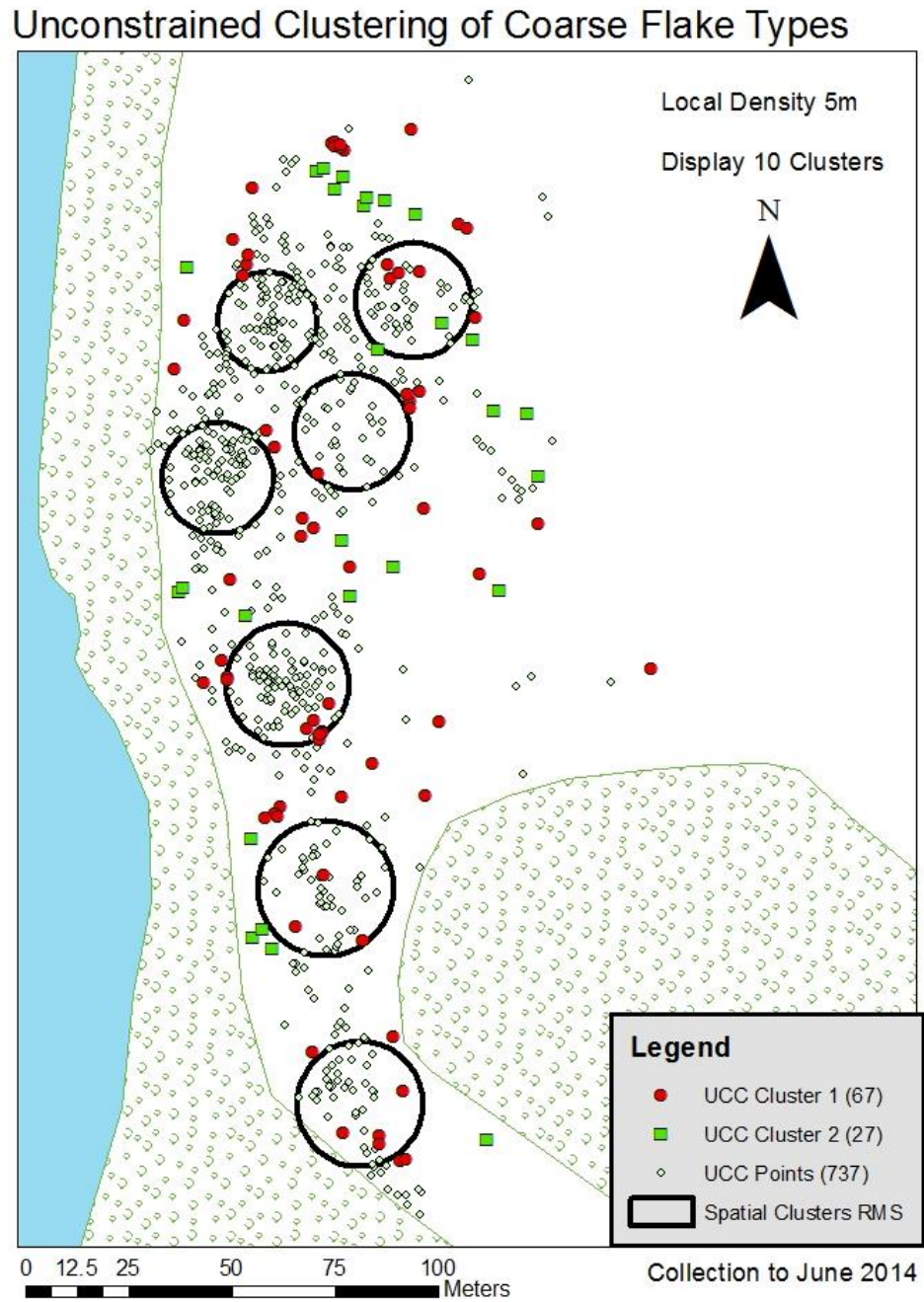
and unknown flake fragments and is clearly the late finishing stage location. In the remaining three activity areas, activity cluster 4 seems to follow after activity cluster 6 with 40% reduction flakes and 60% biface and unknown flake fragments. With these clusters defining the beginning and end of the reduction sequence, this leaves activity clusters 3 and 10 occupying the sequence somewhere between activity clusters 4 and 6. The key difference between these two activity clusters is the percentage of biface thinning flakes and unknown flake fragments. Activity cluster 4 clearly is intermediate between clusters 3 and 5 but activity cluster 10 is difficult to explain without trying to breakdown the unknown flake fragments further. The activity clusters seem then to follow a reduction sequence in the following order: 6, 4, 3 and 5 with activity cluster 10 being problematic.

Concerning the spatial distribution of the activity clusters and looking at activity cluster 3, 4 and 5 (Figure 4-28), these three activity clusters are mostly within and form the bulk of the contents inside the RMS circles marking the main spatial clusters, although the relative proportions vary somewhat. Contrasted to this distribution is the spatial distribution of activity clusters 6 and 10 (Figure 4-29), which occur mostly outside the RMS circles -- the exception is the southeastern most of the four northern clusters already deemed problematic.

In summing up the results of the Unconstrained Clustering interpretation of these distributions, one possibility is that the initial stages of core reduction might have occurred at the periphery of the spatial clusters. At some point in the reduction sequence, the activity is then moved to the core of the spatial cluster where finished bifaces are completed. An alternate and preferred explanation is that site cleaning activities were moving the larger fragments to the periphery of the spatial clusters. Activity cluster 10 remains problematic, but could represent the case where multiple activities are carried out. The tertiary reduction flakes could come from the initial reduction, which tends to occur along the periphery. Many seem to be flakes that represent initial thinning prior to the production of recognizable flakes from biface reduction.

Figure 4-28: Activity Clusters 3,4 and 5

Unconstrained Clustering of Coarse Flake Types
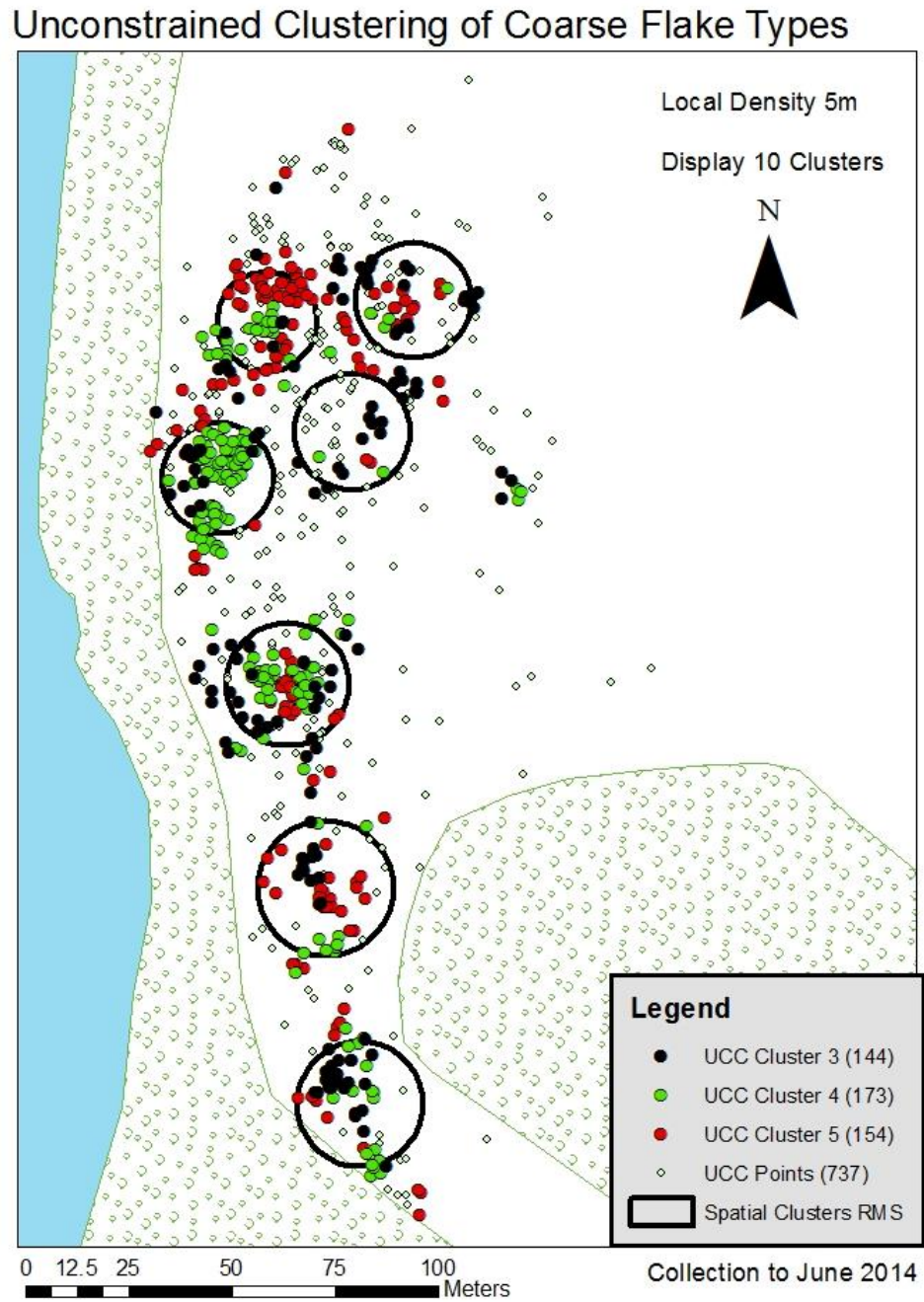
Figure 4-29: Activity Clusters 6 and 10
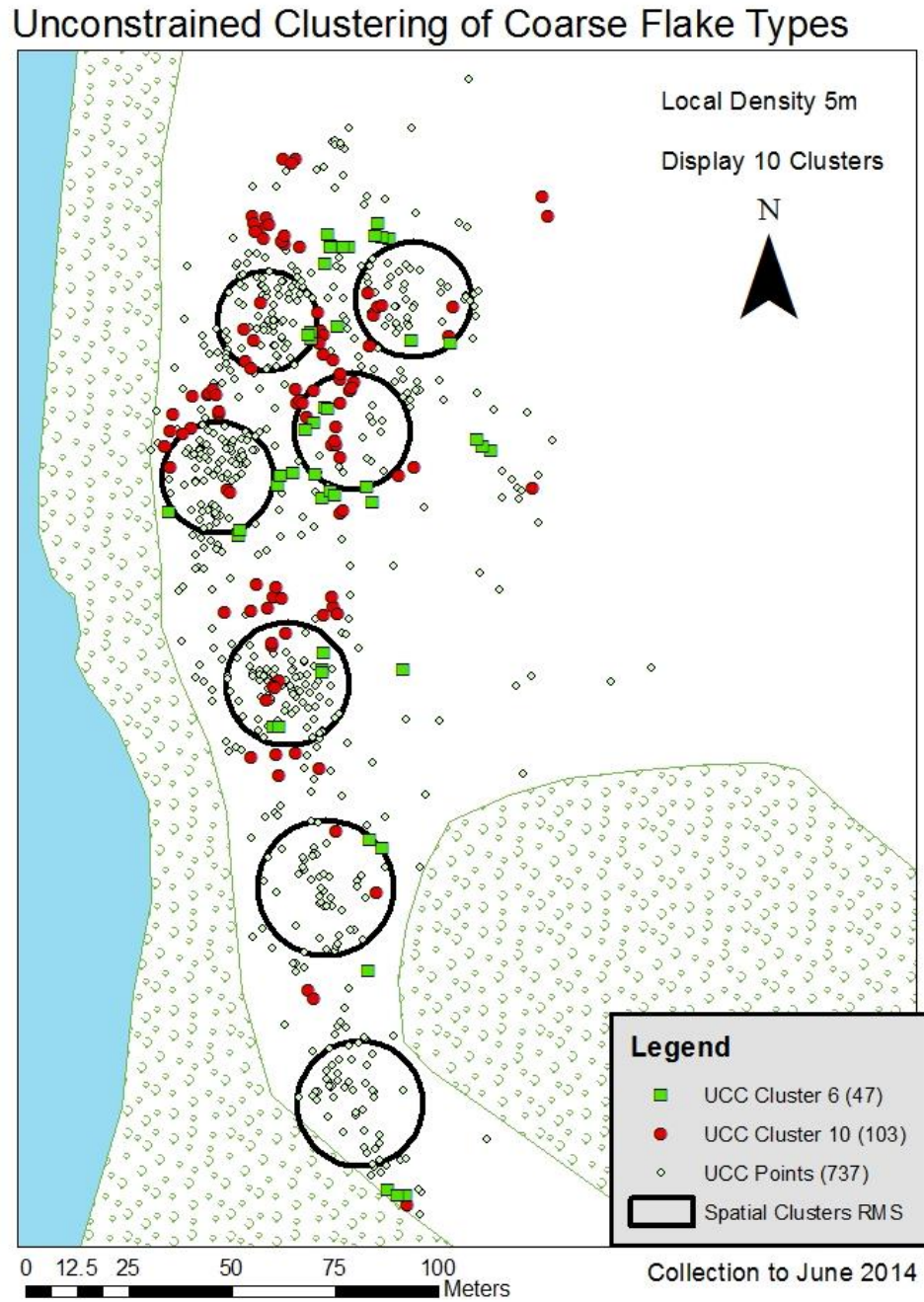
What does not emerge in the Unconstrained Clustering analysis is the nature of the southeastern spatial cluster extension identified above. The two southern most spatial clusters show early stage activity occurring in the extension area, as does the southwestern most of the northern four clusters and perhaps the northwestern most of the northern four. However, the third cluster from the south has early stage activity occurring inside the main spatial cluster. The two easternmost of the four northern clusters, where the southeastern extension was poor to start with, do not show any early stage patterning to the southeast. Given these patterns, it is difficult to advance a definite conclusion as to whether the southern extension relates to the reduction sequence or to some other socially controlled phenomena.

4.5   Formal Artifact Type Distribution

4.5.1   Broad Point Versus Small Point Occupation of the Site

That there was a distinct structure to the site during the Broad Point Archaic, as represented by the coarse flaking debris, is not debatable. This insight was made possible by the large numbers of coarse flakes that are characteristic of the Broad Point Archaic use of the area. In terms of the Small Point Archaic, we cannot use flakes to define component distributions, since Kettle Point chert, the primary chert type used by Smallpoint making people, was also well used by preceding Broad Point people.

The transition from Broad Point to Small Point Archaic was clearly a time of rapid technological change, which could have occurred through changing in situ social values in a resident population. More recently, some authors (e.g. Sassaman 2010) hypothesize such major changes in artifact styles suggest cultural replacement or population movements. At Davidson, this would involve a replacement of Broadpoint producing people by Smallpoint producing groups bringing with them a very different technology. This replacement might explain why stylistically the Broadpoints are closer to materials from sites to the southeast in New York and Pennsylvania, while the Smallpoints resemble finds to the west/southwest in Wisconsin and Illinois. In any case, as noted above (see Figure 4-11), calibrated radiocarbon dates suggest that there are three distinct clusters in time, with the later separation indicating a hiatus between the Broad Point and

Small Point occupations in time. This break might argue against an ongoing occupation of the site throughout the transition and actual hiatuses in occupation. However, as these dates came from the excavations and such a limited portion of the site was excavated, they cannot necessarily be extrapolated to the site as a whole, especially for the Broad Point materials which are more widespread across the site (see below).

While the nature of the Broad Point to Small Point transition is something about which the Davidson Site eventually may have much to say, it is beyond the scope of this study to consider the question. However, the nature of the site usage between the two time periods must be addressed. One possibility is that the site usage might have remained unchanged between the two time periods except that, with only Kettle Point chert in use, we lack the detailed surface distribution that we had with coarse flakes during the Broad Point period. Essentially, Small Point site structure may have continued in an identical fashion, except that we do not have the detail to actually see where the aggregating groups were setting up camp. In the discussion of the statistics, the null hypothesis going into the following discussion is that the Small Point site usage remained constant and identical to the Broad Point usage. We also have to consider the non-statistical evidence that has been obtained through magnetometry, excavation and radiocarbon dating or in essence, the broader site context of our surface collection.

The first step in the analysis will be to consider the relative distribution of the formal Small Point artifacts, the formal Broad Point artifacts, and the coarse flakes. Note that the RMS circles have been retained in the following maps to provide spatial reference.

There are 28 Small Point artifacts and 109 Broad Point formal artifacts (Figure 4-30). The RMS circles from Pure Locational Clustering have been retained for comparative purposes. It is evident that Small Point material, with the exception of one artifact, occurs only on the north end of the site. This area encompasses the four northernmost clusters of Broad Point flakes. However, as the north end of the site has more artifacts, we need to test whether this distribution is within the bounds of normal stochastic fluctuation. An A-statistic yielded a value of $A = .87$, $p = .007$, which is clearly significant implying that the Small Point and Broad Point artifacts are not similarly distributed on the site.

Figure 4-30: Distribution of Small Point and Broad Point Artifacts

Smallpoint/ Early Woodland Artifacts

Legend

● Smallpoint Artifacts (28)

● Broadpoint Artifacts (not flakes) (109)

☐ Clusters9withRMS

■ Excavations

0 12.5 25   50   75   100

Meters

Collection to June 2014
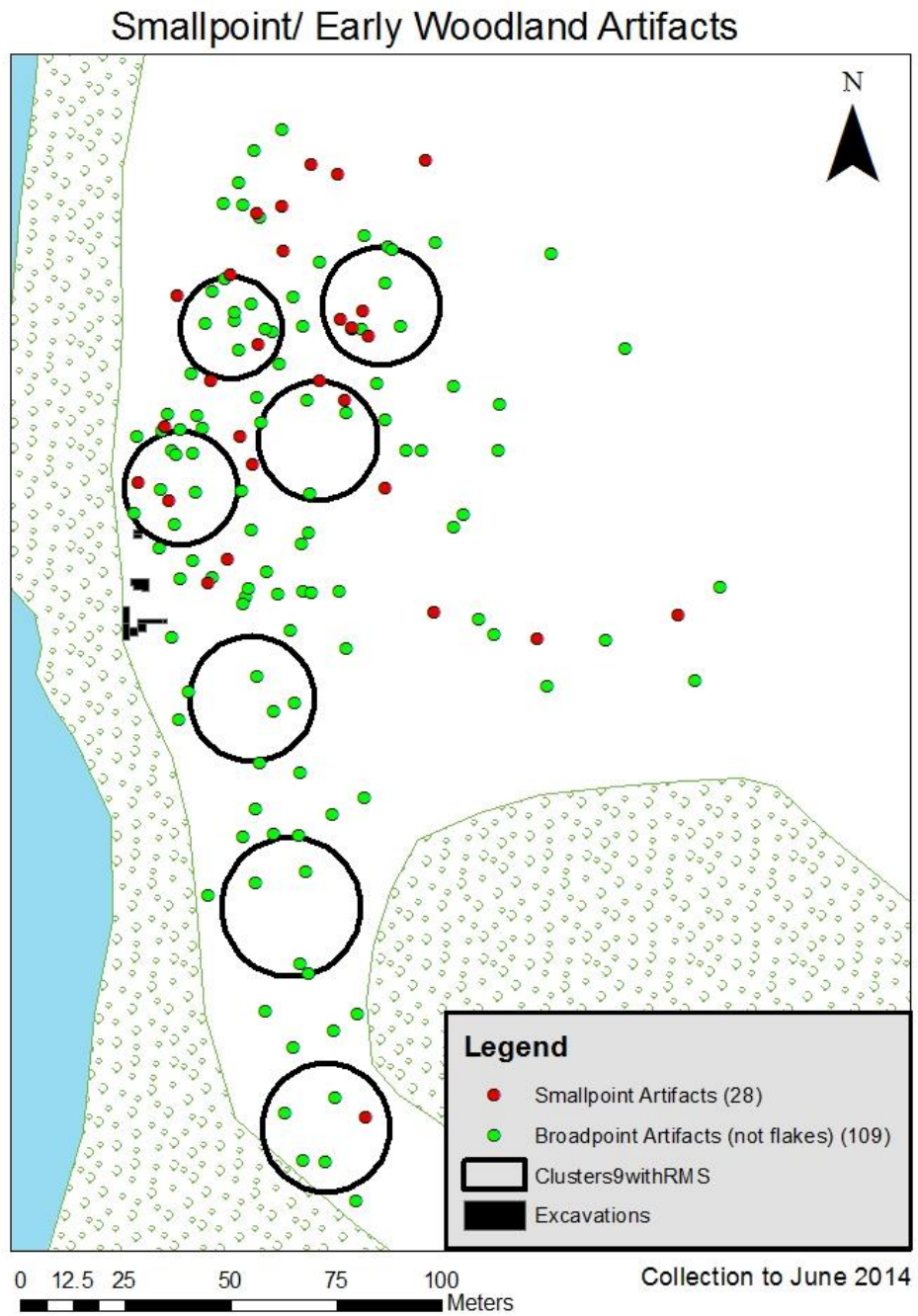
The A-statistic was also used to test the distribution of the Small Point artifacts against the distribution of the coarse flakes, again with highly significant results ($A = .82, p = .003$). Thus the two types are not distributed identically.

As a control, the distribution of Broad Point artifacts was compared to the distribution of coarse flakes ($A = 1.00, p = .21$). Therefore, the statistics support our visual observations that the Small Point material is significantly clustered at the north end of the site and consequently very different from the Broad Point Archaic distribution.

Excavations at the site from 2008-2010 seen in black at the left centre in Figure 4-30 covered only 84 m^2 but many pits, one hearth and four houses were exposed. The bulk of these features relate to the Small Point occupation of the site, although there were several Broad Point features, including one large storage pit and two true middens in refuse filled erosional channels. Some of the pits contained both Broad Point and Small Point material, but the radiocarbon dates placed them during the Small Point Archaic occupation. Several features actually have both an early Broad Point age date of ca. 3600-3800 BP as well as clearly statistically different, much later, Small Point age dates of ca. 3200-2800 BP. These later features had disturbed earlier Broad Point material and included it with the later materials. The clear clustering of dates when such contextual anomalies are ignored (Figure 4-11) supports such an inference. All of the houses discovered were associated with the Small Point occupation (Ellis et al. 2015).

Figure 4-31 shows the locations of the Small Point artifacts over the entire site overlaid on the results of a magnetometer study of the site. Figure 4-32 shows the Small Point artifacts identified by type overlaid on the magnetometer data in the area of Small Point concentration on the northern half of the site. The excavations are shown in red at the lower left. As noted previously, there is an intense band of anomalies/features running from the area of the excavations to the north-north-east that excavation shows are all cultural features (Eastaugh et al. 2013). This band of anomalies coincides well with the distribution of Small Point artifacts and the excavations confirmed that most of the anomalies/features were Small Point associated. Consistent with such an interpretation,

Figure 4-31: Small Point Artifacts and the Magnetometer Data

Smallpoint/ Early Woodland Artifacts

N

Legend

● Smallpoint Artifacts (28)

▭ Clusters9withRMS

■ Excavations

0   15   30   60   90   120   Meters

Collection to June 2014
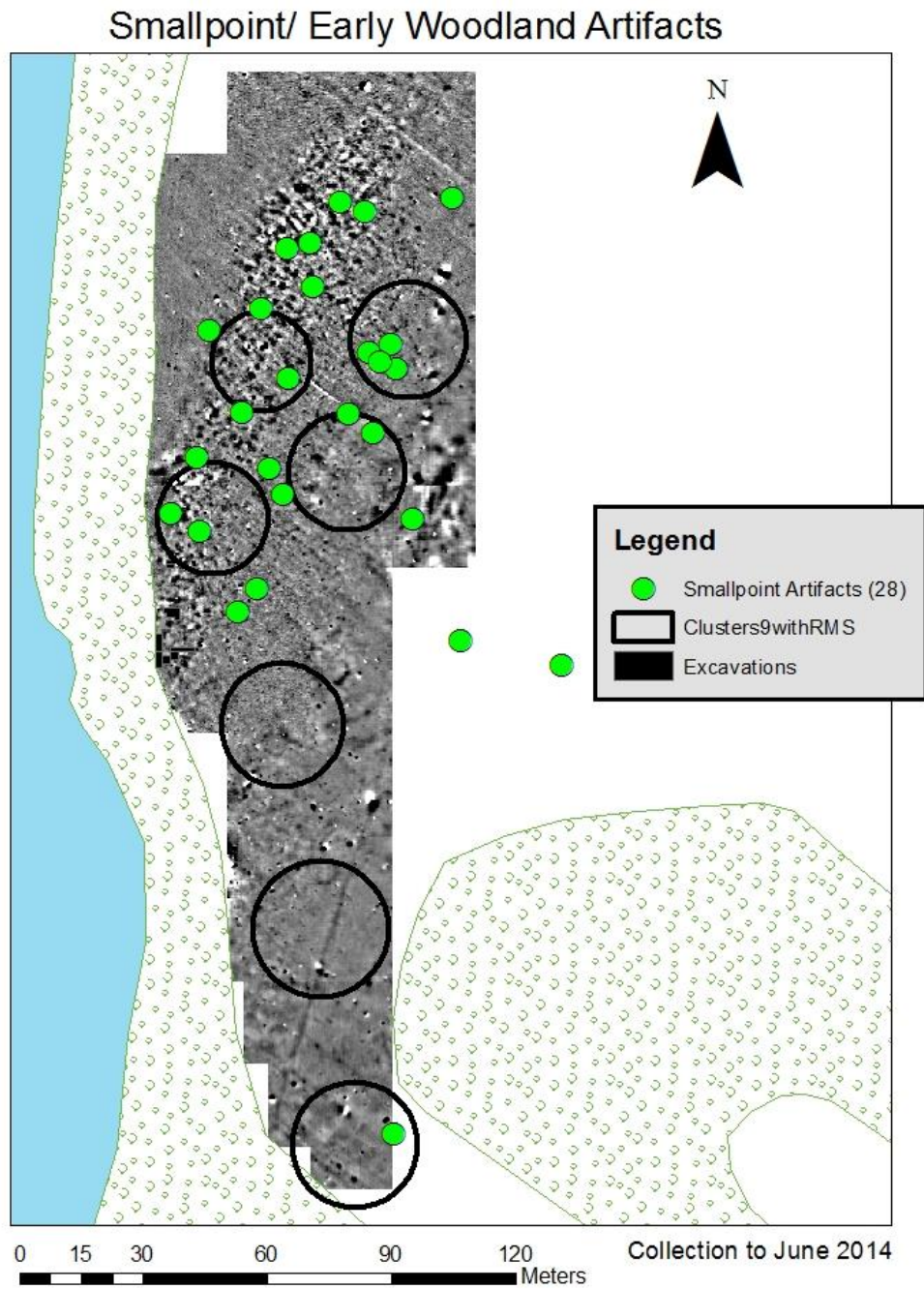
Figure 4-32: Small Point Artifact and Magnetometer Data - North End
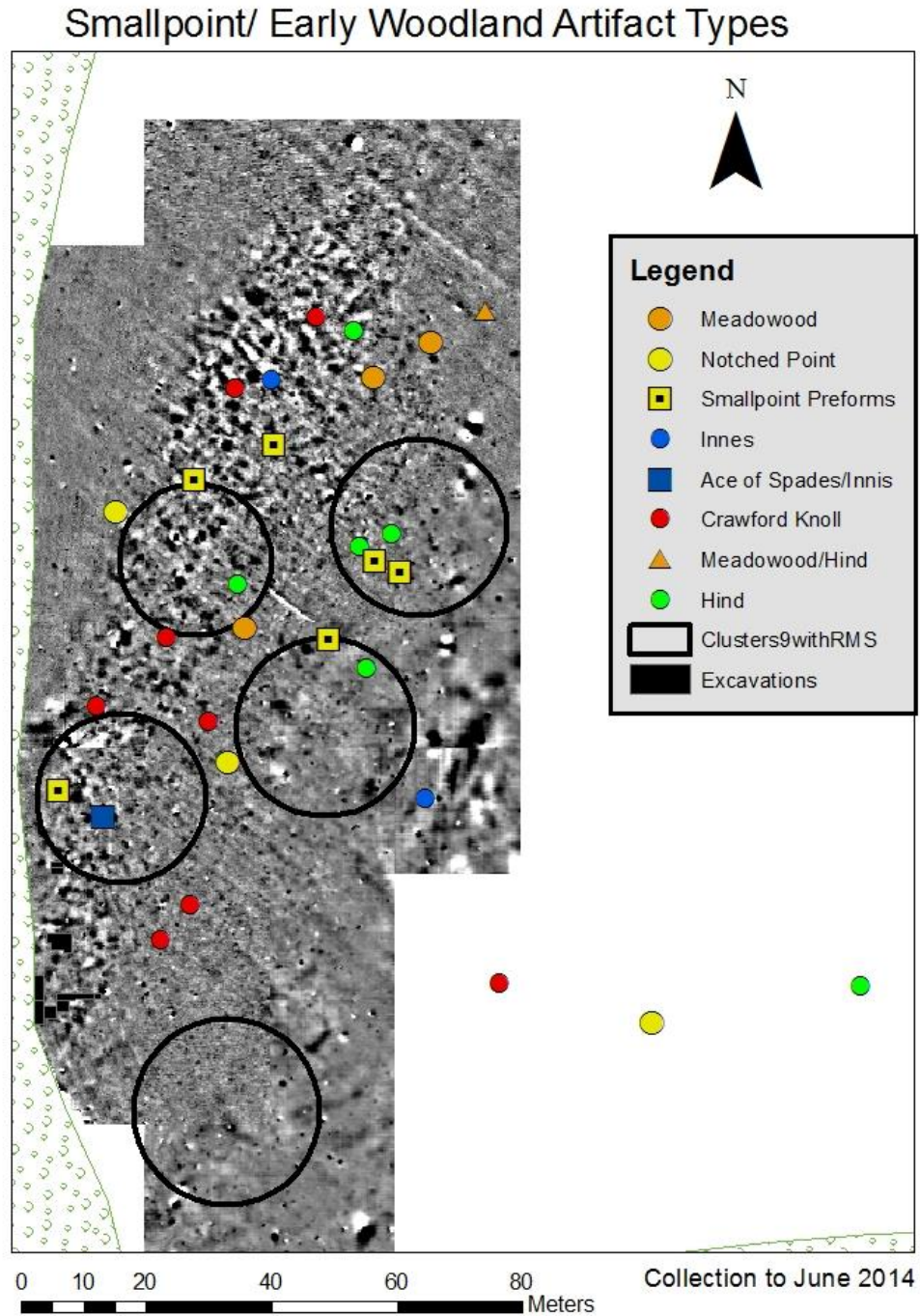
this type of intense feature concentration/anomalies does not occur in the south where the southern three spatial clusters of coarse flakes of Broad Point age are located. It does not show in the two easternmost of the four northern clusters of coarse flakes. In the southern area anomalies are rare but do exist. In the summer of 2014, four of these were excavated and proved to be shallow basin shaped pits and a hearth, most likely all relating to the Broad Point occupation (Ellis 2015).

While still in the early stages of analysis, there is little information about seasonality at the site other than as Ellis et al. (2015) have noted, pithouses are primarily used for winter residence, suggesting that the Small Point peoples used the site during the winter. There is, however, a circular wall trench house with no internal hearth or wall insulation (Ellis and Keron 2011), which suggests a warm weather shelter. There are no Broad Point houses yet discovered at the site. And the presence of fauna such as softshell turtle, fish and flora such as acorn, black walnut and butternut shell as well as strawberry, raspberry, cherry, grape, cleavers do suggest summer to fall use (Ellis et al. 2015).

Considering the surface distributions examined, and the excavation and magnetometer evidence and the C14 dates, we can hypothesize that the Broad Point settlement patterns are different than the Small Point settlement patterns on the site. However, the impact of artifact collectors must also be considered in any analysis of formal artifacts, such as the difference between Broad Point and Small Point distributions. In the case of this comparison of the distributions of the Broad Point and Small Point artifacts, while the density of both of these classes may have been reduced, the relative distributions should remain reasonably constant. The overall conclusion that the pattern of spatial clustering observed for the Broad Point Archaic does not continue on into the Small Point Archaic remains sound.

In the next stage of the analysis we examine the distribution of the formal artifacts across the surface of the site. Given the distinctly different uses of the site between Small Point and Broad Point, each time period will be considered separately below.

4.5.2   Small Point and Early Woodland Distribution

In considering the Small Point artifact distributions, we will also include three Meadowood artifacts which date to the immediately subsequent Early Woodland. The Meadowood artifacts are in the same northern area as the Small Point artifacts. Moreover, some later dating Small Point projectile points are similar to Meadowood points, suggesting a transition from one to the other amongst the same people at ca. 2800-2600 BP (ca. 1000 BC; Spence and Fox 1986; Spence et al. 1990). The one fragmentary projectile point typed as a Meadowood point or similar Smallpoint (a Hind type point; see Kenyon 1989) occurs spatially within metres of the two definitive Meadowood points. It is worth noting that the main Smallpoint types, such as Crawford Knoll, Innes and Hind, were all recovered as well in the excavated area to the south.

Figures 4.30 and 4.31 show the distribution of the Small Point (and Meadowood) artifacts broken down by type. Examining this distribution visually, with the exception of three points, one Crawford Knoll, one Hind, and one untyped notched Small Point to the southeast, the Small Point artifacts occur along the area of magnetic anomalies or just east of it. In this area, there appears to be some patterning of the various types. First, four of the five Hind or Hind-like points occur in a cluster in the northeastern RMS circles within 25 m of each other. One outlier is located 30 m to the north near the northern edge of Small Point artifacts. However, it is adjacent to two of the Meadowood points and a form intermediate between Hind and Meadowood. The Crawford Knoll points tend to be along the westernmost edge of the concentration within the band of magnetic anomalies (Figure 4-32). As is to be expected, Small Point preforms and untyped Small Point projectile points seem to be randomly mixed in with the various types. Finally, Innes points are few and do not seem to cluster.

The spatial distribution of the Small Point artifacts was examined statistically with the A-statistic and Proximity Count. For this analysis some of the type designations were combined as follows. The single "Hind-like" point was combined with the "Hind" points and the "Meadowood/Hind" point was combined with the other "Hind" points. The three projectile points where the type included the word "Innes" were also combined. In running the statistics one set of runs included all the artifacts on the north end of the site

and a second set excluded the three spatial outliers that can be seen at the bottom right of Figure 4-33.

For the A-statistic computations, all types were compared to each other. When the eastern outliers are included, the only pair of artifacts that yielded a significant segregation are Crawford Knoll and Meadowood points ($A = .48$, $p = .02$). When the three outliers were excluded, Crawford Knoll and Meadowood are still segregate ($A = .48$, $p = .03$) and Crawford Knoll and Hind Points are now also segregated ($A = .61$, $p = .05$). The second test for clustering used the Proximity Count routines in R. The results here were similar with the Meadowood points clustering with significance at a range of 15 metres for both the full set ($p = .03$) and the set excluding the three outliers ($p = .05$). The Hind points were not significant in the full set but were significantly clustered at 25-35 m with the set excluding the spatial outliers ($p = .04$). For one further test, Meadowood and Hind Points were combined, since they are adjacent to each other and are considered to be adjacent in time as well. When they are combined and the Proximity Count script is run, the results are significant at all radii except 20 m (see Table 4-8), thus demonstrating the clustering of these two point types. It is unlikely that clustering of the various types in

Table 4-8: Proximity Count

Table 4-8		
Distance	Count	p
10	4	.06
15	6	.05
20	7	.18
25	14	.03
30	18	.03
35	22	.03

different locations is due to ploughing or other post-depositional factors. Likely these types may have been even more tightly clustered prior to the ploughing. Assuming these type distinctions do represent temporal variation, the tendency of these different types to cluster in different areas in the north area suggests variable use of the northern area

Figure 4-33: Small Point and Early Woodland Artifacts by Type

Smallpoint/ Early Woodland Artifact Types
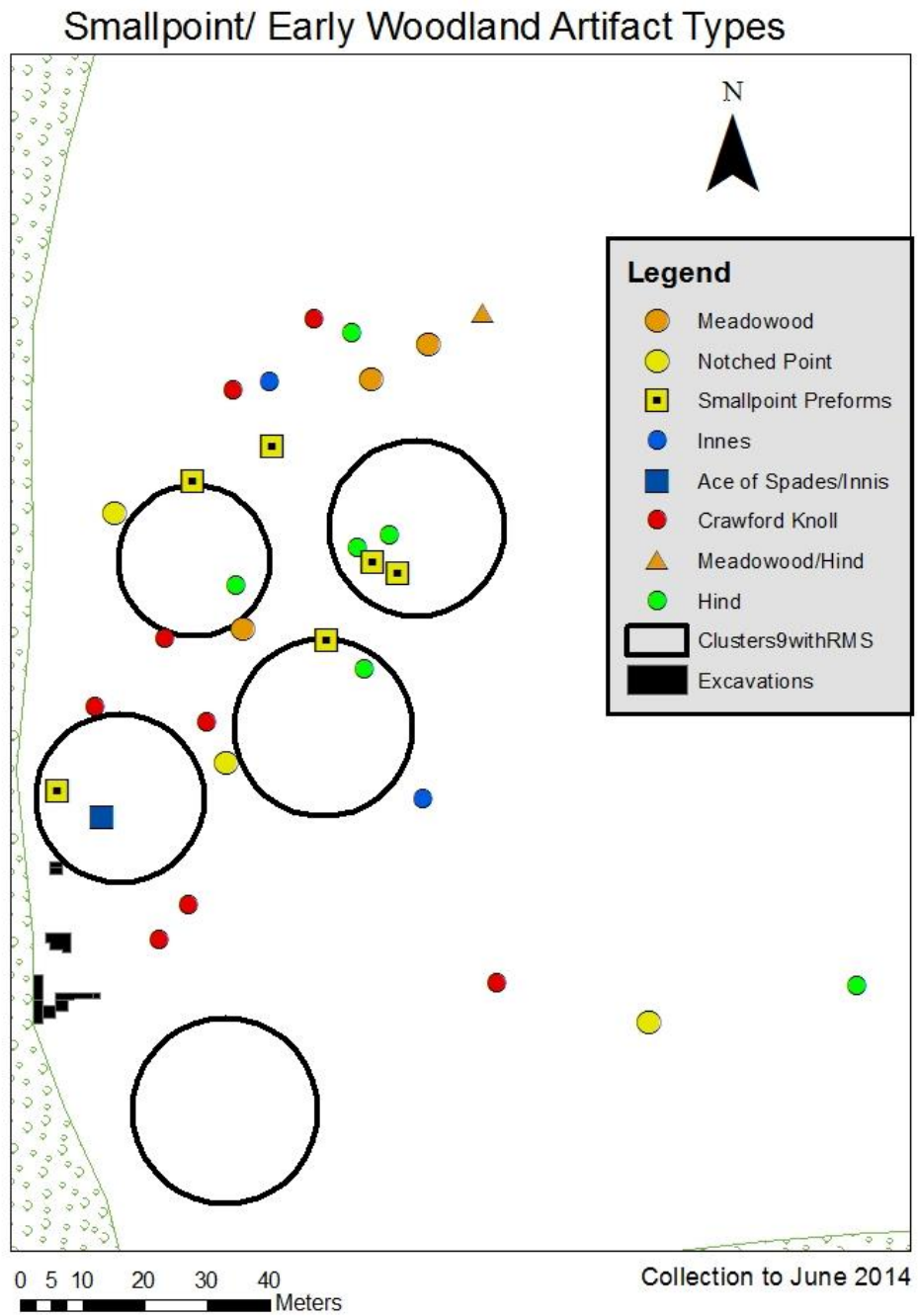
throughout the overall Small Point to Early Woodland time frame. Nonetheless, these groups continually returned to the same general location paralleling the river throughout Small Point times.

Another observation, which could not be tested statistically, was the tendency for the Crawford Knoll Points to cluster within the zone of magnetic anomalies. Certainly they are more widely distributed than the other points, possibly excepting the three Innes and Innes-like points.

4.5.3   Distribution of Formal Broad Point Artifacts

The surface collection from the Davidson site includes 109 formal Broad Point artifacts. These are divided into major classes and plotted in Figure 4-34. Note that the legend shows the number in each class. One outstanding feature of the collection of Broad Point artifacts is that they are almost completely related to the production of projectile points, with the exception of two drills and two retouched flakes. This fact is also congruent with the analysis of coarse flakes that showed a heavy tendency toward biface production. Of course, part of this likely result stems from the fact that large bifaces tend to be the norm during the Broad Point Archaic so that when large bifaces are encountered it is quite reasonable to identify them as representative of that component. There are other formal tools such as scrapers, which would be much more difficult to assign to a specific cultural affiliation. These are considered separately below.

Visually observing the distribution of the Broad Point artifacts (Figure 4-34), what looks interesting is that the clustering of these artifacts differs somewhat when compared to that of the coarse flakes. Looking at the distribution in Figure 4-34 there seem to be many more artifacts outside the RMS clusters than are contained within them, thus contrasting to the distribution of the coarse flakes. Figure 4-35 shows the Kernel Density for the formal artifacts where the densest concentrations seem to be on the periphery or more distantly removed from the RMS circles. In one sense, we should not expect the formal artifacts to be similarly distributed, since the process resulting in the final deposition of

Figure 4-34: Distribution of Broad Point Artifact Types

Broadpoint Formal Artifacts

Legend

- Points (27)
- Preforms (71)
- Biface (6)
- Drill (2)
- Core (1)
- Retouched Flake (2)
- Clusters9withRMS
- Excavations

0 10 20   40   60   80
Meters

Collection to June 2014
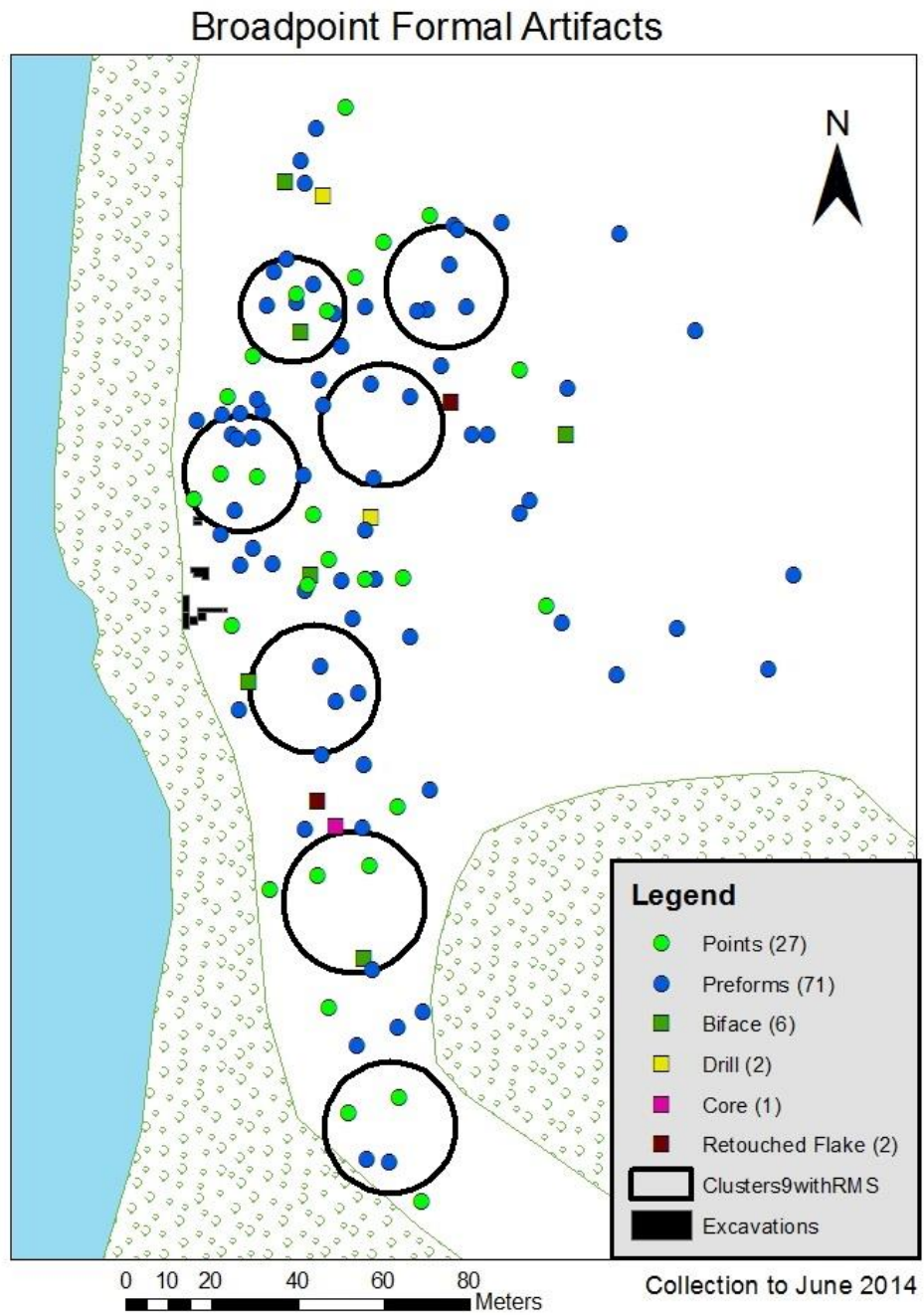
Figure 4-35: Broadpoint Artifact Kernel Density

Broadpoint Formal Artifact Density

Legend

- Broadpoint Artifacts (109)
- Clusters9withRMS
- Excavations

Density

- 0 - 0.005
- 0.005 - 0.01
- 0.01 - 0.015
- 0.015 - 0.02
- 0.02 - 0.025
- 0.025 - 0.03
- 0.03 - 0.035
- 0.035 - 0.04
- 0.04 - 0.046

0 10 20   40   60   80
Meters

Collection to June 2014
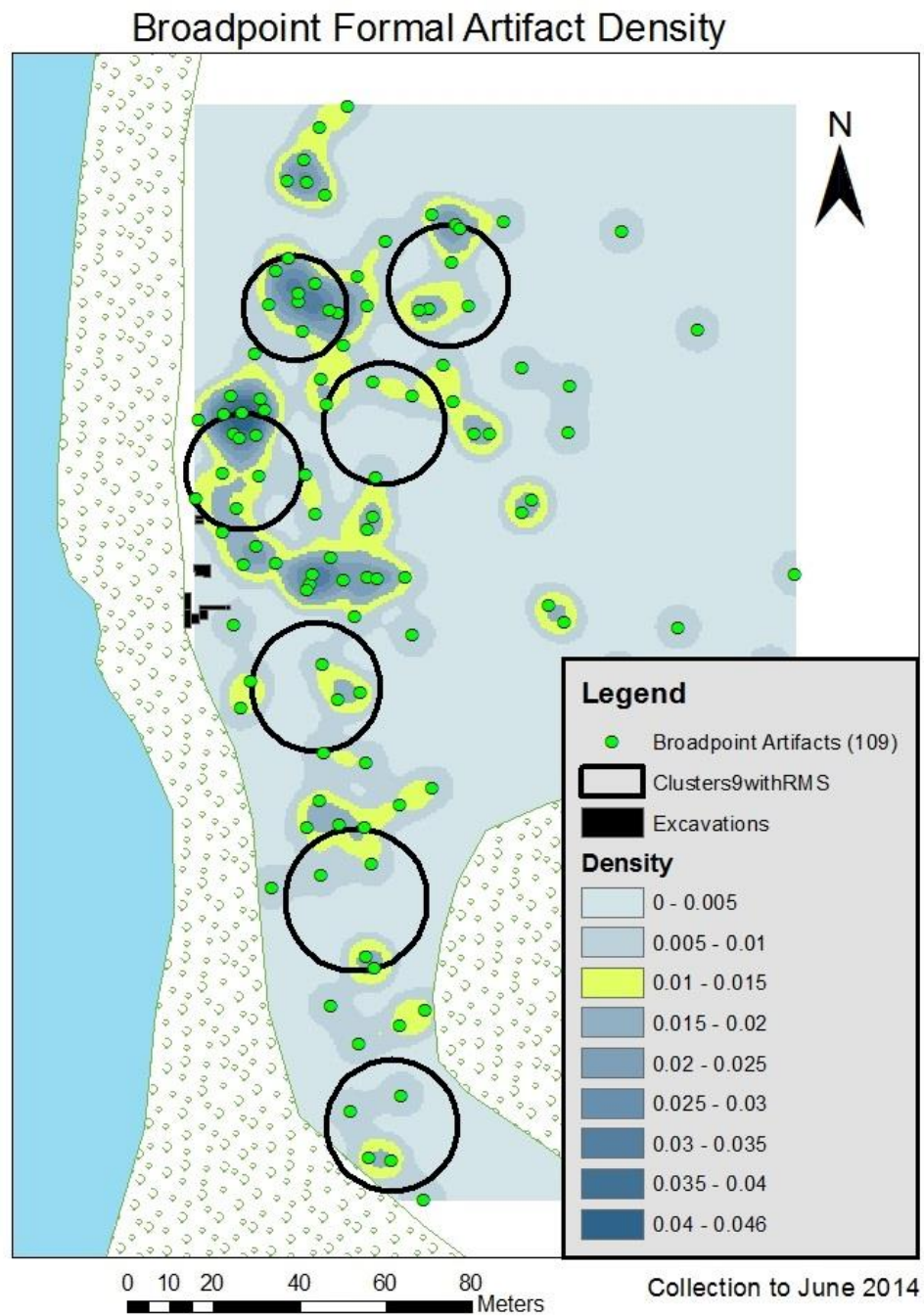
formal artifacts is much more complex. For example, a projectile point knapped at one location could be used at a number of other locations, resharpened and even recycled at yet other locations, before being finally discarded away from the knapping location. The totals of both coarse flakes and Broad Point artifacts inside and outside of the RMS circles were calculated using ArcGIS (Table 4-9) and a G-test was run.

Table 4-9: Count of Broad Point Artifacts - Inside and Outside RMS Circles

Table 4-9			
	Broad	Coarse	Totals
Inside RMS	36	412	448
Outside RMs	73	325	398
Totals	109	737	846

The results were highly significant ($G = 20.15$, $d.f. = 3$, $p < .001$) indicating the observation was real. (Earlier an A-statistic value of 1.0 was calculated with these same two sets of artifacts implying no segregation. While these two results seem contradictory, this is a good example of one of the shortcomings of the A-Statistic, as will be discussed below).

The next analysis is to consider the distribution of the formal Broad Point artifacts with respect to each other. This analysis will examine three sets of data: the raw material distribution, the distribution by artifact category and the distribution of projectile points and preforms by description. For the statistical analysis the null hypothesis is that there are no differences in patterning amongst the various formal Broad Point artifacts.

Figure 4-36 plots the distribution of these artifacts by the raw material. The counts of the various raw material types are shown in the legend of Figure 4-36. In reviewing this map, three raw material types account for most of the Broad Point formal artifact types: Onondaga chert, Kettle Point chert and subgreywacke. Visually, patterning by chert type is absent. Both the A- Statistic and Proximity Count were run on the distribution of raw material, with the result that no significant results were obtained except for Onondaga chert, which tended to be evenly distributed (i.e., equidistant from each other) across the site. This observation was tested using the Nearest Neighbour Statistic - Random Labeling, which also showed a statistically significant tendency towards even spacing

Figure 4-36: Broad Point Artifacts by Raw Material

Raw Material of Formal Broadpoint Artifacts

Legend
- Raw Mat Coarse (7)
- Raw Mat Subgreywacke (31)
- Raw Mat Onondaga (20)
- Raw Mat Kettle Point (45)
- Raw mat Unknown (4)
- Raw mat Quartzite (1)
- Clusters9withRMS
- Excavations

Collection to June 2014

0 12.5 25 50 75 100
Meters
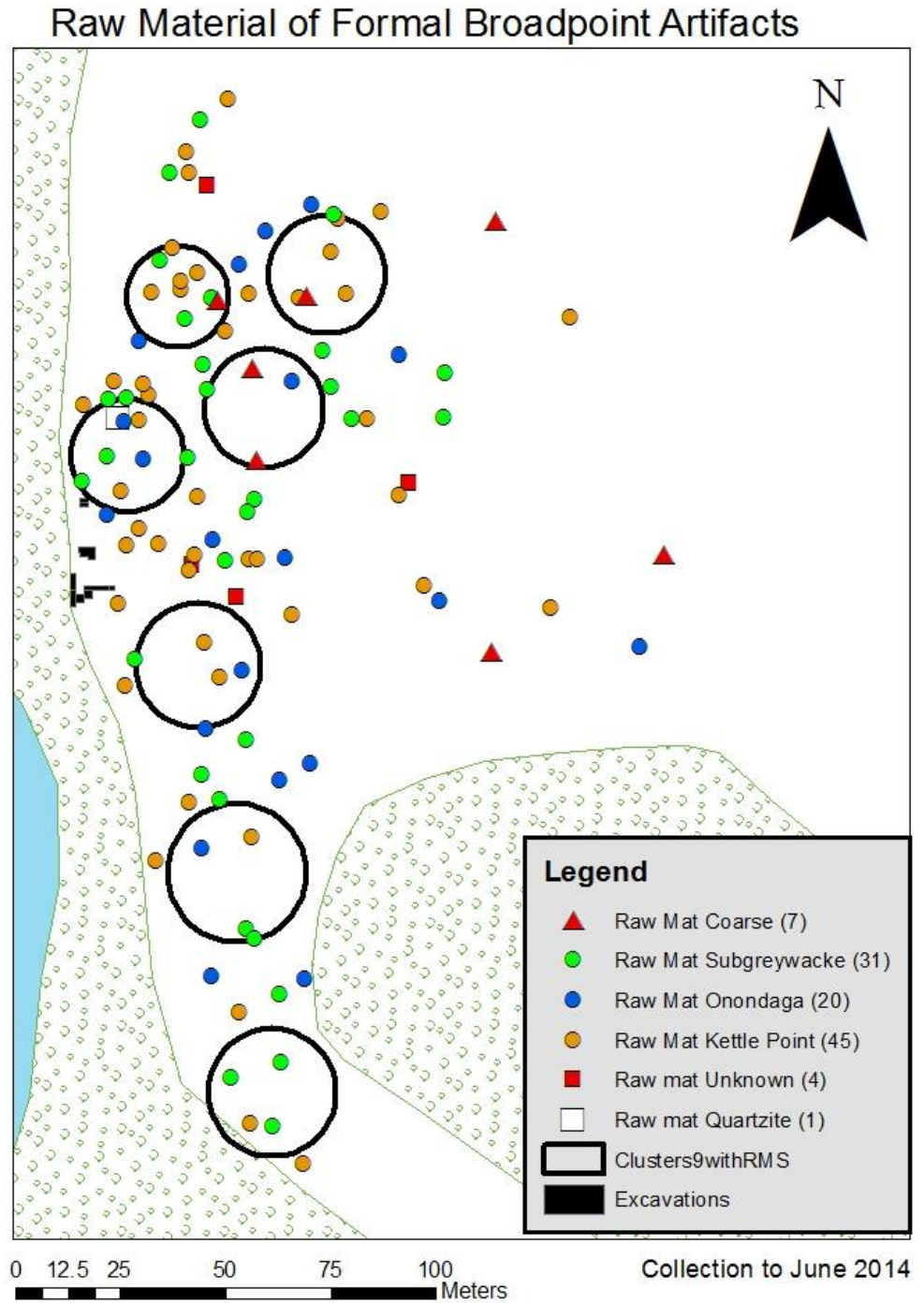
(see Table 4-10). A ratio above 1 indicates even spacing. The even spacing may just be an anomaly in the sample but it does imply that the people using all the various spatial clusters had equal access to the use of Onondaga chert.

Table 4-10: Broad Point Artifacts - Nearest Neighbour

Table 4-10			
ActualAvgNN	RandomAvgNN	NNR	prob
30.23	21.92437	1.37881	.03

The formal Broad Point artifacts were next broken down by category (Figure 4-37). Again there is no visible patterning and the run of both the A-Statistic and Proximity Count indicates no significant patterning of the tool types.

Finally, the distribution of the projectile points and preforms with respect to description is examined (Figure 4-38). Again there is no visible patterning and the run of both the A-Statistic and Proximity Count indicates no significant patterning of the tool types.

Based on the preceding analysis of the distribution of the formal Broad Point artifacts, it is not possible to reject the null hypothesis. The implication of this result is that all areas of the site had equivalences in terms of the site activities (as represented by tool forms and preforms) and the occupants' access to and use of various raw materials. This result is congruent with the analysis of the coarse flakes types, which also showed that each cluster was composed of similar ratios of flake types.

Figure 4-37: Broad Point Artifacts by Type

Major Type of Formal Broadpoint Artifacts

N

Legend
- Points (27)
- Preforms (71)
- Biface (6)
- Drill (2)
- Core (1)
- Retouched Flake (2)
- Clusters9withRMS
- Excavations

0 12.5 25 50 75 100
Meters

Collection to June 2014
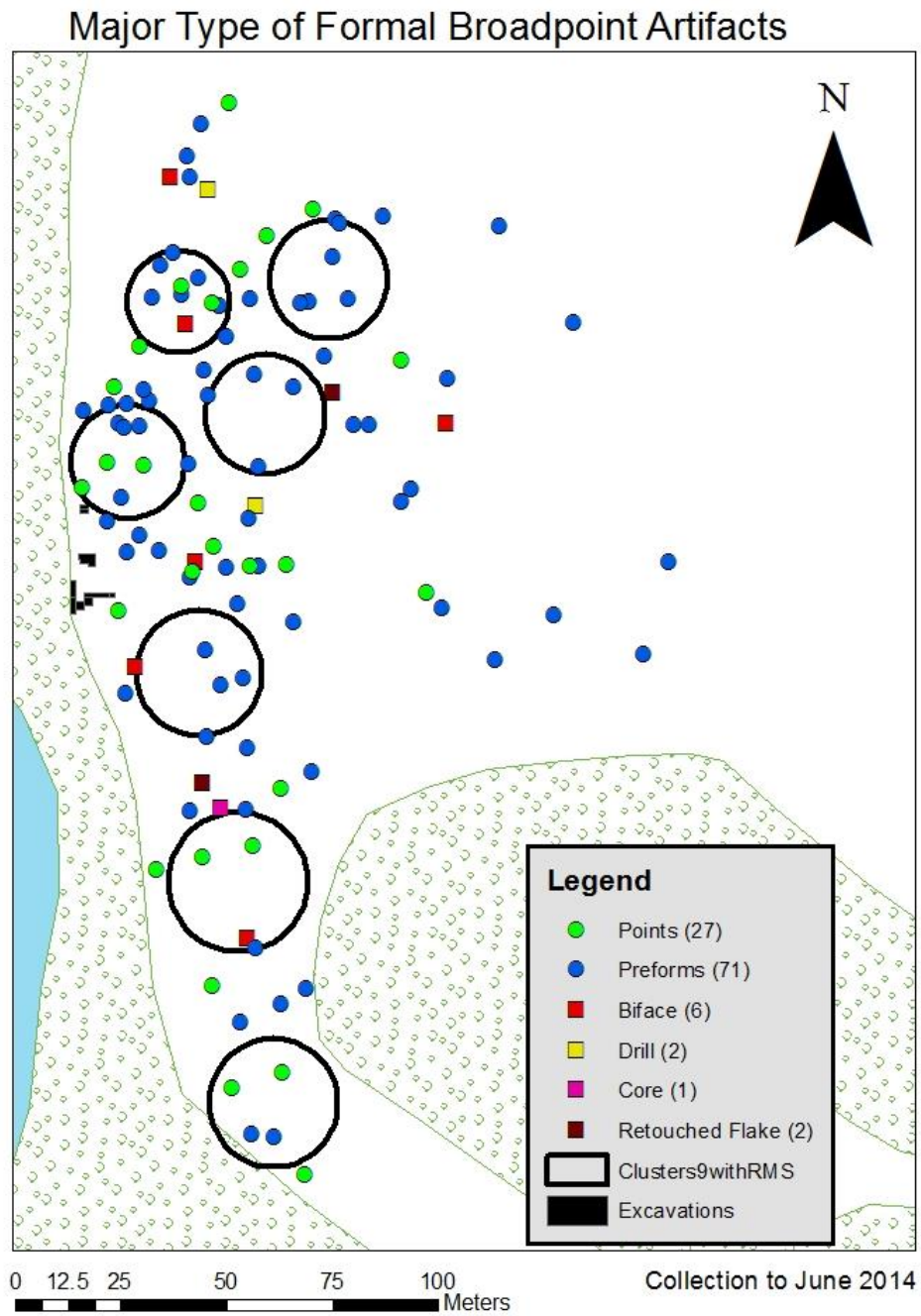
Figure 4-38: Broad Point Artifacts by Description

Broadpoint Points and Preforms by Description

N

Legend
△ Stemmed Points (18)
▲ Non Descript Points (9)
● Stemmed Preforms (10)
● Pentagonal Preforms (24)
● Preform ND (37)
▢ Clusters9withRMS
■ Excavations

0 12.5 25   50   75   100
Meters

Collection to June 2014
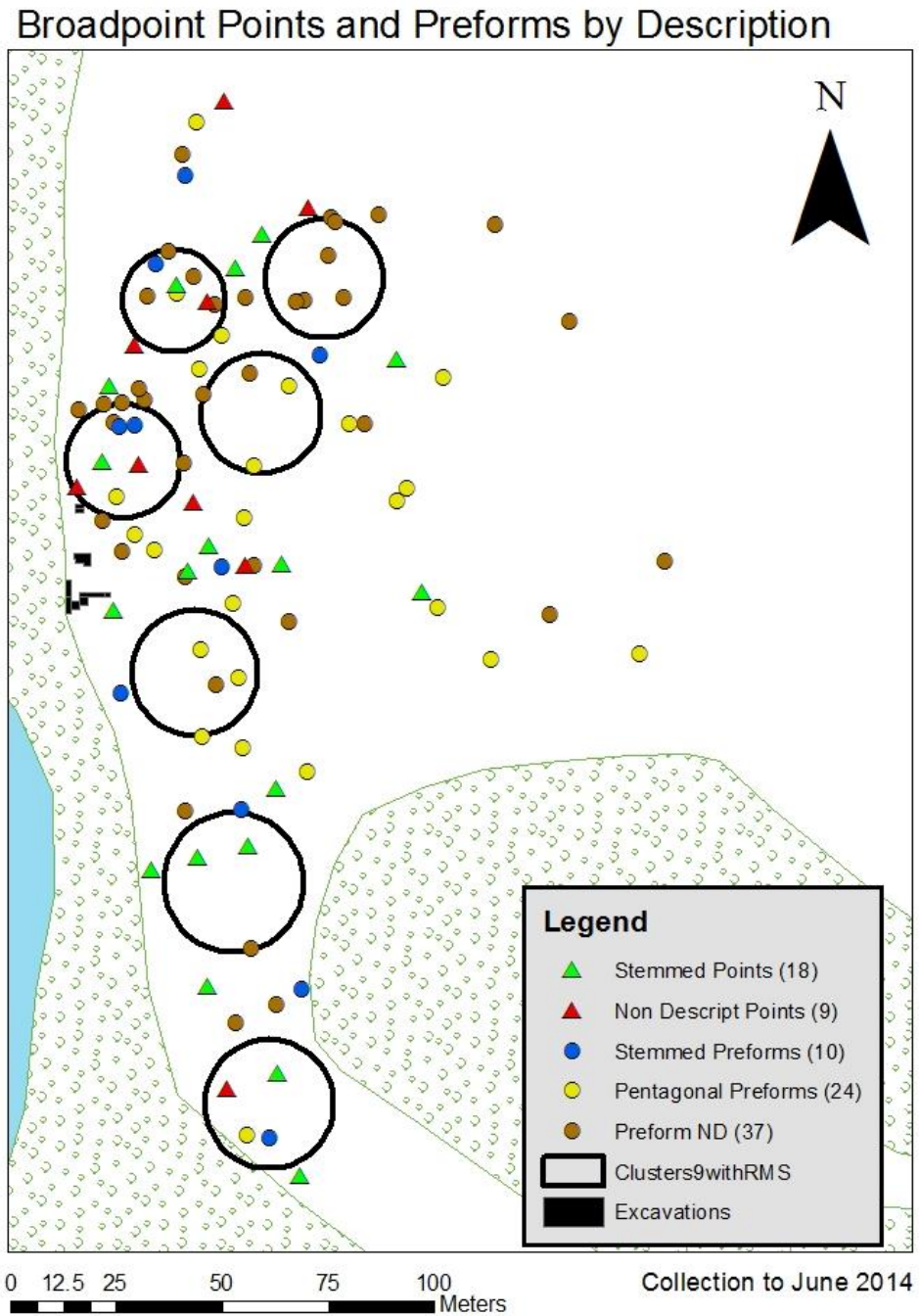
4.5.1 Distribution of Non Time Sensitive Tool Forms

The final phase of this analysis examines the set of both formal and informal artifacts, most of which cannot be attributed to either Broad Point or Small Point. In total, 84 artifacts are included in this analysis (Table 4-11). It is evident that all but a few of these artifacts occur as single instances and only four have a frequency greater than 10.

Table 4-11: Non Diagnostic Tools

Table 4-11 Surface Finds to 2014	
Retouched Flake	15
Scraper	15
Core	14
Drill	11
Piece Ésquillées	6
Shatter	3
Denticulate	2
Hammerstone	2
Netsinker	2
Birdstone	1
Bone, worked	1
Chopper	1
Core or Gouge Preform	1
Groundstone Tool	1
Hammerstone/Whetstone	1
Notched Flake Tool	1
Ochre Stained Pitted Stone	1
Pitted/Anvil Stone	1
Rim/Neck Sherd	1
Adze	1
Anvil Stone	1
Beak	1
Tool	1
Total number of finds	84

The impact of the activities of collectors on this sample will be highly variable by tool type. Our expectations here, based on observations of a number of collections in the past, is that the more formal tools, such as drills or adzes, would have been as heavily collected as the projectile points. In contrast, the expedient tools, such as retouched flakes or piece ésquillées, would be rarely collected and intermediate forms, such as end scrapers, would

have been occasionally collected. Given this differential access, any comparison between the tool types as to total numbers would be inappropriate. Comparisons involving the distribution, while still being problematic, are on a sounder foundation since, as discussed above, removal of specific artifacts from the areas of greatest concentration by collectors would reduce the density in those areas, but the remaining less dense concentration should still be spatially valid.

The distribution of the temporally undiagnostic tools has been restricted to categories where there are more than two instances (Figure 4-39). Cases where there were only one or two instances of a category have been lumped together under the class "Misc Tools". This distribution shows a denser concentration of tools in the northern half of the site. However, this set of artifacts pertains to all occupations of the site, including both Broad Point and Small Point occupations. Thus, with the differing distributions of these two components, it would be expected that there should be more artifacts in the north where these two overlap. One of the original investigative goals at the Davidson site was to document the composition of the poorly known Broad Point tool kit. In analysis of the excavated material, one approach is to look at the tool content in the pure Broad Point age features. The surface collection provides another approach to this, as the southern half of the site is almost completely devoid of Small Point diagnostic artifacts. A visual examination of the distribution (Figure 4-39) indicates that three artifact types, scrapers, retouched flakes, and drills, tend to occur almost exclusively in the northern area of the site. The question, then, is to examine if these trends are statistically significant.

In comparing the different distributions of the various non-diagnostic artifact types to each other, there are no significant results using the A-statistic. When the Proximity Count statistic was run comparing each type to the sum of all others, the only one that generated significant results was the scraper category, which indicated that at all distances over 15 m scrapers were clustered together with significance.

In order to refine this analysis, each category was compared to the distribution of both Broad Point and Small Point artifacts to determine which of the undiagnostic tool categories more closely approximated the distribution of the temporally provenienced

artifacts. Since we have two sets of distribution data for the Broad Point, the formal Broad Point artifacts and the coarse flakes, the test was run against both of these. The initial test consisted of running the A-statistic available in TFQA. This run is summarized in Table 4-12 (Misc Tools are excluded).

Table 4-12: A-statistic Non Diagnostic Tool Forms

Table 4-12:	Number	Small Point Formal	Broad Point Formal	Coarse Flakes
A-Statistic				
Core	14	.82	1.06	1.04
Drill	11	1.06	.94	.91
PE	6	.95	1.11	1.07
Retouched Flake	15	1.03	.91	.89
Scraper	18	.94	.9	.87
Probability				
Core	14	.03	.95	.86
Drill	11	.76	.17	.1
PE	6	.29	.85	.72
Retouched Flake	15	.64	.09	.05
Scraper	18	.14	.05	.02

Figure 4-39: Non Diagnostic Tool Forms

Non Diagnostic Tool Forms
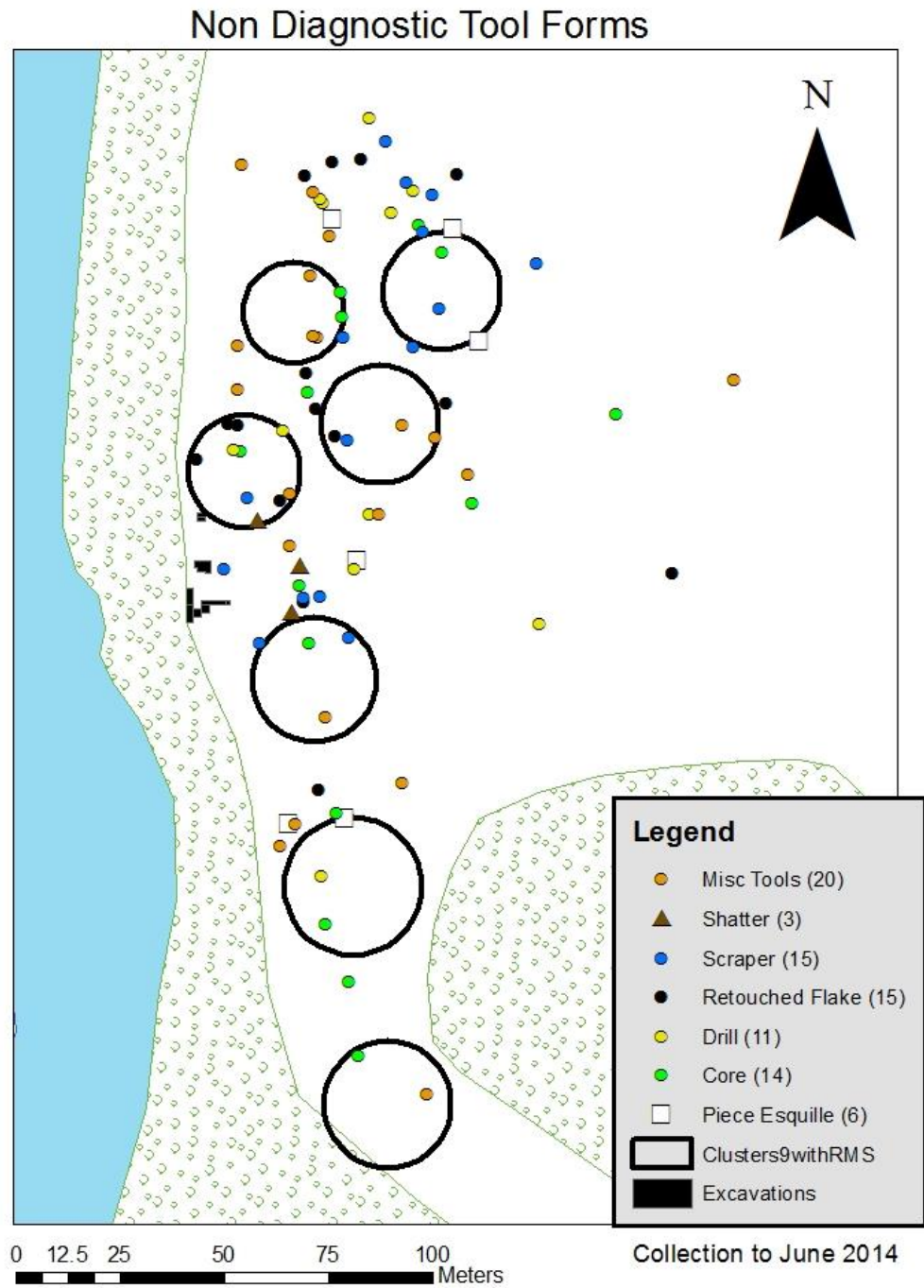
The upper half of the table shows the A-statistic value and the lower half shows the probability of that result under random labeling. This table shows the A-statistic for each of the six artifact classes against the Small Point formal artifacts, the Broad Point formal artifacts and the coarse flakes from the site. Statistically significant results are shaded yellow and results approaching significance are shaded orange.

For the category of cores, the A-statistic indicates that these tend to be segregated from Small Point artifacts ($A = .82$, $p = .03$) with significance. In comparison with both the Broad Point artifacts and coarse flakes, a value close to 1 indicates that they are randomly intermixed. Thus, the distribution of the cores is more in accord with the distribution of Broad Point artifacts.

Examining drills, the A-statistics indicate segregation from both Broad Point distributions ($A = .94$ and $.91$) and random mixing with the Small Point artifacts. However, none of the results is statistically significant, although the comparison between drills and coarse flakes is approaching significance at $p = .1$. Overall, the drill distribution more closely approximates the definitive Small Point artifact distributions, but not with significance. This result is not totally unexpected, as the drill was used by Broad Point people and we have at least two drills which clearly belong to the Broad Point occupations; but it would appear here that drills may be used more often at this site during the Small Point Archaic occupation.

Looking at the piece ésquillées, there are no significant trends.

Considering the retouched flakes, these again tend to approximate the distribution of the Small Point artifacts ($A = 1.03$) and are segregated from the two Broad Point classes ($A = .91, .89$). The results of retouched flakes against the coarse flakes is significant ($p = .05$) while the retouched flakes against the Broad Point artifacts is approaching significance at ($p = .09$). The retouched flakes seem to be primarily associated with the Small Point occupation.

For the scraper category, these are less segregated from the Small Point artifacts ($A = .94$) and are more segregated from the both classes of Broad Point artifacts ($A = .90$ and $.87$)

with significance ($p = .05$ and $p = .02$). The scrapers, then, are most closely associated with the Small Point occupation.

Summarizing these results, while these tools were deposited by both Broad Point and Small Point occupations, it appears that scrapers and retouched flakes seem to be more closely aligned with the Small Point Archaic distribution, while cores tend to be distributed much like the Broad Point Archaic.

4.6   Discussion

The preceding analysis demonstrates various degrees of patterning in the surface material from the Davidson Site. The validity of these patterns varies with the various degrees of statistical significance, as well as the confounding interpretive effects of the artifact collectors and ploughing. Nonetheless, the core information is sufficient to advance some interpretations of the site occupation during Late Archaic times.

This analysis supports the interpretations from our other investigations at Davidson that there are two distinct occupations, one during the Broad Point Archaic and one during the Small Point Archaic. The nature of these occupations varied through time. Spatially, the Small Point occupation is confined to the northern portion of the site in the vicinity of a dense band of magnetic anomalies/features. The Broad Point occupation covers a much larger area extending southward along the old river bank. These occupations will be considered separately.

4.6.1   Broad Point Occupation

Statistical analysis of the Broad Point occupation unequivocally shows a structuring of the site shown by the distribution of the surface material. With the coarse flakes we see that there are five similar sized, regularly spaced clusters adjacent to the river course. In the northern part of the site, there are one and possibly two shadow clusters, which lie behind the riverside clusters. Each cluster involves all stages of biface reduction in similar proportions. These clusters have a similar internal layout with a diameter usually

about 35 m, composed of a larger core cluster with a smaller sub-cluster to the southeast. This patterning with the southeast extension is more evident in the southernmost clusters, but occurs in all six of the definite clusters (Figure 4-40). There is evidence that early

Figure 4-40: Comparison of Spatial Cluster Structure
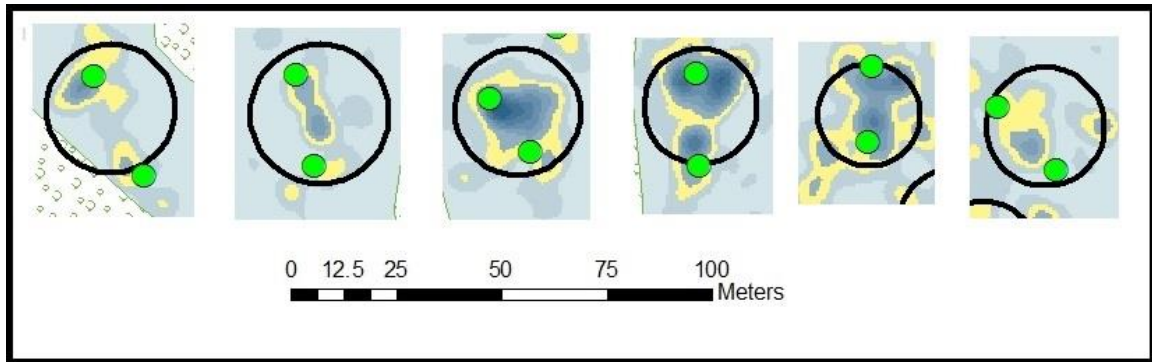
stage reduction of cores might have taken place at the periphery of the cluster and subsequently the reduction process was moved to the centre of the cluster. More likely, the explanation for this trend is the process of site cleaning, although ploughing might be affecting these results too, as the more primary flakes tend to be larger on average. Site cleaning certainly occurred, since we found true middens dating to the Broad Point occupation during the excavations including flaking debris (Eastaugh et al. 2013). Moreover, it has been observed that the process of site cleaning usually results in larger bits of refuse being thrown to the edge of the site (Johnson 1984:79). Further supporting site cleaning as an explanation is the observation that all but one of the cores recovered also occur on the periphery of the RMS circles. It seems that site cleaning would be the most parsimonious explanation, given that the flakes produced during early stage core reduction would be larger than later biface thinning flakes.

The distribution of formal Broad Point artifacts shows a highly significant trend for their location outside of the RMS circles defined by the distribution of coarse flakes. As discussed, the activities of artifact collectors have undoubtedly modified the distribution of Broad Point artifacts such that any conclusions reached here must be provisional. However, the occurrence of the formal artifacts outside the knapping centres indicated by the RMS circles is likely a real phenomenon. While collectors are prone to collect mostly

from concentrations, it is not reasonable to think that they would remove most artifacts from within the RMS circles but miss others directly between them. Also, as discussed earlier, it is possible that some areas at the north end were buried until the early 1980s lessening the effect in those areas beyond Kenyon's (1979) map Area B (Figure 4-9). The area that has likely been much more sparsely collected is the area to the east of the main concentration. The prize finds for collectors was and continues to be complete points, and examination of area collections indicates these were not uncommon. Given the lack of these in our collection, it probably means that most have been removed, leaving this artifact class grossly under represented. Nonetheless, it appears that formal Broad Point artifacts, while following the same general distribution over the site, tend to be differently distributed than the coarse flakes.

An additional factor confounding the interpretation of the formal artifact distribution is the presence of an old fence line/hedge row towards the south of the site (shown in Figure 4-8 and Figure 4-41). It is evident that the concentration of formal artifacts just north of the second coarse flake cluster from the south could have protected this area. This cluster must be ignored in interpretation. As noted above, the area south of this fence line was collected previously, as was confirmed by a visitor to the site who noted that artifacts on coarse grained rocks were present. Surface materials were also evident on the surface in this area even at the time of Kenyon's (1979) work.

Figure 4-35 shows that in the five northernmost clusters there seems to be a trend for formal artifacts to be located on the northern periphery of the RMS circles. This pattern is especially notable with the third cluster from the south where a fairly dense cluster of formal artifacts occurs between it and the next cluster to the north. In looking at the four northern RMS circles, three of these circles show a similar pattern, with the exception of the northernmost riverside cluster, where the density of formal artifacts is very close to the coarse flake density. There would appear to be patterning of the distribution of formal Broad Point artifacts adjacent to the RMS circles and this patterning would be very hard to explain by ploughing, which would not drag artifacts in only one direction.

Figure 4-41: The Old hedge Row / Fence Line
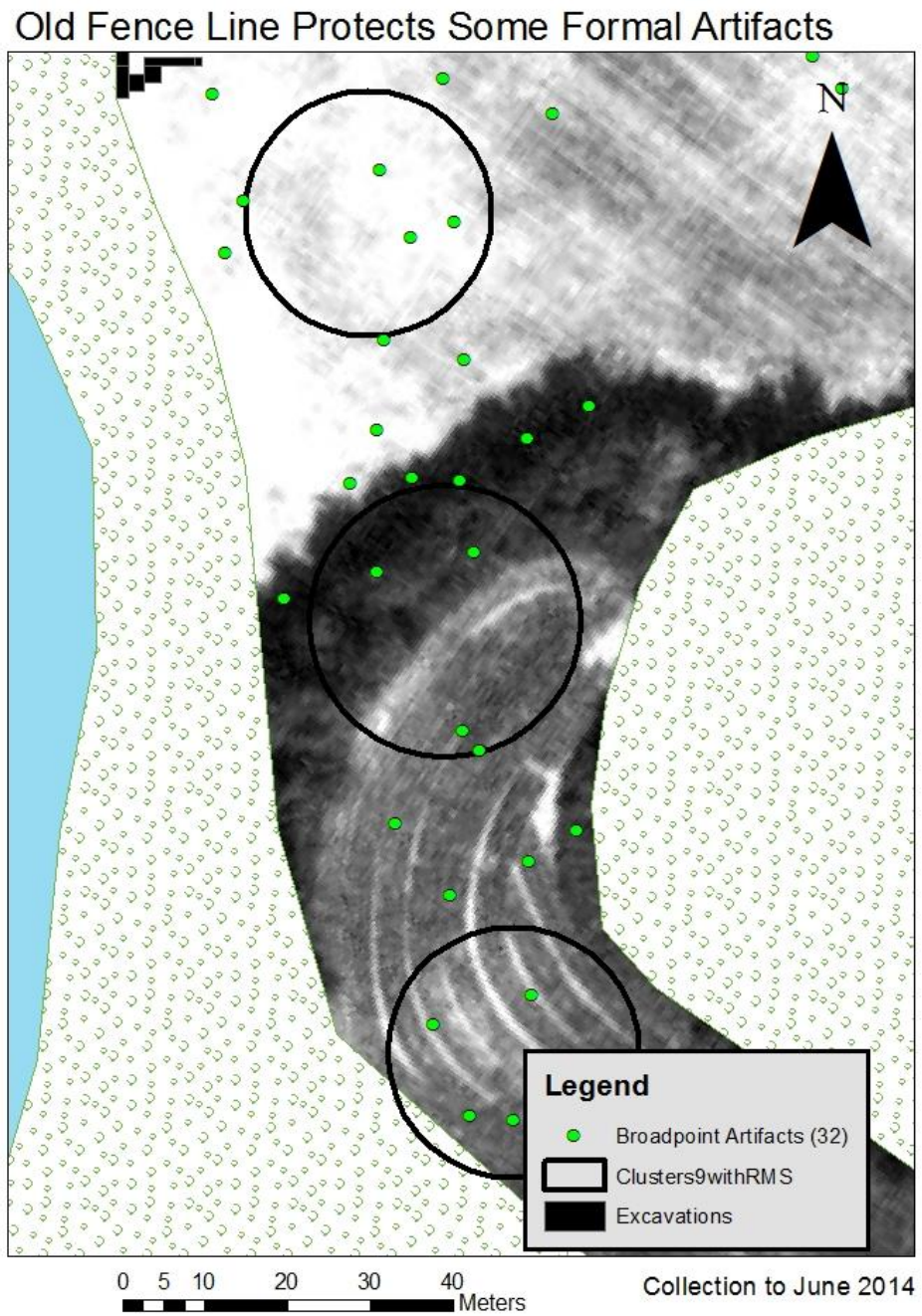
What can explain this pattern? One possibility is that discard of these artifacts after use was more complex and took place in locations different than the knapping activity. However, it could also be because most of the Broad Point artifacts are fragmentary and at least some of them may have been broken through knapping errors, and the deposition on the periphery is simply the result of site cleaning. Given that the representativeness of the formal Broad Point artifacts has been significantly distorted by the activities of collectors, it would be unscientific to interpret the remaining artifacts relative to human behaviour. Future research may be better able to address this issue through consideration of excavated materials rather than surface finds.

Given the clear structure of the site as defined by the distribution of coarse flakes, the question remains as to whether the site represents a single Broad Point occupation or whether the site was used by Broad Point people over a significant portion of the Broad Point Archaic. Of course, the two discrete series of Broad Point dates do suggest it may have been used over a significant period of time and even, taking into account calibration, at least a 700 year period in sidereal years (Figure 4-11). The presence of a few points assignable to the Adder Orchard style of ca. 4000 BP (Fisher 1997), and not just the ca. 3800-3400 BP more Genesee-like styles, suggests an even longer possible period of site use. Of relevance to the possible duration of use and the representativeness of the sample, the Adder Orchard Broadpoints recovered include only three examples, all on chert. All three of these were found at the north end of the site and none were found in the southern spatial clusters of coarse flakes, implying that the coarse flakes relate solely to the Genesee occupation. Excavations at the nearby Adder Orchard Site (Fisher 1997) show that while subgreywacke was used during this earlier time, it was very rare compared to the use of chert (68 of 44810 debitage and 10 of 294 formal tools at that site). In the surface sample we have eight Genesee points, one of which is on subgreywacke, and 8 of 24 wide pentagonal preforms, which almost certainly relate to the Genesee-like occupation. Thus, it appears that the coarse flakes pertain primarily to the Genesee occupation as opposed to the earlier Adder Orchard period of site use. The 700 calibrated year period at ca. 2500-1800 BC is an interpretation that fits better with the radiocarbon dates from the site (Figure 4-11).

The continual or repetitive use of Davidson is supported by the variable density of the respective clusters. In general, the three northern riverside clusters are denser than any of the other four, despite the fact that the cluster sizes are similar. This result may suggest that the three northern riverside clusters were occupied more often than the other clusters, despite their similar spatial sizing. This difference is not a function of our collection, given the number of flakes now plotted and the fact that the entire site was examined. This implies that over time some of the clusters were used more often than the others.

Thus, a parsimonious hypothesis is that the clustering and distribution of coarse-grained flakes represents a palimpsest through time, with a number of reoccupations within the Broad Point Genesee period. However, each subsequent reoccupation of the site was within well-maintained spatial parameters that defined who and where specific occupants should be located at which locations along the river bank. Individual cluster organization remained constant, with the southeastern sub-cluster being maintained as well. That this structure was maintained over considerable time implies cultural continuity through succeeding occupations. Also, the equal spacing implies that several, if not all, of these clusters could be occupied at the same time. This structuring of the clusters bespeaks some form of social/activity organization where the location was maintained over many years and maybe even decades or longer.

An interesting aspect of the site is the presence of one and maybe two shadow clusters beside the two northernmost riverside clusters. The obvious question is why these shadow clusters only occur beside the northern two riverside clusters. It may be that there was a change in settlement patterns, where the southern two riverside clusters relocated to be closer to the northern clusters, which is not unreasonable given the lesser density of the southern two clusters and the two shadow clusters. Alternately, the site could have periodically flooded adjacent to the river bank edge in the northernmost area, rendering it uninhabitable. During those times they likely moved inland. Also possible, as noted, is that the river course moved west or meandered slightly west during the Broad Point period of site use. In this scenario, the more interior and ephemeral northern clusters represent the initial use of the site location and the more dense clusters on the old

evident river bank represent a later period of site use after the river had moved farther west.

Still another possibility is that the southern three clusters are the inland shadow clusters and riverbank erosion to the west may have destroyed the respective riverside clusters beside clusters 2 and 3 from the south. In sum, there may have been five clusters paralleling the river bank. Suggestive of this interpretation is the fact we encountered Broad Point features in the excavated area that might correspond to part of a third river bank cluster. In addition, certainly the initial site discovery occurred because a paleosol containing Broad Point artifacts and features was eroding into the river just south of our excavations (Kenyon 1980; Figure 4-5). Another factor here would also be the presence of historic flood deposits up to a metre thick, which could have obscured remaining portions of the respective riverside clusters farther south. In sum, there may be other clusters buried in wooded areas along the river to the south of the eroded area and west of the coarse-flake clusters out in the southernmost ploughed field area. Of course, the final possibility is that the clusters are as we see them. Unfortunately, with the existing knowledge of the site, it is impossible to distinguish between these options. However, it should be possible to test for a riverside cluster beside the southern cluster where there is room in the forested part of the site. We know a buried paleosol occurs in that area, based on soil probe testing (Ellis 2015) but do not know if it contains cultural occupations. Unfortunately, that area is forested, necessitating test pitting which will make the results spatially restricted and difficult to compare with this analysis.

The final question is how to interpret this pattern of clusters. At this point, the most parsimonious explanation is that the site represents a seasonal aggregation site where various closely related but separate social units gathered at a specific time of the year. This pattern is not unique in pre-Woodland timeframes. The Bull Brook Paleoindian site in Massachusetts has a series of clusters, internally consistent in size and content that are arranged in an evenly spaced, albeit circular, pattern. The site is interpreted as an aggregation site (Robinson et al. 2009). Given the size of the Davidson clusters, with an approximate diameter of 35 m (after ploughing), this area provides sufficient space for a relatively small group to camp, such as one or two extended families. Most Archaic sites

are this size or even smaller. Given the dearth of features in the southern half of the site as compared to the Small Point occupation to the north, it would fit well with a non-winter occupation of the site. Also indicative of several discrete groups occupying the site is the fact that all stages of biface reduction took place in each cluster and analysis of the distribution of formal Broad Point artifacts has shown that these, too, are evenly distributed over the site. Each cluster operated its own reduction process and thus, appears functionally equivalent.

Additional support for this functional similarity hypothesis is the presence of the southeastern sub-cluster within each main cluster. Figure 4-40 shows the six definite spatial clusters. In this Figure the clusters from south to north are shown from left to right. These pictures show the Pure Locational Clustering centres with 20 clusters requested, the Kernel Density at 6 m and the RMS circles from Pure Locational Clustering with 9 clusters. Given that this sub-cluster is not related to the reduction sequence, there is an alternative explanation for this pattern that cannot be discerned currently by looking at the coarse flaking detritus. It should be noted that Wilmsen (1974:112) found a similar internal patterning of different locations over the Lindenmeier, Colorado, Folsom site as a whole. Similar patterned distributions of artifacts, detritus and other waste occurs with the inference that each camp was used for the same purpose, either by a discrete group of people or by the same group of people over time. His example, however, lacked the consistent spacing suggesting the aggregation seen at Davidson. Wilmsen (1974) based his interpretations on the ethnoarchaeological work of Wiessner (1974: Figures 1 & 2). She showed that the camp layouts of San foragers in South Africa had the same repetitive internal layout. In our case, without full excavation and almost certainly no recovered bone from the surface and only limited numbers of formal artifacts recovered, it is unlikely that we can determine the functionality of the southeastern sub-cluster. Nonetheless, the comparable internal clustering suggests repetitive use of each one for the same purposes. Finally, the fact that some of the clusters are not as dense as other suggests that when an aggregation took place, not all of the social subunits might necessarily assemble. There may have been competing choices as to where to aggregate or travel at certain seasons.

Thus, the most reasonable explanation of the clustering is that the site represents an aggregation site where several smaller, probably usually dispersed social groups, came together at a specific time in the yearly round and probably during the warmer months. This interpretation may also explain other unusual and very large Broad Point sites in the Ausable River drainage.

4.6.2   Small Point Occupations

Given the much smaller number of Small Point Archaic artifacts in our sample and the possible impact by the activity of collectors, it is difficult to develop any sound conclusions other than that the distribution is very different from the Broad Point Archaic. Reviewing the AMS radiocarbon dates shown in 4.9, there seems to be a hiatus between the Broad Point occupation and the advent of the Small Point occupation. When the Small Point using people arrived at the site, they chose a very different site organization and most likely season of occupation. The initial Small Point occupation seems to occur in a band at the north end of the site along the then current river bank. During this period numerous subsurface pits and pit houses were constructed in what was most likely a winter occupation, but that may have extended into other seasons or have been flexible in season of use over time (see Ellis et al. 2015). During this time the predominant point types were Innes and Crawford Knoll. The statistical evidence suggests that later occupations characterized by Hind and Meadowood occupations are clustered differently within a smaller circular area behind the band of magnetic anomalies where the houses occur. This cluster does not represent the entire distribution of these points, since we recovered two points somewhat transitional between Hind and Meadowood during our excavations to the southwest along the river bank in an area where historic silting had occurred, burying the original ground surface. Both of these were located above a large pit house and were just above a circular house outlined by a wall trench and have to post date ca. 3000 BP. The exact relationship between these two points and the surface distribution discussed here is unknown. Therefore, it appears that a change in site use occurs within the Small Point Archaic. Speculating, it is possible that there was a winter occupation earlier in the Small Point Archaic all along the old

riverbank, with many pit houses and other pit features of various kinds during the early portion of the Small Point Archaic. Then a change occurred later in the Small Point Archaic to more localized, possibly non-winter occupation that was not as focused on the riverbank area. In reality, excavations have shown that the changing site use during the Small Point Archaic is much more complex than this scenario implies, with a possibility of shifting back and forth between winter and warmer weather occupations (see Ellis et al. 2015). Thus, the patterns in the surface distributions seem to indicate a similar changing use of the site, but these conclusions must be tempered by the earlier caveat that any conclusions based on distributions of formal artifacts can be tenuous because of the depredations by collectors -- although the fact the northern half of the site seems to have been buried for longer periods (e.g. until post-1980) may mitigate somewhat these effects.

The other change occurring between the Broad Point and Small Point Archaic occupations occurs with the broader tool kit. As was shown, the distribution of scrapers and retouched flakes more closely aligns with the Small Point Archaic distributions. There is also a non-significant trend for drills to be closer to the Small Point distributions, despite the fact that there are Broad Point drills recovered from the site. However, these changes may relate to changing activities associated with the change in seasonality.

4.7   Conclusions

The current analysis, through the application of spatial statistical procedures, has provided further understanding of the Davidson site occupied over 1500 years by one or perhaps two different groups of people. Obviously, more work could be done in the future, especially as it relates to doing a complete CSP retaining all flakes and fire-cracked rock. Fire-cracked rock does occur on the southern or pure Broad Point areas of the site and could well provide further insight into the nature of the activities in the coarse flake defined clusters. Similarly, the distribution of Kettle Point chert flakes, especially in the south half of the site, could add further insight into the clusters. For the time being, this analysis has demonstrated the utility of spatial statistical techniques towards a better understanding, especially of these very large sites, and has provided a series of ideas that can be tested in future research.

Chapter 5

5   The Kellis-2 Cemetery.

5.1   Introduction

This case study investigates the use of spatial statistics to analyze intra-cemetery morphogenetic variability in the Kellis-2 (K2) cemetery, Egypt. More specifically, the principle focus is to define the cultural values behind the mortuary program. Molto (2002) identified two possible hypotheses as to decision making process for determining how the burials were added to the cemetery, first, kinship where family members were buried close to each other and, secondly, accretionary where individuals were interred based solely on the order of deaths through time with burials radiating out from an initial interment. The premise is that the kinship organization can be determined by analyzing the relative distributions of the discrete genetic traits. In Molto's (2002) analysis the distribution of several non metric traits were visually clustered which was used to support the kinship hypothesis. This study will examine the distribution of a much larger set of data in an attempt to conclusively determine if this initial observation was correct.

5.1.1   The K2 Cemetery

K2 is located in the Dakhleh oasis in the western desert of Egypt (see Figure 5-1). The data examined here were collected as part of the Dakhleh Oasis project, a multidisciplinary project examining the interaction between humans and the environment over the entirety of human occupation of the area (Birrell 1999; Hope and Mackenzie 1999; Knudstad and Frey 1999; Molto 2001, 2002). K2 is one of several cemeteries in the oasis and derives its name because the remains are from people from the historic town of Kellis. The K2 burial pattern includes single extended burials oriented east-west with the head to the west and an absence of grave goods, the Christian burial pattern (Bowen 2003). From ^{14}C dates it was in use from the first to the fourth centuries A.D. (Molto et al.2006). There is disagreement within the project team between the skeletal biologists and the classical archaeologists with respect to the validity of the earliest ^{14}C dates. However, Pearson (2011) notes a substantial Christian population in Alexandria in the

Figure 5-1: Location of the Dakhleh Oasis
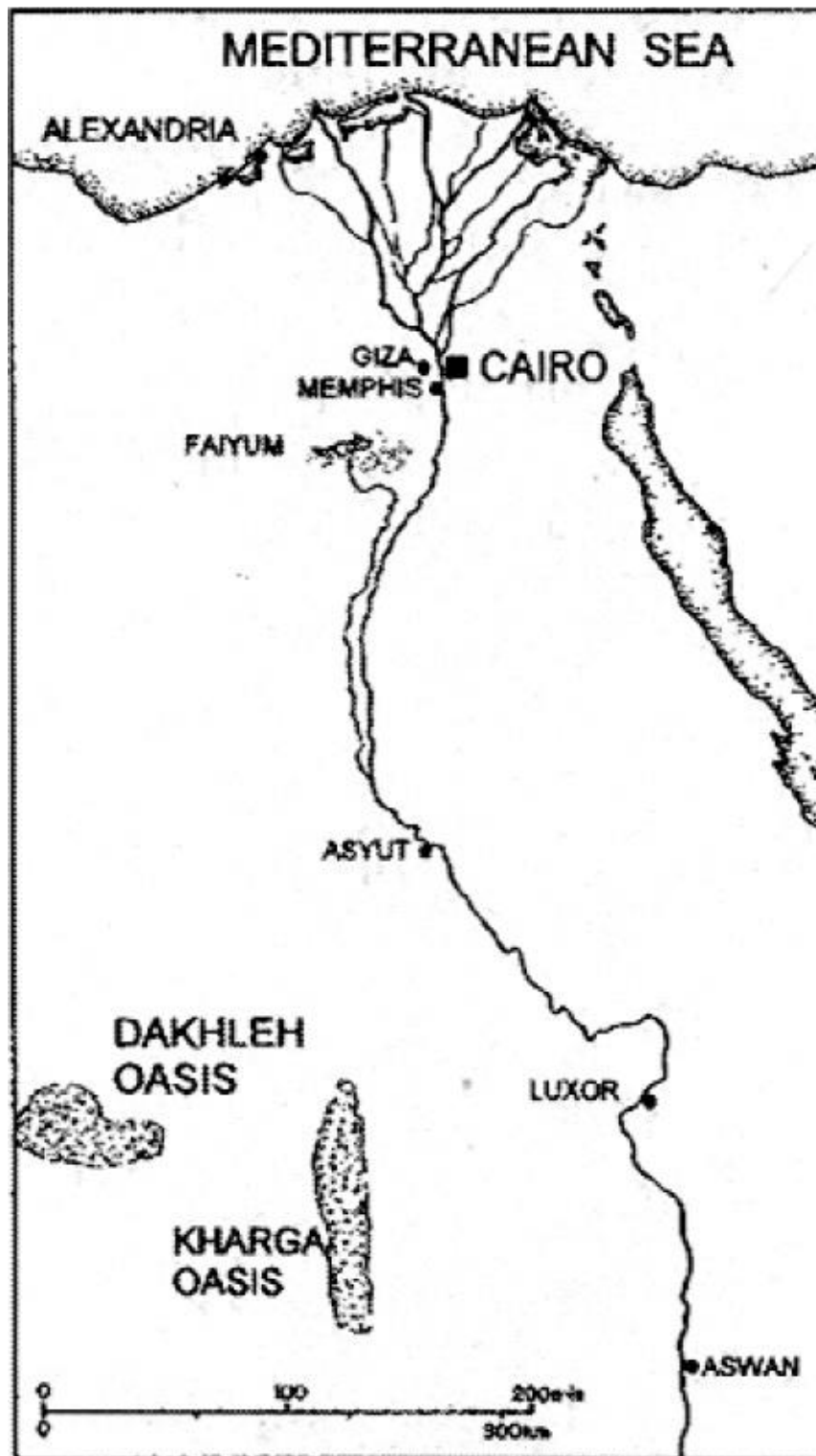
first century and, elsewhere Pearson (2004) discusses the spread of Christianity in Egypt outside of Alexandria in the first century. Based on historical accounts, the first century ^{14}C dates seem entirely plausible and are accepted here.

K2 has a number of tomb superstructures dispersed throughout the cemetery (Figure 5-2).

Figure 5-2: The Full Extent of K2

Kellis 2 Cemetery
Extent of Visible Burials

1997 Survey limits ------
Excavation limits —·—

0m   50m
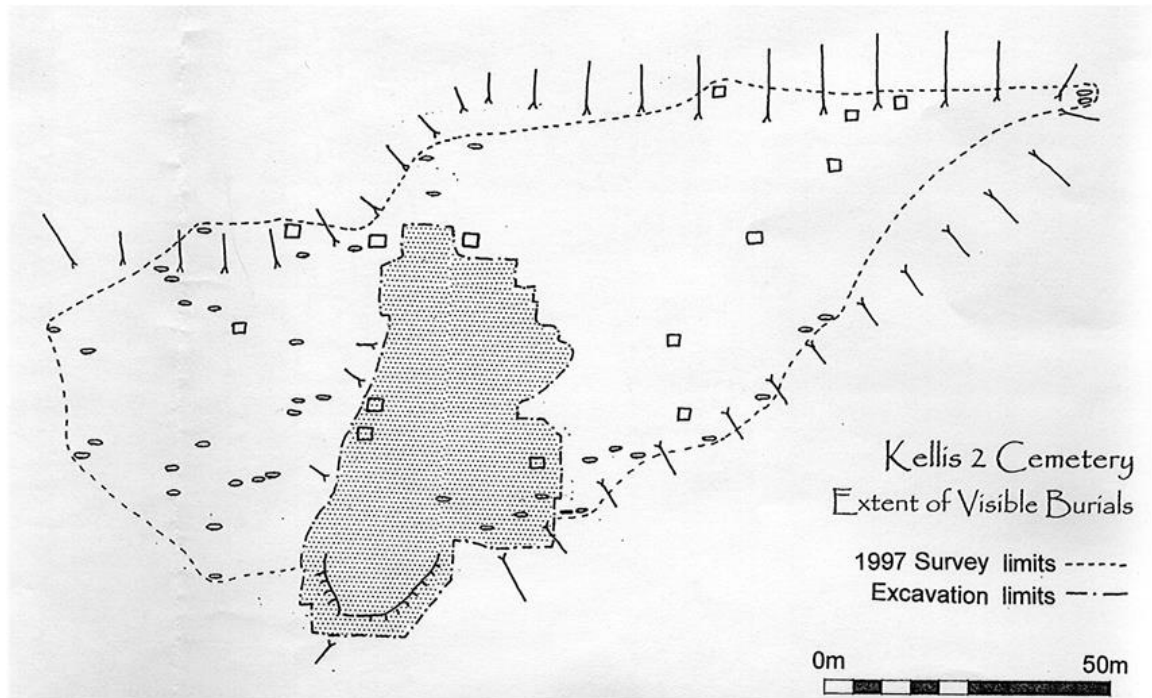
Molto (2002) hypothesized that, when the people of Kellis converted to Christianity in the first century A.D., they switched their burial mode from large crypts found in the preceding cemetery at Kellis 1 to the single burial mode at K2. Radiocarbon dates show that at least three of the tomb superstructures were contemporaneous and date to the early phase (El Molto, personal communication 2015). A portion of K2, containing approximately 700 graves and four tomb structures (Figure 5-3), has been excavated by the Dakhleh Oasis project. The four structures are dispersed in the excavated area and will be referred to here by their spatial locations in the area as northwest, southwest, northeast and southeast respectively. The skeletal analysis of the cemetery population

Figure 5-3: Excavated Portion of K2

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Legend

ExcavatedGraves
Unexcavated
ExcavationLimits
Tombs
EmptyFeature

0 2.5 5   10   15   20
Meters
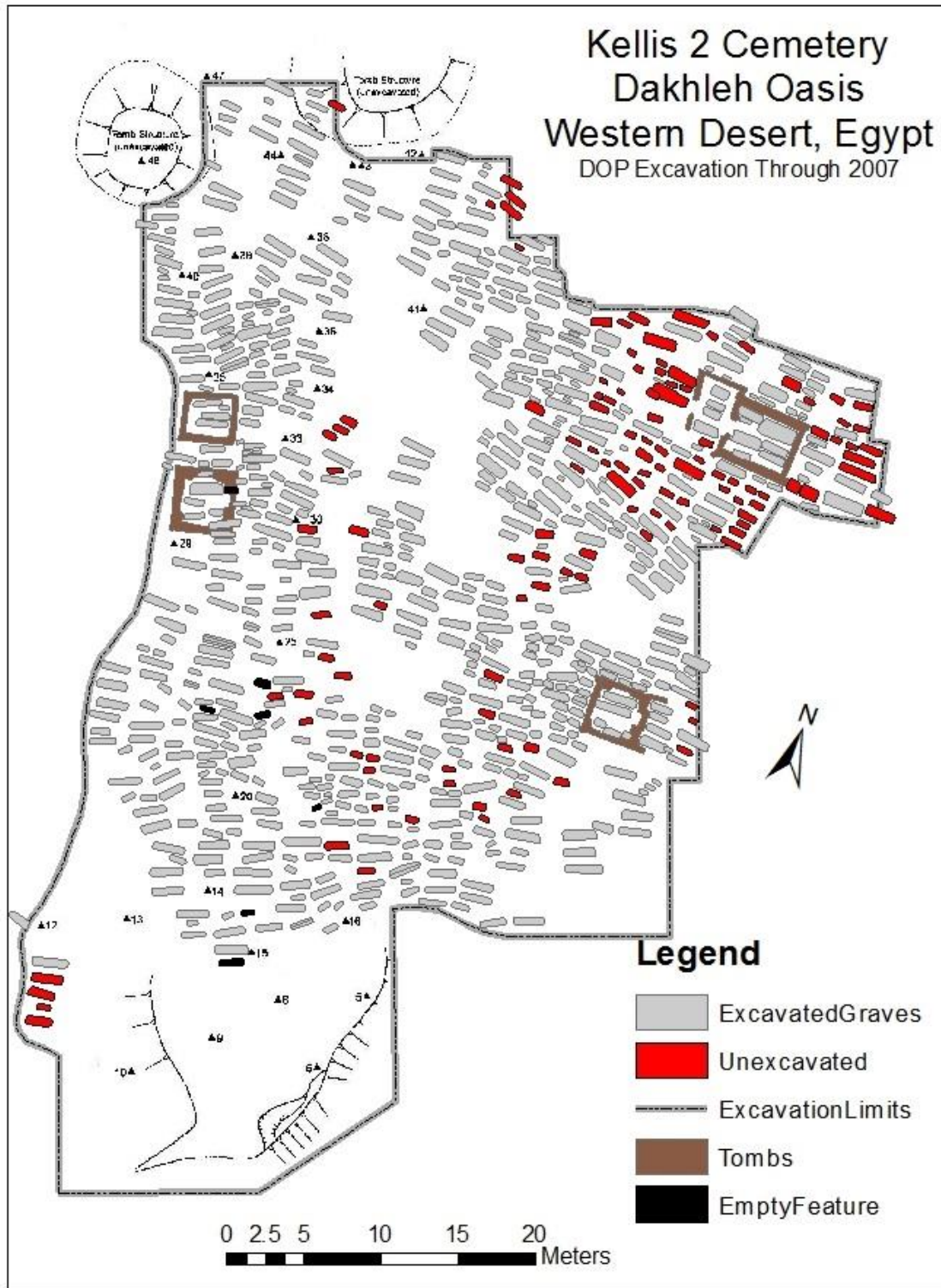
was conducted by Dr. E. Molto. Numerous cross-checks on the skeletal scoring process were employed to ensure consistency in the results (for a detailed description of the process see Brown [2013]). The elements examined in the spatial analysis here are discrete genetic traits or skeletal features (phenotypes) which may or may not show up on a skeleton depending on the individual's genotype. These traits are either present or absent or may show partial expression and, as such, are not scored metrically. For statistical purposes they are nominal data. For this analysis the distributions of 38 of these traits are used. These data were examined by Lisa Brown (2013) and trait description and pictures can be found in that thesis. Finally, for this preliminary analysis the "present" and "partial expression" categories are combined. With scoring tightly controlled by one individual we can assume internal consistency.

5.1.2   Theoretical Orientation

Stojanowski and Schillaci (2009) note that, if the distribution of burials is well defined, then a study of phenotypic variables can be used as a proxy for genotypic variability. They define several different analytic approaches to address this task. Two of these approaches will be utilized herein, first, the search for kinship patterns and second, the examination of post-marital residence patterns.

By identifying areas of family burial, structural statistical analysis of cemeteries seeks to identify patterns that can be used to determine whether cemeteries were organized by kinship patterns including residence or whether the burial practices were accretional and stochastic. For kinship organization, spatially nearby individuals are hypothesized to be more similar genetically than burials further removed spatially. Stojanowski and Schillaci (2009) term this kinship and cemetery structure analysis. As they note, different analytical approaches are required, depending on the nature of the cemetery. They define analytic procedures for three types of cemeteries, first, small graves with typically under 10 individuals, second, spatially structured cemeteries where there are clearly visible spatially segregated divisions in the cemetery, and third, uniformly distributed cemeteries where there are no obvious spatially distinct divisions in the cemetery. The K2 cemetery (Molto 2002) analysis herein treats K2 as a uniformly distributed cemetery. Note that treating K2 as a spatially structured cemetery analysis is possible as was demonstrated by

Haddow (2012). With uniformly distributed cemetery analysis, the primary focus is the application of methodological procedures and spatial statistics. As Stojanowski and Schillaci (2009) note though, identifying kinship as a factor in cemetery organization is probably the least interesting aspect, since most cemeteries are organized at some level on the basis of kinship. However, once the family units are defined, there are other aspects of social organization that can be investigated.

The second form of Stojanowski and Schillaci's (2009) analysis is the discernment of post-marital residence patterns by investigating the distribution of phenotypic variables by sex. They note that the most common types of post-marital residence patterns are: 1) patrilocal, where the couple lives in the vicinity of the husband's parents; 2) matrilocal where residence is with the wife's parents; 3) avunculocal with the mother's brother; 4) bilocal residence where there is choice and hence, residence is variable; 5) neolocal which implies that the couple lives separately from either of their parents; and finally, 6) duolocal where the couple lives separate from one another, each continuing to reside after marriage with their own parents (Stojanowski and Schillaci, 2009: 65). Of course, the obvious question is how do residence practices translate into the mortuary program and how does the cemetery organization reflect the mortuary program? Care must be taken in operationalizing these patterns as it relates to the analysis. One problem with identifying post-marital residence patterns from cemetery organization is that of equifinality, where two different residence patterns lead to the same burial juxtapositions in the cemetery. For example, in a hypothetical patrilineage, is patrilocal residence necessarily practiced? If post marital residence is patrilocal, we could expect clustering of closely related males in a cemetery. However, the actual residence patterns could also be bilocal, neolocal and maybe even duolocal but if the mortuary program stressed the patrilineal kinship organization the burial pattern could see closely related males buried in proximity. Similarly, a matrilineal society with an avunculocal residence pattern could produce a cemetery with clustering of genetically related males that would be only subtly different than a cemetery where burials are organized by patrilineage. Of course, the mortuary program might not even reflect the kinship organization or the post-marital residence pattern of the society. The 17th century Wendat would be a good example there (Trigger 1987). Here a matrilineal society produced ossuaries that are clearly accretional. Another

potential problem would be whether a community was endogamous or exogamous. In the latter, the difference can be tested from analysis of the morphology of the individual skeletons by determining which sex has the most variability.

In general, I challenge Stojanowski and Schillaci's assertion that the post-marital residence pattern can generally be determined from the distribution of phenotypes. More likely is that the kinship system, whether patrilineal or matrilineal, would be the determining factor reflected in the mortuary program, as opposed to the actual post-marital residence pattern, but this is yet another level of abstraction further removed from the archaeological record. To my mind in an analysis of morphogenetic variability the most we can hop to determine is the relatedness of nearby individuals. If this is along male relatedness we could use the term "patrilocal interments". If we can demonstrate a patrilocal interment pattern this could be used along with other contextual data to make inferences regarding the kinship system and post marital residence pattern. Despite these difficulties, it is still worthwhile to examine the data for potential implications regarding the nature of the burial structure as it relates to the kinship system.

While the structuring of this analysis follows Stojanowski and Schillaci (2009), the mathematical processes utilized are different and thus, represent a departure from the methods they describe. In this paper, as noted, I will test the organization of the K2 cemetery in Dakhleh Oasis, Egypt, a cemetery that is ideal for an intra-cemetery statistical spatial analysis.

5.1.3 Application and Hypotheses

Stojanowski and Schillaci's (2009) first form of analysis is the search for kinship patterns indicated by clustering of discrete genetic traits. The null hypothesis examined herein is that K2 was organized randomly by accretion. The accretionary model assumes that burials in the cemetery commenced at some point in time with an initial burial and then expanded out from that point as additional burials were added without regards to the family affiliation of the individual. The kinship model assumes that various kinship groups first established the tomb superstructures and then proceeded to bury family

members either within or adjacent to the tomb structures over time. The expectation would be that for an accretionary model the distribution of genetic traits would be essentially random, whereas a kinship model should show a tendency towards clustering of the discrete genetic traits. Obviously, these two opposing hypotheses are somewhat simplistic. For example, in the accretionary model a discrete genetic trait could be introduced to the community through exogamy late in the use of the cemetery. Thus, it would be clustered in the later used areas and would be absent from the earlier area of the cemetery. Similarly, kinship is culturally defined and family members could easily be unrelated genetically through process of adoption. These scenarios would confound the patterns in the cemetery, but even with both factors operative, as they probably were, the accretionary pattern should still be significantly different than the kinship mode. Another factor that must be considered is that not all traits may display clustering indicative of kinship. Stojanowski and Schillaci's (2009: 53) citing Alt and Vach (1998) note that at the within-site level, rare traits or those considered genetically anomalous are more useful than commonly occurring traits for identifying closely related individuals. Thus, while any given trait may or may not show evidence of clustering with kinship implications, it is the sum of the results of the analysis of all the traits that will support or reject the kinship hypothesis.

Finally, as noted, in normal statistical terms, the null hypothesis will be that there is no spatial kinship structure in the cemetery associated with each trait. Therefore, the null hypothesis equates to the accretionary hypothesis and rejection of the null hypothesis would support the alternative or the kinship hypothesis.

The second analysis is called post-marital residence and sex-specific migration (Stojanowski and Schillaci (2009: 64). These analyses involve examining trait differences and distributions by sex. As noted above I do not believe that we are not studying post-marital residence patterns per se, but are using the burial patterns in the cemetery as a proxy for the residence patterns and/or the kinship system of the society. What we can effectively study is the organization of the cemetery along what were called patrilocal (or matrilocal interment patterns.

Before defining hypotheses as to how various kinship/residence systems would be reflected in the cemetery, it is necessary to look briefly at some previous research on K2. As defined by Stojanowski and Schillaci (2009: 64), post-marital residence and sex-specific analysis focuses primarily on determining which sex in the cemetery has the most variability. The implication is that the members of one sex entered the community from outside through the mechanism of exogamy. Thus, if males show greater genetic variation, then it suggests matrilocality, as the husbands were imported from outside the community. Previous work on K2 has demonstrated that the population of K2 is genetically part of the population of earlier cemeteries in the Dakhleh Oasis. Brown (2013) used the Smith's Mean Measure of Divergence to determine whether the earlier cemeteries could be pooled with K2 and concluded that they represent the same population. Furthermore, Haddow's (2012: 162) analysis of K2 compared male and female populations using discrete dental traits with the Mean Measure of Divergence, which resulted in a MMD value of .000 or meaning that they are identical genetically. Thus, we are clearly looking at an endogamous pattern for the community where spouses are exchanged between families in the community rather than being imported from more distant, genetically different communities.

With endogamy, then, it appears that using Stojanowski and Schillaci's (2009) approach, the actual post-marital residence would be difficult or impossible to determine and we are thus forced to look for other potential indicators of post-marital residence or kinship.

Bagnall and Frier (1994) have analyzed several hundred Roman historical census records from this time period in Egypt and concluded that the predominant form of post-marital residence at the time was patrilocality. Given post marital patrilocality, the most reasonable expectation of the kinship system would be a patrilineage (Murdock 1949) although determination of kinship from archaeological data can be problematic. Based on this, it seems pragmatic to develop testable hypotheses as to what this might look like if it was reflected in the kinship organization of K2.

If patrilocal residence is reflected in the cemetery organization, we assume that males are buried with their father's family and that married females are buried with their husband's

family. Unmarried, separated or potentially widowed females would be buried with their father's family. In this pattern, we expect that males with a specific discrete trait would cluster together along with some of the females, but other females would be more widely dispersed or possibly evenly distributed through the cemetery.

In matrilocal residence, husbands would be buried with their wife's kin. Unmarried boys and separated or potentially widowed males would be found with their mother's family. The morphogenetic indicators of this pattern would result in females clustering and males to be more evenly distributed through the cemetery.

For duolocal residence, a reasonable expectation is that people are buried with their father's family and, consequently, we would not expect to see one sex clustered and the other more evenly distributed.

Neolocal and bilocal residence patterns could be expected to lead to a cemetery organization that more closely represents the accretionary hypothesis, unless the underlying kinship system is what is reflected in the cemetery organization rather than the residence pattern. The other possible confounding factor would apply to avunculocal residence which would result in a pattern similar to a patrilocal organization. Fortunately, these residence forms are rare (Divale, 1977) and we can reasonably expect a patrilocal residence pattern (Bagnell and Frier, 1994) in the society.

Finally, it must be noted that when examining a specific genetic trait, that the first form of analysis, the search for kinship organization in the cemetery, might not indicate any significant trends but the second form of analysis, the search for post marital residence patterns, could indicate a significant clustering. When this situation occurs, a positive result in the second analysis can be considered as demonstrating a kinship based organization in the cemetery despite the fact that there was no significant clustering during the first step. As will be shown, this situation is common.

5.2 Methodology

Since the original data used to produce the site map were not available, the existing paper map was digitized into ArcGIS preserving the original scale. Thus, while true

georeferencing could not be accomplished, the relative positioning of and distances between the graves is accurate, or at least as accurate as the scale of the original map. Thus, the application of spatial statistics is possible and the distances discussed are actual distances rather than relative distances. This digitizing process uncovered several errors in the original map, all with the labeling of the grave numbers. There are six instances of the same grave number appearing twice on the map. These were corrected. In the GIS, each grave is shown as a polygon with the associated excavation grave number from the excavation included in the attribute table. The data showing the discrete traits present were available in an Excel file, with each row keyed by the grave number and the columns representing the presence or absence of each trait. These data were then joined to the GIS map using the GIS "Join" function, so each grave has all the discrete traits listed in its attribute table. This procedure facilitated the generation of maps showing the distribution of each trait. Since the initial statistics development did not include integration into ArcGIS, it was necessary to get the actual XY coordinates out of ArcGIS so that they could be used in the statistical applications. A file of grave numbers and locations was obtained by creating a map layer that identified the centre of each grave as a point and then applying a function called XYtoASCII to this layer. The result was a text file with the grave number and (X,Y) coordinates. The coordinates were then incorporated into the Excel spreadsheet with the discrete traits for the statistical analysis.

In considering the application of spatial statistics to the data shown in Figures 5.2 and 5.3, there are additional features that need to be addressed. First, the cemetery has not been completely excavated. Hence, the impact of edge effects must be considered, especially along the east, west and north edges of the excavated areas. Edge effects result when a grave along the boundary of the excavated area possibly has more in common with graves outside the excavated area than it does with nearby graves inside the excavated area. Also, within the excavated area the four excavated tomb structures also lie along the periphery. Thus, in the kinship model, we might expect the burials to radiate out from the central family tomb and we are, consequently, only capturing a portion of the family burial area. The final issue is that in the northeast portion of the excavated area, which represents the most recent excavations, unexcavated graves are

more prevalent than in other areas of the cemetery. Thus, these "data holes" may distort the spatial relationships of individuals buried in that area of the site.

The sample analyzed here has been restricted to include only adult males and females. As noted, the excellent preservation at K2 assures that sex determination is virtually 100%. There are cases where some traits are present but sex cannot be determined and these have been excluded. Further excluded is one burial, Grave 453, in the extreme southwest, as it is a spatial outlier. Also, several burials appear in the data but not on the map, making determination of location impossible. After these exclusions, the sample analyzed comprises 177 individuals, 107 females and 70 males.

The determination of statistical significance involves the distribution of discrete genetic traits within the overall cemetery structure. This is clearly an examination of second order effects (the genetic traits) within first order effects (the cemetery structure and grave locations). As discussed in Chapter 2, use of Complete Spatial Randomness (CSR) to compute statistical significance is not appropriate. For Kellis, the appropriate choice is an assumption of random labeling where significance is determined by holding the grave locations constant and the labels (discrete traits) are randomized over the cemetery. This procedure used has another advantage in that it markedly reduces the impact of potential edge effects.

In the following analysis, there are three major sections. First, is an analysis of the male/female distribution, second, is an individual analysis of each of the 38 discrete genetic traits, and finally is a simultaneous analysis of a number of traits in order to identify areas in the cemetery where individuals with a similar genetic composition were located. This sequence was selected because it seemed logical in that the results of the first could impact the second and third steps and the results of the second impact the third. Of course, reality is always more complex and, as a result, the analysis required several iterations. For example, the results of step three, in fact, impact our interpretation of step one and some traits in step 2. This confounds the documenting of the results and in some cases necessitates referencing analytical results which appear later in the text. This is, however, unavoidable.

5.3 Male-Female Distribution

Prior to consideration of discrete traits in the K2 cemetery, it is necessary to consider the relative placement of males and females in the cemetery, as this has implications for both the accretion and kinship models. Both of these models require that the sexes be randomly intermixed. Any segregation of the sexes would necessarily invalidate the testing of hypotheses, at least in their generic form. Similarly, hypotheses of a potential patrilocal society would require that male family members be buried together and that consanguinially related unmarried or divorced and possibly widowed women would be included with them. The other expectation is that married women would be buried with their affinal relatives. This practice should lead to a reasonably random mixing of male and female graves. With the accretion model one would expect a series of deaths that would represent a random sequence of males and females and, consequently, a random intermixing of males and females spatially. Consequently, the first question to be examined is whether or not the male and female burials at K2 are random in nature. If they are not random, then our hypotheses on the mortuary program may need to be reexamined or, at least, the succeeding analyses needs to be cognizant of the relative distributions.

In order to evaluate the mixing or segregation of males and females, a larger set of data that includes all the identifiable males and females in the cemetery will be used. The distribution is shown in Figure 5-4 with 142 female burials and 98 male burials ($n = 240$).

The primary concern, prior to analyzing, the spatial distribution, is the numerical difference between males and females in the cemetery. Hypothetically, the number of males versus females should not be statistically significant. However a G-test rejects this hypothesis, as the females far outnumber the males ($G = 8.11$, $p < .01$). Since we assume from demography that adult males and females should occur in almost equal proportions in the overall population, this pattern needs an explanation.

Visual inspection of Figure 5-4 identifies several apparent clusters of male and female burials in K2. In the northwest corner is a group of ten burials, of which nine are male. In the south end, there is a group of eleven males and immediately north and northwest is a

group of 21 females, with only two interspersed males. Also, immediately west of the southeast tomb structure is an apparent cluster of female burials.

These clusters were evaluated using several statistics, the A-statistic, Proximity Count, Local Density Analysis and Cross Nearest Neighbour. The A-statistic gives a value of $A = .99$, which indicates almost random distribution of the sexes.

Second, the Proximity Count statistic was run, first on males and then on females (see Table 5-1). Probability was determined with 999 randomizations over the 240 grave locations.

Table 5-1: Proximity Count - Males and Females

Table 5-1				
	Males		**Females**	
Distance	**Count**	**p**	**Count**	**p**
3	71	.23	144	.23
5	212	.002	374	.45
7	353	.07	699	.27
10	590	.85	1359	.04

This analysis shows that, at a distance of 5 m the males tend to occur closer together with statistical significance than we would expect to be the case under truly random conditions. Even at 7 m we see clustering that is approaching statistical significance. In the same range, females tend to be randomly distributed. As was discussed in Chapter 2, when analyzing second order effects, the distance within which the effects are sought is generally a small percentage of the overall scale of the point pattern being examined. With K2 this is definitely smaller than 15 m and probably around 10 m or less. Consequently, the meaning of the female clustering or dispersion at 10 m is questionable in the Kellis context given the size of the site.

Figure 5-4: Males and Females - Large Sample
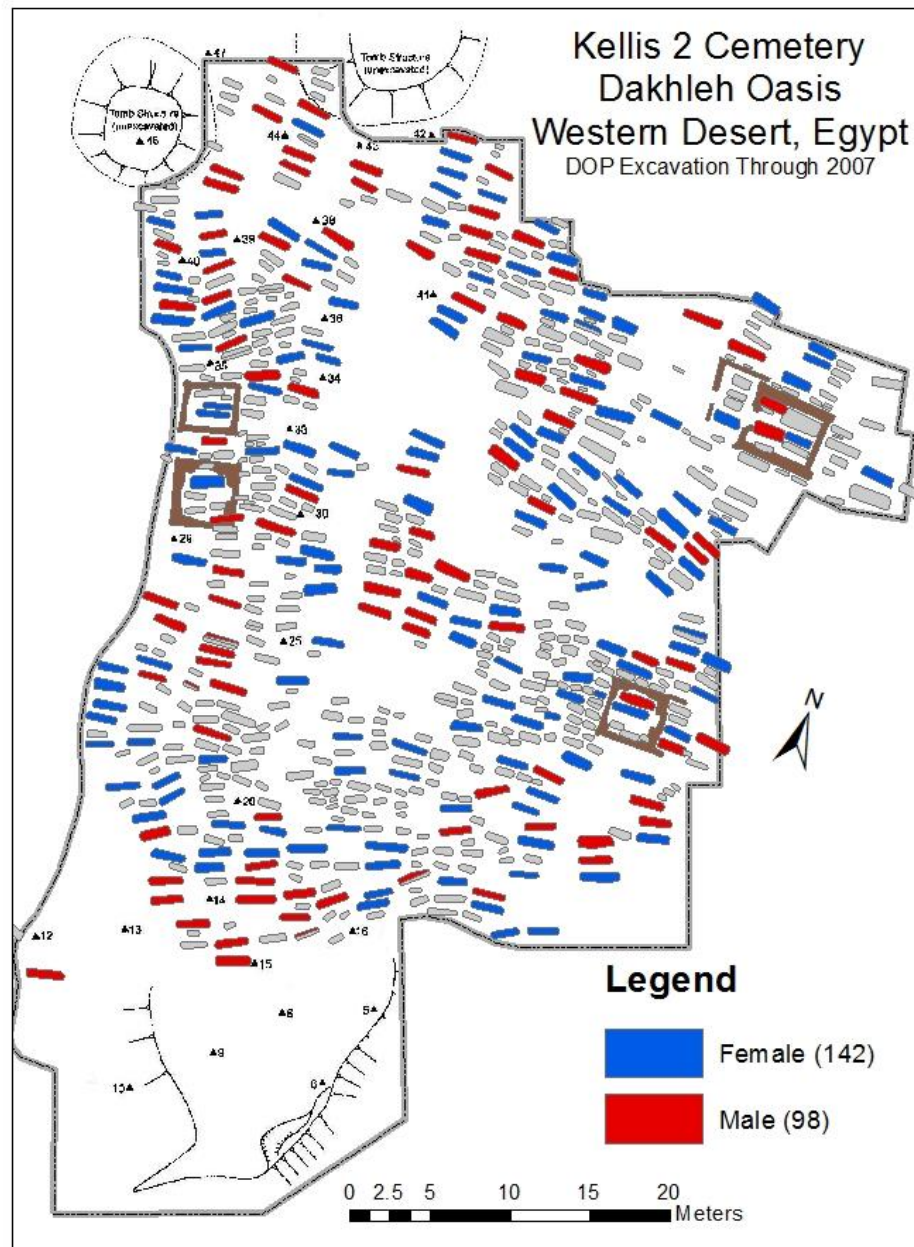
Local Density Analysis (LDA) was calculated for radii of 3, 5, 7 and 10 m given (Table 5-2). The meaning of the statistic, as described in Chapter 3, is that a value of 1 indicates random distribution of the two types, a value below 1 indicates spatial segregation and a value above 1 indicates spatial association. All of the values at all the distances indicate spatial segregation except males/males at 5 m, which indicates spatial association. In addition, for all radii except 10 m, LDA for inter type comparison (Males vs Females) is less than the intra type LDA for both males and females, thus indicating a slight tendency towards segregation; both sexes are closer to their sex than the opposite sex. This corroborates our initial visual observations as well as the Proximity Count results.

The results for the Between Type Nearest Neighbour - Random Labeling are shown in Table 5-3. These show a tendency for males to cluster together ($NNR = .95$) though this result is not significant ($p = .18$). The only result showing statistical significance is a tendency for females to be evenly distributed from males ($NNR = 1.1$, $p = .05$).

Table 5-2: Local Density Analysis Males and Females

Table 5-2				
Radius	Female/Female	Female/Male	Male/Male	Male/Female
3	.96	.86	.86	.99
5	.89	.83	.83	1.06
7	.85	.8	.8	.9
10	.81	.77	.77	.74

Table 5-3: Between Types Nearest Neighbour

Table 5-3				
	NNR	Actual AvgNN	Random AvgNN	prob
Female to Female	1.03	2.03	1.98	.23
Male to Female	1.1	2.16	1.97	.05
Female to Male	1.03	2.45	2.38	.28
Male to Male	.95	2.28	2.39	.18

5.3.1 Discussion – Male/Female Distribution

In summarizing, the first issue of note is the statistical significance ($p < .01$) of the numerical discordance of males and females. This discordance can only be hypothetically addressed.

If the difference is related to some social mechanism whereby extra women and girls were being adopted into the society, one possibility would be polygamy, where the local population needed to seek outside the community for women. However, the early Copts were monogamous. Another possibility is persecution of Christians in the early centuries AD by the Roman Empire. In this scenario, women and children were potentially being sent here to stay with relatives to avoid the larger urban centres, where persecution was more intense. Thus, if these women arrived in this manner and were related to local people, then the hypotheses outlined herein would not be significantly impacted. However, Brown (2013) using Smith's Mean Measure of Divergence, has demonstrated that the pre-Christian population is statistically part of the same deme as the K2 Christian population, so that a large influx of unrelated women seems unlikely or at least we would not be able to evaluate this proposition.

More likely is a mechanism that removed men from the population. It is unlikely that the mortuary program is singling out a significant portion of the men for alternate treatment, although there is a possibility that some status males are being buried elsewhere in the cemetery in an unexcavated area. The removal of 30% of the male population for special treatment does, however, seem excessive. A more likely explanation is that many of the men were dying elsewhere and not being returned for burial. Given the patriarchal nature of the society, it is likely that the men would be traveling to more distant locations than the females and thus more likely to die elsewhere. In support of this scenario, Haddow (2012) notes the male involvement in the caravan trade. If true, the ratio observed here does suggest that travel in those times carried an increased risk of dying. Whether it is disease, crime or religious persecution, the chances of not returning home at some point seems to be high.

Regardless, the disparate sex ratio does not invalidate the kinship versus accretionary hypotheses on the distributions within the cemetery. It may, however, make testing for a patrilocal interment more difficult by reducing the male sample size.

The second issue arising from the above analysis is a tendency for male burials to cluster together primarily at a range of five metres. The best indication of this tendency is the Proximity Count statistics in Table 5-1. The tendency for male clustering is also evident in both the LDA at the five metre distance and in the Nearest Neighbour calculations.

What are the implications of this clustering towards evaluating our hypotheses? First, it should be noted that the size of this cluster spike is fairly small at five metres. It is not the case that major sections of the cemetery are reserved for males and others for females. In the accretion model, these small clusters would be highly unlikely, but they do tend to suggest that something might be taking place at the family level so, if anything, these micro-clusters of males are more in line with the kinship hypothesis. What it does mean for the analysis of the distributions of the discrete traits is that clustering of a discrete trait in the males could show as being closer than expected by chance. Regardless, if the males are all related in these clusters, it can be used to evaluate the kinship hypothesis. However, the other possibility for the presence of male clusters in K2 is a confounding effect, since their absence may not be random. If males tended to be missing more often within some families than others, the results of the statistic would show as an apparent clustering of females when, in fact, it may have been evenly distributed if all of the missing males were buried with their families. As will be shown below, this factor does seem to be relevant.

When it comes to the smaller sample of individuals where the cranial traits are being evaluated (see Figure 5-5), some of the male clusters in the larger sample are not as well-defined. The results of the Proximity Count run against the actual sample being analyzed are shown in Table 5-4. In this case none of the values are significant.

Table 5-4: Proximity Count - Males and Females Small Sample

Table 5-4				
	Males	n = 71	Females	n = 107
Distance	Count	p	Count	p
3	31	.87	77	.83
5	98	.32	206	.77
7	180	.34	396	.57
10	310	.92	790	.18
15	598	.97	1569	.13

While part of this is a result of the reduced sample making statistical significance less likely, the nature of the sample also eliminates or reduces the size of the male clusters identified in the larger sample, particularly the male cluster in the southwest, and also the northwest, leaving a more even distribution of males.

In sum, it appears that the two main hypotheses are not significantly impacted by either the reduced number of males in the cemetery or by the relative distribution of males and females in the smaller sample. Therefore, these data can be used in the analysis of the distribution of discrete traits. However, the uneven distribution of missing males is a confounding factor.

5.4 Individual Trait Analysis

This section discusses the spatial distribution of each of the 38 discrete cranial traits on an individual basis.

5.4.1 Methodology

The distribution of each of the 38 traits is plotted and included in Appendix B, Figures B.1 through B.38. The analysis of each trait was in two steps. First, the analysis by trait is considered regardless of sex and secondly, the analysis by trait within sex is considered.

Figure 5-5: Male Female Distribution - Smaller Sample

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Sex

Legend
Female (107)
Male (70)
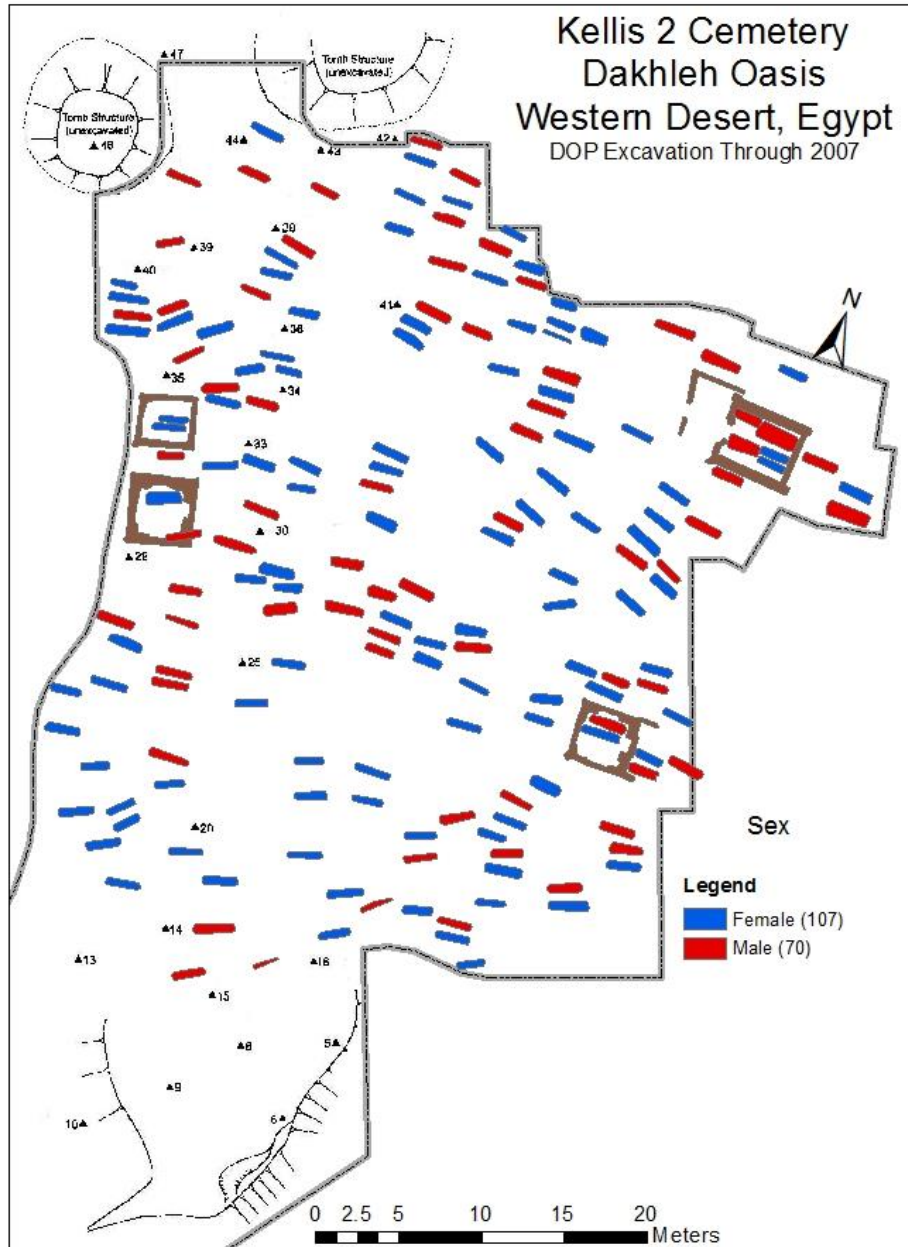
For the first step, three spatial statistics were run. These statistics, defined in Chapter 3, are the A-statistic, Proximity Count, and Nearest Neighbour- Random Labeling. Results are included on the maps of the various traits shown in Figures B-1 to B-38 and are summarized in Table 5-5 under the columns titled "Analysis by Trait". For the A-statistic, values of A greater than .96 are ignored even if significance results, since the A value is very close to the value of 1.0 which signifies random association. For the Proximity Count statistics, distances of 3 m, 5 m, 7 m and 10 m only are included in Table 5-5. Anything over 10 m is too large to provide meaningful values in most cases, given the size of the cemetery. Even the 10 m distance could be problematic in most cases.

If the first step indicated statistical clustering of the trait or if visual examination suggested that there was some patterning by sex, then a further analysis looking at the distribution of the trait by sex was conducted. In some cases, if there were too few individuals of either sex, generally n<5, this step was also bypassed. If this step was bypassed, the reason is noted in Table 5-5 in the Reason-Not-Run column. This step used two statistics, the Cross Nearest Neighbour by Sex and the Cross Proximity Count by Sex, as described in Chapter 3. If neither of these gave significant results, no further analysis was performed.

The term "a tendency to cluster together" is rather obscure, so some discussion of what this terminology means is in order. The issue here is at what level of significance do we reject the null hypothesis? In most cases here, the level will be the normal convention of

Table 5-5: Summary of Individual Trait Analysis

Table 5.5

Discrete Trait	Figure	Males With	Males W/O	Females With	Females W/O	Prox	A-Stat	NN (RL)	Reason Not Run	Nearest Neigh	Prox Count	Kinship/Accretionary	Kinship Type
Accessory Optic Foramen	B.1	1	69	5	101	5m, p=0.08	A=0.89, p=0.15	0.51, p=0.02	Small N	n/r	n/r	Kinship	
Anomalous Temporal Artery	B.2	3	66	5	101	-	-	-	Small N / No Sig stats	n/r	n/r	Accretionary	
Carotico-clinoid Bridge	B.3	22	40	25	77	7m, p=0.04	A=0.96, p=0.06	-		p=0.1	p<0.05	Kinship	Weak Matrilineal
Clino-clinoid Bridge	B.4	15	47	21	82	-	-	-	Run on Visual	p<0.05	P=0.05	Kinship	False Matrilineal
Divided Hypoglossal Canal	B.5	39	30	59	45	-	-	-	No significant stats	n/r	n/r	Accretionary	
Divided Jugular Canal	B.6	20	49	27	76	7m, p=0.99	A=0.96, p=0.04	-		-	p=0.06	Kinship	False Matrilineal
Frontal Grooves	B.7	26	44	36	70	-	-	-	No significant stats	n/r	n/r	Accretionary	
Frontal-Temporal Articulation	B.8	4	65	5	100	-	-	-	Small N / No Sig stats	n/r	n/r	Accretionary	
Infraorbital Suture	B.9	32	37	63	39	7m, p=0.1	A=0.96, p=0.02	-		p=0.09	p<0.05	Kinship	Duolocal
Intermediate Condylar Canal	B.10	32	35	39	67	7m, p=0.1	A=0.96, p=0.02	-		p=0.09	p<0.05	Kinship	Patrilineal
Marginal Foramen	B.11	6	64	11	96	3m, p=0.12	-	0.76, p=0.04	Small N	n/r	n/r	Kinship	
Mendosal Suture	B.12	5	64	10	97	-	-	-	No significant stats	n/r	n/r	Accretionary	
Metopic Suture	B.13	2	67	10	97	3,5,7m sign	A=0.67, p=0.0	0.75, p=0.06	Small N	n/r	n/r	Kinship	
Mylohyoid Bridge	B.14	20	46	15	86	-	-	1.12, p=0.1	No significant stats	n/r	n/r	Accretionary	
Notochord Remnant	B.15	16	54	11	94	-	-	-	No significant stats	n/r	n/r	Accretionary	
Open Foramen Spinosum	B.16	33	37	49	56	-	-	1.07, p=0.1	Run on Visual	p=0.08	p<0.05	Kinship	Patrilineal
Os Japonicum	B.17	3	65	15	89	-	A=0.93, p=0.06	-	Small N	n/r	n/r	Kinship	
Ossified Apical Ligament	B.18	8	59	3	102	5,7m sig		0.74, p=0.06		p<0.05	p<0.05	Kinship	Patrilineal
Parietal Foramen	B.19	33	36	62	42	-		1.06, p=0.12		p<0.05	p=0.12	Kinship	Patrilineal
Pharyngeal Fossa	B.20	23	47	31	72	-	-	-	Run on Visual	p=0.12	p<0.05	Kinship	Patrilineal
Posterior Condylar Canal Absent	B.21	29	38	44	61	5m, sig		0.93, p=0.09		p=0.02	p=0.05	Kinship	False Matrilineal
Precondylar Tubercle	B.22	5	64	1	105	-	-	-	Small N / No Sig stats	n/r	n/r	Accretionary	
Pterygobasal Spur	B.23	32	38	36	71	-	-	-	Run on Visual	-	p=0.05	Kinship	Patrilineal
Pterygospinous Spur	B.24	19	51	10	97	-	-	-	No significant stats	n/r	n/r	Accretionary	
Supraorbital Foramen	B.25	26	43	34	72	5m, p=0.04	A=0.94, p=0.0	-		-	p=0.07	Kinship	
Trochlear Spur	B.26	6	63	11	95	-	A=0.92, p=0.05	0.8, p=0.08		n/r	n/r	Kinship	
Tympanic Dehiscence	B.27	12	58	34	73	-	-	1.11, p=0.1	No significant stats	n/r	n/r	Accretionary	
Zygomatico-facial Foramen Absent	B.28	17	52	31	74	-	-	0.9, p=0.1	Run on Visual	p=0.04	p=0.02	Kinship	Patrilineal
Asterionic Ossicle	B.29	11	57	17	87	-	A=0.95, p=0.05	-		p=0.01	p=0.05	Kinship	Patrilineal
Bregmatic Ossicle	B.30	1	68	0	101	-	-	-	Small N	n/r	n/r	Accretionary	
Coronal Ossicle	B.31	2	66	2	98	-	-	-	Small N	n/r	n/r	Accretionary	
Lambdic Ossicle	B.32	13	55	5	98	-	-	-	Run on Visual	p=0.1	p<0.05	Kinship	Patrilineal
Lambdoidal Ossicle	B.33	31	38	52	51	5m, p=0.95	-	1.07, p=0.1	Run on Visual	p=0.02	p<0.05	M/F segregated	n/a
Occipito-mastoid Ossicle	B.34	7	61	8	96	-	-	-	No significant stats	n/r	n/r	Accretionary	
Parietal Notch Ossicle	B.35	5	63	17	87	-	-	-	No significant stats	n/r	n/r	Accretionary	
Pterionic Ossicle	B.36	7	62	27	77	-	-	-	No significant stats	n/r	n/r	Accretionary	
Sagittal Ossicle	B.37	3	62	7	94	7m p=0.04	A=0.92, p=0.11	-	Small N	n/r	n/r	Kinship	
Squamosal Ossicle	B.38	1	67	8	96	7m, p=0.95	-	1.24, p=0.12	No significant stats	n/r	n/r	Accretionary	

$p = .05$. Normally, this is definitive such that the null hypothesis is rejected at $p = .05$ but could not be rejected at $p = .06$. In statistics, the level of significance is a purely arbitrary level and it is perfectly acceptable to set the significance level at whatever level seems reasonable. Thus, $p = .01$ is used occasionally but also $p = .1$ or even $p = .15$ might, in some cases, be acceptable. In a number of the following analyses of discrete traits, a value between $p = .05$ and $p = .15$ can be frequently found and this result occurred often enough to be suggestive that a genetic process was involved and not just simple chance. However, despite what would normally be considered a "large" number of individuals in osteological analyses, there simply were not enough to establish significance at the $p = .05$ level. Consequently, despite lack of significance at that level, they were included in various ways in additional analyses. In the following text, the term "approaching significance" or "weak significance" will be used to refer to these higher levels of significance when the more mathematically correct term would be "significant at the $p = .1$ (or $p = .15$) level". Further, it should be recalled that even with significance at .05 level, we are making a type 1 error once in every 20 instances.

5.4.2   Individual Analysis of the 38 Cranial Traits

After analyzing each of the 38 traits, it was apparent that describing each one textually in detail would be highly repetitive and formulaic. To compensate, a large table (5.6) was developed to summarize all of the results, of both steps and the implications towards our hypotheses. This table has one row for each of the discrete traits and includes Appendix B figure mapping of that trait's distribution and the numbers of males and females with and without the trait in the sample. Under "Analysis by trait" are the results of the three statistical tests. Under "Analysis by trait Within Sex" are three columns, the first column indicating why the two statistics were or were not run and the next two columns providing a high level summary of the results. Since interpretation of these two statistics is too complex to summarize in a table, a separate textual description for each trait is provided, where applicable. Finally, the last two columns of the table provide conclusions supporting our hypotheses. The column for the kinship/accretionary is labeled kinship if the trait shows significant clustering on its own, or if the analysis for residence type shows significant clustering; otherwise it is labeled accretionary. If the second step on

distribution by sex was run and the kinship model is supported, then an attempt was made to see if the distribution supports one of the residence patterns and the results appear in the final column.

To illustrate use of this table, I use the Accessory Optic Foramen (first row) with the appropriate text in the following paragraph.

Distribution of the individuals showing an Accessory Optic Foramen is shown in Figure B.1. There are only six occurrences present, one male of 70 and five females of 106. The A-statistic at .89 indicates that presence and absence tend to be segregated but with p = .15, is at the extreme upper limit of our "approaching significance" level. Proximity Count is approaching significance at the five metre distance with p = .08 because there are two pairs of female graves in close proximity, suggesting that these two pairs are closely related. The Nearest Neighbour - Random labeling shows significant clustering (NNR= .51, p = .02). The conclusions would be that there is weak support for the kinship hypothesis. No analysis was done on males versus females because of the low numbers.

What follows is a description of each trait where the distribution by sex was run or additional comment was required.

<u>Cartico-Clinoid Bridge</u>

The distribution of the Cartico-Clinoid trait is shown in Figure B.3. Visually there seems to be two main clusters around the southeast tomb and near the northwest tomb. There are also several occurrences of small clusters with 2-4 individuals. Given significant clustering, the trait was analyzed by sex. The Cross Nearest Neighbour by Sex statistic was run, yielding Table 5-6. This indicates that males tend to be more evenly spaced $NNR = 1.07$ but this result is not significant. Two of the statistics are approaching significance and show that females with the trait tend to occur close to both males and females with the trait. The Cross Proximity Count by sex was run, yielding the numbers in Table 5-7. A male with the trait has more females with the trait clustered nearby at 3, 5 and 7 m with significance. Females with the trait cluster with significance at 7 and 10 m and have a cluster of males at 7 m approaching significance. Hence, it is reasonable to

conclude that the trait is strongly clustered and thus, supports the kinship model. There is a weak suggestion that K2 is organized along matrilocal lines, as the females tend to cluster while the males are more randomly distributed.

Given that, in some areas of the cemetery, males are underrepresented, it is necessary to see if the apparent female clusters are real or may be caused by missing males. In this case, examining Figure B.3 and looking ahead to Figure 5-11, we note that for the northeast clusters of *contemporaneous kin groups* (term defined below in section 5.5.7), there are three female instances and one male instance so, while males may be under represented, the numbers are too small to comment. In the southern group the numbers are about evenly split, with seven males and nine females so, again, missing males in these two groups of contemporaneous kin groups do not seem to cause a false indication of matrilocality. What seems to create the tendency towards matrilocality is cluster 3, which includes and surrounds the southeast tomb structure. That cluster has seven females and only one male despite the fact that males and females are reasonably equally represented (seven males and ten females – see Table 5-40). Consequently, this weak tendency towards matrilocal interment cannot be created by missing males.

Table 5-6: Cartico-clinoid Bridge - Cross Nearest Neighbour by Sex

Table 5-6				
	Actual AvgNN	RandomAvgNN	NNR	p
Male to male	5.36	5	1.07	.26
Male to Female	4.39	4.61	.95	.38
Female to Female	4.14	4.69	.88	.12
Female to Male	4.04	4.82	.84	.1

Table 5-7: Cartico-clinoid Bridge - Cross Proximity Count by Sex

Table 5-7								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	2	.79	8	.8	17	.57	26	.85
Male to Female	12	.02	27	.06	50	.02	79	.27
Female to Female	5	.34	14	.18	29	.05	55	.04
Female to Male	12	.38	27	.32	50	.1	79	.23

<u>Clino-clinoid Bridge</u>

Distribution of the individuals showing the occurrences of Clino-clinoid Bridge is shown in Figure B.4. None of our primary statistics show anything approaching significance, but a visual inspection indicates what appear to be several clusters of female burials while the males seem to be more evenly spaced, so the analysis by sex was conducted.

The Cross Nearest Neighbour by Sex produced the statistics as seen in Table 5-8. The interesting result here is that females with the trait tend to be more remote from males with the trait than would be expected with significance (*NNR*= 1.35, *p* = .03). The Cross Proximity Count by Sex run yielded the results as shown in Table 5-9. As suspected by the visual examination, the females with the trait tend to cluster with significance at the 5 m distance.

This result again argues in favour of a kin-based deposition into the cemetery. With females clustered and males more evenly spaced, it would tend to indicate a matrilocal kin-based pattern. However, examining the distribution of contemporaneous kin groups (Figure 5-11 and the distribution of this trait in Figure B.4), we note a tight cluster of four females in Cluster 6 within the southern group with low male counts. This cluster accounts for 6 of the 13 females pairs with the trait and cluster 6 is very low in respect to male burials, with 4 males and 11 females (Table 5-40). In this case it is reasonable to assume that the lack of males in this southern group may well have skewed the results to indicate matrilocality, so this result will be rejected.

Table 5-8: Clino-clinoid Bridge Cross Nearest Neighbour by Sex

Table 5-8				
	Actual AvgNN	RandomAvgNN	NNR	p
Male to male	5.57	6.35	.88	.19
Male to Female	6.81	5.03	1.35	.03
Female to Female	5.1	5.2	.98	.42
Female to Male	6.46	5.98	1.08	.74

Table 5-9: Clino-clinoid Bridge Cross Proximity Count by Sex

Table 5-9								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	0	1	3	.8	7	.62	12	.66
Male to Female	3	.92	9	.88	17	.89	33	.97
Female to Female	5	.12	13	.05	17	.28	31	.37
Female to Male	3	.9	9	.76	17	.75	33	.84

Divided Jugular Canal

Distribution of the individuals showing the occurrences of Divided Jugular Canal is shown in Figure B.6. Visually, there appears to be some clustering of females on the west side of the excavated area, so the analysis by sex was conducted. The Cross Nearest Neighbour by Sex gave the results shown in Table 5-10 and the Cross Proximity Count by Sex appears in Table 5-11. Of these, the only result approaching significance is that the females tend to cluster at 7 m ($p = .06$). These results confirm a kin-based organization to the cemetery. The clustering of females would argue against a patrilocal organization in the cemetery, but is not significant. However, considering the two groups of clusters that are low in males (Figure 5-11), we note cluster 5 in the southwest corner shows a cluster of females with the trait but is low in male burials. Given the apparent

absence of males in this cluster and also in cluster 14 just east of cluster 3, clustering of females in this area cannot be taken as evidence of matrilocal interment.

Table 5-10: Divided Jugular Canal - Cross Nearest Neighbour by Sex

Table 5-10				
	Actual AvgNN	RandomAvgNN	NNR	p
Male to male	4.51	5.33	.84	.1
Male to Female	5	4.46	1.12	.83
Female to Female	4.49	4.53	.99	.44
Female to Male	5.44	5.11	1.06	.73

Table 5-11: Divided Jugular Canal Cross Proximity Count by Sex

Table 5-11								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	3	.41	9	.29	14	.48	20	.85
Male to Female	7	.86	15	.96	34	.81	69	.73
Female to Female	6	.31	13	.52	34	.06	59	.11
Female to Male	7	.61	15	.82	34	.55	69	.61

Infraorbital Suture

Distribution of the individuals showing the occurrences of an Infraorbital Suture is shown in Figure B.9. Visually, there are no apparent clusters, but some of the trait level statistics show significance, so the trait distribution by sex was run. The results of the Cross Nearest Neighbour by Sex and Cross Proximity Count by Sex are shown in Tables 5.12 and 5.13 respectively. The results here indicate a rather different pattern, where male/male and female/female burials tend to be spread out while male/female and female/male burials occur in clusters. This seems to indicate a completely different burial

pattern, where male and female family members are buried together regardless of intervening marriage. As such, it would seem to support a duolocal residency pattern, but inferring this residence pattern from the distributions of graves is problematic. The more likely explanation is that this patterning is simply a statistical anomaly.

Table 5-12: Infraorbital Suture Cross Nearest Neighbour by Sex

Table 5-12				
	Actual AvgNN	RandomAvgNN	NNR	p
Male to male	4.41	4	1.1	.09
Male to Female	2.73	2.87	.95	.3
Female to Female	3.06	2.95	1.04	.76
Female to Male	3.8	4	.95	.24

Table 5-13: Infraorbital Suture Cross Proximity Count by Sex

Table 5-13								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	7	.52	22	.44	39	.48	63	.74
Male to Female	30	.71	76	.47	162	.04	309	.01
Female to Female	18	.99	69	.62	140	.34	302	.02
Female to Male	30	.57	76	.42	162	.04	309	.1

Intermediate C ondylar Canal

Distribution of the individuals showing the occurrences of an Intermediate Condylar Canal is shown in Figure B.10. Visually, there are no apparent clusters, but there may be a tendency to be absent from the northeastern area. However, the A-Statistic shows a significant tendency to segregate, but the A-statistic is only slightly below the value of 1 ($A = .96$, $p = .02$) and the Proximity Count indicates a tendency to cluster at 7 m, but the significance level is $p = .11$. The Cross Nearest Neighbour by Sex and Cross Proximity Count by Sex statistics were run and the results are given Tables 5.14 and 5.15

respectively. These results show a definitive cluster in the 5-7 m range for males, while women are well dispersed at 5 m and, indeed, tend to occur farther apart in general as shown with the female to female Nearest Neighbour number. The value is only approaching significance. In general, this result supports a kin-based organization with patrilocal interment.

Table 5-14: Intermediate Condylar Canal Cross Nearest Neighbour by Sex

Table 5-14				
	Actual AvgNN	RandomAvgNN	NNR	p
Male to male	4.07	4	1.02	.6
Male to Female	3.55	3.61	.98	.48
Female to Female	4.09	3.69	1.11	.09
Female to Male	4.08	3.89	1.05	.72

Table 5-15: Intermediate Condylar Canal Cross Proximity Count by Sex

Table 5-15								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	3	.99	30	.01	52	.02	85	.01
Male to Female	19	.59	48	.57	97	.24	186	.44
Female to Female	8	.83	18	.99	50	.66	98	.75
Female to Male	19	.62	48	.61	97	.24	186	.2

Open Foramen Spinosum

The distribution of Open Foramen Spinosum is shown in Figure B.16. Visually and statistically, clusters are not apparent when sex is not considered. However, when considering the sexes, clusters are apparent so the statistics by sex were computed and appear in Tables 5.16 and 5.17. Note that there is a tendency for males to cluster with significance at 5 m and females 7 m. Noteworthy is that females with the trait do not generally have a male with the trait in close proximity, as the "Female to Male" show in these tables. This result also supports a kin-based organization with patrilocal interment.

Table 5-16: Open Foramen Spinosum Cross Nearest Neighbour by Sex

Table 5-16				
	Actual AvgNN	RandomAvgNN	NNR	p
Male to male	4.12	4.03	1.02	.62
Male to Female	3.54	3.24	1.09	.84
Female to Female	3.46	3.36	1.03	.66
Female to Male	4.39	3.9	1.13	.08

Table 5-17: Open Foramen Spinosum Cross Proximity Count by Sex

Table 5-17								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	10	.1	27	.05	43	.19	76	.08
Male to Female	22	.69	51	.77	99	.66	204	.42
Female to Female	14	.77	48	.17	100	.03	192	.02
Female to Male	22	.84	51	.96	99	.99	204	.98

Ossified Apical Ligament

The distribution of the Ossified Apical Ligament is shown in Figure B.18. Visually, two clusters are apparent; one adjacent to the southeast tomb and another immediately north of the northwest tomb. Despite there being only three females, the sex computation revealed apparent male clusters. The results are shown in Tables 5.18 and 5.19. The male clustering is, however, not overall significant (*NNR*=.78, p = .13) and (*Count* = 3 at 5 m, p = .1). The three females are close to the males with the OAL but the small sample size precludes any definitive interpretations. Again, evidence for kinship organization is strong and evidence for patrilocal interment is present but weak.

Table 5-18: Ossified Apical Ligament Cross Nearest Neighbour by Sex

Table 5-18				
	Actual AvgNN	RandomAvgNN	NNR	p
Male to male	6.94	8.94	.78	.13
Male to Female	7.36	14.01	.53	0
Female to Female	17.52	16.48	1.06	.6
Female to Male	3.17	8.31	.38	.02

Table 5-19: Ossified Apical Ligament Cross Proximity Count by Sex

Table 5-19								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	0	1	3	.1	4	.14	4	.51
Male to Female	2	.11	6	0	6	.02	9	.01
Female to Female	0	1	0	1	0	1	1	.39
Female to Male	2	.04	6	0	6	0	9	0

Parietal Foramen

Figure B.19 shows the distribution of the Parietal Foramen. Visually and statistically, the trait does not seem to be cluster. However, visual inspection of the sexes hints at clustering. Statistical analysis (Tables 5.20 and 5.21) for males and females shows a slight tendency to cluster, but they are only approaching significance. The Nearest Neighbour value for males to males is significant ($NNR = .86$, $p = .04$) while the Proximity Count is weak ($Count = 26$ @ 5 m, $p = .12$). It could reasonably be concluded that there is weak support for the patrilocal interment model.

Table 5-20: Parietal Foramen Cross Nearest Neighbour by Sex

Table 5-20				
	Actual AvgNN	RandomAvgNN	NNR	p
Male to male	3.43	4.01	.86	.04
Male to Female	3.2	2.87	1.11	.12
Female to Female	3.02	2.93	1.03	.69
Female to Male	4.45	3.96	1.12	.06

Table 5-21: Parietal Foramen Cross Proximity Count by Sex

Table 5-21								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	8	.35	26	.12	43	.22	69	.35
Male to Female	28	.37	67	.86	139	.48	259	.68
Female to Female	30	.12	72	.31	134	.53	272	.32
Female to Male	28	.82	67	.78	139	.75	259	.92

Pharyngeal Fossa

The distribution of the pharyngeal fossa is shown in Figure B.20. Visually, the traits do not seem to be clustered and the statistics support this interpretation. However, there appears to be a greater tendency for males to cluster while the females seem to be more evenly dispersed. Analysis by sex shown in Tables 5.22 and 5.23 for the Cross Nearest Neighbour by Sex and the Cross Proximity Count by Sex respectively supports this conclusion. Again, this result supports the kinship hypothesis with patrilocal interment.

Table 5-22: Pharyngeal Fossa Cross Nearest Neaighbour by Sex

Table 5-22				
	Actual AvgNN	Random AvgNN	NNR	p
Male to male	4.58	4.88	.94	.29
Male to Female	3.94	4.12	.96	.39
Female to Female	4.64	4.17	1.11	.12
Female to Male	4.24	4.69	.9	.2

Table 5-23: Pharyngeal Fossa Cross Proximity Count by Sex

Table 5-23								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	8	.02	13	.15	19	.45	31	.56
Male to Female	11	.59	32	.2	57	.37	109	.41
Female to Female	4	.92	11	.97	33	.55	60	.8
Female to Male	11	.68	32	.37	57	.09	109	.03

Posterior Condylar Canal Absent

The spatial distribution of the posterior condylar canal absent is shown in Figure B.21. Visually, several distinct clusters seem apparent and the Proximity Count statistic supports this, showing significant clusters at a 5 m range while a 3 m range is approaching significance. The distribution by sex statistics are shown in Tables 5.24 and 5.25. Using the Cross Nearest Neighbour by Sex, males with the trait are more dispersed than would be expected, but this dispersion only approaches significance ($NNR = 1.12$, $p = .1$). Females to females and females to males analyses cluster with significance. The Proximity Count by Sex also indicates the males are further apart than would be expected, as evidenced by the high probability numbers. This result is especially significant at the 7 m range, but approaches significance at 3 m and 10 m. Females with the trait show significant clustering at the 5 m range and both male to female and female to male are approaching significance at 5 m and 3 m range respectively. These results

support the kin-based model, but more likely with a matrilocal interment organization, as the females clustered and males were more evenly dispersed. In examining the contemporaneous kin groups from Figure 5-11, a number of females with the trait occur in both the southern group and the northeastern group. In fact, four of the clusters in these two groups have 19 females with the trait and only 5 males with the trait. Given the prevalence of the trait in contemporary kin groups where males are missing, it is not reasonable to infer matrilocal interment in the society.

Table 5-24: Post Condylar Canal Absent Cross Nearest Neighbour by Sex

Table 5-24				
	Actual AvgNN	RandomAvgNN	NNR	p
Male to male	4.78	4.27	1.12	.1
Male to Female	3.22	3.46	.93	.28
Female to Female	2.98	3.48	.86	.02
Female to Male	3.5	4.25	.82	.02

Table 5-25: Post Condylar Canal Absent Cross Proximity Count by Sex

Table 5-25								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	3	.93	14	.83	22	.98	44	.94
Male to Female	27	.19	55	.07	95	.29	176	.39
Female to Female	15	.29	44	.05	74	.2	131	.55
Female to Male	27	.08	55	.21	95	.15	176	.2

Pterygobasal Spur

The distribution of the Pterygobasal Spur is shown in Figure B.23. Clustering is not apparent visually, which is supported statistically. However, analysis by sex does suggest some clustering (Tables 5.26 and 5.27). The Cross Nearest Neighbour by Sex indicates a tendency for a male with the trait to be close to a female with the trait, whereas females

with the trait tend to be more dispersed-- but neither of these results is significant. The Proximity Count Statistic shows a male cluster, which is significant at the 5 m range and approaching significance at the 3 m and 7 m range. When the number of females is counted around male burials with the trait, there is a low count at 7 m that is significant. These results again support a patrilocal interment system.

Table 5-26: Pterygobasal Spur Cross Nearest Neighbour by Sex

Table 5-26				
	Actual AvgNN	RandomAvgNN	NNR	p
Male to male	3.87	4.04	.96	.29
Male to Female	3.37	3.77	.89	.16
Female to Female	4.13	3.93	1.05	.72
Female to Male	4.12	3.92	1.05	.73

Table 5-27: Pterygobasal Spur Cross Proximity Count by Sex

Table 5-27								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	10	.09	27	.05	46	.08	64	.64
Male to Female	20	.12	42	.36	79	.41	155	.54
Female to Female	6	.88	21	.7	41	.71	88	.48
Female to Male	20	.77	42	.84	79	.97	155	.87

<u>Supraorbital Foramen</u>

The supraorbital foramen spatial distribution is shown in Figure B.25. Visually, the trait seems to occur more frequently on the east versus the west side of the cemetery. Analysis by sex is shown in Tables 5.28 and 5.29. There are no tendencies evidenced in the Cross Nearest Neighbour by Sex statistics. There is a tendency for males to have a female with the trait nearby at the 3 m and 5 m range, but these are only approaching significance.

Definitve clustering of the trait supports the kinship hypothesis, but there are no inferences possible as to the residence pattern.

Table 5-28: Supraorbital Foramen Cross Nearest Neighbour by Sex

Table 5-28				
	Actual AvgNN	RandomAvgNN	NNR	p
Male to male	4.34	4.44	.98	.4
Male to Female	3.72	3.92	.95	.36
Female to Female	3.8	3.97	.96	.31
Female to Male	4.11	4.33	.95	.31

Table 5-29: Supraorbital Foramen Cross Proximity Count by Sex

Table 5-29								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	4	.68	16	.32	31	.15	47	.32
Male to Female	18	.11	43	.07	68	.2	133	.1
Female to Female	8	.51	25	.17	46	.16	82	.37
Female to Male	18	.21	43	.11	68	.3	133	.11

Zygomatico-facial Foramen Absent

The distribution of the zygomatico-facial foramen absent is shown in Figure B.28. Visually and statistically there is no clustering evident. However, visually there does seem to be clusters of male burials, but females are more widely distributed. The statistical analysis by sex shows that there is a significant tendency for males to have a nearby female with the trait (Tables 5.30 and 5.31). The Cross Proximity Count by Sex shows a significant tendency for males to cluster within 3 m. These results indicate a weak confirmation of a patrilocal interment.

Table 5-30: Zygomatico-facial Foramen Absent Cross Nearest Neighbour by Sex

Table 5-30				
	Actual AvgNN	RandomAvgNN	NNR	p
Male to male	5.29	5.89	.9	.21
Male to Female	3.17	4.16	.76	.04
Female to Female	3.86	4.15	.93	.22
Female to Male	5.1	5.58	.91	.28

Table 5-31: Zygomatico-facial Foramen Absent Cross Proximity Count by Sex

Table 5-31								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	5	.02	7	.25	9	.65	14	.84
Male to Female	9	.32	21	.72	41	.35	79	.35
Female to Female	7	.47	16	.67	29	.82	71	.24
Female to Male	9	.57	21	.3	41	.38	79	.22

AsterionicOssicle

The Asterionic Ossicle's spatial distribution is shown in Figure B-29. Visually, it seems to be more common in the north side of K2 and more evenly dispersed in the rest of K2. Given the visual distribution of the female burials, the analysis by sex (Tables 5.32 and 5.33) was conducted. The average distance from one female with the trait to the nearest female with the trait is greater than expected and significant, implying that the females with the trait are more dispersed than expected stochastically. The only significant clustering with the Cross Proximity Count by Sex occurs with males and females with the trait at 7 m. The reverse is less significant ($p = .10$) probably because the female burials are more dispersed. This evidence provides weak support for the kin-based, patrilocal interment.

Table 5-32: Asterionic Ossicle Cross Nearest Neighbour by Sex

Table 5-32				
	Actual AvgNN	RandomAvgNN	NNR	p
Male to male	6.64	7.66	.87	.21
Male to Female	4.82	5.56	.87	.27
Female to Female	7.58	5.86	1.29	.01
Female to Male	7.03	7.11	.99	.53

Table 5-33: Asterionic Ossicle Cross Proximity Count by Sex

Table 5-33								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	0	1	2	.66	4	.55	5	.87
Male to Female	4	.32	8	.2	18	.05	28	.17
Female to Female	0	1	4	.74	8	.74	16	.8
Female to Male	4	.31	8	.32	18	.1	28	.34

Lamdic Ossicle

The distribution of the Lambdic Ossicle is shown in Figure B.32. Visually, the traits seem to be evenly dispersed throughout the site, with perhaps one cluster in the west central region. The statistics were non-significant. Given the apparent cluster of males in the west central portion of the site, the analysis by sex (Tables 5.34 and 5.35) only indicates a tendency for the males and females with the trait to be further away from each other than would be expected. The results are only approaching significance ($p = .1$ and $p = .14$). The Proximity Count indicates that the males with the trait tend to cluster with significance at the 7 m range but approach significance at all ranges. Alternatively, the females tend to be more dispersed than a random distribution would expect. Similarly, the females and males with the trait are spatially remote from each other. This distribution supports the kin-based patrilocal interment organization of the cemetery.

Table 5-34: Lamdic Ossicle Cross Nearest Neighbour by Sex

Table 5-34				
	Actual AvgNN	RandomAvgNN	NNR	p
Male to male	6.08	6.76	.9	.25
Male to Female	13.57	10.84	1.25	.1
Female to Female	11.47	11.8	.97	.49
Female to Male	7.81	6.15	1.27	.14

Table 5-35: Lambdic Ossicle Cross Proximity Count by Sex

Table 5-35								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	3	.07	6	.12	12	.02	16	.07
Male to Female	0	1	0	1	1	.99	5	.96
Female to Female	0	1	0	1	0	1	1	.8
Female to Male	0	1	0	1	1	.99	5	.9

LambdoidalOssicle

The Lambdoidal Ossicle's spatial distribution is shown in Figure B.33. Visually, the traits seem to be evenly dispersed over K2 and the primary statistics support this inference. Examining the distribution, it appears that the sexes occur in separate clusters. The Cross Nearest Neighbour by Sex and Proximity Count analyses (respectively in Tables 5.36 and 5.37) loan themselves to variable interpretations. The males tend to cluster together but the results are only approaching significance (Cross Nearest Neighbour, male to male, $p = .12$; Proximity Count at 5 m, $p = .11$). There is a tendency for the females to cluster at the 7 m radius but the significance is at the $p = .13$ level. Unusual though, is a very clear tendency for the males and females with the trait to be segregated within the cemetery with significance or approaching significance in the 3 m to 7 m range.

Interpretation of this pattern presents some difficulties. The even distribution at the 3 m and 5 m was compared to the Nearest Neighbour result against the random labeling statistic. This comparison also suggests this tendency, although it was only approaching significance ($NNR = 1.07$, $p = .08$).

This even distribution supports neither the kin-based nor the accretionary model and is probably simply an interesting anomaly in the data. This pattern may be a concomitant of the Lambdoidal Ossicles being the most common accessory ossicle (Brown 2013). It clearly highlights the risks of making inferences from single traits.

Table 5-36: Lambdoidal Ossicle Cross Nearest Neighbour by Sex

Table 5-36				
	Actual AvgNN	RandomAvgNN	NNR	p
Male to male	3.76	4.16	.9	.12
Male to Female	3.49	3.08	1.13	.09
Female to Female	3.39	3.27	1.03	.69
Female to Male	4.73	3.94	1.2	.02

Table 5-37: Lambdoidal Ossicle Cross Proximity Count by Sex

Table 5-37								
Radius Within	3		5		7		10	
	Count	p	Count	p	Count	p	Count	p
Male to male	8	.22	24	.11	41	.14	65	.3
Male to Female	16	1	46	1	99	.97	213	.58
Female to Female	15	.76	46	.58	102	.13	190	.38
Female to Male	16	.98	46	.96	99	.94	213	.93

5.4.3 Discussion of Single Traits

The question emerges as to what the individual traits tell us about the competing main hypotheses, namely the kinship versus the accretionary models. Obviously, using individual traits is fraught with a number of confounding variables, with key ones including; the lack of control over the temporal dimension, the disparate number of males versus females, the variable genetic contributions of genetic and epigenetic factors for each trait, the novel statistical methodologies used and, of course, the statistical fact that, just by chance using the traditional $p \leq .05$ level, 2 of the 38 traits would be expected to show significance where none existed. Still, finding that 21 of the 38 traits (55.3%) or ten times the expected amount of significance provides unequivocal support for the kinship model ($G = 16.15$, p < .001) that was hypothesized for K2 from visual inspection (Molto 2002). Stated alternatively, Kellis 2 was not randomly organized which, as noted earlier, is expected of normal human mortuary customs.

Human kinship presents a multiplicity of alternative interacting patterns organizationally that should be revealed spatially but with many confounding variables. The key organizations are inheritance through the male (patrilineal) versus female (matrilineal) lines, coupled with associated residence practices (patrilocal and matrilocal). In its simplest manifestation, in a patrilineal society with patrilocal residence, males would be related and would share the presence of greater number of traits than females, with the reverse being true of the matrilineal-matrilocal model. A key confounding variable to the statistical analysis is the fact that non-relatives (e.g. foreign servants, slaves, etc.) could be incorporated into the cemetery population. This incorporation may even be a greater problem for an early Christian population like Kellis where, even though they lived in an isolated region, their early Christian proselytization led to an early brotherhood of non-related Christians. Still, for the spatial statistical analysis, we have to assume that the local morphogenetics would override foreign DNA in the Kellis community.

What then did the single trait analysis show relative to the kinship structuring of the K2 cemetery? In this case, the statistics were again clear, nine traits showed support for patrilocal interment model and only one for matrilocal ($G = 6.6$, $p = .016$). Clearly, despite the limitations of using individual traits, K2 was organized along patrilocal

interment lines, thus rejecting both null hypotheses (i.e., general kinship versus accretion, no male-female patterning). It should also be noted that this same set of statistics looking for kinship organization in K2 was applied in a recent study using discrete genetic traits on the vertebral column with similar results (Sarfo, 2014).

5.5   Multi-Trait Analysis

Despite the positive testing of the uni-trait analysis, research has shown that more sensitive indicators of biological affinity are gained via multi-trait analyses (Brown 2013). This is addressed in this section. Because the cemetery was in use for 300 years or more, any conglomerate of individuals defined by multi-trait groups cannot be considered a family, but could be considered extended kin groups, with some individuals being contemporaneous.

The appropriate statistics, in my view, for this type of analysis is a variant of Whallon's Unconstrained Clustering (1984) which can be implemented in TFQA. Whallon's method was originally designed to determine activity areas in hunter-gatherer sites through the co-location or segregation of a number of tool types, which herein is transformed to analyze the co-occurrence of nonmetric traits. I feel this is justified, as they both deal with nominal data in association in space. A limitation of the 'Unconstrained Clustering program' is that it is limited to 30 variates, and, as noted, this study has 38 nonmetric traits. Not included in this list are events where a nonmetric trait scores as "absent". To further reach the upper trait limit proposed (n = 30), I culled eight traits (Accessory Optic Foramen, Anomalous Temporal Artery, Frontal-Temporal Articulation, Precondylar Tubercle, Bregmatic Ossicle, Coronal Ossicle, Occipito-mastoid Ossicle, Parietal Notch Ossicle, and Pterionic Ossicle), resulting in a list of 29 epigenetic traits. The traits were culled for various reasons (e.g. low prevalence {n < 10); no significant spatial clustering, etc.).

Operationally, additional considerations using Unconstrained Clustering are required. First, the graves had to be reconfigured in the Tables. A unique type in the table has the X,Y coordinates for the graves and for trait presence. For example, the marginal foramen is present in 17 individuals and the table includes 17 rows with two columns – one each

for the X,Y coordinates – and a third arbitrarily assigned number representing the marginal foramen trait, since TFQA uses a numeric value to represent each type. Each grave can have multiple traits and therefore, multiple coordinates but this is not problematic (Keith Kintigh, personal communication 2014). A second consideration with Unconstrained Clustering is the local density radius, a parameter that is used to calculate relative trait densities for all traits at each event location. Since there are no constraints for selecting this value, it can only be determined by a series of computations, each with different values applied to the radius parameter. It was determined that radii of 5 m, 7.5 m, did not provide meaningful spatial data and were culled. Even 10 m were somewhat questionable, but it was retained with larger radii (i.e., 15 m, 20 m and 25 m).

Another of the parameters required for Unconstrained Clustering is the number of expected clusters. Here the approach is to originally request more clusters than it would be reasonable to expect. For each number of clusters a goodness of fit statistic, called the Sum Square Error (SSE), is calculated with lower values indicating better fits. The best approach for analysis is to plot these errors and then select for plotting the number of clusters where the graph of the SSE goes flat, essentially the knee of the curve, as it is frequently called. What became evident with the Kellis data is that a good upper limit was 25 clusters and so, all runs were done with 25 clusters.

The strategy adopted here was to conduct several tests with different combinations of traits and different LDA radii and then evaluate the effectiveness of each set by tracking the %SSE. This procedure represents an unusual additional step to Unconstrained Clustering but is justifiable, as discussed above. In the following analysis, five combinations of traits were tested: 29 traits for all individuals; 15 traits showing significant clustering for all individuals; 14 traits with clustering and Brown's (2013) correlations for all individuals; 29 traits male only; and 29 traits female only.

5.5.1   Unconstrained Clustering of 29 Traits/All Individuals

This combination of traits includes everything and is therefore, in effect, the base-line. The expectation here is that this clustering analysis would generate the worst fit to the

data, since all of the spurious non-clustering traits were included in the data. The results of four runs with differing local density radii are presented graphically in Figure 5-6.

Figure 5-6: %SSE Values from All Individuals and 29 Traits
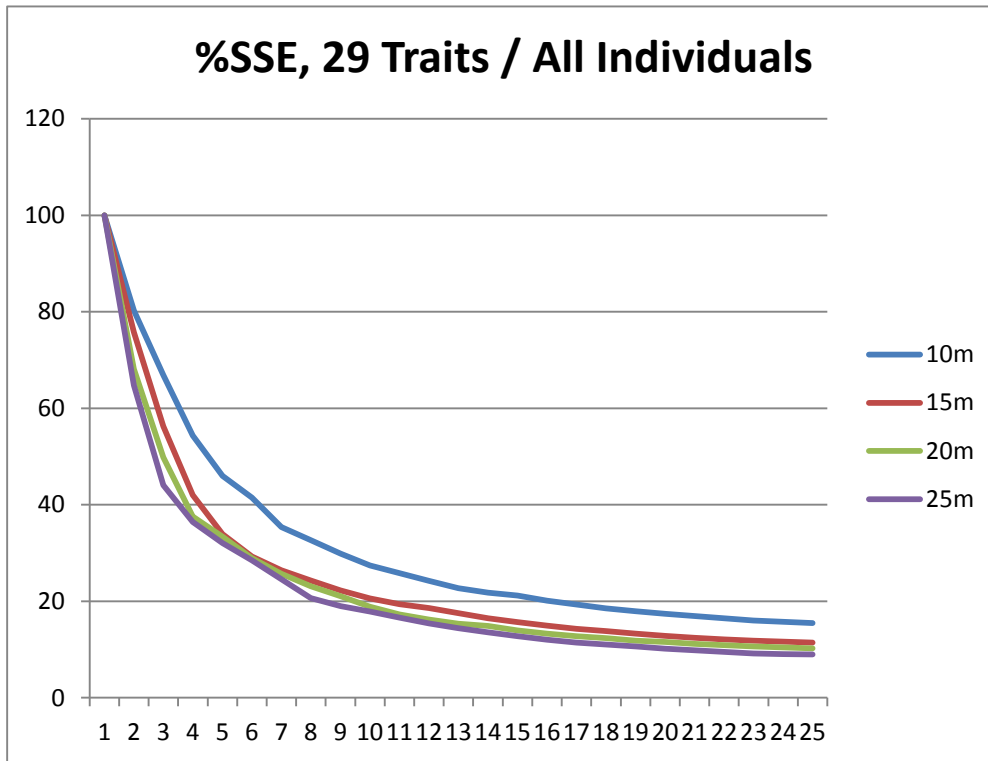
Examining these results shows 25 m provides the best fit but the results are not substantially different from 15 m and 20 m. 10 m appears to give the worst results.

5.5.2 Unconstrained Clustering of 15 Traits with Significant Clustering

This particular run included only traits which showed significant spatial clustering either overall or when the sexes were separated (see Table 5-5). The traits included here are shown in Table 5-38. This selection included all but three individuals who had none of these traits.

Table 5-38: 15 Traits Used for Second Run

Table 5-38	
Ca	Carotico-clinoid Bridge
Cl	Clino-clinoid Bridge
Ic	Intermediate Condylar Canal
Mf	Marginal Foramen
Mt	Metopic Suture
Os	Open Foramen Spinosum
Oa	Ossified Apical Ligament
Ph	Pharyngeal Fossa
Pc	Posterior Condylar Canal Absent
Pb	Pterygobasal Spur
Sf	Supraorbital Foramen
Ts	Trochlear Spur
Zf	Zygomatico-facial Foramen Absent
Lb	LambdicOssicle
So	Sagittal Ossicle

The graph for these figures appears very similar to Figure 5-6 so the graph is not shown here. Again, a local density radius of 25 m, 20 m, 15 m provide a better fit than the smaller radii**.** However, comparing these results to the base-line of all traits and all individuals, we note that the %SSE amounts have been marginally improved, implying that a division based on these 15 traits provides a better data fit than the baseline. The details of the best run are graphed below.

5.5.3   Unconstrained Clustering of 14 Traits with Correlation

The third set is composed of 14 traits which were selected based on a propensity to demonstrate spatial patterning, as well as including a number of traits that were statistically correlated, as identified by Brown (2013). These are traits that occur in association with each other in greater numbers than would be expected by chance in the Kellis 2 population sample. Brown found a much higher than expected number of pairs in her analysis of the same cranial data used in this study. The results are indicative of the population being closely related. This "correlation" is something that must be eliminated in preparing for the application of the Mean Measure of Divergence, but in this analysis it

is useful for including closely related individuals. The traits in this sample are listed in Table 5-39 and the pairs of traits showing correlation from Brown's thesis are As/Om, Oj/As, Ca/Mh, Mt/Is, Is/Ms, Mt/So, and Oj/Is. This sample includes all but nine individuals who had none of these traits.

Table 5-39: Traits Used for the Third Run

	Table 5-39
As	Asterionicossicle
Ca	Carotico-clinoid bridge
Is	Infraorbital Suture
Ic	Intermediate Condylar Canal
Mf	Marginal Foramen
Ms	Mendosal Suture
Mt	Metopic Suture
Mh	Mylohyoid bridge
Om	Occipito-mastoid ossicle (Om)
Oj	OsJaponicum
Oa	Ossified Apical Ligament
So	Sagittal ossicle (So)
Sf	Supraorbital Foramen
Ts	Trochlear Spur

These results are different than the other runs of Unconstrained Clustering in that the best %SSE results occur with a local density radius of 10 m. These results are again better than our baseline and also better than the 15 traits selected strictly on the basis of spatial clustering. Because inter-trait correlations provide enhanced genetic meaning, this result is very significant. The details of the best run are graphed below.

5.5.4   Unconstrained Clustering of 29 Traits by Sex

The final two runs consider all 29 traits for males and females separately.

For the male computations there are 79 individuals. As with the baseline results, values at 10 m are generally the worst, while those at 15 m, 20 m and 25 m are the best and are very close. However, the best %SSE results occur at a local density radius of 15 m. This

result is better than the baseline and the 15 clustered traits and only marginally worse than 14 correlated traits. The details of the best run are graphed below.

For the female computations, there are 107 individuals. The local density radius of 25 m yielded the best results in most cases. As in most other runs, the 10 m values are the worst, while values for 15 m, 20 m and 25 m are very close. In terms of the higher number of clusters, it is only marginally better than the base-line and in terms of the lower number of clusters, it is actually worse. The details of the best run are graphed below.

5.5.5   Generation of Distribution Map of Identified Clusters

Of note first is that in all runs of Unconstrained Clustering on the K2 data the results were highly significant. Unfortunately, the program does not give an actual p-value, but the programs chart plots the 95% confidence envelopes. For the base-line run with all traits and all individuals (see Figure 5-7) the lighter lower line is the actual run and the

Figure 5-7: Confidence Envelopes for All Traits and All Individuals
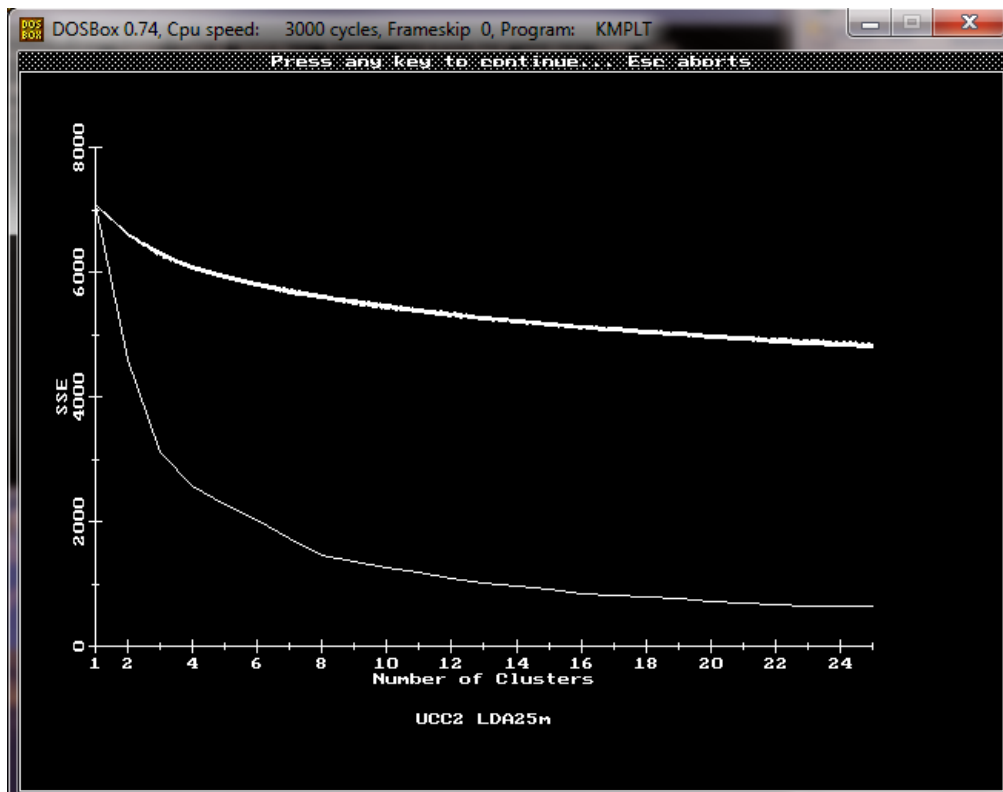
wider line above represents the confidence envelope. The confidence interval was calculated by running a random labeling Monte Carlo technique 99 times. The results show the Unconstrained Clustering on the actual data and it exceeds the plotted confidence interval by a wide margin. Thus, independent of the trait combinations, the results are highly significant. Significant results of various trait combinations in all five of our Unconstrained Clustering runs provide further support for a kinship based organization of K2.

Additionally, the local density radius with the best %SSE values from each combination of traits was selected for comparison (see the LDA radius in the accompanying charts). Three of these were 25 metres, one was 10 metres and one was 15 metres. The actual meaning of these LDA distances is uncertain, but is most likely an indication of the nature of the spatial patterning. Note that the two runs with the best %SSE values had the smaller radii. The %SSE values by cluster for these five runs are plotted in Figure 5-8.

Figure 5-8: %SSE by Cluster for the Best Radius from Each Run
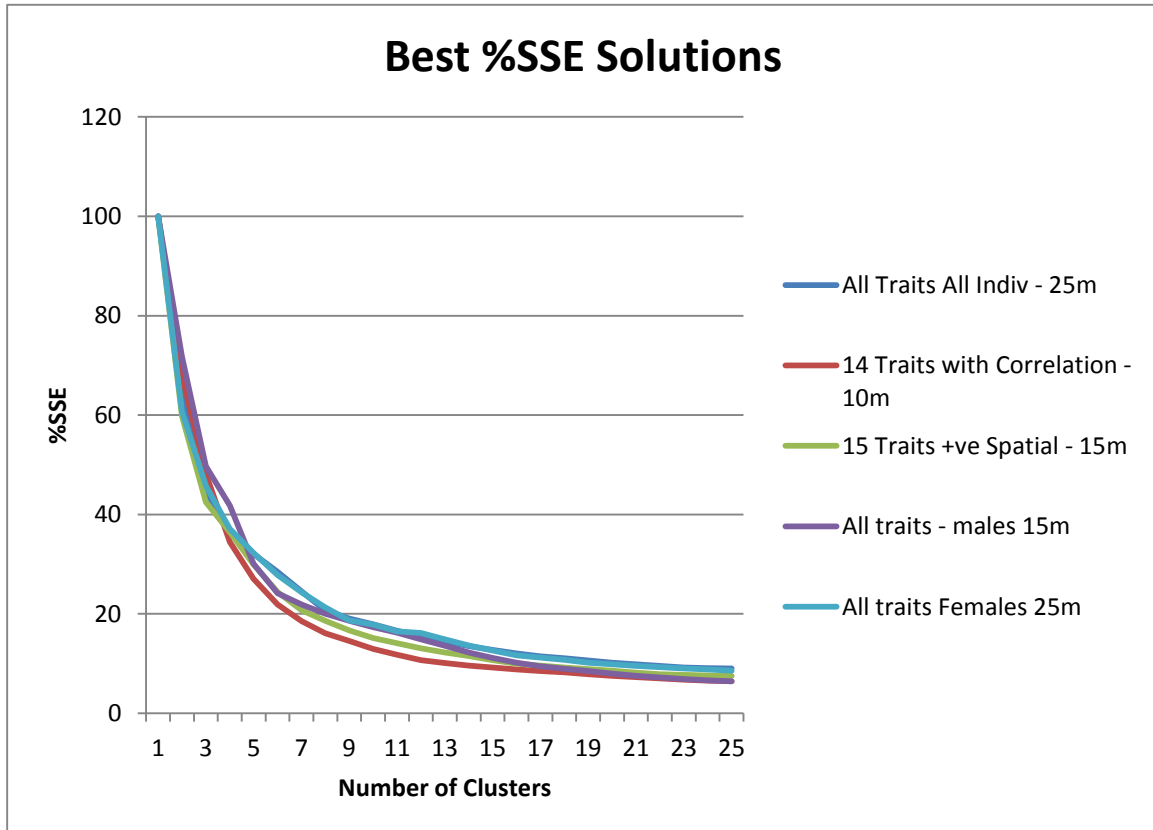
Upon initial inspection, there are not many differences on a macro scale between any of these runs. However, closer inspection of the values above 10 clusters (see Figure 5-9), indicates there are subtle differences that emerge and these will now be discussed.

Figure 5-9: Close Up of Figure 5-8 with the Higher Cluster Numbers
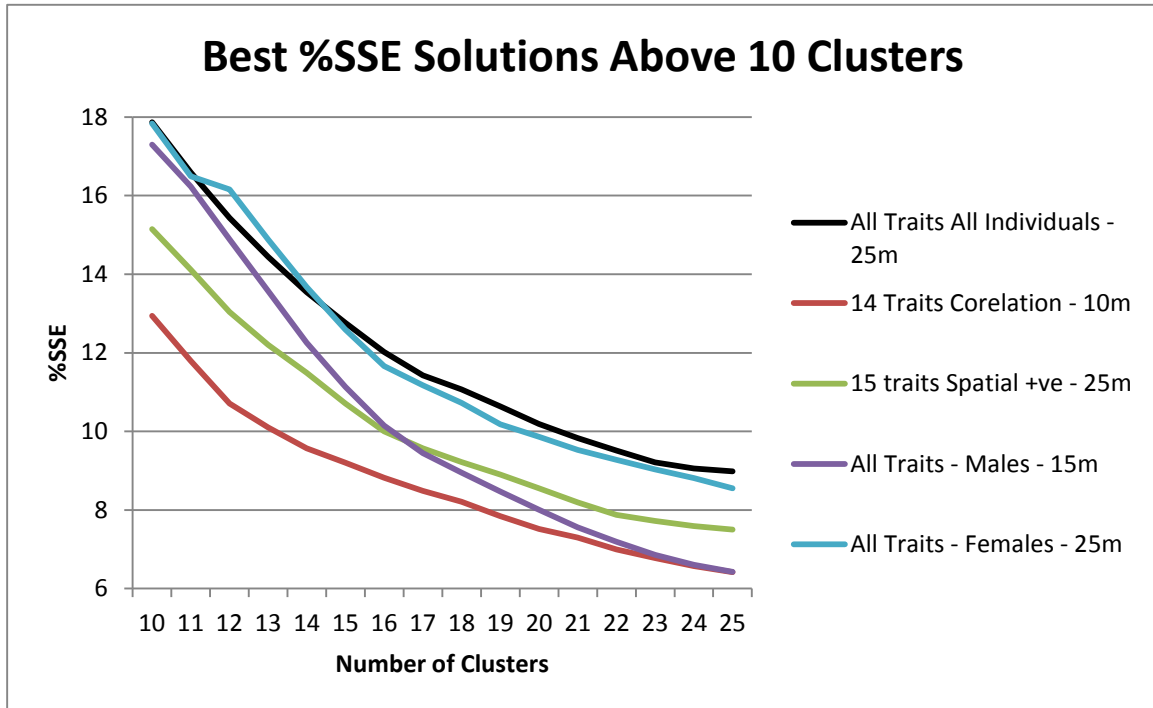
One of the interesting differences in %SSE can be seen by inspecting the three runs with 29 traits, the base-line with all individuals, the males and the females. What clearly emerges is that the males have a lower %SSE than either the females or all individuals. At 10 clusters the differences are small but increases when more clusters are created. This result is expected from the analysis of the individual traits showing K2 was organized patrilocally. Therefore, we should expect that males-only should give a better fit than females or all individuals.

The other runs, as noted, involved all individuals but with a subset of traits, the first with 14 traits based on spatial patterning and some of the traits that showed inter-trait correlations from Brown's (2013) analysis. The second run selected 15 traits that showed spatial clustering of some form as identified in the individual trait analysis above (Table 5-5). The %SSE values both improved over the base-line. Unexpectedly, the best results

were obtained with the sample that included some traits with spatial clustering and some correlated traits. In fact, some of the correlated traits did not show any clustering in the individual trait analysis contra positive to what I expected. In any event, both of these selections improved the %SSE values, but only marginally.

Overall, the best set of %SSE values resulted from the 14 trait "all individuals" run, although the "all traits males only" run matches the results in the 22 -25 cluster range.

The final step in this analysis is plotting the clusters, which requires selecting a specific number of clusters. This is accomplished by examining %SSE curve and by selecting the number of clusters that marginally exceeds expected improvements. Essentially, a number just beyond the knee of the curve is selected. Observing Figure 5-8, this suggests 15 clusters. As a further check, a short mathematical calculation in Excel was concocted. It divided the average of two %SSE values in the column by the average of the two succeeding %SSE values and selected the value where the results drop below unity. This process indicated that overall 16 clusters worked well in most cases, but there was some variation between the five runs. Rather than showing the confusing plots from the TFQA, the cluster assignment of each grave was joined to the GIS for display. To show the clusters, the run with all individuals and 14 traits was selected. This run, with the correlated traits included, was the one which gave the best overall %SSE values. The results, after including the cluster assignment into the GIS, can be seen in Figure 5-10.

5.5.6   Discussion of Multi-Trait Analysis

In paleogenetic research using non metric traits to determine genetic affinities usually involves using multiple traits together with distance statistics (Molto 1983). A major assumption for the use of non metric traits to determine biological affinities between populations is that the variates used are genetically independent of each other (Molto 1983). This argument is based on the conceptual argument that co-related traits provide redundant genetic information. However, reversing the argument, morphogenetic non-metric traits that are known to be generally independent but which are found to be correlated within population samples, provide greater genetic meaning -- they represent a channeling of the allelic variation. Within-group testing typically utilizes rare non metric

Figure 5-10: Cluster Assignments for 14 Traits and All Individuals

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Unconstrained
Clustering

LDA=10, Clusters=15, Data=UCC1

Legend
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
Cluster 6
Cluster 7
Cluster 8
Cluster 9
Cluster 10
Cluster 11
Cluster 12
Cluster 13
Cluster 14
Cluster 15

0 2.5 5 10 15 20 Meters
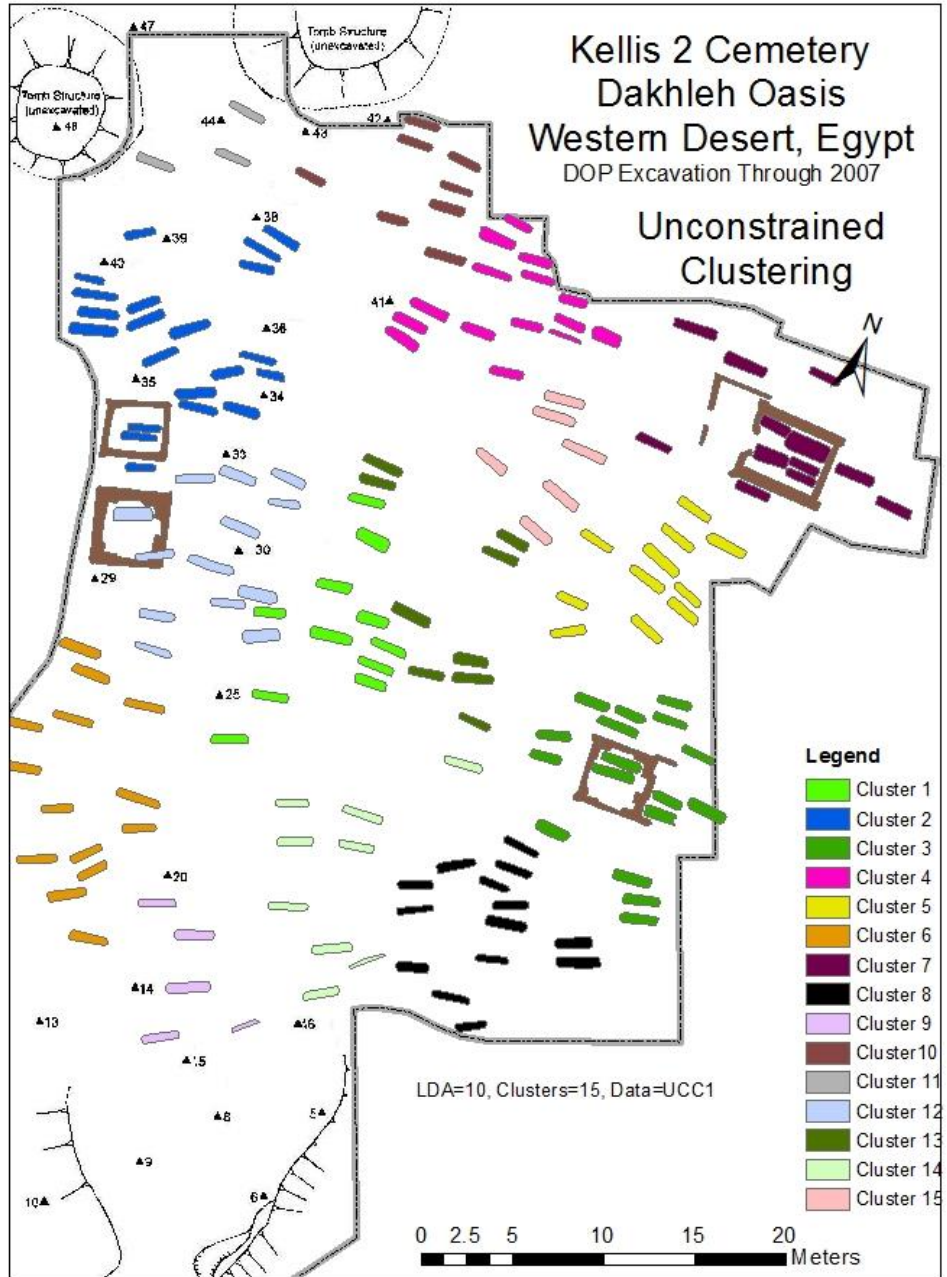
traits to determine who is related to whom. To test within group relationships spatially, the latter approach, though valuable, is limited by the fact that rare traits are uncommon and may not be useful in the bigger picture of determining kinship patterns, residence patterns, etc. in a large cemetery.

It is clear that the analysis of multiple traits together provide strong support for K2 being organized by patrilocal interment. The fact that the strongest statistical evidence is provided by the computations involving the co-related traits (Brown 2013) provides a unique theoretical foundation for within group genetic affinities. Given the fact K2 was used for over a 300 year period, the clusters of non metric cranial traits can be used to suggest extended family groups temporally. For discussion here I will use the term *contemporary kin groups* to describe these clusters. From the analysis, we know that individuals in each cluster are more closely related to each other than they are to individuals in other clusters. Specifically, cluster 1 and cluster 12 might actually be the same patrilineage over the long run, but the genetics may have changed substantially so that they cannot really be equated as the same patrilineage. A patrilineage is a cultural construct that long outlasts a particular combination of genetics. Given this change over time in a patrilineage's genetics, it is a reasonable assumption that most individuals in the group are also close in time. Note, though, that this does not imply that all individuals in each contemporary kin group are either closely related in either genetics or time. It merely implies that most are.

It should also be pointed out that in the construct of the kinship hypothesis Molto (2002) posited that superstructures at K2 were first established when the families at K1 in the early Roman shifted to the Christian burial mode at K2. The families then buried their dead adjacent to the tomb super-structure. Over time, the area filled up and the zones between the superstructures narrowed. This hypothesis is supported by the fact each tomb is located entirely within one of the clusters. For example, the southeast tomb is entirely contained within cluster 3. Beyond that clusters 8 and 13 could derive from cluster 3 and maybe cluster 5, although it is located directly between the northeast tomb and the southeast tomb. Similarly, the two tombs on the west, although closely spaced, divide cleanly between cluster 2 and cluster 12. The northeast tomb is also similarly in the

middle of cluster 7. However, with the nature of the unexcavated portion of the cemetery on three sides of this tomb, it would be rather speculative to try and link other clusters to this tomb. In fact, linking cluster to the superstructures will likely remain an ongoing hypothesis, although at this point it is definitely supported by this non metric spatial analysis. The fact that the tombs are all cleanly located within specific clusters is also an indicator as to the validity of applying Unconstrained Clustering to discrete genetic traits. At this point, no attempt has been made to apply a significance test to this result, but simple consideration of this likelihood says such a result should be significant.

With contemporary kin groups defined, it is now possible to return to the question of the disparity in numbers between males and females. As discussed above, the most reasonable explanation for this discrepancy is that a significant number of males are missing from the cemetery. One possible explanation for this is the involvement of males in the caravan trade (Haddow 2012), thus exposing them to risk factors that have a significant mortality rate due to violence or disease exposure, leading to burial removed from the community. Table 5-40 shows the 15 clusters from Figure 5-10 along with the number of males and females in each cluster. Only two clusters show marginally fewer numbers of females than males, while six show a substantially higher number of females than males. A Chi-Squared Test was run on a number of the clusters with extra females comparing actual to expected numbers of males and females. On first pass, only cluster 14 shows statistically significant difference but another three, clusters 4, 6 and 15 are approaching significance. This result is largely due to the fact the counts in each are not high enough to give statistical significance. However, looking closer at the data, a number of the clusters with extra females tend to be contiguous, forming two groups. Clusters 4, 5 and 15 form in one group to the northeast and clusters 6, 8, and 14 form another contiguous area to the south. Cluster 8 could be dropped from the southern group but has been included here, as it still has a lower ratio of males to females. Dropping it from the southern group would not substantially alter the results. Combining the counts per cluster for each of the northeastern and southern groups and then running the Chi-Squared test, we end up with the northeast group significant at $p = .002$ and the south group with a $p = .004$.

Table 5-40: Males and Females by Cluster Number

Table 5-40	Males	Females	Indiv p	Location	Combined
1	6	5			
2	8	13	.27	Tomb	
3	7	10		Tomb	
7	7	5			
10	5	3		Tomb	
11	2	1			
12	6	7		Tomb	
13	3	6	.32		
9	3	2			
6	4	11	.07	South	
8	5	9	.28	South	p = .004
14	1	8	.02	South	
4	3	11	.03	Northeast	
5	3	8	.13	Northeast	p = .002
15	1	5	.1	Northeast	
total	64	104			

Thus, it appears that the missing males most definitely belong to a subset of the contemporary kin groups and that this patterning contributes to some of the issues described above in the analysis of the distributions of males and females (Section 5.3). One potential explanation of this pattern is that routes in the caravan trade were family-owned, a situation identified elsewhere in ethnography (Trigger 1987), and that this exposed those families to higher male mortality abroad.

Figure 5-11 shows the two groups of contemporary kin groups with reduced numbers of males. Another noteworthy fact from this table is that none of the four clusters centred on the tombs show a measurable absence of males, excepting possibly cluster 2 with 8 males and 13 females. For some reason the contemporary kin groups occupying the tombs do not seem to be susceptible to the same remote male mortality as the members of the two groups of clusters. There are potentially a number of explanations for this difference. One

Figure 5-11: Clusters with Excessive Missing Males
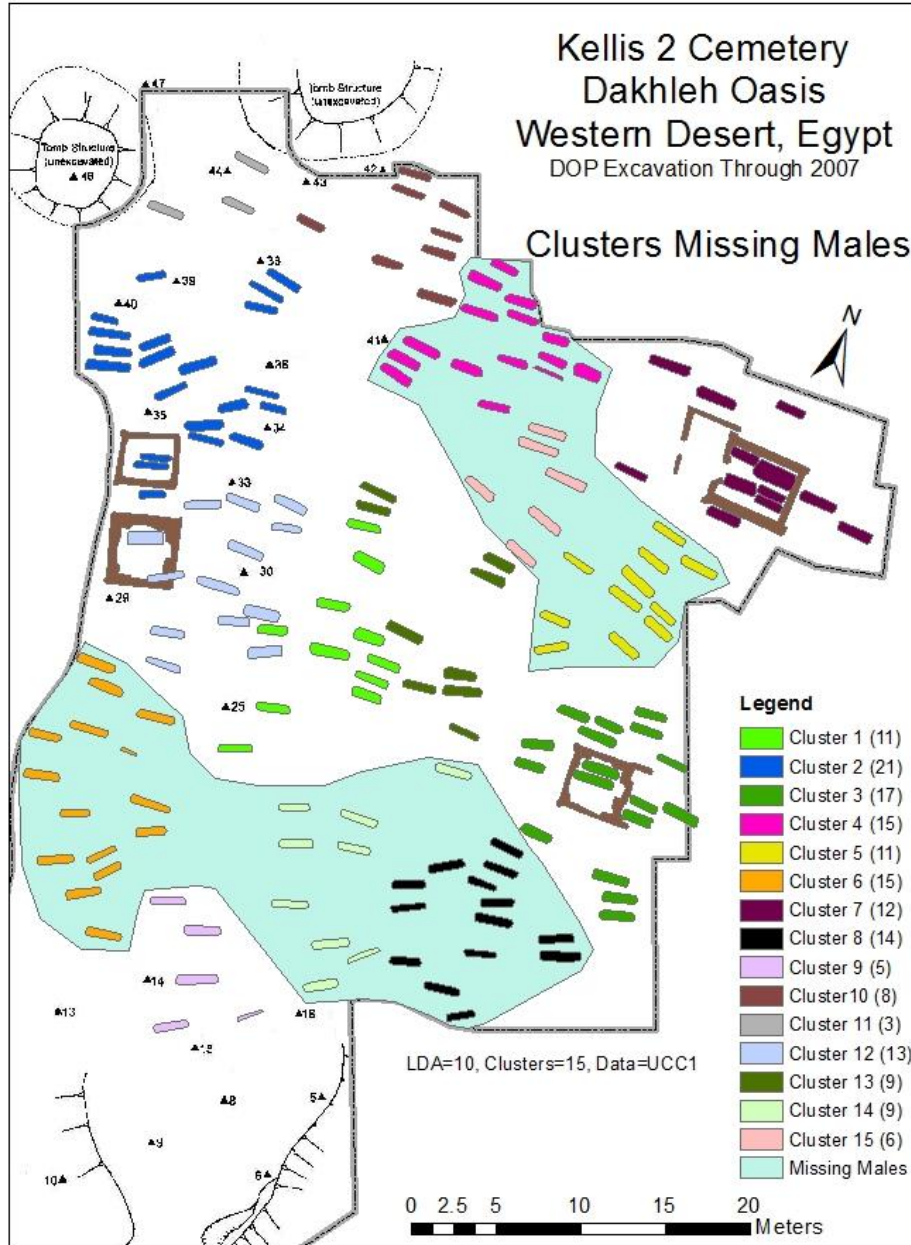
explanation may be that if the tombs represent early use of the cemetery in the first century and early second century AD, that the K2 people were not as involved with the caravan trade at the time and that involvement increased with time. The other potential explanation is that the people in and close by the tombs may represent some form of elite group that controlled the trade routes by sending others out on the more dangerous occupation. However, without a large number of dates on various graves, it will be difficult to distinguish which of these hypotheses is most correct and of course, getting accurate dates, if it can be done at all, is expensive.

In a separate line of thought, with this mathematically derived set of clusters in the cemetery it is possible to evaluate the effectiveness of Haddow's (2012) four part division of the cemetery that he used for spatial analysis in his dissertation. His division was created by looking for natural subdivisions in the spacing of graves in the cemetery. Comparing Haddow's (2012: 145) Figure 5-43 and my Figure 5-10, we see that his boundaries line up very well with the cluster boundaries developed here. A few graves are displaced (for example, look immediately below the unexcavated tomb to the north) but in general there is a very good fit between his four groups and the clusters defined herein, so that his analysis based on the four groups should be spatially valid.

5.6   Conclusions

In conclusion, we can synthesize what all of the results discussed above mean as far as the organization of K2 is concerned.

First, this statistical analysis supports Molto's (2002) kinship hypothesis that was based on visual inspection of distribution of non metric traits in K2. Both the individual trait analysis and the multi-trait analysis support this idea with highly significant results. Secondly, as expected from historical sources (Bagnall and Frier1994), it is also clear that the kin basis for the cemetery is influenced by a patrilocal residence pattern. Of more interest is the fact that the absence of males is restricted to a subset of the contemporary kin groups and the statistical analysis of the two groups indicates this difference is significant. While the final explanation will remain elusive, we clearly see that some contemporary kin groups had fewer males interred, with the missing males most likely

dying elsewhere. This pattern most likely relates to involvement in pursuits like the caravan trade. It also implies that the occupation taking them away tends to be organized along kin group lines, suggesting at least differential participation in caravan trade routes and possibly differential ownership of trade routes. It further suggests a specialization within the community in terms of occupation.

What was unexpected, though, is that the four contemporary kin groups centred on each of the four tombs do not seem to display differential sex inclusion. They are all close to being even or at least what might be expected by normal stochastic variation. There are two feasible hypotheses for this result. First, they could represent early interments to the cemetery, as has been hypothesized, and at that time participation in trade routes was not as developed as it was in later times. Second, they could represent some form of elite who could stay close to home and directed others into the risky trade route business. However, it is not possible to choose between these alternatives with present evidence.

In summary, the application of novel spatial statistics has provided clear answers to the kinship hypothesis and the patrilocal interment structuring of the K2 cemetery which, until now, had been hypothetical. It also provides some novel insights into the K2 community in the Romano-Christian period.

Chapter 6

6   Summary and Discussion

The previous chapters have defined a conceptual structure for point pattern analysis in archaeology (and bioarchaeology) and conducted two detailed case studies. This final chapter will review the results from a broader, often more theoretical, perspective.

The approach to developing this dissertation was to first develop the analysis of the two case studies. The Kellis 2 analysis was done first, followed by the Davidson site analysis. Individual statistics were developed in R or used as they were required in the execution of each case study. After completing the Kellis study, several of the sections that appear in Chapter 2 (and 3) were written primarily to provide background to my supervisors as they reviewed the case study. After completing the Davidson case study, Chapter 2 was developed in the form provided here, since the Davidson case study proved to have very different needs than the Kellis study. In one sense, the execution of the two case studies has imposed a limiting factor on the theoretical approach as defined in Chapter 2. The two case studies were approached first in the absence of such an approach and the lessons learned in doing so were used to develop the concepts of the structured approach. Thus, unless a specific statistic or conceptual structure was encountered in the two case studies, it would not be included in the conceptual structure. For example, if the only case study had been distribution of discrete genetic traits in the Kellis 2 cemetery, the entire first order analysis of the structure of the point pattern at the Davidson site would have been missing. Similarly, there are almost certainly other situations not encountered in these two case studies which might further refine the chapter on the structure of analysis. One potential approach that comes to mind is the use of alternate models for determining statistical significance, as outlined by O'Sullivan and Unwin (2003). In this study the only alternate to CSR used is random labeling -- but there could well be other models that could be tested.

Similarly, the statistical tools used here are those that were required to complete the two case studies and there certainly are others which are available or could have been defined. Two of these, described in various texts such as Bailey and Gattrell (1995) and O'Sullivan and Unwin (2003) are the F and G functions which, much like the K function described in Chapter 3, condense a point pattern to a graph with manipulations on Nearest Neighbour.

While I have never encountered a situation where they could be useful, there may well be such situations. One routine that could have proven useful here is a K function tested against random labeling. This tool could prove to be one of the more effective tools for examining second order effects such as were encountered herein. I believe it could also provide an alternate solution to the clustering of larynx cancer as examined in Gatrell et al. (1996). While this tool could have proven useful, the Proximity Count statistic, although less elegant, provides essentially the same analytical information and is conceptually much easier to understand, obviating the need to develop a K function testing against random labeling. However, the K function against random labeling needs to be developed in the near future.

Despite potential refinements just discussed, I believe the structure of analysis as laid out in Chapter 2 provides a conceptually solid basis for approaching most point pattern problems in archaeology. First, and foremost, I would stress an understanding of the concepts of first and second order effects in approaching the analysis since, as can be seen in Tables 2.3 and 2.4, this concept is fundamental to the choice of statistical options and indeed, the entire thrust of the analysis. As was discussed in Chapter 2, the differences between first and second order effects are not always obvious but in most archaeological examples we are either looking at the structure of the overall distribution without reference to the differences between various events, or we are looking at the relative distribution within a labeled point pattern. Here the overall distribution is a first order effect and the labeled point pattern is a second order effect. So the choice of statistical tools for these conventional analyses is simplified, at least as far as the differences between first and second order effects. Where the differences between first and second order effects are most important is when it comes to choosing a criterion for measuring statistical significance.

Probably the most important decision to be made in a PPA is the choice of what criteria to use to measure statistical significance. In most cases, this measure will be either CSR or random labeling. This choice is important since the two alternatives can generate different numbers, the results of which could well lead to different conclusions. While tests for random labeling do exist in PPA, for example see Baddeley's Spatstat (2015), most of the discussions of PPA that I have read do not make this distinction clearly. The closest is the discussion in O'Sullivan and Unwin (2003) but while this excellent text clearly recognizes CSR and its limitations, and states that other models are possible, and in most cases would be preferable,

it does not introduce any other models including random labeling. Similarly, processes for dealing with labeled point patterns are well-defined in Baddeley's Spatstat (2015) but again that package does not make a clear distinction between the choice of model against which to test statistical significance. While there is a test for random labeling, it is not clear what statistic is being used within the test and the K function included with this package only uses CSR.

While O'Sullivan and Unwin's (2003) assertion that, in human endeavour, CSR is the least likely thing to ever occur, and that there are other models against which a given pattern may be tested is certainly valid, the nature of statistical significance limits what can actually be "proven". Suppose there is a feasible model that might account for the observed pattern. In statistical terms this model would form the null hypothesis. If our actual point pattern were the result of the hypothesized process, then the results of the test could, at best, say that the null hypothesis could not be rejected -- but whether or not the hypothesized process was the cause could not be "proven". However, if the test differs from the hypothesized process, then we could say with certainty that the hypothesized process is not what caused the given distribution of events. In other words, using statistics we can only show that the hypothesized process is not what caused the result. We cannot prove that it is what caused the result. Thus, showing something is "not random" remains the best approach, but it is critical to realize that there are choices against which to test randomness. In any event, the case studies provide good examples of testing against both CSR and random labeling and the appropriate situation for each test.

It may be that part of the reason for this situation is that testing significance against random labeling may have its best application with archaeological data. Looking at the spatial utilities within Kintigh's TFQA, several of these, such as the A-Statistic and Unconstrained Clustering, actually use random labeling as the basis against which to test statistical significance. However, archaeological data is merely the reflection of human dwelling in the past so it would be reasonable to expect the same applicability within geography -- at least as far as one is examining the results of current cultural activity. Of course, it could also be something in the nature of archaeology or the training of archaeologists that leads to the use of random labeling. Speaking personally, one of the first tests developed during execution of this study was the Proximity Count statistic. Even prior to the development of the

conceptualization of choices in calculating statistical significance as outlined in Chapter 2, I naturally gravitated to a measurement of significance using random labeling.

The other concept introduced in Chapter 2, and used mostly in the Davidson case study, was that of the resolution focus. While this is not as critical as first/second order effects and choices in statistical significance, it is nonetheless useful as a way to properly link use of different techniques for analyzing first order effects, as was done with the coarse stone flakes in the Davidson case study. While not as important, this concept does, nonetheless, make the point that various methods of analyzing distributions should give similar results when the resolution focus matches. Typically the extremes of resolution focus, either too large or too small, will give results that are not at all informative. However, in the mid-ranges differing scales of analyses may well provide different insights into the structure of the point pattern, as occurred in the Davidson case study with the distribution of the coarse flakes.

Finally, a section in Chapter 2 which is somewhat open-ended is the one titled "structure of analysis." While this discussion, along with Tables 2.3 and 2.4, provide a good model for selecting the appropriate statistical routine, where possible it would be advantageous to provide a better structure to the higher levels of analysis. One example of this occurs in the Kellis case study where the very first step was examining the distributions of males relative to females. It would have been possible to just run statistics on the various discrete genetic traits, but without a clear understanding of the distribution of the two sexes, the results would have been less clear since, on first pass, some of the analysis of discrete traits tended to indicate a matrilocal burial plan. In reality, where this occurred was in areas of the cemetery underrepresented with males. In the Kellis case, I might generalize this step, saying that it is first necessary to examine the data for potentially confounding factors. With the Davidson case study the first stage in the analysis was the first order distribution of coarse flakes, which determined the locations of the various spatial clusters. I would not refer to this example as a confounding factor but, in some ways, it made sense as the first step in the analysis. Without having done this step first, the subsequent analysis, such as the Unconstrained Clustering of the coarse flake types, might simply have left the impression that there was no structuring in the site. Thus, while there is a logical structure to this high level design of the analysis, at this point in time I cannot provide a uniform structure/approach to such analyses. It is mostly a case of knowing the data extremely well,

which obviously requires a lot of exploratory data analysis and potentially some trial runs of various statistics, and then developing a logical, well-reasoned approach to analyzing the structure of the data.

Looking at the various statistical routines used in this study, the tools for analyzing first order effects all worked well and provided a reasonable consistency, as seen in the Davidson case study, once the issue around resolution focus was understood.

The same cannot be said of the set of tools used in analyzing the second order effects. What I had hoped for was two or maybe three tools that would give a clear indication of structure in a labeled point pattern. At one point early on, after reading Hill (2004) who used three of the TFQA utilities (the A-statistic, Local Density Analysis and Nearest Neighbour) to do an analysis of second order effects related to site locations, it appeared that this might be relatively straight-forward. While the three techniques worked well in that study, when applied to the Davidson data, these statistics gave confusing and sometimes contradictory results. Similarly, when doing the analysis on the Kellis data, several statistics were run on the distribution of each discrete genetic trait but frequently only one would show a statistically significant clustering while the others did not. While this might be considered disconcerting, the simplistic explanation being that the labeled point pattern either shows significant clustering or it does not, what I believe is happening is that the different statistics can, in effect, "see" different things. In general, all these routines condense a complex point pattern with somewhat simplistic mathematics to one global statistic (either one number as in Nearest Neighbour or a range of numbers as in a K function). What this means is that all kinds of detail is lost and the nature of the different mathematical contractions each lose different aspects of the point pattern. A good example of this occurs in the Kellis case study when examining the distribution of individuals with an accessory optic foramen (Figure B.1). Here neither the A-statistic nor Proximity Count shows statistical significance, but the Nearest Neighbour-Random Labeling does. What this discussion all indicates is the absolute necessity to use multiple statistics to examine any given distribution of a labeled point pattern. One tool simply is not sufficient.

Turning to some of the individual tools themselves, I first consider Hodder and Okell's A-statistic. While initially impressed that the mathematics of the statistic seemed to take everything into account by including all points of both types in the calculations, in the end I

am decidedly disappointed with it as a statistic. In some cases, it seems to give strange results, as in where a value of $A = .96$ turns out to be significant (e.g. see Figure B.6 where $p = .04$). The value is so close to 1.0 that the only reasonable explanation is that that there is no segregation of the two types, but what does the statistical significance mean? Another problem with the A-statistic is that it cannot see a checkerboard pattern where, for example, all items of type A are on white squares and all items of type B are on black squares. While the types are clearly segregated, the statistic shows them randomly intermixed. An example of this result was encountered in the Davidson case study, where comparing Broadpoint artifacts to coarse flakes gave a value of $A = 1.0$ but subsequent analysis showed that these categories were clearly segregated, with Broad Point artifacts separate from the coarse flakes. The A-statistic really only tends to give good results when the pattern is obvious enough that you can see it with a simple visual plot/examination, such as occurred in the Davidson case study concerning the difference between the distribution of the Small Point and Broad Point artifacts --its use should be restricted simply to quantifying the observable distribution.

I started the analysis with a poor opinion of the Nearest Neighbour statistic and in fact, the simpler versions of the statistic did tend to be largely useless, even when evaluated against random labeling. I still maintain that the basic form of Nearest Neighbour, called the Evans and Clarke R statistic, is really only useful in archaeology for quantifying events that are evenly distributed over the study area. The between types variants did prove more useful though, especially in the Kellis analysis comparing the distributions by sex. Interestingly, the between types variants were developed in the field of archaeology in the late seventies and early eighties.

The statistic which proved the most useful overall was the Proximity Count, in that it most frequently captured concentrations of labeled events in the overall distribution. As described above, this statistic grew out of discussions on the Kellis cemetery, but it should be pointed out that it has a very similar mathematical structure to the K function; both of these statistics count the density of similar events in a series of circles widening out from each event with the specified label. The only difference is that with Proximity Count the total count within the specified radius is reported, whereas with a K function the average density within the same radius is reported. This fact was not realized until late in the analysis and substituting a K function against random labeling would certainly be an option, but it was decided to keep the

Proximity Count since the results are good and the statistic is much easier to understand than the K function. Several implementations of the K function are available, but all of these determine statistical significance against CSR. ArcGIS has an implementation as does Baddeley's Spatstat (2015).

One archaeologically developed statistic is Local Density Analysis (Johnston 1984), which was used to a limited extent in this study. This statistic could be useful but is hampered by the lack of the ability to test for statistical significance as implemented in TFQA. Kintigh (personal communication 2013) says that in theory it would be possible to build such a test, but he has not done that. This statistic also calculates density within ever increasing radii, so I suspect that it would give results similar to the K function or Proximity Count. Evaluating this suspicion could make an interesting project at some point in the future.

Unconstrained Clustering (Whallon 1984) was used in both case studies with good effect. The Davidson case study used it in the conventional manner for which it was designed to try and locate activity areas in the knapping of coarse-grained rocks. In the Kellis case study, the use was unconventional in that I was trying to locate areas within the site with similar genetic composition. At this point, I am not aware of a similar tool available anywhere outside archaeology. While it might have been nice to develop another such tool, say for example, an implementation of Carr's (1984) polythetic sets, time constraints prevented doing so. In using Unconstrained Clustering, there is a parameter required in the first step using LDEN in TFQA that can best be viewed as a parameter defining the resolution focus as defined in chapter 2. With Unconstrained Clustering this parameter is the local density radius, which is similar in concept to the radius used in Kernel Density or Proximity Count. As with the other statistics where the resolution focus comes into play, differing radii give different results. In some cases, where the radii are obviously too high or too low, the results are easily rejected. What is not clear at this point, though, is whether or not differing radii between the two extremes give different but complimentary views of the event structure. In the future it might make sense to implement Carr's (1984) polythetic sets and compare the results.

In summary, the tools for determining non-random distribution of labels in a labeled point pattern are problematic but do work. The best approach to ameliorate this weakness is to run multiple statistics and compare the results carefully.

As a final consideration, it is necessary to examine how this suite of tools fits into the overall discipline of archaeology. Forty-five years ago Watson, LeBlanc and Redman (1971) published what might be termed a processual polemic outlining the hypothetico-deductive methodology for proper archaeological inquiry, which stressed the importance of quantitative methods. These ideas ran their course and the next enlightenment was the advent of post-processual archaeology, the strong form of which labeled quantitative tools and mapping systems as tools of oppression of indigenous peoples by Euro-American hegemonies. While this debate is still with us to some extent, we need to get past the stale old processual versus post-processual debates. As Trigger noted, "much of what has passed as theoretical debate has focused on rhetoric, political issues and self-justification" (Trigger 2006: 482). True, in many situations processual explanations are overly simplistic, but equally true is that the strong form of post-processualism, with its rejection of numerical methods, logic and science, has led to investigative techniques where, for example, an archaeologist wanders the modern landscape with the expectation that his feelings might resemble those of the original native dwellers. Ethnography would suggest otherwise. Personally, I am rather fond of what Bruce Trigger (2006), in the 2nd edition of the *History of Archaeological Thought,* called a "pragmatic synthesis" where the useful positions of various theories are retained and the nonsense discarded. In this pragmatic synthesis, I would suggest that spatial statistics have an important role to play.

However, I do not see the application of spatial statistics as being able to explain any given set of observations. As noted in the introduction, spatial statistics are best viewed as an extension of our observational capabilities (Wheatley and Gillings 2002). As seen in the case studies, some patterns can be seen with the naked eye by doing a simple plot of the events under consideration, such as the difference between the distributions of Broad Point and Small Point artifacts at the Davidson site. Others, such as the determination of the genetic relatedness of nearby graves into what were termed contemporary kin groups, are completely impossible with a simple plot. Therefore, the application of Unconstrained Clustering enabled a view of the data that would forever be beyond the ability of a human mind to perceive without the application of the mathematical procedures.

As was identified during the critiques of spatial methods in the 80s and 90s, spatial methods are only one portion of the analysis. It is equally important to carefully consider context in the analysis and determine what other non-spatial arguments bear on the analysis being considered, as occurred with the Small Point distribution discussion in the Davidson case study. Carr (1991) argued for the use of contextual information in developing interpretations along multiple lines of evidence. I would suggest that the use of spatial and even classical statistics is but one step on the road to explanation. It is not an end in itself, although for some of us interest flags after the statistics part. However, more important is the use of contextual information and multiple lines of evidence. Statistical inference is but one of these lines. Thus, in both of the case studies presented, I believe the patterns determined are real and, having been observed, can be incorporated into an interpretational argument that could be guided by either processual or post-processual theory or, better still, Trigger's (2006) pragmatic synthesis. There is no magic in spatial statistics. They are just another widget in the archaeologist's tool kit, much like a microscope or a Munsell soil colour chart. The job of interpreting the implications of all of our archaeological observations, statistical and otherwise, is and always will be the responsibility of the archaeologist.

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Appendices

Appendix A: Glossary of Terms

Activity Cluster/Spatial Custer These are two terms which are applied in the Davidson Site case study. The latter term refers to the six or seven clusters of coarse flakes each with a diameter of 30-40 m that occur along the river. Activity Cluster is a much smaller unit defined through unconstrained clustering where similar percentages of the various flake types are found. This on spatial cluster can contain a number of activity clusters.

Complete Spatial Randomness (CSR) This is a term used within point pattern analysis to describe a process creating a point pattern where the location of every event is independent of all other events. In effect each event within the study area is placed randomly without regard for the location of any other point.

Complete Surface Pickup (CSP) This is a field technique in archaeology where the surface of a field is searched on regular intervals, usually referred to a transects, and all cultural material on the surface is recovered and the location of each artifact is mapped.

Events This is a term used in point pattern analysis which refers to the spatial location, usually recorded with Cartesian coordinates, of each item of interest in the study area. It may be a simple point pattern containing just the locational information or could be a Labeled Point Pattern.

Labeled Point Pattern This is a point pattern composed of a series of events which have attributes attached describing the nature of that specific event. For example in a CSP each event could contain information about the specific artifact recovered such as artifact type, raw material, length etc.

Random Labeling This is a process used to calculate statistical significance where the location of events in a labeled point pattern are held constant and a the labels of all points are randomly distributed over the point pattern a number of times with a Monte Carlo technique to calculate statistical significance.

Resolution Focus This is a term used in this dissertation with respect to conducting density estimate. Different analystical techniques (e.g. kernel density, pure locational clustering and quadrat analysis using Getis-Ord Gi*) have various parameters which as they are modified give progressively finer or more coarse grained results in density estimation. In kernel density this concept s well developed and is call bandwidth estimation. The use of this term reflects the fact that the concept has a wider application across several different techniques. When the Resolution Focus is adjusted for each analytical technique it is possible develop two different maps which give similar results.

Spatial Autocorrelation This is a term used in spatial statistics to reflect the fact that in geographic space locations in space that are close to each other tend to have more similar values when compared to more distant locations. Autocorrelation is problematic in applying classical statistics.

Appendix B: Kellis Figures

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.1

Accessory Optic Foramen

Legend

Females/Absent (101)
Females/Present (5)
Males/Absent (69)
Males/Present (1)

Hodder & O'Kell's A	
Value	p=
0.89	0.15

Nearest Neigh - RL	
Value	p=
0.512828	0.02

Proximity Count	
Value	p=
1(3)	0.202
2(5)	0.081
2(7)	0.259
3(10)	0.307
6(15)	0.184

0 2.5 5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.2

Anomalous
Temporal Artery

Legend
Females/Absent (101)
Females/Present (5)
Males/Absent (66)
Males/Present (3)

Hodder & O'Kell's A	
Value	p=
0.99	0.40

Nearest Neigh - RL	
Value	p=
0.963001	0.43

Proximity Count	
Value	p=
0(3)	1.000
0(5)	1.000
2(7)	0.581
8(10)	0.032
13(15)	0.046

0 2.5 5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.3

Carotico-clinoid Bridge

Legend
Females/Absent (77)
Females/Present (25)
Males/Absent (40)
Males/Present (22)

Hodder & O'Kell's A	
Value	p=
0.96	0.06

Nearest Neigh - RL	
Value	p=
0.988225	0.44

Proximity Count	
Value	p=
19(3)	0.206
49(5)	0.149
96(7)	0.036
160(10)	0.240
285(15)	0.682

0 2.5 5 10 15 20 Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.4

Clino-clinoid
Bridge

Legend

Females/Absent (82)
Females/Present (21)
Males/Absent (47)
Males/Present (15)

Hodder & O'Kell's A	
Value	p=
0.99	0.24

Nearest Neigh - RL	
Value	p=
1.069593	0.23

Proximity Count	
Value	p=
8(3)	0.713
25(5)	0.418
41(7)	0.724
76(10)	0.874
128(15)	1.000

0   2.5   5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.5

Divided Hypoglossal Canal

Legend

- Females/Absent (45)
- Females/Present (59)
- Males/Absent (30)
- Males/Present (39)

Hodder & O'Kell's A	
Value	p=
0.98	0.06

Nearest Neigh - RL	
Value	p=
1.001478	0.52

Proximity Count	
Value	p=
70{3}	0.556
181{5}	0.583
337{7}	0.700
668{10}	0.318
1306{15}	0.370

0 2.5 5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.6

Divided Jugular Canal

Legend

Females/Absent (76)
Females/Present (27)
Males/Absent (49)
Males/Present (20)

Hodder & O'Kell's A	
Value	p=
0.96	0.04

Nearest Neigh - RL	
Value	p=
0.943928	0.23

Proximity Count	
Value	p=
16{3}	0.468
37{5}	0.750
82{7}	0.252
148{10}	0.466
294{15}	0.408

0   2.5   5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.7

N

Tomb Structure (unexcavated)
▲48

Tomb Structure (unexcavated)

▲47

44▲

▲42 42▲

▲39

▲29

▲40

41▲

▲36

▲35

▲34

▲33

▲30

▲29

▲26

▲20

▲14

▲13

▲18

▲15

▲8 5▲

▲9

10▲ 6▲

Frontal Grooves

Legend

Females/Absent (70)
Females/Present (36)
Males/Absent (44)
Males/Present (26)

Hodder & O'Kell's A	
Value	**p=**
1.04	0.69

Nearest Neigh - RL	
Value	**p=**
1.032349	0.31

Proximity Count	
Value	**p=**
28(3)	0.597
69(5)	0.765
115(7)	0.990
238(10)	0.979
497(15)	0.770

0   2.5   5   10   15   20
Meters

234

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.8

Frontal-Temporal Articulation

Legend
Females/Absent (100)
Females/Present (5)
Males/Absent (65)
Males/Present (4)

Hodder & O'Kell's A	
Value	p=
1.04	0.71

Nearest Neigh - RL	
Value	p=
1.021767	0.47

Proximity Count	
Value	p=
0{3}	1.000
3{5}	0.143
3{7}	0.457
4{10}	0.734
9{15}	0.595

0 2.5 5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.9

Infraorbital Suture

Legend

Females/Absent (39)
Females/Present (63)
Males/Absent (37)
Males/Present (32)

Hodder & O'Kell's A	
Value	p=
0.96	0.02

Nearest Neigh - RL	
Value	p=
1.02476	0.28

Proximity Count	
Value	p=
55{3}	0.943
167{5}	0.606
341{7}	0.097
674{10}	0.006
1360{15}	0.002

0   2.5   5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.10

Intermediate
Condylar Canal

Legend

Females/Absent (67)
Females/Present (39)
Males/Absent (35)
Males/Present (32)

Hodder & O'Kell's A	
Value	p=
0.96	0.02

Nearest Neigh - RL	
Value	p=
1.055066	0.15

Proximity Count	
Value	p=
30(3)	0.941
96(5)	0.600
199(7)	0.109
369(10)	0.157
770(15)	0.020

0 2.5 5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.11

Marginal Foramen

Legend

Females/Absent (96)
Females/Present (11)
Males/Absent (64)
Males/Present (6)

Hodder & O'Kell's A	
Value	p=
0.98	0.22

Nearest Neigh - RL	
Value	p=
0.760691	0.04

Proximity Count	
Value	p=
4(3)	0.126
6(5)	0.356
11(7)	0.323
15(10)	0.839
37(15)	0.438

0 2.5 5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.12

Mendosal Suture

Legend

Females/Absent (97)
Females/Present (10)
Males/Absent (64)
Males/Present (5)

Hodder & O'Kell's A	
Value	p=
0.98	0.29

Nearest Neigh - RL	
Value	p=
0.951566	0.37

Proximity Count	
Value	p=
2(3)	0.432
2(5)	0.930
6(7)	0.732
14(10)	0.516
27(15)	0.547

0 2.5 5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.13

Metopic Suture

Legend

Females/Absent (97)
Females/Present (10)
Males/Absent (67)
Males/Present (2)

Hodder & O'Kell's A	
Value	p=
0.67	0.00

Nearest Neigh - RL	
Value	p=
0.747193	0.06

Proximity Count	
Value	p=
3(3)	0.050
6(5)	0.040
13(7)	0.003
19(10)	0.003
35(15)	0.002

0 2.5 5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.14

Mylohyoid Bridge

Legend

Female/Absent (86)
Female/Present (15)
Male/Absent (46)
Male/Present (20)

Hodder & O'Kell's A	
Value	**p=**
0.98	0.12

Nearest Neigh - RL	
Value	**p=**
1.121864	0.10

Proximity Count	
Value	**p=**
8{3}	0.658
21{5}	0.708
42{7}	0.561
74{10}	0.838
144{15}	0.861

0   2.5   5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.15

Notochord
Remnant

Legend

Females/Absent (94)
Females/Present (11)
Males/Absent (54)
Males/Present (16)

Hodder & O'Kell's A	
Value	p=
1.00	0.45

Nearest Neigh - RL	
Value	p=
1.092504	0.18

Proximity Count	
Value	p=
4{3}	0.822
13{5}	0.690
22{7}	0.884
39{10}	0.978
104{15}	0.370

0   2.5   5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.16

Open Foramen
Spinosum

Legend

Females/Absent (56)
Females/Present (49)
Males/Absent (37)
Males/Present (33)

Hodder & O'Kell's A	
Value	p=
0.98	0.06

Nearest Neigh - RL	
Value	p=
1.067339	0.10

Proximity Count	
Value	p=
46{3}	0.681
126{5}	0.451
242{7}	0.293
472{10}	0.120
935{15}	0.097

0 2.5 5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.17

Os Japonicum

Legend

Females/Absent (89)
Females/Present (15)
Males/Absent (65)
Males/Present (3)

Hodder & O'Kell's A	
Value	p=
0.93	0.06

Nearest Neigh - RL	
Value	p=
0.957944	0.38

Proximity Count	
Value	p=
2(3)	0.661
6(5)	0.512
12(7)	0.382
25(10)	0.199
59(15)	0.015

0 2.5 5   10   15   20
Meters

244

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.18

Ossified Apical Ligament

Legend

Females/Absent (102)
Females/Present (3)
Males/Absent (59)
Males/Present (8)

Hodder & O'Kell's A	
Value	p=
0.98	0.30

Nearest Neigh - RL	
Value	p=
0.742374	0.07

Proximity Count	
Value	p=
2(3)	0.176
9(5)	0.000
10(7)	0.011
14(10)	0.026
21(15)	0.086

0 2.5 5 10 15 20 Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.19

Tomb Structure (unexcavated)

Tomb Structure (unexcavated)

N

Parietal Foramen

Legend

- Females/Absent (42)
- Females/Present (62)
- Males/Absent (36)
- Males/Present (33)

Hodder & O'Kell's A	
Value	p=
1.00	0.52

Nearest Neigh - RL	
Value	p=
1.055493	0.12

Proximity Count	
Value	p=
66{3}	0.395
165{5}	0.574
316{7}	0.499
600{10}	0.572
1207{15}	0.314

0 2.5 5 10 15 20 Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.20

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.21

Posterior
Condylar
Canal Absent

Legend

Females/Absent (61)	
Females/Present (44)	
Males/Absent (38)	
Males/Present (29)	

Hodder & O'Kell's A	
Value	p=
0.98	0.11

Nearest Neigh - RL	
Value	p=
0.929136	0.09

Proximity Count	
Value	p=
45{3}	0.090
113{5}	0.046
191{7}	0.285
351{10}	0.589
720{15}	0.265

0 2.5 5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.22

Precondylar Tubercle

Legend

Females/Absent (105)
Females/Present (1)
Males/Absent (64)
Males/Present (5)

Hodder & O'Kell's A	
Value	p=
0.97	0.32

Nearest Neigh - RL	
Value	p=
0.88138	0.34

Proximity Count	
Value	p=
0(3)	1.000
0(5)	1.000
0(7)	1.000
3(10)	0.307
5(15)	0.335

0   2.5   5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.23

Pterygobasal
Spur

Legend

Females/Absent (71)
Females/Present (36)
Males/Absent (38)
Males/Present (32)

Hodder & O'Kell's A	
Value	p=
1.01	0.91

Nearest Neigh - RL	
Value	p=
1.012068	0.42

Proximity Count	
Value	p=
36(3)	0.370
90(5)	0.422
166(7)	0.451
307(10)	0.718
625(15)	0.446

0 2.5 5 10 15 20 Meters

250

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.24

Pterygospinous
Spur

Legend

Females/Absent (97)
Females/Present (10)
Males/Absent (51)
Males/Present (19)

Hodder & O'Kell's A	
Value	p=
1.01	0.66

Nearest Neigh - RL	
Value	p=
1.076479	0.23

Proximity Count	
Value	p=
4(3)	0.843
14(5)	0.653
23(7)	0.896
44(10)	0.974
107(15)	0.483

0   2.5   5   10   15   20   Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.25

Supraorbital Foramen

Legend

Females/Absent (72)
Females/Present (34)
Males/Absent (43)
Males/Present (26)

Hodder & O'Kell's A	
Value	p=
0.94	0.00

Nearest Neigh - RL	
Value	p=
0.9751	0.36

Proximity Count	
Value	p=
30{3}	0.270
84{5}	0.039
145{7}	0.081
262{10}	0.215
499{15}	0.377

0   2.5   5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.26

Trochlear Spur

Legend
Females/Absent (95)
Females/Present (11)
Males/Absent (63)
Males/Present (6)

Hodder & O'Kell's A	
Value	p=
0.92	0.05

Nearest Neigh - RL	
Value	p=
0.803332	0.08

Proximity Count	
Value	p=
3(3)	0.295
6(5)	0.356
8(7)	0.738
25(10)	0.081
42(15)	0.185

0   2.5   5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.27

Tympanic Dehiscence

Legend

- Females/Absent (73)
- Females/Present (34)
- Males/Absent (58)
- Males/Present (12)

Hodder & O'Kell's A	
Value	p=
0.99	0.17

Nearest Neigh - RL	
Value	p=
1.10813	0.10

Proximity Count	
Value	p=
17(3)	0.292
38(5)	0.535
70(7)	0.630
143(10)	0.356
298(15)	0.139

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.28

Zygomatico-facial
Foramen Absent

Legend

Females/Absent (74)
Females/Present (31)
Males/Absent (52)
Males/Present (17)

Hodder & O'Kell's A	
Value	p=
1.01	0.84

Nearest Neigh - RL	
Value	p=
0.907798	0.10

Proximity Count	
Value	p=
21{3}	0.141
44{5}	0.447
79{7}	0.557
164{10}	0.208
310{15}	0.326

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.29

Asterionic Ossicle

Legend

Female/Absent (87)
Female/Present (17)
Male/Absent (57)
Male/Present (11)

Hodder & O'Kell's A	
Value	p=
0.95	0.05

Nearest Neigh - RL	
Value	p=
1.07	0.23

Proximity Count	
Value	p=
4{3}	0.793
14{5}	0.545
30{7}	0.259
49{10}	0.612
96{15}	0.650

0 2.5 5 10 15 20 Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.30

Legend
Female/Absent (101)
Male/Absent (68)
Male/Present (1)

Bregmatic
Ossicle

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.31

Coronal Ossicle

Legend
Female/Absent (98)
Female/Present (2)
Male/Absent (66)
Male/Present (2)

Hodder & O'Kell's A	
Value	p=
0.96	0.32

Nearest Neigh - RL	
Value	p=
0.677698	0.15

Proximity Count	
Value	p=
0(3)	1.000
1(5)	0.207
1(7)	0.356
1(10)	0.591
1(15)	0.893

0 2.5 5 10 15 20 Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.32

Lambdic Ossicle

Legend

Female/Absent (98)
Female/Present (5)
Male/Absent (55)
Male/Present (13)

Hodder & O'Kell's A	
Value	p=
0.99	0.31

Nearest Neigh - RL	
Value	p=
1.0455	0.37

Proximity Count	
Value	p=
3{3}	0.416
6{5}	0.609
13{7}	0.378
22{10}	0.576
42{15}	0.682

0 2.5 5   10   15   20   Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.33

Lambdoidal
Ossicle

Legend

Female/Absent (51)
Female/Present (52)
Male/Absent (38)
Male/Present (31)

Hodder & O'Kell's A	
Value	p=
1.01	0.75

Nearest Neigh - RL	
Value	p=
1.06839	0.10

Proximity Count	
Value	p=
39(3)	0.977
116(5)	0.948
242(7)	0.550
468(10)	0.541
954(15)	0.282

0 2.5 5   10   15   20 Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.34

Occipito-mastoid
Ossicle

Legend

Female/Absent (96)
Female/Present (8)
Male/Absent (61)
Male/Present (7)

Hodder & O'Kell's A	
Value	p=
1.01	0.49

Nearest Neigh - RL	
Value	p=
1.046163	0.39

Proximity Count	
Value	p=
1{3}	0.792
4{5}	0.546
8{7}	0.441
15{10}	0.441
27{15}	0.573

0   2.5   5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.35

Parietal Notch
Ossicle

Legend

Female/Absent (87)
Female/Present (17)
Male/Absent (63)
Male/Present (5)

Hodder & O'Kell's A	
Value	p=
1.03	0.88

Nearest Neigh - RL	
Value	p=
0.877072	0.16

Proximity Count	
Value	p=
4{3}	0.410
8{5}	0.621
15{7}	0.641
27{10}	0.808
55{15}	0.793

0   2.5   5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.36

Pterionic Ossicle

Legend

Female/Absent (77)
Female/Present (27)
Male/Absent (62)
Male/Present (7)

Hodder & O'Kell's A	
Value	p=
1.00	0.40

Nearest Neigh - RL	
Value	p=
0.922732	0.20

Proximity Count	
Value	p=
8(3)	0.558
17(5)	0.863
32(7)	0.930
72(10)	0.689
149(15)	0.515

0   2.5   5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.37

Sagittal
Ossicle

Legend
Female/Absent (94)
Female/Present (7)
Male/Absent (62)
Male/Present (3)

Hodder & O'Kell's A	
Value	p=
0.92	0.11

Nearest Neigh - RL	
Value	p=
0.834166	0.19

Proximity Count	
Value	p=
0{3}	1.000
4{5}	0.095
7{7}	0.041
11{10}	0.048
16{15}	0.157

0 2.5 5   10   15   20
Meters

Kellis 2 Cemetery
Dakhleh Oasis
Western Desert, Egypt
DOP Excavation Through 2007

Figure B.38

Squamosal
Ossicle

Legend

- Female/Absent (96)
- Female/Present (8)
- Male/Absent (67)
- Male/Present (1)

Hodder & O'Kell's A	
Value	p=
1.02	0.52

Nearest Neigh - RL	
Value	p=
1.246365	0.12

Proximity Count	
Value	p=
0(3)	1.000
1(5)	0.776
1(7)	0.949
4(10)	0.720
7(15)	0.868

0 2.5 5   10   15   20
Meters

Appendix C: R Routines

This appendix provides a listing of the R routines used in this study. There are two sections, one for the main routines and a second for the reusable functions.

One of the concerns about the use of R is that unlike conventional statistical packages such as SPSS, it leaves the opportunity for making a programming error which could result in errant results. A number of steps, based on many years in the information technology business were taken to ensure the accuracy of the results.

First some of the routines developed can be cross checked against other statistical packages. For example the A-Statistic, Nearest Neighbour and Between Types Nearest Neighbour are all available in TFQA although of these only TFQA's A-Statistic uses random labeling. Thus the R based A-statistic is accurate as are the calculation of the basic measure in both of the Nearest Neighbour statistics.

Second, it was easy to verify the Proximity Count statistic by accessing the GIS and by using the measure function to actually count the number of graves within the given radius. This ensures the accuracy of the Proximity Count value.

Third, by making extensive use of reusable functions in R, once the calculation has been verified, it can be assumed to be accurate in all subsequent uses. For example there is one function used which calculates the distance between two points using the Pythagorean theorem. Similarly the function used to test random labeling in the A-statistic can then be used with a good presumption of accuracy in all other R routines.

Base R Routines

Hodder and Okells A Statistic

```
######## Hodder and Okells A ###########################
#
# Note the input file must have 3 columns labeled x,y,and type all lower case
#
#  Set variables ###############
infilename <- "SPBF.txt"
typeA <- 9
typeB <- 0
randNum = 99
#
####################################

# Read the Input File
infile <- read.delim(infilename, header=TRUE, sep="\t", dec=".")
n <- length(infile$type[infile$type == typeA])
x <- numeric(n)
y <- numeric(n)
j <- 1
for (i in 1:length(infile$x))
{
        if (infile$type[i]==typeA)
        {
                x[j] <- infile$x[i]
                y[j] <- infile$y[i]
                j <- j+1
        }
}
type1 <- data.frame(x,y)

m <- length(infile$type[infile$type == typeB])
x <- numeric(m)
y <- numeric(m)
j <- 1
for (i in 1:length(infile$x))
{
        if (infile$type[i]==typeB)
        {
                x[j] <- infile$x[i]
                y[j] <- infile$y[i]
                j <- j+1
        }
```

```
}
type2 <- data.frame(x,y)


##########################################################
# Calculate Hodder and Okells A of actual type 1 vs actual type2
aStat <- hoddersA(type1,type2)
xtitle <- "Hodders A "
xtitle
aStat
###################################################################

# Set up to run Monte Carlo on the at risk points.
resultsList <- numeric(randNum)
set.seed(14541)
for (j in 1:randNum)  {
        myList <- randABSplit(infile,n)
        s1 <- myList$a
        s2 <- myList$b
        resultsList[j] <- hoddersA(s1,s2)
}
#####################################################################
probLessThan <- pValueLessThan(resultsList, aStat)
probLessThan
#
#
####End
```

Proximity Count

```
### Script Start###########################
#
#  Note that the input file must have 3 columns labeled "x, y, and type"  (lower case)
#
################Set critical variables ###############################
#Set the Radius Parameter
mDist <- c(10,15, 20, 25, 30)
#
# set the type to be counted
intype <- 5
#
# Set the input file name
infilename <- "PPOPFR.txt"
#
# set number of randomizations
randNum <- 999
```

```
############################################################################
# Read and extract the type to be counted from the overall file
#
infile <- read.delim(infilename, header=TRUE, sep="\t", dec=".")
#
prob <- numeric(length(mDist))
actCount <- numeric(length(mDist))
for (p in 1:length(mDist))
{
#############################Regular oop####################
n <- length(infile$type[infile$type == intype])
x <- numeric(n)
y <- numeric(n)
j <- 1
for (i in 1:length(infile$x))
{
        if (infile$type[i]==intype)
        {
                x[j] <- infile$x[i]
                y[j] <- infile$y[i]
                j <- j+1
        }
}
actuals <- data.frame(x,y)
############################################################################
# Calculate the actual count of points withing the specified distance
#
actCount[p] <- proxCount(actuals,mDist[p])
######################################################################
# Set up to run Monte Carlo on the at risk points
#
resultsList <- numeric(randNum)
    set.seed(14541)

for (j in 1:randNum)  {
        samplePoints <- randSampleXY(infile,n)
        resultsList[j] <- proxCount(samplePoints,mDist[p])
}
#######################################################################
prob[p] <- pValueGreaterThan(resultsList, actCount[p])
}
results <- data.frame(actCount,mDist,prob)
infilename
results
#
#
```

####End

Cross Proximity Count by Sex

```
### Script Start############################
# Cross Proximity Probability Script.
################################################
# This script is designed to allow the comparison of the presence or absence
#of a discrete genetic trait to be compared by sex. By counting the number of pairs of graves
# with traits present within a User defined radius.
# 1. Counts the number of pairs looking only at male data
# 2. Counts the number of pairs of male/female trait presence starting wih the males
# 3. Counts the number pf pairs looking at females only
# 4. Counts the number of oairs of female/male trait presence starting with the females.
#      Note the count for 2 and 4 will be identical but the probabilities can be different.
#
#Note that the input file must have 4 columns labeled "x, y, sex and type"  (lower case)
#
#     sex Must be 'M' or 'F'
#     type has two values absence '1' and presence '9' .
#
#  Note that all of these are case sensitive
##########################################################################
#
################Set key variables #################################
#Set the Radius Parameter
mDist <- 7
#
# set the type to be counted Mostly 9
traitPresent <- 9
#
# Set the input file name
infilename <- "metaT.txt"
#
# set number of randomizations
randNum <- 999
#########################################################################

Table <- numeric(4)
Table[1] <- "Male to male"
Table[2] <- "Male to Female"
Table[3] <- "Female to Female"
Table[4] <- "Female to Male"
Dist <- numeric(4)
```

```
Dist[1] <- mDist
Dist[2] <- mDist
Dist[3] <- mDist
Dist[4] <- mDist
Count <- numeric(4)
Prob    <- numeric(4)

# Read and extract the type to be counted from the overall file
#
infile <- read.delim(infilename, header=TRUE, sep="\t", dec=".")
#   head(infile)
##########Split the file into two dataframes based on sex#######
#
#############select all males#########################################
n <- length(infile$sex[infile$sex == "M"])
x <- numeric(n)
y <- numeric(n)
trait <- numeric(n)
j <- 1
for (i in 1:length(infile$x))
{
        if (infile$sex[i]=="M")
        {
                x[j] <- infile$x[i]
                y[j] <- infile$y[i]
                trait[j] <- infile$type[i]
                j <- j+1
        }
}
allMales <- data.frame(x,y,trait)

#########select all males with thetrait#######
n <- length(allMales$trait[allMales$trait == traitPresent])
x <- numeric(n)
y <- numeric(n)
lenMalesWith <- n
j <- 1
for (i in 1:length(allMales$x))
{
        if (allMales$trait[i]==traitPresent)
        {
                x[j] <- allMales$x[i]
                y[j] <- allMales$y[i]
                j <- j+1
        }
}
```

```
malesWith <- data.frame(x,y)
lengthMalesWith <- n

############select all females
n <- length(infile$sex[infile$sex == "F"])
x <- numeric(n)
y <- numeric(n)
trait <- numeric(n)
j <- 1
for (i in 1:length(infile$x))
{
        if (infile$sex[i]=="F")
        {
                x[j] <- infile$x[i]
                y[j] <- infile$y[i]
                trait[j] <- infile$type[i]
                j <- j+1
        }
}
allFemales <- data.frame(x,y,trait)

####################################################
##########select all females with the trait #######
n <- length(allFemales$trait[allFemales$trait == traitPresent])
lenVaried <- n
x <- numeric(n)
y <- numeric(n)
j <- 1
for (i in 1:length(allFemales$x))
{
        if (allFemales$trait[i]==traitPresent)
        {
                x[j] <- allFemales$x[i]
                y[j] <- allFemales$y[i]
                j <- j+1
        }
}
femalesWith <- data.frame(x,y)
lengthFemalesWith <-n

#############################################################################
# Calculate the actual count of points withing the specified distance
#

Count[1] <- proxCount(malesWith,mDist)
Count[2] <- crossProxCount(malesWith,femalesWith,mDist)
```

```
Count[3] <- proxCount(femalesWith,mDist)
Count[4] <- crossProxCount(femalesWith,malesWith,mDist)


####################################################################
# Set up to run Monte Carlo on the at risk points.
####################################################################
 set.seed(14541)
###############Male to Male ####################################
resultsList <- numeric(randNum)
for (j in 1:randNum)  {
        samplePoints <- randSampleXY(allMales,lengthMalesWith)
        resultsList[j] <- proxCount(samplePoints,mDist)
}
Prob[1] <- pValueGreaterThan(resultsList, Count[1])
#################Male to Female
####################################################
resultsList <- numeric(randNum)

for (j in 1:randNum)  {
        samplePoints <- randSampleXY(allFemales,lengthFemalesWith)
        resultsList[j] <- crossProxCount(malesWith,samplePoints,mDist)
}
Prob[2] <- pValueGreaterThan(resultsList, Count[2])
################Female to
Female########################################################
resultsList <- numeric(randNum)
for (j in 1:randNum)  {
        samplePoints <- randSampleXY(allFemales,lengthFemalesWith)
        resultsList[j] <- proxCount(samplePoints,mDist)
}
Prob[3] <- pValueGreaterThan(resultsList, Count[3])
###############Female to
Male########################################################
resultsList <- numeric(randNum)

for (j in 1:randNum)  {
        samplePoints <- randSampleXY(allMales,lengthMalesWith)
        resultsList[j] <- crossProxCount(femalesWith,samplePoints,mDist)
}
Prob[4] <- pValueGreaterThan(resultsList, Count[4])


#############################################################################
results <- data.frame(Table,Dist,Count,Prob)
"Cross Proximity Probability Analysis"
"randomizations"
randNum
```

results
#
###END

Nearest Neighbour – Random Label Script

```
#############################################################################
# Nearest Neighbour Random Label Script
#################################################
# This script calculates the average nearest neighbour for two given types.
#
#Note that the input file must have 3 columns labeled "x, y, and type"  (lower case)
#
#    type should have two values ;0' and presence '9'
#    Note this implementation has not been generalized to allow multiple types ie 0,1 and
9)
#
#  Note that all of these are case sensitive
#############################################################################
#
################Set key variables #################################
# set the type to be counted Mostly 9
traitPresent <- 9
#
# Set the input file name
infilename <- "Sq.txt"
#
# set number of randomizations
randNum <- 999
#############################################################################

# Read and extract the type to be counted from the overall file
#
infile <- read.delim(infilename, header=TRUE, sep="\t", dec=".")
#   head(infile)
#
#############select all males#########################################
n <- length(infile$type[infile$type == 9])
x <- numeric(n)
y <- numeric(n)
j <- 1
for (i in 1:length(infile$x))
{
        if (infile$type[i]==9)
        {
                x[j] <- infile$x[i]
```

```
                    y[j] <- infile$y[i]
                    j <- j+1
            }
    }
traitn <- data.frame(x,y)


#####################################################################
#################
Title <- "Trait Value"
ActualAvgNN <- avgNNDist(traitn, traitn)


##################################################################
# Set up to run Monte Carlo on the at risk points.
##################################################################
 set.seed(14541)
###############Male to Male ###################################
resultsList <- numeric(randNum)
for (j in 1:randNum)  {
        randList <- randSampleXY(infile,n)
        resultsList[j] <- avgNNDist(randList,randList)
}
RandomAvgNN <- mean(resultsList)
prob <- pValueLessThan(resultsList, ActualAvgNN)
nnratio <- ActualAvgNN / RandomAvgNN
#



#####################################################################
###########
results <- data.frame(Title,traitPresent, ActualAvgNN,RandomAvgNN,nnratio,prob)
"Nearest Neighbour - Random Labeling"
"randomizations"
randNum
results
#
####End###
```

Cross Nearest Neighbour Script

```
#####################################################################
# Cross Nearest Neighbour Script
###############################################
# This script calculates the average nearest neighbour for two given types.
#
#Note that the input file must have 3 columns labeled "x, y, and type"  (lower case)
#
```

```
#    type should have two values ;0' and presence '9'
#    Note this implementation has not been generalized to allow multiple types ie 0,1 and
9)
#
#  Note that all of these are case sensitive
############################################################################
#
################Set key variables ##################################
# set the type to be counted Mostly 9
traitPresent <- 9
#
# Set the input file name
infilename <- "MFDist.txt"
#
# set number of randomizations
randNum <- 99
############################################################################

# Read and extract the type to be counted from the overall file
#
infile <- read.delim(infilename, header=TRUE, sep="\t", dec=".")
#   head(infile)
#
############select all males#######################################
n <- length(infile$sex[infile$type == 9])
x <- numeric(n)
y <- numeric(n)
j <- 1
for (i in 1:length(infile$x))
{
        if (infile$type[i]==9)
        {
                x[j] <- infile$x[i]
                y[j] <- infile$y[i]
                j <- j+1
        }
}
allMales <- data.frame(x,y)
numMales <- length(allMales$x)

###########select all females
n <- length(infile$sex[infile$type == 0])
x <- numeric(n)
y <- numeric(n)
j <- 1
for (i in 1:length(infile$x))
```

```
{
        if (infile$type[i]==0)
        {
                x[j] <- infile$x[i]
                y[j] <- infile$y[i]
                j <- j+1
        }
}
allFemales <- data.frame(x,y)
numFemales <- length(allFemales$x)

###########
Table <- numeric(4)
Table[1] <- "Male to Male"
Table[2] <- "Male to Female"
Table[3] <- "Female to Female"
Table[4] <- "Female to Male"

ActualAvgNN <- numeric(4)
RandomAvgNN <- numeric(4)
prob    <- numeric(4)
nnratio <- numeric(4)

###################################################################
# Set up to run Monte Carlo on the at risk points.
###################################################################
 set.seed(14541)
###############Male to Male ####################################
ActualAvgNN[1] <- avgNNDist(allMales, allMales)
resultsList <- numeric(randNum)
for (j in 1:randNum)  {
        randList <- randSampleXY(infile,numMales)
        resultsList[j] <- avgNNDist(randList,randList)
}
RandomAvgNN[1] <- mean(resultsList)
prob[1] <- pValueLessThan(resultsList, ActualAvgNN[1])
nnratio[1] <- ActualAvgNN[1] / RandomAvgNN[1]
#

#################Male to Female
#####################################################
ActualAvgNN[2] <- avgNNDist(allMales, allFemales)
resultsList <- numeric(randNum)

for (j in 1:randNum)  {
        myList <- randABSplit(infile, numMales)
```

```
        rm <- myList$a
        rf <- myList$b
        resultsList[j] <- avgNNDist(rm, rf)
        }
RandomAvgNN[2] <- mean(resultsList)
prob[2] <- pValueLessThan(resultsList, ActualAvgNN[2])
nnratio[2] <- ActualAvgNN[2] / RandomAvgNN[2]
#
###############Female to
Female####################################################
ActualAvgNN[3] <- avgNNDist(allFemales, allFemales)
resultsList <- numeric(randNum)
for (j in 1:randNum)  {
        randList <- randSampleXY(infile,numFemales)
        resultsList[j] <- avgNNDist(randList,randList)
        }
RandomAvgNN[3] <- mean(resultsList)
prob[3] <- pValueLessThan(resultsList, ActualAvgNN[3])
nnratio[3] <- ActualAvgNN[3] / RandomAvgNN[3]
#
##############Female to
Male######################################################
ActualAvgNN[4] <- avgNNDist(allFemales, allMales)
resultsList <- numeric(randNum)
for (j in 1:randNum)  {
        myList <- randABSplit(infile, numFemales)
        rf <- myList$a
        rm <- myList$b
        resultsList[j] <- avgNNDist(rf, rm)
        }
RandomAvgNN[4] <- mean(resultsList)
prob[4] <- pValueLessThan(resultsList, ActualAvgNN[4])
nnratio[4] <- ActualAvgNN[4] / RandomAvgNN[4]


################################################################################
##########


################################################################################
##########
results <- data.frame(Table,ActualAvgNN,RandomAvgNN,nnratio,prob)
"Cross nearest neighbour Analysis"
"randomizations"
randNum
results
#
```

```
#
####End
```

Cross Nearest Neighbour by Sex

```
################################################################
# Cross Nearest Neighbour Script
#############################################
# This script calculates the average nearest neighbour for all combinations of
#of a discrete genetic trait and sex. By counting the number of pairs of graves
# with traits present within a User defined radius.
#
#Note that the input file must have 4 columns labeled "x, y, sex and type"  (lower case)
#
#     sex Must be 'M' or F'
#     type has two values absence '1' and presence '9'.
#     Note this implementation has not been generalized to allow multiple values (ie 0,1
and 9)
#
#  Note that all of these are case sensitive
################################################################
#
################Set key variables ################################
# set the type to be counted Mostly 9
traitPresent <- 9
#
# Set the input file name
infilename <- "Lo.txt"
#
# set number of randomizations
randNum <- 999
################################################################

# Read and extract the type to be counted from the overall file
#
infile <- read.delim(infilename, header=TRUE, sep="\t", dec=".")
#   head(infile)
#########Split the file into two dataframes based on sex#######
#
###########select all males#######################################
n <- length(infile$sex[infile$sex == "M"])
x <- numeric(n)
y <- numeric(n)
trait <- numeric(n)
j <- 1
for (i in 1:length(infile$x))
```

```
{
        if (infile$sex[i]=="M")
        {
                x[j] <- infile$x[i]
                y[j] <- infile$y[i]
                trait[j] <- infile$type[i]
                j <- j+1
        }
}
allMales <- data.frame(x,y,trait)


##########select all males with thetrait#######
n <- length(allMales$trait[allMales$trait == traitPresent])
x <- numeric(n)
y <- numeric(n)
lenMalesWith <- n
j <- 1
for (i in 1:length(allMales$x))
{
        if (allMales$trait[i]==traitPresent)
        {
                x[j] <- allMales$x[i]
                y[j] <- allMales$y[i]
                j <- j+1
        }
}
malesWith <- data.frame(x,y)
lengthMalesWith <- n


############select all females
n <- length(infile$sex[infile$sex == "F"])
x <- numeric(n)
y <- numeric(n)
trait <- numeric(n)
j <- 1
for (i in 1:length(infile$x))
{
        if (infile$sex[i]=="F")
        {
                x[j] <- infile$x[i]
                y[j] <- infile$y[i]
                trait[j] <- infile$type[i]
                j <- j+1
        }
}
allFemales <- data.frame(x,y,trait)
```

```
#######################################################
#########select all females with the trait #######
n <- length(allFemales$trait[allFemales$trait == traitPresent])
lenVaried <- n
x <- numeric(n)
y <- numeric(n)
j <- 1
for (i in 1:length(allFemales$x))
{
        if (allFemales$trait[i]==traitPresent)
        {
                x[j] <- allFemales$x[i]
                y[j] <- allFemales$y[i]
                j <- j+1
        }
}
femalesWith <- data.frame(x,y)
lengthFemalesWith <-n
################################################################################
#################
Table <- numeric(4)
Table[1] <- "Male to male"
Table[2] <- "Male to Female"
Table[3] <- "Female to Female"
Table[4] <- "Female to Male"

ActualAvgNN <- numeric(4)
RandomAvgNN <- numeric(4)
prob    <- numeric(4)
nnratio <- numeric(4)


####################################################################
# Set up to run Monte Carlo on the at risk points.
####################################################################
 set.seed(14541)
###############Male to Male ###################################
ActualAvgNN[1] <- avgNNDist(malesWith, malesWith)
resultsList <- numeric(randNum)
for (j in 1:randNum)  {
        randList <- randSampleXY(allMales,lengthMalesWith)
        resultsList[j] <- avgNNDist(randList,randList)
}
RandomAvgNN[1] <- mean(resultsList)
prob[1] <- pValueLessThan(resultsList, ActualAvgNN[1])
nnratio[1] <- ActualAvgNN[1] / RandomAvgNN[1]
```

```
#
#################Male to Female
#########################################################
ActualAvgNN[2] <- avgNNDist(malesWith, femalesWith)
resultsList <- numeric(randNum)
for (j in 1:randNum)  {
        variableFrom <- randSampleXY(allMales,lengthMalesWith)
        variableTo <- randSampleXY(allFemales,lengthFemalesWith)
        resultsList[j] <- avgNNDist(variableFrom, variableTo)
}
RandomAvgNN[2] <- mean(resultsList)
prob[2] <- pValueLessThan(resultsList, ActualAvgNN[2])
nnratio[2] <- ActualAvgNN[2] / RandomAvgNN[2]
#
################Female to
Female###############################################
ActualAvgNN[3] <- avgNNDist(femalesWith, femalesWith)
resultsList <- numeric(randNum)
for (j in 1:randNum)  {
        randList <- randSampleXY(allFemales,lengthFemalesWith)
        resultsList[j] <- avgNNDist(randList,randList)
}
RandomAvgNN[3] <- mean(resultsList)
prob[3] <- pValueLessThan(resultsList, ActualAvgNN[3])
nnratio[3] <- ActualAvgNN[3] / RandomAvgNN[3]
#
###############Female to
Male##########################################################
ActualAvgNN[4] <- avgNNDist(femalesWith, malesWith)
resultsList <- numeric(randNum)
for (j in 1:randNum)  {
        variableFrom <- randSampleXY(allFemales,lengthFemalesWith)
        variableTo <- randSampleXY(allMales,lengthMalesWith)
        resultsList[j] <- avgNNDist(variableFrom, variableTo)
}
RandomAvgNN[4] <- mean(resultsList)
prob[4] <- pValueLessThan(resultsList, ActualAvgNN[4])
nnratio[4] <- ActualAvgNN[4] / RandomAvgNN[4]

###################################################################################
###########
results <- data.frame(Table,ActualAvgNN,RandomAvgNN,nnratio,prob)
"Cross nearest neighbour Analysis"
"randomizations"
randNum
results
```

```
#
#####End###
```

R Functions Used
All functions here are combined into a single script.

```
########################################################################
#
#    Spatial Analysis Routines for Archaeology in R
#              SARA-R
#
#    V 0.1   Feb 17, 2014   (best considered an alpha version)
#
#    Created by Jim Keron, Western University  jkeron@uwo.ca
#
#    This script is a series of R functions which must be executed before using any of the
routines.
#     They will eventually be built into an R Library but not yet there.
#
########################################################################
#
# This function calculates the distance between two points in Cartesion Space
#   given by (x,y)  (ie two dimensional space
#
########################################################################

abDistance <- function(x1,y1,x2,y2)
{

dist <- sqrt((x1-x2)^2+(y1-y2)^2)
return(dist)
}


########################################################################
#
# This function selects a random set of points of size n from an input data frameisk list
#    without replacement
#    The result is a data frame of points (x,y)  of size n
#    All remaining points not selected are put into a second dataframe
#
########################################################################
randABSplit <- function(indata,n)
{

###############Select sample for Type A
#create index list to randomly select as sample the same size as the actuals file
```

```
indexList <- 1:length(indata$x)
indexSample <- sample(indexList, size=n, replace=FALSE)

# set up x and y list of size from input n
x1 <- numeric(n)
y1 <- numeric(n)

for (i in 1:n) {
        x1[i] <- indata$x[indexSample[i]]
        y1[i] <- indata$y[indexSample[i]]
                }
typeASamp <- data.frame(x1,y1)

#Assemble the left overs###

m <- length(indata$x)- n
x2 <- numeric(m)
y2 <- numeric(m)
o <- m+n

p <- 1

for(i in 1:o)  {
        alreadySelected <- 0

        for (j in 1:n) {
                if (indexSample[j]==i) {
                        alreadySelected <- 1
                        }
                }
        if(alreadySelected==0) {
                x2[p] <- infile$x[i]
                y2[p] <- infile$y[i]
                p <- p+1
                }
        }
typeBSamp <- data.frame(x2,y2)


#  done
return(list("a"=typeASamp,"b"=typeBSamp))
}
#####################################################################
#
# This function calculates the p value from a set of statistics from a
#  in a vector that were calculated from a set of randomizations
```

```
#
#############################################################################

pValueLessThan <- function(resultsList,actualStat)
{
        randomizations <- length(resultsList)
        countR <-0
        for (i in 1:randomizations)
        {
                if(resultsList[i]< actualStat)
                {
                countR <- countR+1
                }
        }
probabilty <- countR/randomizations

return(probabilty)
}
# endfunction
##############################Function#####################################
#########
#
#This counts the number of pairs of points withing the distance specified
#
#Input          listArray is the number of points to be checked
#                       mDist  is the within-which distance
#
#############################################################################
#########

proxCount <- function(listArray,mDist)
{
nPoints <- length(listArray$x)
count <- 0
k <- nPoints-1


for (i in 1:k) {
        l <- i+1
        for (j in l:nPoints)   {
                aDist <-
abDistance(listArray$x[i],listArray$y[i],listArray$x[j],listArray$y[j])
                if (aDist < mDist) {
                        count <- count +1
                }
        }
```

```
}
return(count)
}
#
#############################################################################
#
# This function calculates Hodder and Okells A statistc
#
#############################################################################

hoddersA <- function(a,b)
{
# Calculate RAA###################
n <- length(a$x)
sumd <- 0
k <- n-1
for (i in 1:k)  {
        l <- i+1
        for (j in l:n)     {
                d1 <- abDistance(a$x[i],a$y[i],a$x[j],a$y[j])
                sumd <- sumd + d1
        }
}
raa <- sumd/((n^2-n)/2)
# Calculate RBB###################
n <- length(b$x)
sumd <- 0
k <- n-1
for (i in 1:k)  {
        l <- i+1
        for (j in l:n)     {
                d1 <- abDistance(b$x[i],b$y[i],b$x[j],b$y[j])
                sumd <- sumd + d1
                }
}
rbb <- sumd/((n^2-n)/2)
# Calculate RAB###################
n <- length(a$x)
m <- length(b$x)
sumd <- 0
for (i in 1:n)  {
        for (j in 1:m)   {
                d1 <- abDistance(a$x[i],a$y[i],b$x[j],b$y[j])
                sumd <- sumd + d1
        }
}
```

```
rab <- sumd/(n*m)
# Calculate A-Staistic
a <- (raa*rbb)/rab^2
return(a)
}
#end function
##########################################################################
#
# This function calculates the p value from a set of statistics from a
#   in a vector that were calculated from a set of randomizations
#
##########################################################################

pValueGreaterThan <- function(resultsList,actualStat)
{
        randomizations <- length(resultsList)
        countR <-0
        cv <- unlist(actualStat)
        for (i in 1:randomizations)
        {
                if(resultsList[i]>=cv)
                {
                countR <- countR+1
                }
        }
probabilty <- countR/randomizations

return(probabilty)
}
# endfunction


##########################################################################
#
# This function selects a random set of points of size n from an At-Risk list
#     without replacement
#     The result is a data frame of points (x,y)  of size n
#
##########################################################################
randSampleXY <- function(atRiskList,n)
{


x <- numeric(n)
y <- numeric(n)

indexList <- 1:length(atRiskList$x)
```

#create index list to randomly select as sample the same size as the actuals file

```
indexSample <- sample(indexList, size=n, replace=FALSE)

for (i in 1:n) {
        x[i] <- atRiskList$x[indexSample[i]]
        y[i] <- atRiskList$y[indexSample[i]]
                }
samplePoints <- data.frame(x,y)

return(samplePoints)
}
#################################Function#####################################
#########
#
#This counts the number of events one type within a fixed distance of a second (fixed)
type
#
#Input          The fixed points
                    The varied points
#                   mDist  is the within-which distance
#
##############################################################################
#########

crossProxCount <- function(fixedSex,variedSex,mDist)
{
count <- 0
fixedCount <- length(fixedSex$x)
variedCount <- length(variedSex$x)


for (i in 1:fixedCount) {
        for (j in 1:variedCount)  {
                        aDist <-
abDistance(fixedSex$x[i],fixedSex$y[i],variedSex$x[j],variedSex$y[j])
                        if (aDist < mDist) {
                                count <- count +1
                }
        }
}
return(count)
}
##############################################################################
#
```

```
#
#   Nearest Neighbour calculations
#
############################################################################
#
# Two sets of data are passed, from and to.
#    fromData is the set of point from which the nearest neighbour is calculated.
#    toData is the set of points which can form the nearest neighbour
#    They can be the same et of points for a traditional NN analysis
#    Or they can be different for a Cross NN analysis
#
#    The value returned is the average nearest neighbour between from and to.
############################################################################
#####
avgNNDist <- function(fromData,toData)
{
totDist <- 0
nFrom <- length(fromData$x)
nTo <- length(toData$x)
avg <- 0

for (i in 1:nFrom) {
        nnDist <- 999999999
        for (j in 1:nTo)   {
                        aDist <-
abDistance(fromData$x[i],fromData$y[i],toData$x[j],toData$y[j])
                        if (aDist < nnDist &  aDist>0) {
                                nnDist <- aDist
                        }
                }
                totDist <- totDist + nnDist
        }
avg <- totDist/nFrom
return(avg)
}
#
#### End Function
```

Curriculum Vitae

Name: James R. Keron

**Post-secondary
Education and
Degrees:**

University of Waterloo
Waterloo, Ontario, Canada
1965-1970 B.Math.

The University of Waterloo
Waterloo, Ontario
1972-1986 (part time) B.A.

The University of Western Ontario
London, Ontario, Canada
1996-2003 (part time) M.A.

The University of Western Ontario
London, Ontario, Canada
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**Honours and
Awards:**

Western Graduate Research Scholarship, 2008-2012

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**Related Work
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Teaching Assistant
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2011-2012

Instructor, Statistics for Bioarchaeology
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Publications:

Keron, James R. (1979). The Role of the Amateur Archaeologist. *Kewa* 79-8: 5-7.

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--- (2006). The Harrietsville Site (AfHf-10): An Earthwork Surrounded Neutral Village in Middlesex County. Paper given at the OAS Symposium session in honour of Michael Spence

--- (2009). The Mammoth Kill Place: Landscape and Implications of Clovis Mammoth Hunting. Paper presented at the 42nd Annual Meeting, Canadian Archaeological Association,   Thunder Bay, Ontario, May.

--- (2011). The Davidson Site as a Persistent Place. Paper presented at the 43rd Annual Meeting, Canadian Archaeological Association Halifax Nova Scotia, May.

--- (2012). Archaeology and Spatial Statistics. Paper presented at the 44th Annual Meeting, Canadian Archaeological Association Montreal Quebec, May.

--- (2012). A Spatial Analysis of the Surface Material from the Late Archaic Davidson Site (AhHk-54). Paper presented logy at the 39th Annual Meeting, Ontario Archaeological Society, Windsor, Ontario, November.

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