ABSTRACT

A Study of Medieval Intrasite Find Distribution on the San Giuliano Plateau, Lazio, Italy

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The San Giuliano Archaeological Research Project (SGARP) excavates a site in Lazio, Italy known as San Giuliano, which has an occupation history spanning from the Bronze Age to the medieval period. The project has been active from 2016 to 2019 and aims to understand the long-term transitions and habitation patterns of the societies that occupied the region. The medieval component of the San Giuliano site is a local manifestation of the widespread, but still poorly understood "incastellamento" process (the relocation of large parts of the medieval Italian population into defensible, fortified sites between AD 700 and 1200). This honors thesis presents a GIS analysis of artifact location and attributes within the medieval fortification excavation atop the San Giuliano plateau. By employing ArcGIS to run statistical analyses of artifact distribution patterns and their associated features within the medieval castle zone, analyses reveal artifact densities and patterning related to site use and refuse deposition throughout the fortification. The interrelationship of finds and archaeological features reveal key transitions in the use of space atop the fortified plateau. GIS analysis of the finds ultimately provides an integrated view of the spatial and social dynamics of an Italian castle and contributes to our understanding the wider process of incastellamento.

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A STUDY OF MEDIEVAL INTRASITE FIND DISTRIBUTION ON THE SAN GIULIANO PLATEAU, LAZIO, ITALY

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CHAPTER ONE

Introduction

The San Giuliano Archaeological Research Project (SGARP) is an ongoing archaeological investigation of the San Giuliano Plateau and its surrounding landscape. The San Giuliano region is a diachronic landscape that shows evidence of occupation from the Bronze Age to the medieval period. The project has been active for four field seasons, from 2016 to 2019, and has collected data from a medieval fortification atop La Rocca, the central San Giuliano Plateau, as well as several Etruscan tombs. The primary goal of the project is to understand the long-term changes in occupation across the landscape, spanning the site's earliest Bronze Age evidence to the period of medieval abandonment.

The medieval period at San Giuliano has in the past lacked any in-depth or well-documented excavations to inform the purpose or identity of the region, with the Etruscan period historically being a priority for archaeological investigation. In addition, the San Giuliano fortification and surrounding medieval features lack any conclusive documentary or historical evidence to shed light on useful dates or events at the site during the Middle Ages. Key questions concerning purpose for site occupation and motivation for site abandonment drive the excavation of La Rocca. The occupation appears to be a facet of the *incastellamento* process, a mass population movement from dispersed rural farms to concentrated, defensible fortified sites. The reasons for the site's abandonment, however, are unclear. The nearby town of Barbarano Romano, situated on an adjacent plateau, also originated in the Middle Ages, raising questions of why and how Barbarano continues to thrive and endure, while San Giuliano fell into disuse.

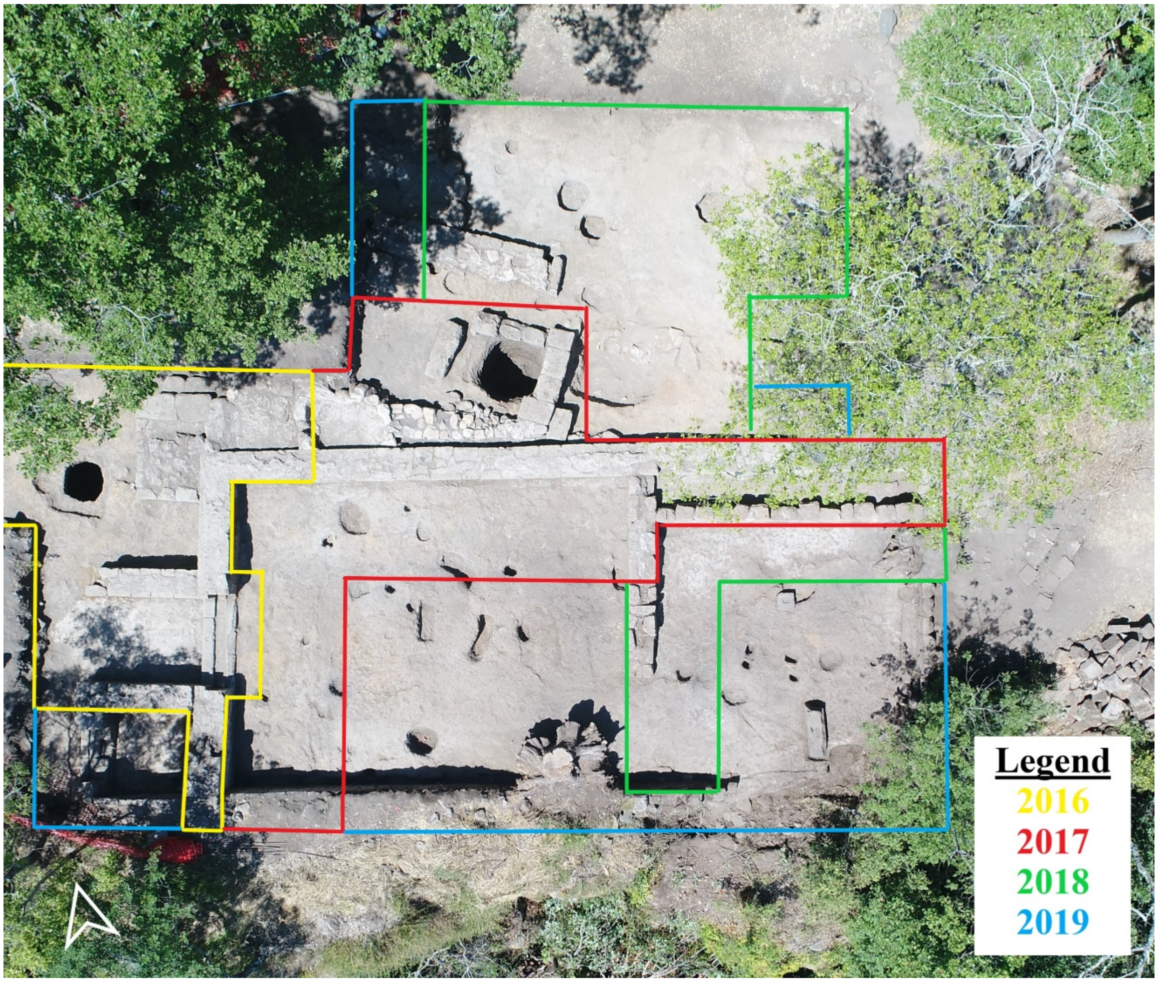


Figure 4: San Giuliano Plateau, Trench 1 Yearly Expansions from: SGARP Drone Photos, Emily Varley 2019

The medieval portion of San Giuliano was opened in 2016, after identifying the rubble of a medieval tower and investigating its surrounding context had been accomplished in a preliminary site exploration in 2015. The 2016 field season reached bedrock and unearthed several sturdy architectural wall bases, a tower base, pits, and a defensible threshold (as evidenced by the multiple closure mechanisms carved into the threshold stones). The 2017 season exposed a narrow eastern transect of the main structure's interior and reached the bottom of the previously discovered granary. The 2018 season focused on the northern exterior of the site and identifying a large number of waste pits and ambiguous architectural phases of building and rebuilding. Lastly, the 2019 field season expanded the remaining extent of the main structure's interior, a northern transect to identify the extent of C144, and the interior of a western guard room. Figure 1 illustrates the various yearly expansions, with the 2016 season outlined in yellow, the 2017 season outlined in red, the 2018 season outlined in green and the 2019 season outlined in blue. Various features are unfortunately hidden by shadows or tree cover but the comprehensive image is accurately outlined. For a labeled illustration of all architectural contexts and pits, Figure 2 is a digitized format of Trench 1.

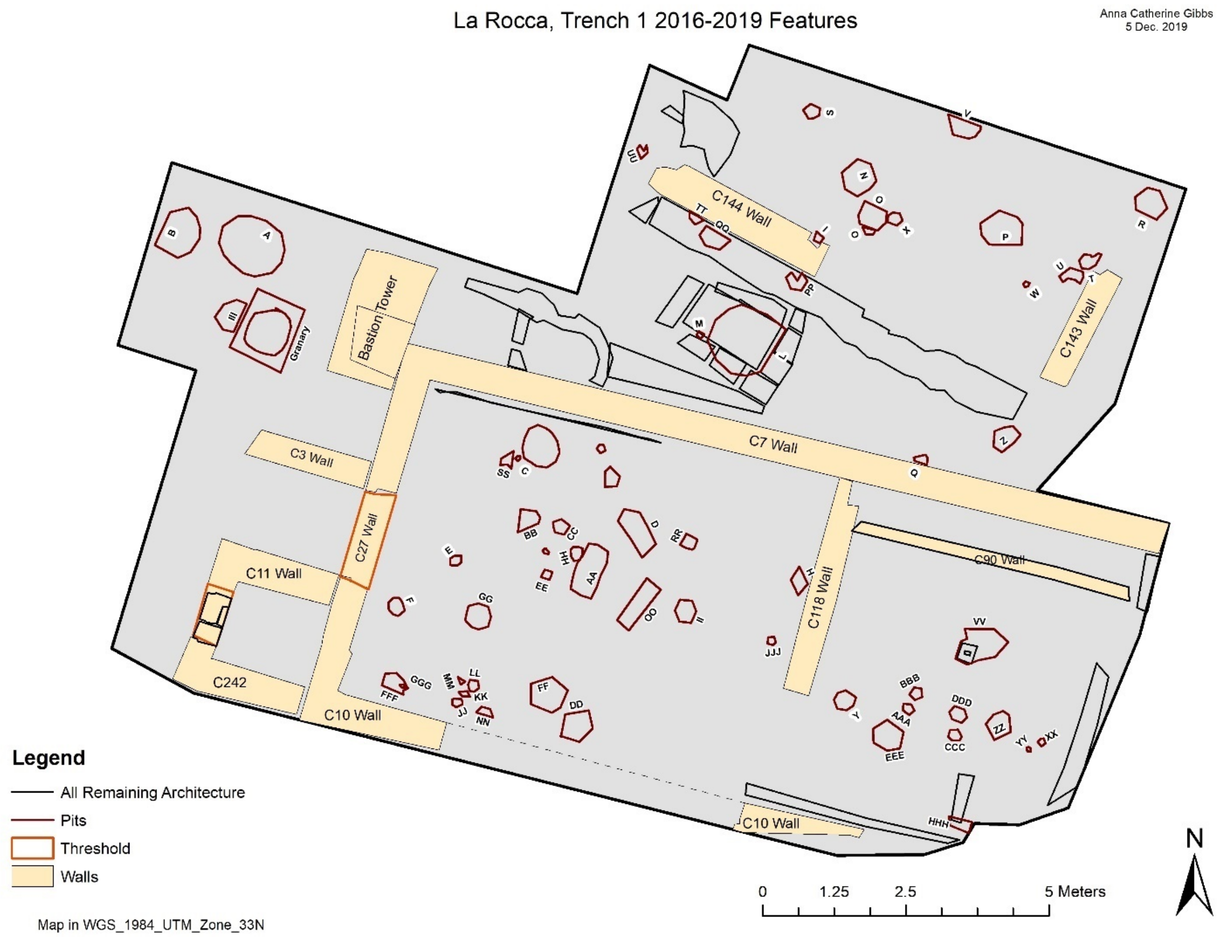


Figure 5: Comprehensive Basic Features of Trench 1 on the San Giuliano Plateau as Digitized in ArcGIS

The goal of this thesis is to utilize new technological insights to better quantify and analyze both the architectural layout and the artifact distribution within a closed site. By utilizing Total Station data and implementing statistical analyzes in the program ArcGIS (Geographic Information Systems), data outputs will indicate a statistically significant clustering of artifacts within the fortification's interior structures and will group the rarer, most diagnostic finds together in statistically significant groupings. The application of these ArcGIS programs is relatively new to intra-site analyzes, making this thesis also an investigation of the efficacy of these specific tools on a high-density, high-point variability dataset in a small geographic area. By applying these statistical analysis programs to the artifact dataset for the San Giuliano fortification, investigation of the fortress's spatial usage and cultural role may be better interpreted through the lens of artifact type, artifact density, and artifact clustering.

Chapter Two of this study establishes the historical context of medieval San Giuliano. Following the collapse of Rome, Italy entered into the Middle Ages, a period of intense political fragmentation and social change. The central location of San Giuliano features an area of frequent boundary shifts and regional uncertainty, requiring a comprehensive analysis of the Middle Ages and the various possibilities for fortification function and date. The San Giuliano fortification includes a wide variety of attributes that could potentially date the site anywhere from AD 500 to 1200, and Chapter Two includes an archaeological and historical analysis of the various options.

Chapter Three addresses the ArcGIS methods and archaeological theory applied to the San Giuliano data. This chapter unpacks the processes of data organization and standardization, Cluster Analyses, Kernel Density Analysis, and the Kolmogorov-Smirnov Test. This chapter also addresses certain processual biases inherent in utilizing ArcGIS, as accepting statistical outputs requires the exclusion of certain higher-order archaeological variables. In order to supplement the processual biases in interpreting the data outputs, this chapter also addresses the archaeological theory of Behavioral Archaeology, which provides a framework for managing intuitive hypotheses about the data, and methodologically interpreting in an effective way.

Chapter Four provides the concrete data from the four years of excavation at San Giuliano and explains the steps of data collection and analysis through ArcGIS. This chapter analyzes and discusses several maps produced through the Grouping Analysis tool in ArcGIS, the field find density maps produced with the Kernel Density Analysis, and the distribution curve graphs from the Kolmogorov-Smirnov Test. This chapter also presents the interpretation of the results, indicating that the field finds on the San Giuliano plateau are 1) statistically significantly clustered according to type, and 2) distributed more densely within interior structures, indicating high-traffic areas. Lastly, these interpretations are put into potential historical contexts, interpreting how the artifact data interacts with the spatial boundaries of the site, and how these correlates may indicate specific historical and social practices.

CHAPTER TWO

Medieval Historical Context for the San Giuliano Plateau

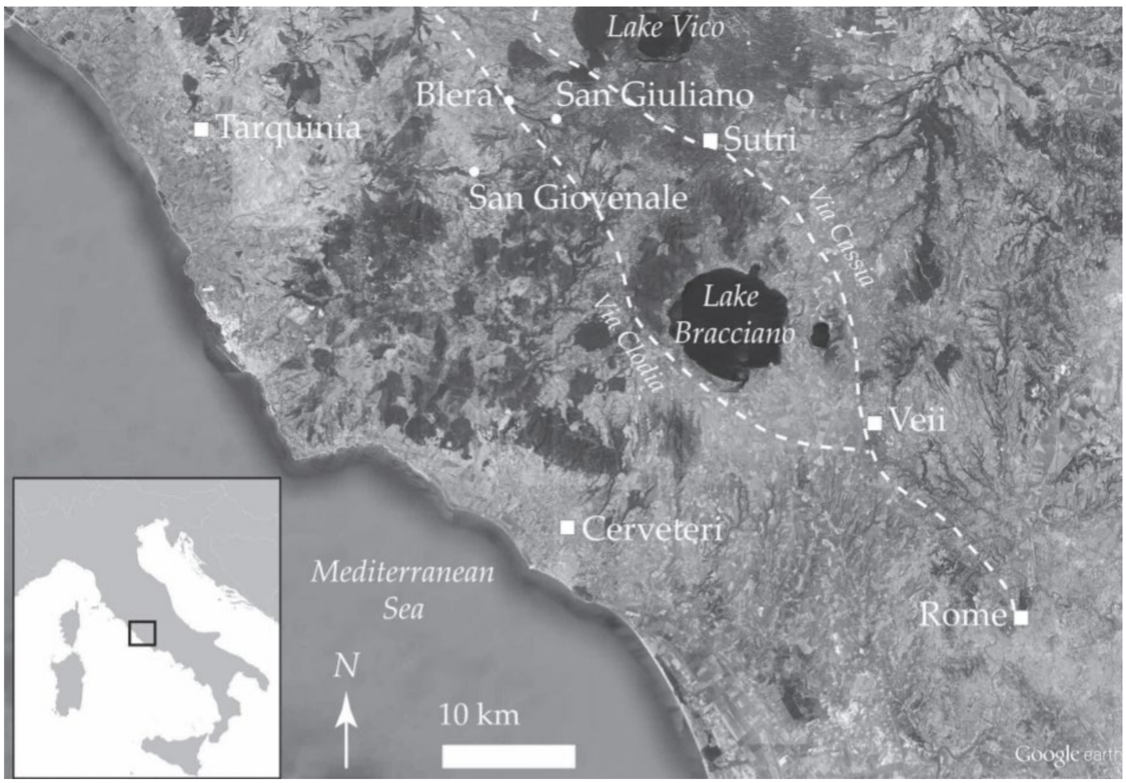


Figure 6, Map of Western Central Italy from: Davide Zori,*et. al*. 2017. San Giuliano Archaeological Research Project: Investigating Long-term Change from Etruscan Urban Center to High Medieval Fortified Village in Lazio. *Temporis Signa: Archeologia della Tarda Antichità e del Medioevo* 11 (2016). Pp. 1

The medieval remains atop San Giuliano Plateau have a hypothesized occupation date between the 7th and 11th centuries. The San Giuliano Plateau, while clearly being a significant locale based on the quantity of archaeological evidence, has extremely limited and debated documentary evidence, making the process of dating and classifying the fortification difficult. San Giuliano fortification sits the region of Lazio, Italy, a heavily disputed, dynamic region, approximately an hour north of Rome. The site was therefore subjected to several borders and political regimes throughout the Middle Ages. Throughout the Middle Ages the area of Lazio northeast of Rome was influenced by the Byzantines, the Ostrogoths, the Lombards to a lesser degree, the Franks and the Papacy.

Throughout the four years of active excavation at San Giuliano, the leading archaeologists have established three potential historical models for the San Giuliano fortification that can be considered By comparing the archaeological evidence, the hypothesized dates, and the history of the region of San Giuliano: 1) Lombard or Byzantine border fort, 2) feudal castle, or 3) fortified village. These three models parallel the shifting political influences of the Middle Ages at San Giuliano and are not mutually exclusive, providing the option that the fortification was utilized differently during different cultural scenes (Zori, D. *et. al*. 2016: 9). The changing socio-cultural and political scene at San Giuliano throughout the Middle Ages provides the opportunity for dynamic change, and the available dates at the site offer insight into all of these options.

2.1 Model One: Lombard or Byzantine Fort

While there is little evidence of Roman occupation at San Giuliano, limited to a reutilized Roman *spolia* column in the nearby medieval San Giuliano church, Roman basalt *basoli* or Roman road stones, and Hellenistic roof tiles, the fall of Rome in AD 476 undoubtably affected San Giuliano, sending cultural ripples of change not just through this medieval site, but the whole Italic peninsula. In an effort to remove the Ostrogothic pressures from nearby Constantinople and the Byzantine Empire, emperor Zeno bid the Ostrogoths go to Rome and overthrow Odoacer to return Byzantine rule in Italy. The Ostrogothic king, Theodoric ruled from AD 493 to 526 and established Ostrogoth reign throughout the central and northern portions of the Italic peninsula. Theodoric's title as ruler, however, was not King of Italy, but "patricius" or "provincial governor for the eastern emperor," which reiterates his position as a delegate for Byzantine rule and his lack of instating an Ostrogothic regime (Backman 2003: 94). In 526, however, Theodoric died after a brief resistance to Byzantine rule and in 568 the Ostrogoths were overwhelmed by the Lombards from the north and the Byzantines from the south, splitting Italy into a Lombard-Byzantine dichotomous landscape (Backman 2003: 59).

With limited documentary evidence and a location in central Italy, the San Giuliano area may have seen quick transitions from Ostrogothic to Byzantine to Lombard, any of whose cultural influences may have produced portions of the archaeological evidence at the site. This Lombard-Byzantine scene endured until AD 774 with the conquest of the Franks.

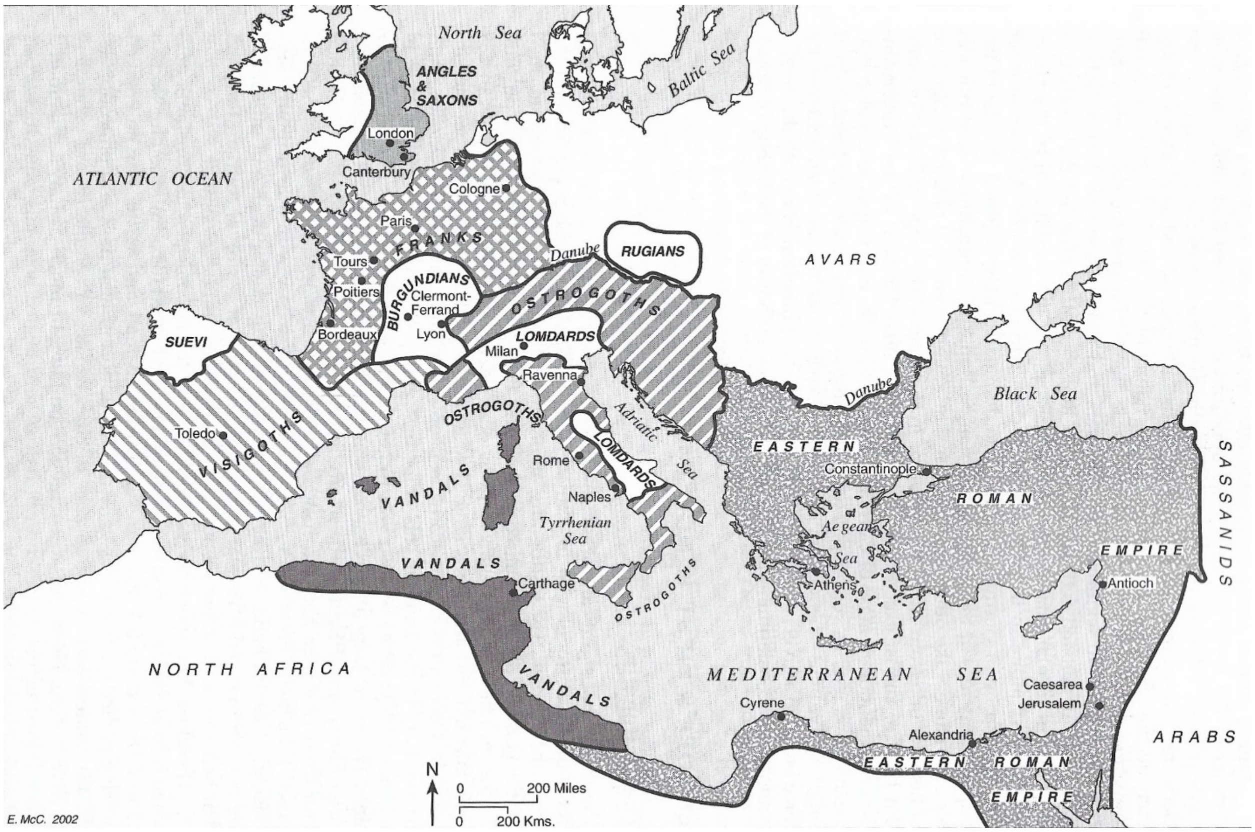


Figure 7, Germanic Kingdoms of Europe, AD 493 from: Backman, Clifford R. *The Worlds of Medieval Europe*. Oxford Univ. Press, 2003. Pp. 58.

2.1.1 An Architectural Examination

The Lombard-Byzantine dichotomy is a difficult one to bisect as the political turn overs resulted in various pockets of individualized culture. While there were cultural differences at this time, the most notable feature of the Italic peninsula's landscape was the general independent identities that developed, allowing for cultural diffusion to shape regions in indeterminate ways. Both the Lombard and Byzantine cultural divides from 568 to 774 are poorly articulated in both the archaeological record and the documentary record. The Byzantine culture endured in Italy through the Ostrogothic period, in its pseudo-Byzantine rulership and eventual reclaiming of parts of southern Italy, while the Lombard invasion was disorganized and unable to establish a unified identity throughout their new land (Wickham 1989: 70). These indeterminate borders and cultures resulted in "regional distinctions that were not directly related to the Lombards" with "every zone of Italy [developing] its own customs and peculiarities" (Wickham 1989: 70). Therefore, identifying exact archaeological evidence for a Lombard-Byzantine border fort can prove a challenge, but several notable characteristics from the San Giuliano Plateau contribute to a plausible model.

The San Giuliano fortification itself is situated atop a central plateau coined 'La Rocca' in a heavily forested area of smaller clustered plateaus. In comparison to other known Lombard fortifications from this period certain slightly circumstantial but still characteristic attributes can be paralleled. Lombard fortifications are known to be "generally based on hilltops of relatively modest height, but with good natural defences, either isolated or with independent features" (Christie 2006: 391). San Giuliano's steady incline and isolated nature provides an effective defensive location in an area of nondescript cultural boundaries.

A known Lombard fortification, which bears some similarity to San Giuliano, is the Invillino site in Friuli, Italy. This site with known origins in the 5th century and was zenith in the 8th century shares some similar attributes with San Giuliano (Finney 2017: 689). In addition to Invillino's location atop naturally defensible hilltop, "excavations at Invillino […] did reveal at least one tower overlooking the main access point," similar to the tower at San Giuliano (Christie 2006: 391). Excavations at San Giuliano were begun atop La Rocca because of the evident fallen remains of what was once a prominent tower, and directly below the tower rubble, evidence of a gated threshold was unearthed (Zori, C. 2017: 34). The issue with these comparisons, however, is this period sees much more similarity across style of architecture and function of fortifications, making it a challenge to systematically differentiate between styles, especially on evidence of function that would serve to separate fortifications utilized by the Goths, Byzantines, or the Lombards. Volker Bierbrauer formulated a prominent hypothesis for this period of settlement in Italy in which when little clear 'Lombard' evidence is discovered, there is potential for a "largely autochthonous, nucleated site, only periodically employed by Goths, Byzantines, or Lombards as a defensive/military castrum" or castle, in which to serve as a border fort if and when the need arises, but stylistically may appear cross-culturally identical (Bierbrauer 1987: 844; Christie 2006: 393). While San Giuliano has evidence for later occupation, this does not exclude the possibility for a model one occupation, where site utilization originated at this phase, but further habitation and architectural transitions still occurred at a later date.

2.1.2 Tombe a Loggette

Further archaeological evidence with inconclusive dating or sourcing, but typological similarities to the Lombard period can be found in a structure adjacent to the main San Giuliano fortress and Trench 1. In 1991, a trench was excavated on La Rocca by the local community and discovered four east-west oriented graves cut into the bedrock within an isolated approximately rectangle-shaped room (Zori, D. *et. al*. 2016: 10). This structure was reopened and re-excavated in this past 2019 field season and revealed a total of ten distinctive cuts, either burial or structural in nature with various assemblages of skeletal remains in each (Zori. C. 2019). The number of distinctive east-west oriented adult-sized grave cuts was raised to a total of five, with the other five bedrock cuts being along the sidewalls of the room in a peripheral nature. While the five peripheral grave cuts have yet to be systematically understood, the five east-west grave cuts adhere to a certain style of early medieval grave, dating to probably first half of the 8th century, known as *tombe a loggette* (Guerrini 2001: 69). This style of grave is generally "found within the known 8th century borderlands between the Byzantine and Lombard zones of control" (Zori, D. *et. al.* 2016: 10). The *tombe a loggette* are traditionally cut in a trapezoidal-anthropomorphic form, are oriented along a west-east axis, and are in conjunction with the foundations of a chapel or church (Halsall 1995: 16-17). This style of tomb, while often attributed to the Lombards, took on several variations of format and identity throughout Italy during the Middle Ages, therefore offering indications of date and culture, but no definitive character. This the style of burial meets the criteria for a classically Lombard-Byzantine style of burial in that dates to approximately AD 500-800, around the period and context of a Lombard-Byzantine border fort, engaging the historical reliability for model one of the San Giuliano fortification.

While the function of the small burial structure remains under dispute, following the 1991 excavations it identified as resembling the style of tombe a logette and was structured in a style that was "often associated with a building of worship" (Guerrini 2001: 68). This possibility could be useful in drawing another archaeological parallel between the San Giuliano fortification and another medieval fort in the Lazio region, Mola di Monte Gelato. Monte Gelato is a medieval site that can be compared with San Giuliano for its regional similarities and features a small church, erected in the fifth century that serves "as an example of how sites became redefined in Late Antiquity through the creation of a chapel/church (generally with burials)" (Christie 2006: 443).

While the burial structure's identity as a chapel remains plausible but not verifiable, the style of burial meets the criteria for a classically Lombard-Byzantine style of funerary practice, in the period and context of a Lombard-Byzantine border fort, engaging the historical reliability for model one of the San Giuliano fortification.

2.2 Model Two: Feudal Castle

The Lombard-Byzantine era ended in AD 774 with the Siege of Pavia. The northern Lombard kingdom was beginning to face a growing aggression from the Franks before this date, however, with the Carolingian dynasty growing in power and proclivity for expansion. When Pepin took the Frankish throne in AD 741 with a blessing from the pope, the Franks marched into Italy to defeat the Lombards, who were at the time attacking the Church (Backman 2003: 114). Following Pepin's venture into Italy and in a continued effort to appease the papacy, it is hypothesized that *the Donation of Constantine* was forged during this period – approximately during the 8th century – and allocated "the central portion of the peninsula (roughly the middle third) to the papacy as an autonomous state" (Backman 2003: 114). This supposed land transition included the region of Lazio and the San Giuliano Plateau. The Lombards began to lose land from that point on, coming to a head in AD 774 at the Siege of Pavia, where Pepin's successor, Charlemagne, won a definite victory over the Lombards and began to use the title 'Charles, king of the Franks and of the Lombards.'

This transition in leadership and culture was both more organized and more all-encompassing than the previous amalgamation of cultural transitions from Roman to Germanic and Byzantine. Charlemagne continued to expand his empire and "for practical purposes he divided his empire into administrative units called counties, and placed his most loyal followers, whether lay or religious, in charge of them" (Backman 2003: 121). With the goal of a more effective political system the Frankish empire attempted to unify and organize a large part of the Italic peninsula, extending to and slightly past the Papal State. Despite this organization, the Franks failed in creating cultural homogeneity, but did create the basis for a new economic and social system that would eventually dominate western medieval Europe.

Figure 8, The Carolingian Empire, AD 774 from: Backman, Clifford R. The Worlds of Medieval Europe. Oxford Univ. Press, 2003. Pp. 118.

Even as the Carolingian empire began to fail in power and prestige, the system set in place established that "peasants worked for the most part on individual family farms that they rented from great lords of the manors that the Carolingians had distributed to their followers" and provided the foundational political and economic structure for feudalism (Backman 2003: 125). The Carolingian empire fragmented with the Treaty of Verdun in AD 843, when it was divided into three separate kingdoms. This time period saw a political division that halted effective trade and economic prosperity. In addition to these societal shifts, extremely clement weather from roughly AD 1050 to 1300 as discovered from tree ring observation and pollen analysis contributed to a mass movement of individuals from isolated family farms to congregate in small, concentrated communities" (Backman 2003: 156). The mild weather, the need for local economic ties and general political collapse of the Frankish rule served as a catalyst to propel individuals into congregated living situations, offering opportunities for specialization, collaboration and in the case of an attack, protection

2.2.1 Incastellamento

This phenomenon of incastellamento or castle-building process is "usually associated with a 10th century rise of a rural elite that manifested their political and martial powers in their private castles" (Gasparri 2002: 81; Zori, C. 2017: 28). While this phase of incastellamento does appear to have been caused by a shift of fortification function in the region, the variation of how the incastellamento process took shape ended in a variety of economic, political and social systems. Debate remains as to whether the "impetus for this incastellamento was the desire of the landlords to […] consolidate jurisdiction and control," being intent upon strategies for defense and sovereignty, or a "programme of resettlement and economic development," with a priority on maximizing land use based on grants or occupation agreements (Abulafia 2004: 162). Both of these models offer motivation for population movements, where regardless of stimulus, populations were being met with benefits to drive relocation. This rise in fortified castelli throughout Italy met societal needs for local, defensible spaces, as well as protected agricultural lands, making it economically inefficient to not join in the societal reorganization of your region (Toubert 1973: 313). The rise of incastellamento throughout the period of political unrest seems to "derive from a number of actions, whether promoted by the State, by the Church, or by the elite, is often seen as symptomatic of incipient feudalization" (Augenti & Galetti 2018: 436). The dissolving rule of the Frankish empire during the 10th and 11th centuries manifests itself in a established feudal system but a collapsed unified regime. This collapse of organization at a time of strict social, political and economic hierarchies allows for a rapid need for societal reordering. With a plethora of rationales for some semblance of unification and dispersed settlements in a chaotic time, this period sees a widespread transformation of the Italic peninsula settlement pattern.

2.2.2 Documentary Evidence

One catalyst of incastellamento were land grants by local lords, issued to either consolidate power or to facilitate resettlement. Both functions provided exigence for nobility to exert their attributed authority to create functional political and economic systems in their region. The first mention of San Giuliano in a historical document is noted a donation document to the municipality of Viterbo by Count Farulfo in AD 1141 (Guerrini 2003: 162). Count Farulfo donated the two castles of San Giuliano and San Angelo, and while the location cannot be proven, it is most probable that the castle of San Giuliano refers to the San Giuliano fortification atop La Rocca. This donation was reconfirmed by Count Farulfo's daughter, Kleria in AD 1154, and in later documents Margherita of Viterbo refers to the castle of San Giuliano with a "definition best suited to the situation on the San Giuliano plateau near Barbarano" (Guerrini 2003: 162). With several affirmative accounts that fit the setting of the San Giuliano fortification, the probability of the municipality donation is likely, the variability lies in the date of the donation, which can effectively span two potential models for the San Giuliano fortification. While land grants were often characteristic of incastellamento, the early 12th century date could also with the less common but still plausible model of a communal, fortified village.

2.3 Model Three: Fortified Village

While throughout the rise of feudalism and incastellamento, the Italic peninsula also saw a rise in political fragmentation and diversity as individual regions adopted and curated their own systems of economy, policy and autonomy. The period from AD 900-1200 saw a diverse spectrum of systems from a communal-urban model in the north to a feudal-monarchical model in the south (Backman 2003: 201). With San Giuliano's centralized, non-specific locale and lack of documentary evidence, these differentiations provide opportunity to speculate about the historical and material criteria for not just the southern feudal castle model, but also the northern communal model. In the eleventh century a rapidly increasing birth rate, increased agricultural production, and the rediscovery of Roman law contributed to the ideal conditions for curating a boom of urban communes (Backman 2003: 201). After the Frankish imperial collapse German rule claimed Italian lands, and while German emperors maintained technical control of Italy, most Italian cities at this time claimed a form of "de facto independence". Otto of Freising, a German imperial chronicler, traveled through Italy from AD 1111 to 1158, and wrote this of his experience at the time.

> In the government of cities and in the management of civil affairs they also imitate the skill of the ancient Romans. Furthermore, they love liberty so well that, to guard against the abuse of power, they choose to be ruled by the authority of consuls, rather than by princes. They are divided into three classes, namely, "captains", vavasors, and the people. To prevent the growth of class pride, the consuls are chosen from each class

> in turn and for fear that they may yield to the lust of power, they are changed every year.
>
> It has come to pass that almost the whole country belongs to the cities, each of which forces the inhabitants of her territory to submit to her sway. One can hardly find, within a wide circuit, a man of rank or importance who does not recognize the authority of his city….In order that there shall be no lack of forces for tyrannizing over their neighbors, the cities stoop to bestow the sword-belt and honorable rank upon youths of inferior station, or even upon laborers in despised and mechanical trades, who, among other peoples, are shunned like the pest by those who follow the higher pursuits. To this practice it is due that they surpass all other cities of the world in riches and power; and the long-continued absence of their ruler across the Alps has further contributed to their independence (Robinson 1906:141).

Otto of Freising purports a system that functionally adheres almost exclusively to local authority. The political shifts that arose in the urban-commune model of societal organization supported a diversified system of rule, but maintained the ruling be from "the richest civic elites, of landowners, and sometimes merchants, usually including some castle-owning lords" (Wickham 2016: 108-109). The system was new in apparent functionality, but remained stratified in its players, with the wealthy in places of power and the poor in places of allocating allegiance. These communal models were not isolated to large cities, but included smaller towns and fortified *castelli,* throughout northern Italy and sending ripples of political transition through the rest of the region (Hyde 1973: 57). These transitions, however, do not exhibit a lack of elite or central power, merely a localization of that power, where allegiance and adherence to policies focuses on proximity to authority. In accordance with Otto of Freising's observations, "cities as a whole were being ruled over by annually changing collectives of ruling officials called 'consuls,'" but were less universal in their leadership selection, maintain leadership in favor of the *seigneuries banales* (private political lordships) (Wickham 2016: 109). The domination of cities throughout rural areas in northern Italy may also be exhibited through the document by Count Farulfo in AD 1141, specifying the allocation of the castle of San Giuliano to the municipality of Viterbo (Guerrini 2003: 162). While this is still hypothesized to be referring to the San Giuliano fortification currently being excavated, it would suggest that this fort had some local allegiance to a city, supporting the potential locally oriented leadership and allegiance system characteristic of the communal model.

While the San Giuliano fortification most likely did not experience the exact systematic communal life to which Otto of Freising observed in northern Italy, through the late 11th and 12th centuries, communal living did emerge in various degrees and regions across the peninsula. During this period there was a rise in the territorialization of lordly power or signoria, and villages evolved centers of policy and identity, at the loss of extreme centralized power (Wickham 2002: 140, Zori, C. 2017: 28). San Giuliano's most compelling evidence for a communal lifestyle exists not atop the plateau, but in the caves carved into its steep rockface. These caves have been typologically and chronologically ordered, indicating that their purposes varied from habitation to animal husbandry to religious. The most notable characteristics of these caves allow for the categories to be drawn based on the presence or absence of a manger, jambs, ventilation shaft, and the architectural shape. One unique cave was once an Etruscan tomb that has since been reutilized as a religious space and depicts a 13th century fresco of San Simon and the Presentation at the Temple (Ricci 1992). These various and crudely reworked cave structures serve to further the hypothesis that non-elite community members were able to live and work in relation to the San Giuliano fortification.

2.4 Examination of Further Documentary and Physical Evidence

The three proposed models for the San Giuliano fortification rest on historical context, archaeological evidence and the lack of documentary evidence, between approximately AD 500 and 1200. The first verifiable documentary evidence about the San Giuliano fortification occurred when Bishop Binnariono visited the site in AD 1573. It is clear that the site existed long before this.

Lastly, an evaluation of the architectural formation at San Giuliano can provide insight into its specific date range through an analytical look at its different phases of tufa building blocks. The San Giuliano fort clearly has several phases of building, with the earliest portions of La Rocca and the ring wall around the western edge of the plateau being dated to no earlier than the 11th century, however, this date lacks a source and may be subject to reevaluation (Zori, C. 2017: 27). The earliest observed phase from the excavated portion of the San Giuliano fort appears to be context 7, a central, sturdy wall that connects with the main entrance threshold for the fort and which every subsequent wall abuts. Context 7 features blocks spanning 24-46 cm in length, with an average of 38 cm, and heights spanning 28 to 30 cm with an average of 28.4 cm. When calculating average dimensions for all primary structure walls, the average length is 35 cm and an average height between 28-33 cm (Zori, C. 2019: 45). According to ta typology established by David Andrews in “Medieval Masonry in Northern Lazio: Its Development and Uses for Dating,” medieval central Italian architectural blocks that most closely parallel the dimensions and characteristics of San Giuliano belong to a transitional category of medieval architecture over the period of 1150 to 1250. This style features courses that range in height from 20-36 cm and average about 28-32 cm, while the lengths are rectangular and approximately 30-50 cm (Andrews 1978: 397). This size, while spanning a wide margin, very closely nears the style of the earliest phase of lasting architecture at San Giuliano.

In addition to the size similarities, characteristic features of Andrews' typology closely resemble that of San Giuliano. San Giuliano's oldest architectural walls feature blocks that have aesthetic flat outward faces, but coarse, unworked back faces, so that as the blocks are fed into the wall structure, the uneven interior will better adhere to the mortar and maintain the walls durability. Andrews mentions a similar concept in the typology from 1150 to 1250, in which "block are approximately squared, but the sides of the adjacent stones no longer fit neatly together, and this greater degree of inaccuracy is compensated for by thicker beds of mortar" (Andrews 1978: 397). This functional attribute provides an identifiable stylistic marker for pairing a chronological typology with the archaeological record of San Giuliano.

While the typology Andrews' specifies from 1150 to 1250 correlates most closely with San Giuliano's primary structural walls, indicating an original building phase of somewhere in the twelfth century, the emphasis on the lack of mutual exclusivity between models and the dynamic nature of central Italian habitation phases bears repeating. Andrews also lists other types of architectural blocks in his typology that may be present in the San Giuliano fort and may evidence both earlier, and later, dates for the site. The earliest type examined originated in AD 850 and "consists of large tufa blocks 45-50 cm high, about 50-60 cm long, quite well cut, and bonded with a thick, yellow, lime and sand mortar" (Andrews 1978: 393). The blocks that comprise what appears to be the preliminary and primary structure adhere to architectural type listed above. But, surrounding the most prominent pit of the San Giuliano fort are seven blocks of prominent size and unique shape. These blocks form a rectangle around the pit and are described as large and pillowy. While still being made of tufa, these blocks average a length of 56-65 cm and a height of 30-53 cm and during excavation were noted to be held together loosely by “crumbly grey mortar” (Zori, C. 2019: 50). While these blocks have the appearance of being placed in a later stage, the possibility of their reutilization is not out of the question, as their style is most similar to the earliest known tufo block architecture in medieval central Italy.

CHAPTER THREE

Methods of Data Collection and Intra-Site Find Distribution Analysis

This chapter presents my methodological approach for data collection and intra-site find distribution analysis on the San Giuliano Plateau. I examine artifacts within an isolated sample area atop the plateau, according to their individual characteristics and spatial layout in order to shed light on how artifacts correlate with past spatial function and organization. The application of GIS (Geographic Information Systems) is a new and effective way to handle a considerable amount of data while simultaneously providing the possibility of producing single or combined maps according to different criteria, at different scales (Fontana 1999: 111). While GIS has primarily been applied to landscape studies and "generally refers to archaeological analysis undertaken at a regional or intersite scale," the utilization of GIS at an intra-site scale allows for a feasible investigation of densely clustered, interrelated artifacts in a comparatively homogenous setting, as opposed to data being dispersed across topography and heterogeneous features (Wheatley 2004: 3). GIS applications also have the added benefit of increased precision, both in field data collection and quantitative and theoretical analyses. In the past, "prior to the development and application of sophisticated quantitative methodologies, archaeologists relied on the visual interpretation of artefact distributions for the identification or spatial patterning within archaeological levels" (Anderson 2008: 2275). Now, utilizing a technology to triangulate three-dimensional coordinates and inputting this data into the GIS program, these more exact GPS points can be statistically clustered, interpreted, and mapped to produce consistent, conclusive results about the material record. The application of GIS technologies opens a route for interpreting archaeological data, specifically artifact distribution in a clearly defined structure or small-scale area, in a more accurate and reliable way. Even within a comparatively small area defined by the extent of excavations, variables of context and properties can produce challenges for interpreting artifacts. In such a narrow geographical area with large numbers of individual artifacts, "GIS play[s] a decisive role in the identification of the spatial trends of archaeological data through the contextual or selective treatment of spatial variables" (Galotti 2011: 373). Implementing GIS applications allows for intrasite spatial patterns to be revealed as different variables are identified, classified, and prioritized. GIS is furthermore an effective program in its ability to adapt to new information, changing hypotheses, and an active excavation.

The San Giuliano Archaeological Research Project has been a progressively expanding venture, with data increasing exponentially with every field season. Analyses through GIS applications provide an opportunity to test hypotheses and continuously "update the distribution maps on the basis of new data/results from other kinds of analyses" (Fontana 1999: 111). By addressing the most recent data from field seasons spanning from 2016 to 2019, through the lens of intra-site find distribution with GIS applications, conclusions about how the San Giuliano fortress acted as a social space on the landscape will be effectively drawn. This chapter will delve into the methods of data collection in the field, data processing through the program of GIS and the eventual theoretical applications that will provide substance to the static statistical results. By recognizing the processual theoretical biases that come with working in a mechanized, limited-variable program such as GIS, and expanding upon a theoretical backing of post-processual structuralism, to support the multifaceted nature of human agency and action, conclusions about the San Giuliano fortress as a dynamic social space with evolving functions and events may be drawn.

3.1 Data Collection

Data collection in the field depends on precision and efficiency, as the San Giuliano Plateau contains significantly clustered and stratified artifact data from rooms, open areas, and pits within the fortress. In order to manipulate the complex stratigraphy and meet the need for recording new artifact data *in situ*, the project utilizes the Total Station to record data points of the material record on maps (Galotti 2011: 276). A Total Station is an electronic/optical instrument comprised of an electronic theodolite and an electronic distance meter (EDM), that triangulates three-dimensional point locations by emitting and reflecting frequencies to a portable prism from a stationary, georeferenced position. Total Station data precisely measures “the location and extent of archaeological entities,” and creates portable data packages for transfer to the GIS program (Katsianis 2008: 659). While in the field, every point or dataset that is collected is inputted in tandem with a unique survey ID, and a coded description. Since the beginning of SGARP, datapoints have been collected beginning at unique survey ID *SS0001*, to the most recent point from 2019, *SS4012*. While every individual point has a unique survey ID, every data unit collected also has coded description attributed along certain criteria. Each description has a prefix, depending on the location of the excavation site throughout San Giuliano. While my research pertains to the prefix ‘R’ for La Rocca, the name of the central plateau, other prefixes used include: ‘R2’ and ‘R3’ for separate La Rocca trenches, ‘G12_062’ for Tomba Rossi in the surrounding Etruscan necropolis, and ‘SSP’ for Early Etruscan burials on the San Simone Plateau. The prefix is then followed by an underscore and specifies the context of the feature, which is then followed by an underscore and specifies the feature itself. A complete coded description would be: ‘R_C298_OUTLINEBOTTOM’. This coded description would be describing the outline of the bottom of context 298, in trench 1 on the central La Rocca plateau. To identify field finds, the nomenclature is the same, but includes the division of ‘FF’ for general field finds, ‘FI’ for iron field finds, and ‘FG’ for glass field finds. These field finds also include the unique field find number that is assigned upon discovery. A coded description for a field find would be: R_C298_FI609’. This would be an iron field find, found in context 298, with the field find number 609. These coded descriptors, given in the field, allow for a more efficient system of data processing, because data can be uniquely tracked and identified. With such large quantities of data being collected every year, it is vital that a system be in place to prevent incorrect data from infiltrating conclusions or useful data being lost.

3.2 GIS Methods

3.2.1 Cluster Analysis

The data accrued over four field seasons (2015-2018) require significant organization and processing in order to transition from independent geo-points recorded in the field to conclusive maps, clusters and features that can confirm and falsify hypotheses. In order to glean information about spatial usage, social interaction, and structural function, these independent artifacts must be understood as a cohesive unit.

With such a complex dataset, however, “the huge number of finds discovered […] makes it difficult to obtain accurate impressions of their spatial distribution in any normal conceptual manner; so the topological features of GIS are used to create maps derived from the data and present it as frequency analyses, or to obtain density values and to schematize the distribution trends (concentrations or dispersals) of artifacts” (Galotti 2011: 377). GIS allows for the prioritization of relevant data points and data attributes, to create maps according to hypotheses-oriented research needs. The goal of using the cluster analysis function in GIS is to be able to visualize where clear statistically likely breaks in artifact type and concentration arise. The cluster analysis function draws in both the variables of artifact attribute and spatial layout to construct likely groupings according to these variables, which in turn may confirm or negate hypotheses about structural function and social space utilization.

The ideal for understanding a seemingly random dispersal of artifacts on La Rocca, is to be able to factor in all the relevant variables equally and observe whether any concentrations are statistically-significantly clustered. A feature in GIS that allows for this ideal statistical analysis, especially for intra-site distribution concerns, is the GIS K-means cluster program, which uses point attributes and randomized seed locations to identify optimal clustering solutions in three dimensions (Anderson 2008: 2279). Ripley’s K-means cluster function is an application that runs a statistical analysis on selected variable attributes, and “can be used to summarize a point pattern, test hypotheses about the pattern, estimate parameters and fit models” (El-Shaarawi 2002: 1). The program’s resultant cluster groupings indicate statistically probable relationships based on attributes of location and material composition. The K-means cluster function first identifies a random "seed" point as a base for subsequent group clustering, and then identifies the variables of concern. The K-means cluster function rapidly runs statistical equations through large masses of data, and plugs provided data variables into mathematical equation variables. To sufficiently quantify point clustering, with an emphasis on proximity, the first relevant property of a spatial point pattern is the number of points per area, while the second, to better understand relevant attribute dispersal, is the expected number of points *N* within a distance *r* of another point (Kisowski 2009: 1095). The K-function uses the original seed point to gauge similar data within a neighboring distance and subsequently groups based on the "second property [being] normalized by the density (or intensity) of the number of points per area λ" (Kisowski 2009: 1095). The function can be run several times, focusing on different attributes for different hypotheses, serving as an adaptable model of statistical analysis. The GIS program produces a new attribute field in the artifact point feature group and an examination of the contents of each cluster defined for a specific test helps establish which clusters contain non-random artifact concentrations (Anderson 2008: 2279). Simple visual evaluation of artifact clusters can miss key factors of contextual three-dimensionality and material variability, making the GIS K-means function program optimal for considering all potentially critical artifact traits. Identifying non-random artifact clustering allows for conclusions to be drawn about statistically significant field find attribute clustering, which can subsequently by utilized to identify potential high-traffic and social activity areas (Anderson 2008: 2279). With a desire to better understand the San Giuliano fortress as a social space, with differences in spatial construction and usage, the indication that there are statistically significant and relevant differences between many clusters, indicates a differential use of space (Anderson 2008: 2280). My hypotheses stand on the hope that there will be clear differences between clusters based on attributes and distance such as coins and dice clustered differentially from items such as spindle whorls, as these items have significant differences in function and social identity. Glass and iron would hypothetically be concentrated in high-traffic areas, as highly utilized items, but glass should also be concentrated in isolation, as a prestige item. All items' locality should ideally indicate what features of the architecture were more or less populated, which sectors were more or less elite, and how the structure as a whole informed the medieval landscape for a whole society.

3.2.2 Kernel Density

While Cluster Analysis is effective in grouping artifacts according to their makeup and proximity to one another, it is also important to understand how artifacts generally amass in terms of spatial density. Type of artifact, while significant, does not play into how sheer quantity of artifact in some areas of the fortress, affects an understanding of utilized space. In order to simply visualize high-traffic areas throughout the medieval fortress, without the added complexity of artifact attributes, the Kernel Density analysis is another GIS function that displays the spatial layout of field find concentrations throughout a space. Kernel Density maps differ from statistical cluster analysis in that while cluster analyses focus on a consideration of multivariate factors in grouping finds, based on distance and attributes, Kernel Density analysis relies simply on spatial aggregation. While this GIS feature may seem less effective because of its simplicity, the application of Kernel Density analysis identifies areas of a low and high density that would not necessarily have been recognized without the application of a statistical density evaluation (Sycamore 2014: 369). A basic map that reveals areas of intense field find concentration has the potential to disclose spaces of heavy traffic and consistent usage. This technique, beyond this thesis, provides a concise, easily evaluated map of high-traffic, densely populated areas of utilization in the medieval fortress. A Kernel Density analysis outputs a useful raster map that can be applied to understanding general artifact concentration for official reports and long-term research. This application presents a method to visualize how artifacts have amassed over the last four years of excavation and presents an opportunity to hypothesize where densities may continue or lead to in terms of future excavation trenches.

3.2.3 The Kolmogorov-Smirnov Test

The Kolmogorov-Smirnov Test (KS-test) is a goodness-of-fit test used for multivariate distributions of two-sample datasets (there is a one-sample KS-test, but for our purposes that test is inapplicable). The goal of the KS-test is to compare the distribution of two different datasets by standardizing their values over a common divisor and statistically evaluating the difference in their graphed curvatures to determine whether to reject or fail to reject a preliminary null hypothesis. To perform this test through ArcGIS, the analysis begins with a single dataset of interest, for this study it will be all field find data on the San Giuliano plateau. Next, after observing the total number of points in the original dataset, using the Create Random Points tool, select a constraining area of interest (for example, the area of Trench 1), and create three times the number of original points. The Create Random Points tool functions by a random number generator selecting a random value on the x-axis and a random value on the y-axis of the selected extent, and these values subsequently become the x and y coordinates for a random point. This process is repeated, moving to the next unused value on the random number stream, eventually creating a Uniform distribution of points with a minimum and maximum being the minimum and maximum of the selected *x* extent, and similarly for the *y* extent (*Create Random Points,* Pro.ArcGIS.com). The produced dataset mirrors the original dataset in extent but is reliably "random" in its distribution and has triple the original number of points, providing a wide margin of comparison. The goal of this preliminary step is to effectively contrast a known dataset, where the level of clustering and distribution is unknown, with a randomly distributed extrapolated dataset, to observe how similarly random, or dissimilarly systematic our known dataset's distribution is. Within the statistical equations, *n,* functions as the number of actual points, and *m,* represents the values of extrapolated points.

The two datasets are then analyzed using the Sample tool, which creates numerical location values for each data point according to how each point is in relation to the underlying raster. This step is the data standardization, in that while the actual and extrapolate sets are different in values and number of points, each dataset is given new values based on the same raster, represented by variable, *d*. This raster serves to set the contrasting datasets to scale, so that their levels of comparison correlate when attempting to graph and observe differential values.

Lastly, these two new datasets of quantified spatial distribution, are graphed, displaying the spatial distribution values, $\frac{n}{d}$ and $\frac{m}{d}$, along the x-axis and the D_n and D_m values on the y-axis (Wheatley 1995: 174). The D_n and D_m values are calculated by finding the respective probability of each point. In other words, the lowest spatial distribution value in the actual dataset will have a y value of:

$$\frac{1}{total\ \#\ of\ values\ in\ dataset} = D_n$$

Subsequently the highest spatial distribution value in the actual dataset will have a value of 1. This equation is utilized again for the extrapolated dataset to produce D_m, only the denominator is now 3 times the denominator of the actual dataset.

The difference between the two resultant curves (D) is then measured at the point of highest deviation, D_{max}, and compared with the critical value to determine levels of statistical significance in the dataset's distributions (Justel 1997: 252). Our critical value can be calculated by inputting *n* our value of 324 into the equation below:

$$d \approx \frac{1.3581}{\sqrt{n}}$$

(Wheatley 1995: 174)

The above equation is specified to a significance level, α, of .05, based upon the selected confidence interval of 95%. A D_{max} that exceeds the critical value correlates to a rejection of the null hypothesis, H_0, while a D_{max} that is less than the critical value means that we must fail to reject H_0. By establishing H_0 and H_a hypotheses that are concerned with the respective spatial boundaries of the site, the resultant statistical values may provide insight into whether the San Giuliano medieval field find data are randomly or non-randomly distributed.

3.3 Theory on Social Space

Results from GIS analyses provide useful probable groupings and maps to understand spatial function. The jump from statistical results to conclusions about them however, requires an additional facet of reasoning. The question of how we interpret the

GIS results rests on a desire to humanize data that has been disconnected from its acting agents. The material record exists as a static result of dynamic occurrences, and it that way demands a theoretical framework to be interpreted. The danger of interpretation can be that inductive reasoning and predisposed biases can taint GIS outputs and result in faulty conclusions, if the theoretical framework does not come around GIS results to assign limitations and direction. In this section, it is recognized that GIS requires some processual interpretations to be found as reliable, because the statistical and limited-variable system relies on an understanding that not all factors can be accounted for in a systematic output. The data collected and inputted into GIS systems to create the maps and clusters used as conclusive evidence is limited to the cultural and environmental determinants that remain in the record, and therefore constitute the observed results. There are, however, some biases that require recognition as well, because despite the archaeological record providing a narrow scope of the past that can be collected and processed by GIS, there is the undeniable certainty that the past involves far more variables and unpredictability that can be quantified. This reality requires the use of a post-processual framework to access the dynamic side of past reconstruction.

3.3.1 Processualism

New Archaeology gained recognition in the 1940s, when traditional British Archaeology faced a decline contemporaneously with a reorientation away from diffusionist modes of explanation towards more economic and evolutionary schemes with direct emphasis upon spatial patterning (Wheatley and Gillings 2002: 4). New Archaeology focuses on a processual mode of archaeological study by applying the scientific method to inquiry and utilizing logical positivism to understand the observable cultural facets of technology and subsistence. New Archaeology frames archaeological sites as shaped by their environment and evolutionary needs. From a processual theoretical bent, GIS applications can be applied to "the mapping of archaeological sites […] on a regional scale, with the express purpose of studying the adaptation of social and settlement patterns within an environmental context i.e. to find causal linkages" (Wheatley and Gillings 2002: 5). GIS is a highly effective program for analyzing the relationship between an archaeological site and an environment through the engagement of large-scale topographical, landscape data mapped and analyzed in conjunction with small-scale architectural and artifact data. GIS applications also permit a degree of certainty within mapped and statistical results, based upon the confirmation of correlative predictive models. Correlative predictive models indicate strong statistical correlation between predictive modeling and the inputted data, therefore allowing for conclusions to be drawn from confirmed hypotheses in GIS outputs. Applying GIS programing to archaeological material is a method of recognizing "that the past [can] not be fully understood simply from the examination and characterization of de-contextualized artefacts, or from the study of the sequences derived from individual sites in isolation," but instead requires a system of weaving together the environment and the relationship between archaeological materials to form a more holistic, processual picture (Wheatley and Gillings 2002: 5). Applying GIS to the study of intra-site find distribution acts under the assumption that reliable results can be drawn from inputting archaeological data about the environment and the physical structure of a site in tandem with individual artifacts.

3.3.2 Biases

The danger of atheroretical GIS application to the archaeological record "can lead to unsatisfactory, misinformed, inaccurate or (worst of all) incorrect outputs" (Burg 2017: 115). GIS results are absent of interpretation, meaning that the products of a statistical analysis or intricate spatial investigation can only inform to the extent of its input. GIS outputs cannot be the goal of an archaeological study but serve as a tool for future investigation and a method for falsifying hypotheses. In order to utilize GIS, not as a conclusive decider in scientific results, but as a "paradigm shifter in the field of archaeology, […] a skeptical and theory-laden approach to GIS usage by academic users should be employed at all stages of inquiry and, as much as is possible, such high-end applications should be adopted in other segments of archaeological investigation" (Burg 2017: 115). Accepting GIS through a purely positivistic, processual lens allows for GIS results to be an end-goal, because processual archaeology presumes a degree of environmental determinism and concrete observable results. In an effort to correlate artifact distribution within various architectural regions of a site, "the tendency, in the absence of conscious theorizing, [may be] for the available technology to dictate the questions which archaeologists investigate" and prevent reliable, unbiased explanations to be reached (Wheatley 2004: 2). As opposed to simply curtailing the archaeological excavation at the assumption that coins and dice being clustered in a statistically significant manner indicates potential gambling, the investigation can reach further into more abstract questions of thought. Instead of halting at the concrete intuitive leaps permitted by GIS, these outputs can be used to observe where coin and dice clusters are in comparison to prestige glass items, and whether these items are divided by significant architectural barriers. These results in tandem with an understanding of the historical context of other medieval fortresses and medieval social hierarchy in central Italy may provide a way to move past simple singular step answers to higher-order concerns of cultural constructs and social space usage.

Moving forward with a solely processual theoretical bent may allow confirmation bias to command how GIS results are interpreted, without recognizing that within the GIS community, and in the literature, it has been widely recognized that there are significant issues inherent in this simplistic model of non-critically accepting GIS outputs as finite results and the use of correlative predictive models as a form of archaeological explanation (Wheatley 1996: 6). To understand structural function and social behavior within a site, an examination of archaeological sites requires the recognition that "asserting the primacy of correlations between behavior and environmental characteristics is reductionist to the extent that it effectively de-humanizes the past" (Wheatley 1996: 6). Human agency and socio-cultural factors combined with post-depositional processes generate the artifactual record, therefore requiring a concession that the meaningful human actors we are seeking to understand cannot be reduced to automata who behave according to a rule that connects their behavior to their environment (Wheatley 1996: 6). While the obvious reality that humans created the archaeological record, and therefore cannot be reduced or eliminated from its study is true to some degree, there is also some desire when drawing conclusions to make assumptions and fit results into a certain idealized and expected product. This hope does not necessarily dictate humans as automata or dehumanize the remains but can be reductionist in the way it expects certain results and argues predictability. Human acting on the material record means that reconstructing it goes beyond simple maps, clusters, and data points. GIS results are concrete and accurate, they require some form of theoretical supplementation to avoid the assumption that their outputs are absolute and not inductively confirming prior suppositions.

3.3.3 Behavioral Archaeology

Behavioral Archaeology is a processual theory centered on the inherent connection between people and objects and the assumption that to holistically understand either facet of the material record, both people, objects and their past interactions must be factored into formulated hypotheses and conclusions. This theoretical foundation attempts to avoid an isolated deduction that assumes “the impetus for behavior entirely within the human actor (behavior arising from mental states), or as coming entirely from outside (behavior as a response to environmental stimuli)” (LaMotta 2012: 64). This conjunction of human agency and material objects is then met with another paired framework, of understanding the inherent relationship between people and objects, through generalized and particularistic approaches. These two approaches are described as “modes” and attempt to both generally describe “how behavior works,” given certain boundaries and conditions, but also trying to understand particular cases of behavioral change (LaMotta 2012: 65). In summation, Behavioral Archaeology is a theoretical framework focused on describing the inherent relationship between people and their objects by attempting to codify broad behavioral patterns, and how they affect particular behavioral changes. This theory is systematically put to use through establishing a null hypothesis with certain boundaries, and determining whether the null hypothesis may be rejected, or fail to be rejected within those established boundaries and conditions.

This theory, however, has come under critique at times, as some argue that a method of establishing a null hypothesis based off of pre-existing boundaries and conditions is dangerously “inductive,” creating a hypothesis that is specifically formulated to fit a generalized behavior observation. While utilizing broad generalizations determined by “how we think behavior works,” could potentially be an arbitrary process, I would argue that this theoretical framework in tandem with ArcGIS analyses takes on a useful and legitimate form (LaMotta 2012: 65). While forming and evaluating null hypotheses based on observation and preconceived notions may be an ineffective technique, and therefore rightly reevaluated and critiqued, the method in its framework has many merits and can be supplemented to become extremely functional. By establishing a null hypothesis that function within a legitimate and mathematical statistical analysis, this study becomes reliable, quantifiable and oriented towards concrete data. As mentioned in section 3.2.3, the KS-test functions through a null hypothesis test but works through archaeological data to reliably reject or fail to reject the null hypothesis. Therefore, a system that unites the theory of Behavioral Archaeology with quantifiable data effectively provides a more holistic and reliable system of data interpretation.

3.3.4 Post-Processualism

Post-Processual archaeology allows for a theoretical framework that is abstract and is concerned with humans as social and dynamic agents in the archaeological record. A post-processual outlook, when applied to GIS products should allow for a connection to be drawn between the static material record and the reality of the medieval fortress as a social space. After identifying the benefits and evident drawbacks of a processual theoretical examination of GIS outputs, theoretical analysis may take a more positive note by concentrating on what can be done rather than negating what should not (Wheatley 2004: 2). In the 1970s, the gaps and biases found in New Archaeology became more pronounced and renounced by archaeologists, giving way to the new theoretical framework of Post-Processual archaeology. This form of archaeological thought argued for a much more abstract analysis of the material record, building on processual thought with the pluralistic notion that there are many different 'truths' which might stem from different theoretical perspectives. The different theoretical perspectives, when used in tandem leave the contradictions between processual and post-processual approaches to archaeological interpretation intact but less problematical (Wheatley 2004: 2). By utilizing the processual archaeological framework to accept the legitimacy of GIS outputs, but adopting a post-processual technique for GIS interpretation, a recognition of how the material and metaphysical culture existed together in the past may be applied to hypotheses of San Giuliano as a social space.

In section 3.2.2, it was recognized that humans respond to their environment, but are not exclusively defined by their physical setting. By uniting that theory, with a post-processual recognition of other definitive factors in human decision, a path into the complexity of environment and culture as separate but contemporaneous influences can be reached. While the environment and structure of the past did shape the material record observed today, "to many contemporary archaeologists, the physical environment directly contributes little to the behavior of individuals whose relationship with the physical world is mitigated through the social world, best understood by concepts such as 'habitus' (Bourdieu 1977) or 'structuration' (Giddens 1984)" (Wheatley 1996: 7). Habitus is the theory that individuals react to the social world and form habits and behaviors based upon social interaction more than their environmental experiences. Structuration is a similar understanding that humans create their own social and physical environment with an emphasis on individual and societal agency, a complete antithesis to environmental determinism. Constructing a useful theory of spatial archaeological technologies is an abstract, but necessary process.

I believe the best way to enact the informative and conclusive nature of GIS outputs is to implement GIS as a stepping-stone leading backwards. GIS provides statistics and analyses of the archaeological end result, therefore observing that end result and identifying the mechanisms which produced it is the ideal of archaeological practice. With less emphasis on pattern recognition and physical measurement as goals in their own right, and more concern with interpretation of the historical processes which result in such patterns, a method for using GIS to understand social action within the medieval fortress is possible (Gaffney 1995: 378). The structuration perspective honed by Giddens can help dictate how artifact distribution maps are interpreted by assuming that "material culture does not passively reflect society but is actively manipulated to construct society," and therefore material culture patterns can inform how space is interpreted (Hodder 1994: 68). The material culture being manipulated in my GIS analysis of the San Giuliano Plateau deals with individual, densely concentrated finds. This this will proceed under the supposition that "all material culture has both use and meaning, style and function, and perhaps all material culture has all four types of meaning (emotional, aesthetic, semiotic and experiential) to some degree," conclusions about how micro-material culture informs the function of social space will be grounded in statistically, methodologically sound analysis and theoretically constructive scrutiny (Hodder 1994: 67). The San Giuliano Plateau was a dynamic locale for social interaction and culture, as evidenced by the material record. Therefore, processing GIS data as reliable and conclusive, while simultaneously understanding that the material record is dictated by both observable and metaphysical circumstances, allows for the most holistic picture of past space usage.

3.3.5 Experiential Realism

The last, and arguably most important aspect of the theoretical frameworks surrounding a GIS analysis is founded on where we begin our investigation. The foundation of this study is grounded in using the spatial layout and features of the San Giuliano fortification to analyze the distribution of artifacts. The spatial boundaries of the site both provide the data constraints while simultaneously being the interpretative goal, with the observed artifact distribution yielding cluster and density information *about* the spatial usage. Essentially, the spatial layout of the site is just as an important of a variable in this study as the artifacts, with the results of the analysis revealing information about how significantly the spatial boundaries of the fort are in relationship with the artifact distribution. The foundational theory that the space we observe in the material record would inform the artifact distribution we analyze is based in a theory of Experiential Realism. This theory features space as more than a "an inert backdrop, but as an active component of human activities," with dynamic past actors who were constantly engaging with and interpreting the space (Blake 2004: 235). Interpreting space as something beyond its physical characteristics is the foundation of experiential realism, "which asserts that spatial cognition is structured by sensorimotor or bodily experience and influenced by cultural traditions" (Freundschuh & Egenhofer 1997: 362). People build and understand their environment through their senses, in systematic and recurrent ways, creating a kind of interpretative unity between historical and modern experiences of settings. These recurrent patterns of understanding are termed "image schemata," and are seen in the regularities of shapes, patterns, function and conceptions of space (Freundschuh & Egenhofer 1997: 362). By matching these image schemata with how space is studied and represented in GIS, a more effective method for interpreting the data *within* space is established. The reality is that spatial boundaries articulate social space optimization, where cultural usage is dictated by how and why people maneuver throughout a closed spatial system. Therefore, interpreting these spatial boundaries as intuitive rules for how we analyze artifact data is a useful tool. This theory translates into factoring in not just artifact proximity when observing clusters and densities, but factoring in clear spatial boundaries (i.e. walls, thresholds and pits) as relevant and necessary features construing the artifact data's extent and relationships. Experiential Realism argues that spatial experiences are recurrent and relevant to understanding features that occupy space, making this theory foundational in an artifact distribution analysis.

CHAPTER FOUR

Spatial Analysis of Medieval Find Distribution Using GIS on the San Giuliano Plateau

In this chapter I apply GIS analysis to understand how people used the space within the San Giuliano fortification. Specifically, I apply both cluster analysis tools and a Kolmogorov-Smirnov Test, to reveal the statistical significance of various field find distributions and will provide insight into the utilization of space.

Figure 9: San Giuliano Plateau, Trench 1 from: SGARP Drone Photos, Emily Varley 2019

Figure 6 displays a drone image of the full San Giuliano fortification. Figure 7 depicts the same trench digitized and projected in ArcGIS. By overlaying this detailed outline of Trench 1 with field find data and running specific statistical tools in GIS, I will show whether or not field find distributions respect specific spatial boundaries (i.e. walls, thresholds and pits).

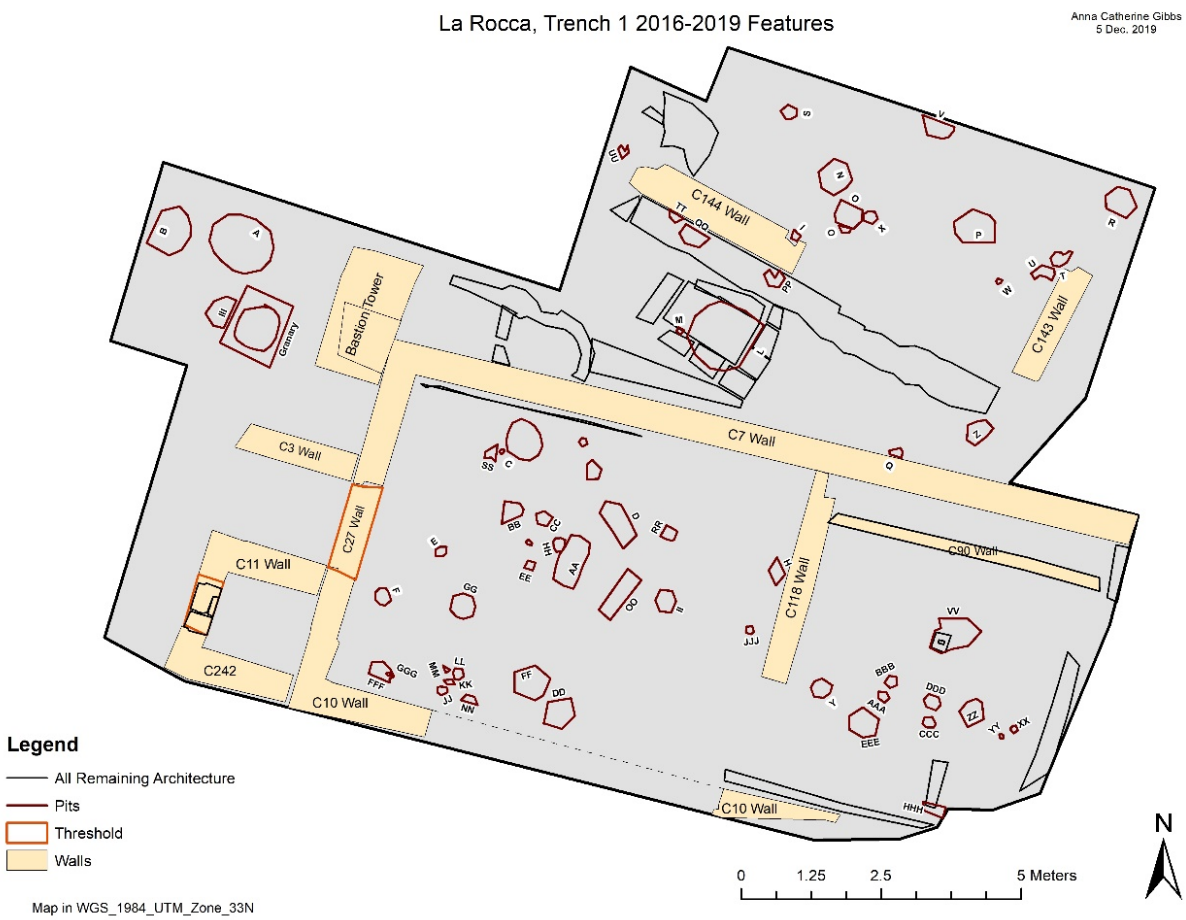


Figure 10: Trench 1, Basic features on the San Giuliano Plateau in ArcGIS

4.1 Organizing Field Find Data

After initial data collection, artifact information requires significant organization and attribute supplementation. As mentioned in Chapter 3, data is uploaded to ArcGIS with a x, y, and z coordinates, a unique “SS” ID number, and a shorthand Description identifying it as a context outline or field find, with its context number and/or field find number. In order to elaborate on the artifact’s function, style, or unique features, more information must be input into ArcGIS. This find-by-find process also allows for a comparison against field notes and identification of finds that were overlooked or ineffectively collected. Over the four years of excavation at San Giuliano, Total Station processes have gotten successively more detailed and systematic, meaning that in the earlier years of the project, some field finds were not collected with the Total Station, therefore were not be analyzed as relevant data. With the goal of accurately understanding the nature of specific artifact types within the medieval fortification, neglecting to factor in data, especially diagnostic finds such as coins, dice and bodkin points, affects the outcome of the find distribution analysis.

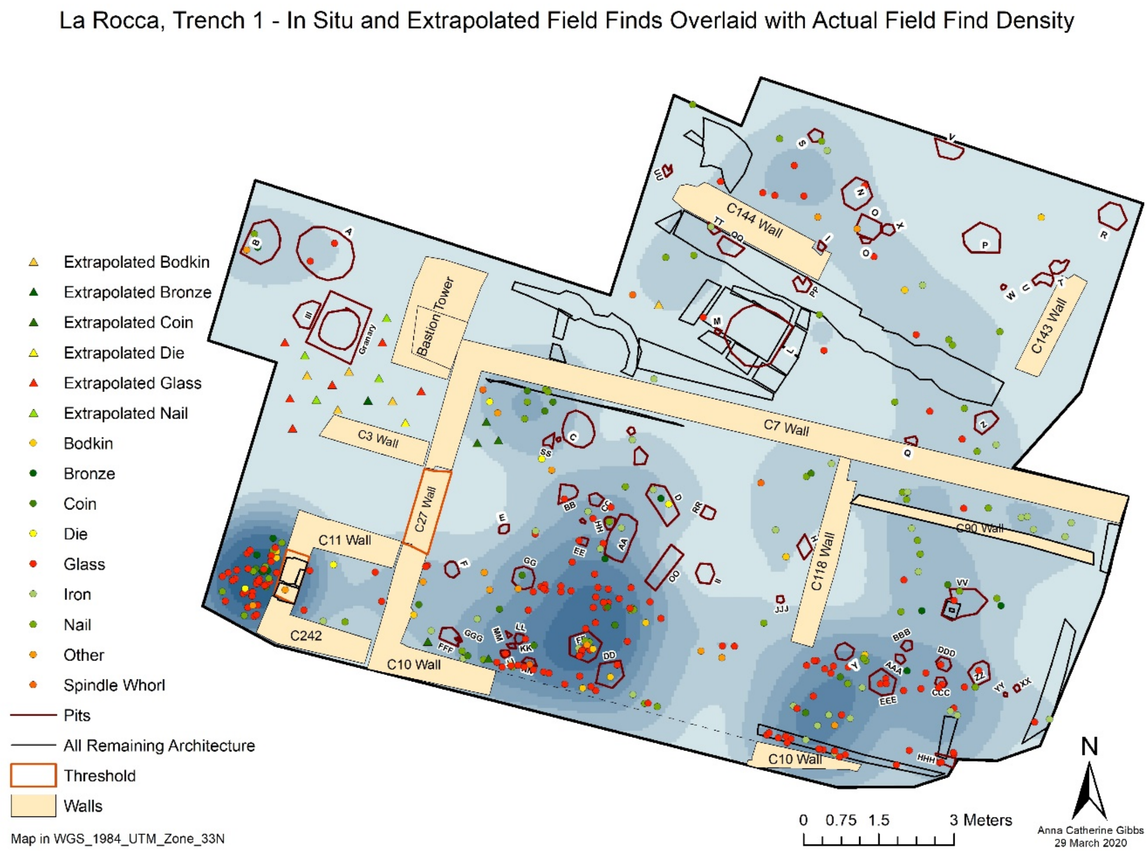


Figure 11: Both the actual and extrapolated field find data over the actual field find density raster, illustrating density discrepancies.

In order to analyze a comprehensive representation of the medieval fort's artifact distribution, the missing artifacts must be extrapolated and created based upon their recorded context. The "Find Centroid" tool in ArcGIS creates the geometrical centroid of any given polygon, allowing for an unbiased creation of missing artifact points to be created centrally within the context they were found. Figure 8 illustrates both the in-situ and extrapolated artifacts in conjunction, demonstrating how the previously missing artifacts dramatically affect the distribution and concentration of the site as a whole.

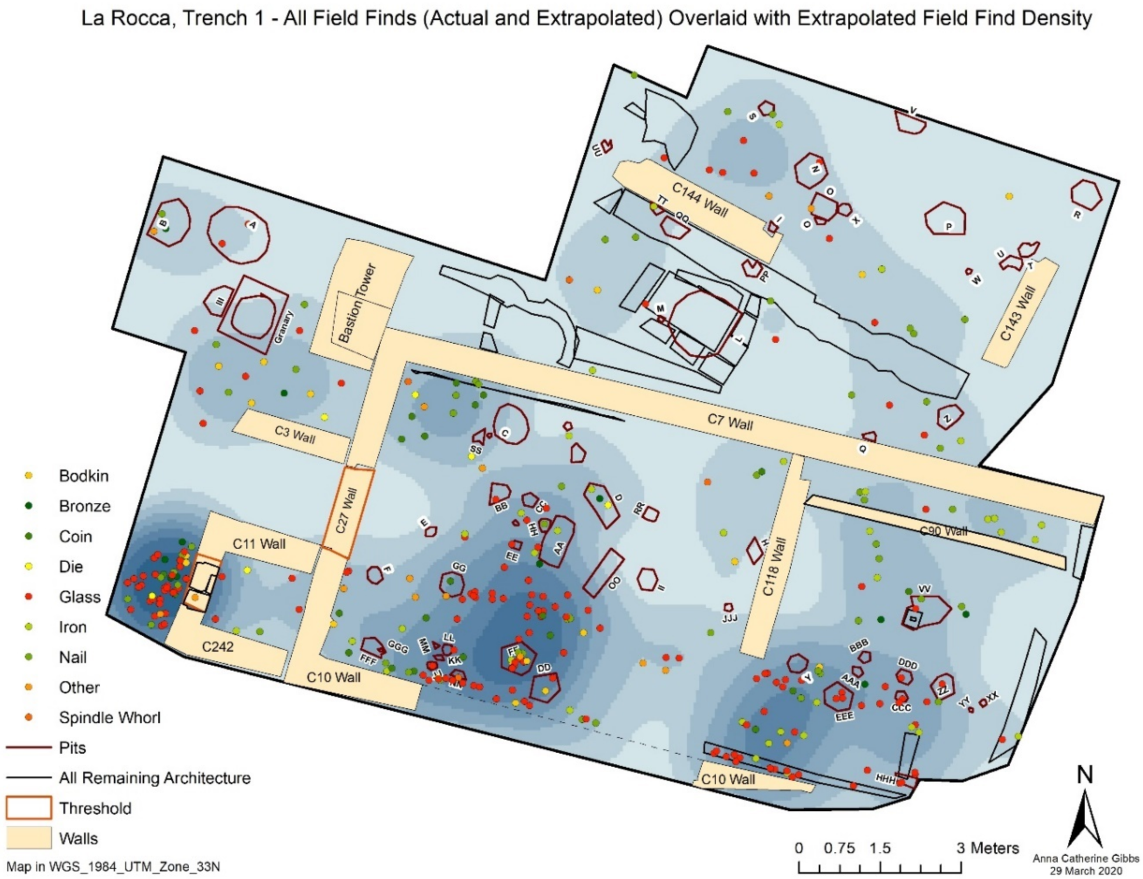


Figure 12: Merged actual and extrapolated field find density over a merged field find density raster, illustrating the most accurate field find density.

The raster image beneath Figure 8 depicts the field find density of *only* the in-situ finds, therefore contrasting the lack of field find density in locales where extrapolated field finds have been added. Figure 9 integrates the extrapolated field finds in with the actual field finds and is overlaid with an updated field find density raster, providing the most accurate and to-date depiction of field find data for the San Giuliano fortification.

In addition to extrapolating the missing field find data for Trench 1, I created additional attribute fields to quantify the characteristics of the artifacts. The Grouping Analysis tool functions by running a statistical equation on selected fields of point data, and produces optimal groupings based upon similar fields, factoring in both attribute and location of the points. In order for this analysis to be run on the field find data, all physical attributes must be transitioned to numerical data. Additional fields were added for the physical attributes of Iron, Glass, Bronze, Bodkin Points, Coins, Dice, Spindle Whorls, and Nails, and then the spatial attributes of trench area and specific pit locale. While the Grouping Analysis tool runs a k-means function that inherently factors in point data proximity as a variable in creating cluster groups, Area is also added manually as a relevant field because many clear spatial divides exist with Trench 1 that would not be factored into the proximity analysis. The Area field is divided based upon clear spatial barriers such as walls and thresholds, in order to lessen the chance that finds would be grouped together based on proximity, while ignoring the clear spatial separation of a wall.

Table 1. Created fields for field find data, quantifying structural areas by regional separation (i.e. a different number for each area or pit), and quantifying artifact attributes by either the presence (1) or the absence (0) or a certain characteristic.

Area	1 – Exterior (west of C27)	4 – DAZO Interior (Small enclosure between C11 and C242)
	2 – Exterior (north of C7)	5 – EEEL Extension (Small enclosure between C118, C90 & C7)
	3 – Interior (east of C27)	6 – East LA (East of C118)
Pit	1 – A; 2 – B; 3 – D; 4 – N; 5 – O; 6 – AA; 7 – BB; 8 – DD; 9 – FF; 10 – GG; 11 – HH; 12 – JJ; 13 – NN; 14 – TT; 15 – VV; 16 – ZZ; 17 – CCC; 18 – DDD; 19 – EEE; 20 - HHH	
Iron	0 – General	1 – Iron
Glass	0 – General	1 – Glass
Bronze	0 – General	1 – Bronze
Bodkin Point	0 – General	1 – Bodkin Point
Coin	0 – General	1 – Coin
Die	0 – General	1 – Die
Spindle Whorl	0 – General	1 – Spindle Whorl
Nail	0 – General	1 - Nail

Table 1 provides a comprehensive table of all attribute to numerical value correlates. These numerical values are then able to be evaluated based on the presence, or absence of certain attributes and can be compared, contrasted, and grouped according to the most relevant similarities.

4.2 Cluster Analyses

The cluster analyses of the Trench 1 field finds were performed using a tool ArcGIS called Grouping Analysis. The Grouping Analysis feature requires the specification of a point layer to group, the selection of all relevant fields within that point layer, the aimed number of output groupings, and selected spatial constraints apply to the data. As expanded upon in Chapter 3, the Grouping Analysis feature is a k-means statistical function, that plugs the provided data into mathematical equations, factoring in the number of points, within a certain area, within a certain distance from neighboring points, and which points are characteristically similar. These variables produce optimal, but random groupings, that will also be slightly different with every random generation.

While this GIS tool was run several times in the interest of trial-and-error and attaining optimal results, for every test, two variables remained constant: the number of groups was always set to 6 and the option “No Spatial Constraint” was always selected. The selection of the number of groups for a cluster analysis is a challenge, and arguably, an arbitrary one, as you can select anywhere from 2 to 15 groups, or select the option to “Evaluate Optimal Number of Groups,” which automatically generates what s*hould* be the ideal number of groups for effective grouping. The challenge with this feature unfortunately, is “the tool will stop if division into additional groups becomes arbitrary” (*Grouping Analysis,* Pro.ArcGIS.com). Traditionally, this cluster analysis feature is applied to inter-site studies with fewer loci variables, and more dynamic distances, making this intra-site application experimental. The nature of the “Evaluate Optimal Number of Groups” feature means that the field find data being analyzed was not being effectively analyzed through optimized group number generation and needed a set number of groups to populate with data. Setting the standard of 6 cluster groupings allows for the number of available groupings to be one less than the input diagnostic fields. For this analysis, two different standards of the Grouping Analysis tool were run, one with a “No Distinction” standard, inputting and evaluating all ten of the possible attribute fields, and a "Type" standard, inputting only seven of the possible attribute fields. In both standards, however, the diagnostic fields available are Coins, Dice, Bodkin Points, Spindle Whorls, Nails, Bronze, and spatial Area. Pits, while relevant, do not appear to have a pattern of distinct clustering and Iron and Glass are found in such large quantities that their presence in a distribution analysis serves to simply dilute the more informative and rarer field finds. The elimination of Iron and Glass does not make the assertion that these find types are not conclusive, or even not evidently clustered, but that their *quantity* dilutes the test. This issue will also be addressed when considering the Grouping Analysis tool's potential shortcomings, as the ideal for this tool would be to thoughtfully include every field find, under the reality that every find bears weight in the material record and has consequence in how we interpret the data. However, because of the dilution issue, 6 cluster groups provide the necessity for discriminatory groupings, where not every field can be directly fed into a subsequent identical group, but distinctions are made between the optimally clustered characteristic, whether it be a spatial connection, or a characteristic one.

The other variable when running the Grouping Analysis tool that served as an experimental constant was the selection of "No Spatial Constraint." Within the Grouping Analysis tool there are options to impose extra spatial constraints on your data, requiring certain proximity standards for data to be grouped together. The "No Spatial Constraint" option simply allows the awareness that some of the Trench 1 field find data will be spatially related over an indeterminate amount of distance, and allows for the location and attribute variables to weighted, not under requirements that may limit grouping options, but according to what grouping is optimal, even if two data points are not exactly proximal to one another In other words, it is better for points to be grouped together if their attribute similarities are more significant than their proximity, and not have proximity eliminate better groupings on arbitrary spatial requirements.

4.2.2 No Distinction in Artifact Cluster Analyses

The first standard for a cluster analysis on the field finds from Trench 1 was a "No Distinction" standard, meaning that every attribute field for field finds was included (all 10 fields from Table 1). A "No Distinction" standard allows for a baseline grouping, with every variable considered, so as analyses are streamlined and limited, a look-back comparison is available. Figure 10 below illustrates a "No Distinction," 6 group Grouping Analysis output.

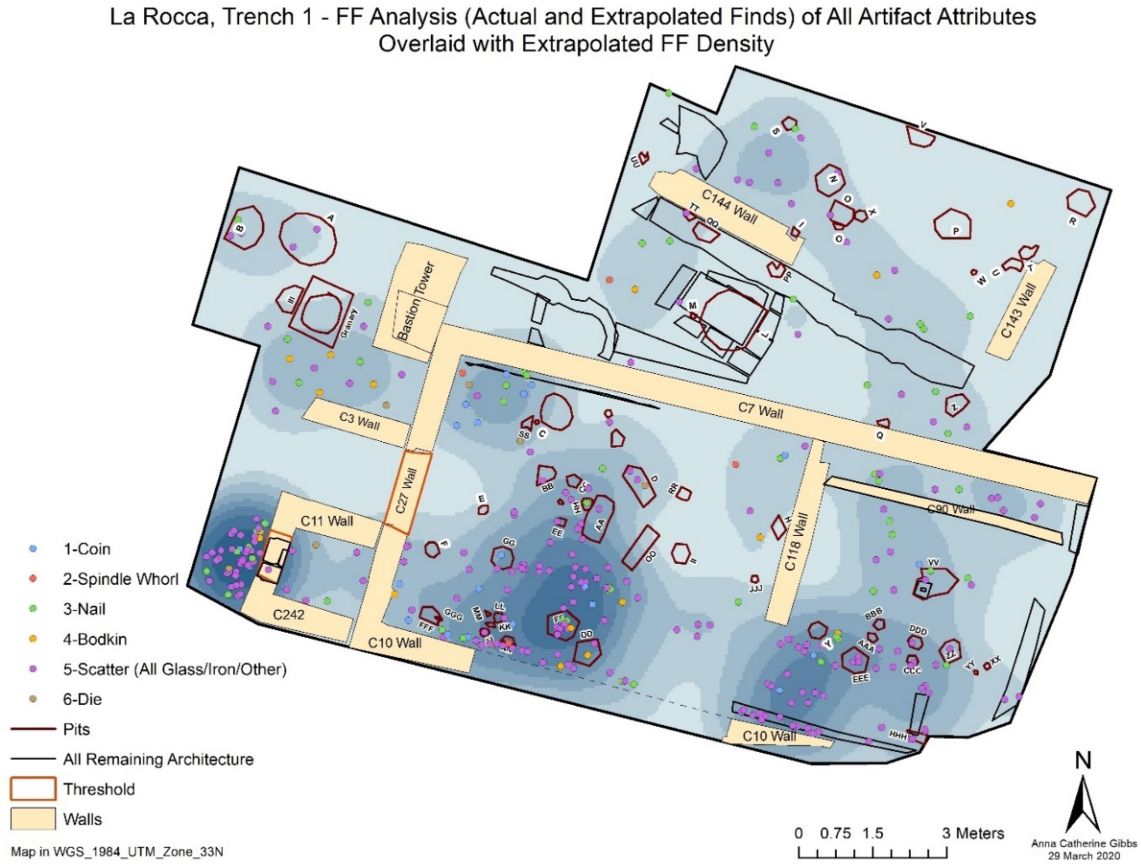


Figure 10: Results of Cluster Analysis with "No Distinction," factoring all 10 possible attribute fields into statistical analysis.

The most notable characteristics of this output are the isolated groups of *all* diagnostic field finds. Glass, Iron and Other artifacts (unidentified or unclassifiable) are all grouped together in a "scatter," despite their wide dispersal. This output can be interpreted as either: 1) the spatial and characteristic similarities between all other find types is too significant, making them *all* significantly distributed, or; 2) the Glass, Iron and Other field finds diluted the test results because they are so generally dispersed and in high quantities that creating effective groupings with the limited and similar diagnostic finds intermingled would be less optimal than arbitrarily grouping Glass, Iron and Other together. This indeterminate dichotomy between interpretative possibilities creates the need for a more discriminatory test, where Glass and Iron are not factored in as relevant fields, to better isolate the diagnostic finds, and determine whether they would still be grouped together, or if they get shuffled because of their non-significant distribution. This discriminatory test, however, does not remove all the known margins of error, and, does unfortunately create more blind spots. While Iron is a more ubiquitous find type, not just at San Giuliano but in all medieval sites, and can therefore be removed from the analysis without greatly affecting the characterization of the site, Glass is generally a prestige marker for sites and bears weight in how we interpret the data. The issue remains, however, that the Glass quantity, as exhibited in its classification as "scatter" in Figure 10 (and in numerous previously run cluster analyses throughout data analysis trial-and-error), numerically outweighs the other finds of interest. The issue is most likely related to each glass shard being marked as a point, therefore 157 glass shards would most likely correlate to half that many glass vessels but quantifying that would require more tests and a great deal of estimation.

4.2.3 Discriminatory Artifact Cluster Analysis

A discriminatory cluster analysis allows for an evaluation of the specific finds that are relevant to the study of distribution. To optimize the cluster analysis results, eliminating the sway of Glass and Iron fields narrows the fields of interest to diagnostic field finds or finds that have a lower quantity and therefore more information to be gleaned from the presence or lack thereof a statistically significant clustering. While Glass and Iron are fairly evenly distributed throughout the site and vastly outnumber the other finds, Coins, Dice, Bodkin Points, Bronze, Nails, and Spindle Whorls all could potentially inform the interpretation spatial usage in different areas of the site. Figure 11 below displays the discriminatory cluster analysis results according to desired type.

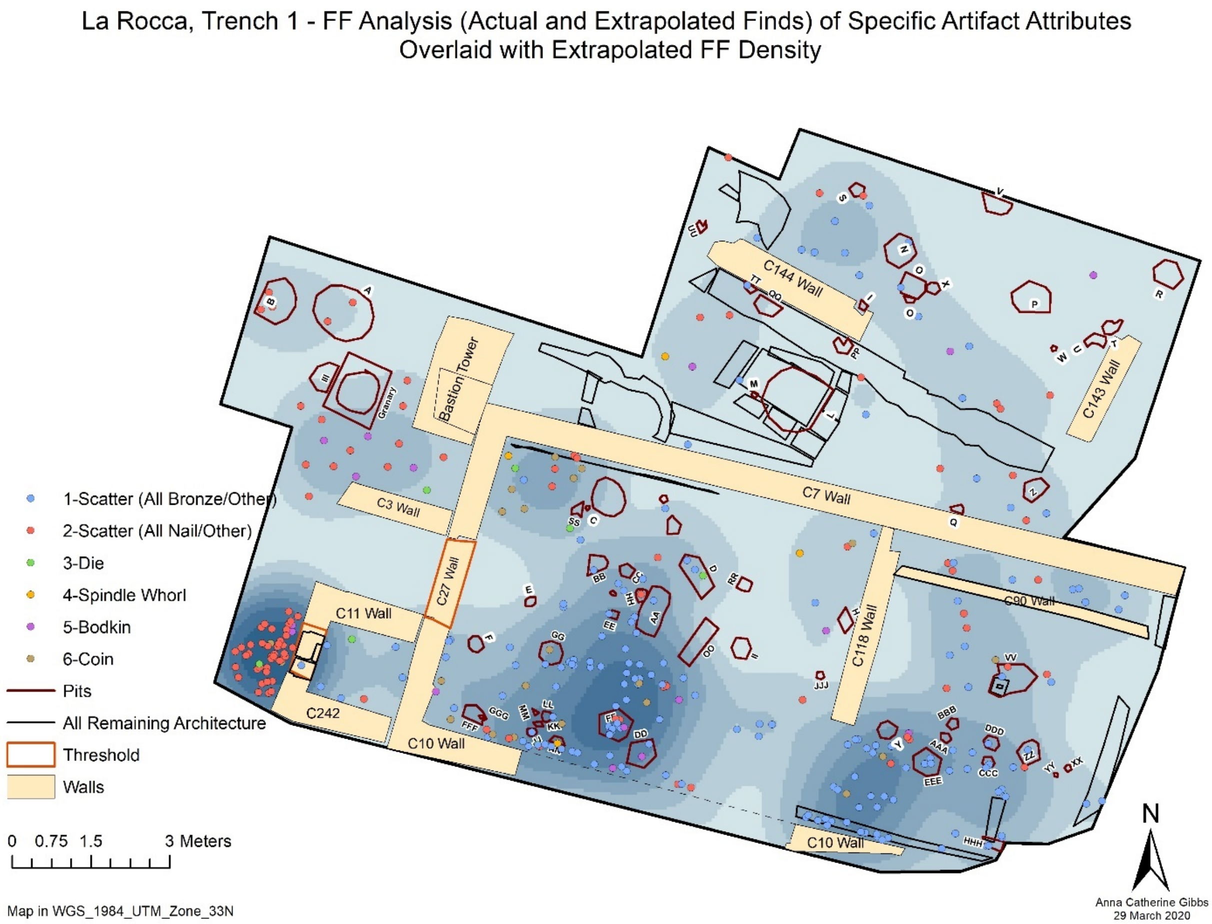


Figure 11: Results of "Discriminatory" Cluster Analysis, factoring all attribute fields but iron, glass, and pits to narrow the statistical analysis.

With Glass and Iron no longer being an influential factor in the outcome of created groups, the output now displays two groups of "scatter," as opposed to one, but Dice, Spindle Whorls, Bodkin Points and Coins are all still grouped together, in correlation with the "No Distinction" test run previously. The change is most notable in the fact that Nails are now classified in a "scatter" group, whereas in the previous test, they were isolated. By looking back at the Figure 9 map it is clear that spatially, the nail field finds have little in common and are dispersed very widely across Trench 1, similarly to their general Iron counterparts. Bronze is also classified in a “scatter” group, which is no change from the “No Distinction” test.

There are both observable and theoretical interpretations to be gleaned from these cluster analyses. Firstly, through both tests, coins, bodkin points, spindle whorls, and dice were clustered in their own groups. These consistent groupings indicate a statistically significant distribution, where attribute similarities within these find type groups outweigh any spatial disparities that might have led to their grouping dispersal. This grouping dispersal is then evidenced in the Nail group, where while the nails were previously grouped together in the “No Distinction” test, after the dilution of Glass and Iron fields were removed, the nails were then grouped in a “scatter” group, indicating that their attribute similarities were not statistically significant enough to outweigh their random spatial distribution.

4.2.4 Methodological Shortcomings

The challenge with the Grouping Analysis tool in ArcGIS is the reality that is most generally applied to inter-site analyses, not intra-site analyses. Despite producing and evaluating only two maps from two cluster analyses, this program can be run several times, in numerous different ways, to produce a plethora of outcomes. One of the greatest problems with the Grouping Analysis tool still rests on the ability to independently and arbitrarily select the number of output groups, in addition to the short-out of the “Evaluate Optimal Number of Groups” feature when the data becomes overwhelming. While personal knowledge and experience can optimally inform the decision for the number of groups, as is the case for logically selecting 6 output groups in this study, "user defined parameters such as *k* groups builds significant subjectivity into analysis" (Grubesic 2001:8). The mathematical and scientific standards for truly understanding how to effectively select the ideal number of grouping outputs is a challenge and can also not be resolved with the "Evaluate Optimal Number of Groups" feature, as clearly that has limits that were surpassed by the quantity and variability of intra-site field find data.

This feature also faced challenges with manipulating the variability in the natural groupings within the artifact data. The wide span of group size for different fields stretches from only 4 spindle whorls to 147 marked pieces of glass. These wide margins make fitting field find data to equal or diagnostically relevant groups a challenge. Generally, when applied to inter-site analyses, this function is applied to more uniform data, and analyzing one type of feature, with multiple variables. In the case of this study, when I use the term "variability" it essentially means, evaluating a wide variety of different features. For example, instead of analyzing many similar caves (the feature), each with different attributes (the variables), this study analyzes many different features in and of themselves (the artifacts acting as both the feature in question and the variables). This typological issue, while not a debilitating barrier in running this analysis, does put into question how effective this method is. While I do believe this study produced reliable clustering, once the glass and iron were removed, the issue remains that the glass and iron are relevant and ideally would not need to be removed. This also does not address the fact that I did not and cannot exhaust all trouble-shooting methods, and new ways of utilizing this tool may be available and useful.

4.3 The Kolmogorov-Smirnov Test

The Kolmogorov-Smirnov Test (as was described in detail in Chapter 3) is a goodness-of-fit test that allows for the empirical comparison of a set of known distributed data against an expected set of distributed data. Through the plotting of the comparative, cumulative distributions, and measuring the maximum difference between the two curves, the resultant difference, D_{max}, is then set against the critical value *d,* to determine whether to reject or fail to reject the null hypothesis. The first portion of this study is testing the distribution of Trench 1 as a whole, while the second portion is interested in specific types of field find distribution.

- H_0 – that the artifacts are distributed irrespective of the clear architectural boundaries of the site; and
- H_1 – that the artifacts are not distributed irrespective of the clear architectural boundaries of the site.

- H_0 – that *x* artifact type is distributed irrespective of the clear architectural boundaries of the site; and
- H_2 – that *x* artifact type is not distributed irrespective of the clear architectural boundaries of the site.

In ArcGIS this process is possible through the function "Create Random Points." This tool uses a randomly generated location selection system along variable *x* and *y* axes to meet a requested number of points. For the Kolmogorov-Smirnov test the recommended number of random points is three times the number of sample points, to effectively disperse the expected values and to achieve a distinct curve of comparative data, as the Kolmogorov-Smirnov test is a two-sample distribution test designed to compare two unequal samples. Within the "Create Random Points" tool the entire Trench

1 outline was selected as the extent for random point processing, to limit the expected distribution to the same spatial constraints as the comparative sample. After the random point field is generated to provide the expected values, the "Sample" tool in ArcGIS is used. The Sample tool produces a table of assigned numerical values according to the spatial distribution of both the sample and expected point values against the same kernel density raster. In mathematical terms, the sample point values (the actual field finds) are variable n, the expected point values (our randomly generated points) are variable m, and the greatest common divisor for both m and n is d, the kernel density raster. These produced numerical values that represent our field finds and random points are the datasets to be graphed and compared for the KS-test.

4.3.1 Total Trench Artifact Distribution

The first KS-test to be performed analyzed the 324 original field find points and the 972 expected points. Figure 12 shows the comparative output of original field finds to randomly generated ones.

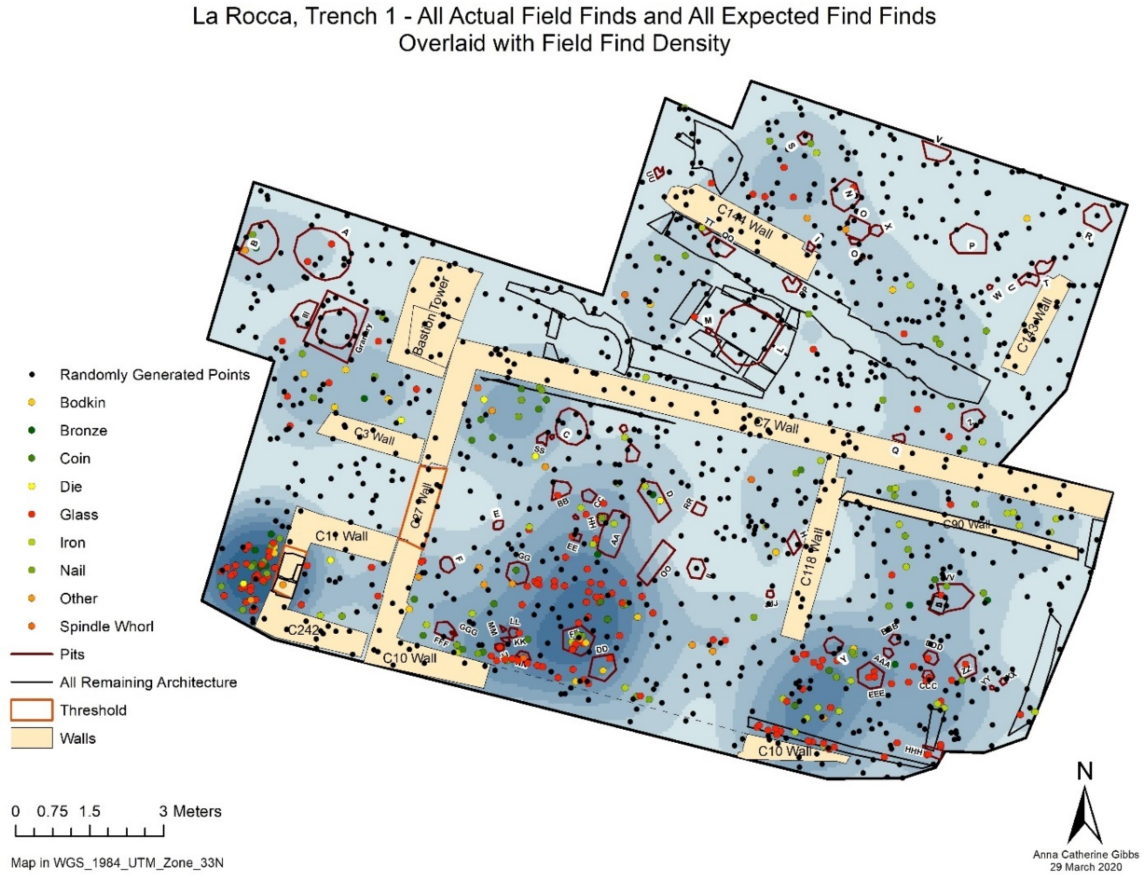


Figure 12: Results of a "Randomly Generated Points" field, overlaid with actual field finds and actual field find density, displaying a contrast between the actual and random distribution.

From this map it can already be observed that the randomly generated finds appear to be more evenly dispersed than the actual Trench 1 field find data, but by applying the KS-test to observe how that distribution fits into a mathematical model will be able to confirm or negate this hypothesis. The inputting of n = 324 points and m = 972 points into the KS-test formula and graphing the output produces Figure 13.

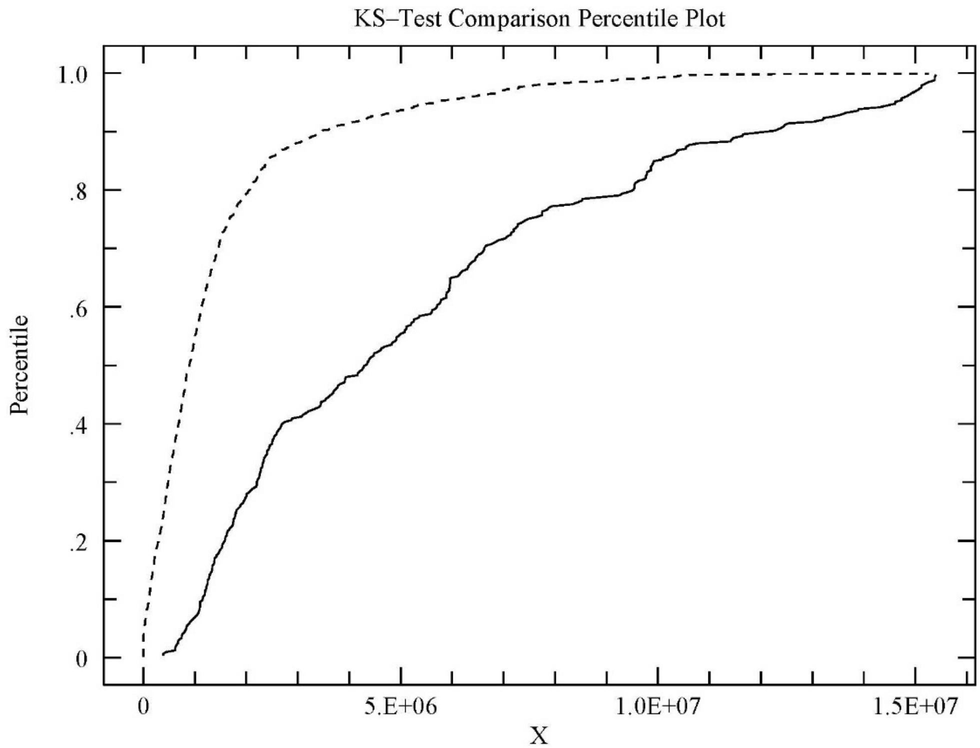


Figure 13: KS-Test for the Total Field Find Data in Trench 1: Solid curve – actual data, *n*; Dashed curve – extrapolated data, *m; x*-axis – dataset's numerical values, $\frac{n}{d}$ *and* $\frac{m}{d}$, *y*-axis – *D* values, probability of value occurrence.

The x-axis labeled "X," displays each data point's numerical value when calculated by dividing either their *n* or *m* value by the common divisor *d.* The y-axis labeled "Percentile" marks each data point's *D* value of probability, where the first data point for the sample field find data is $\frac{1}{324}$ and the last value for the sample field find data is $\frac{324}{324}$ or 1. The same *D* value system applies to the expected field find data, where the first value of that data set is $\frac{1}{972}$ and the last is $\frac{972}{972}$ or 1.

The statistical output for a total trench artifact distribution KS-test produced a measured D_{max} of .5388. The D_{max} is then set against the critical value, also denoted as *d,* to determine whether to reject or fail to reject our original H_0 – that the artifacts are distributed irrespective of the clear architectural boundaries of the site. Our critical value can be calculated by inputting *n* our value of 324 into the equation below:

$$d \approx \frac{1.3581}{\sqrt{n = 324}}$$

(Wheatley 1995: 174)

The resulting *d* critical value is .07545. The D_{max} exceeds the *d* critical value, meaning that the sample distribution is sufficiently different from the expected distribution, and H_0 may be rejected. The significance level, α, for determining the critical value, *d,* was .05, based upon the selected confidence interval of 95%. Therefore, we can be 95% confident that the artifacts are not distributed irrespective of the clear architectural boundaries of the site.

4.3.2 Bodkin Point Distribution

The next KS-test to be performed analyzed the 17 original field find points and the 51 expected points. Figure 14 shows the comparative output of original field finds to randomly generated ones. This map is isolated to the known sample bodkin points and the randomly generated expected bodkin points, overlaid on a bodkin point density raster.

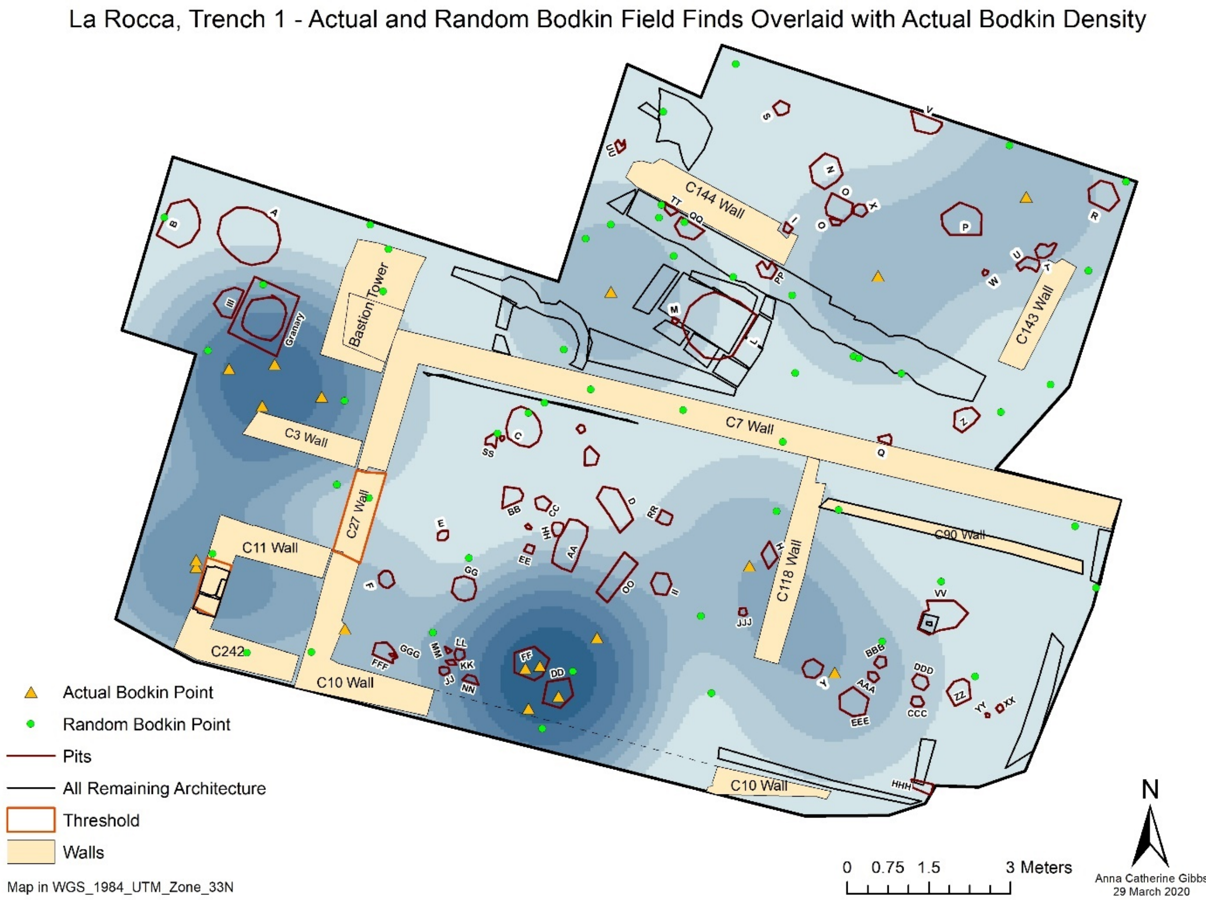


Figure 14: Results of a "Randomly Generated Bodkin Points" field, overlaid with actual bodkin finds and actual bodkin find density, displaying a contrast between the actual and random distribution.

Yet again, the assumption can be made that simply based on observation, the randomly distributed artifacts do not correlate well to the bodkin point hotspots and are more widely dispersed than the sample finds. However, the actual bodkin points do appear to have a fairly widespread scatter, so the KS-test will be able to provide numerical logic to the find distribution observations. Figure 15 below provides the output graph comparing the sample and the expected bodkin point curves.

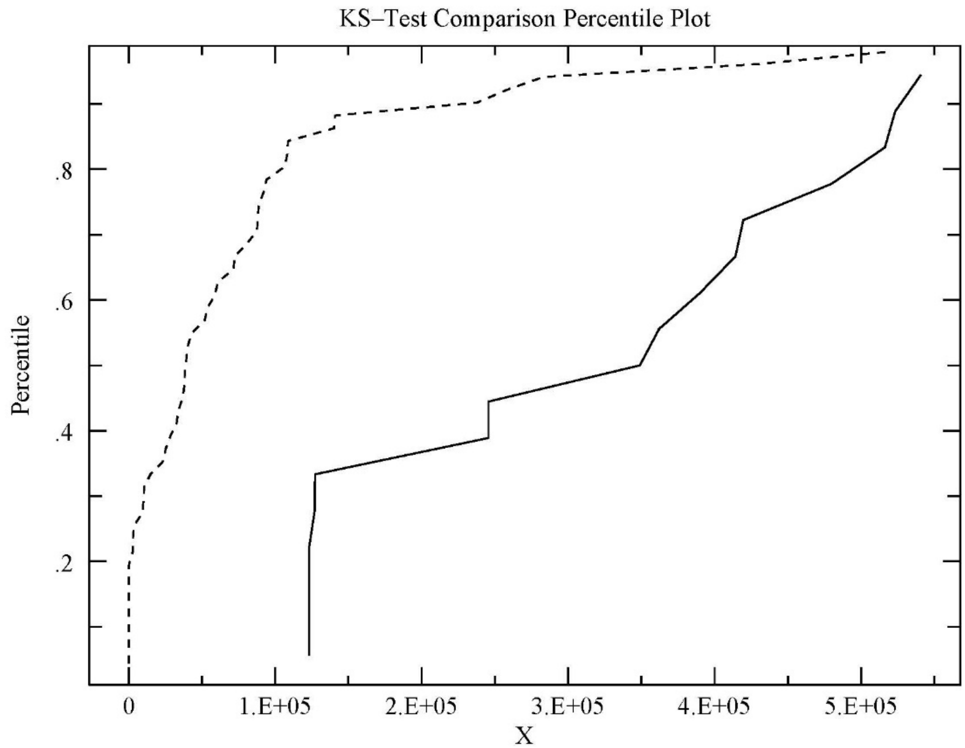


Figure 15: KS-Test for the Bodkin Point Field Find Data in Trench 1: Solid curve – actual data, *n*; Dashed curve – extrapolated data, *m; x*-axis – dataset's numerical values, $\frac{n}{d}$ *and* $\frac{m}{d}$, *y*-axis – *D* values, probability of value occurrence.

The x-axis labeled "X," and the y-axis labeled "Percentile" have the same functions as in the Fig. 13 graph, except that the values for the "Percentile" axis have changed from $\frac{1}{324}$ to $\frac{1}{17}$ for the sample values and $\frac{1}{972}$ changed to $\frac{1}{51}$ for the expected values. The x-axis still represents the numerical values $\frac{n}{d}$ and $\frac{m}{d}$, and the y-axis still displays the *D* values.

The statistical output for a bodkin point artifact distribution KS-test produced a measured D_{max} of .8600. The D_{max} is then once again set against the critical value, *d,* to determine whether to reject or fail to reject our second null hypothesis, regarding specific artifact distribution: H_0 – that *x* artifact type is distributed irrespective of the clear architectural boundaries of the site. Our critical value can be calculated by inputting *n* our value of 17 into the equation below:

$$d \approx \frac{1.3581}{\sqrt{n = 17}}$$

(Wheatley 1995: 174)

The resulting *d* critical value is .3294. The D_{max} exceeds the *d* critical value, meaning that the sample distribution is sufficiently different from the expected distribution, and H_0 may be rejected. As in the total artifact distribution KS-test, the significance level, α, for determining the critical value, *d,* was .05, based upon the selected confidence interval of 95%. Therefore, we can be 95% confident that the bodkin points are not distributed irrespective of the clear architectural boundaries of the site.

The conclusion that the bodkins are both clustered together and distributed according to the clear spatial boundaries of the site allows for some conclusions to be drawn about spatial utilization. While it does appear based upon Figure 14 that bodkin points are scattered in several different area classifications (Area 1, 2, 3 and 6), this dispersal does not negate a non-random distribution, as evidenced by the statistical results of the KS-test. Area 1 and Area 3 have bodkin points in prominent clusters, indicating regions of more significant usage. Furthermore, in contrast to other diagnostic field finds, that are most often clustered at within "interior" structures or at thresholds of interiors, bodkin points are scattered and clustered both in interiors and exteriors. This further confirms an understanding of "interior" and "exterior" at San Giuliano, as artifacts for defense would be utilized in more freely accessible, vulnerable spaces.

4.3.3 Coin Distribution

The last KS-test to be performed analyzed the 21 original coin field find points and the 63 expected points. Figure 12 shows the comparative output of original field finds to randomly generated ones. Because the coins are only found to be distributed within the interior and exterior west of C27 thresholds, the search area and density raster were executed slightly differently. Limiting the raster and the expected points to the clear observable boundaries of the coin distribution allows for a more useful model within the Trench 1 structure. Because it is more intuitively obvious that the coins are isolated to specific areas of the medieval fortification, investigating the distribution within these specific areas will more closely investigate the distribution within the higher density areas of the structure. Figure 16 displays the higher density areas factored into the coin distribution KS-test.

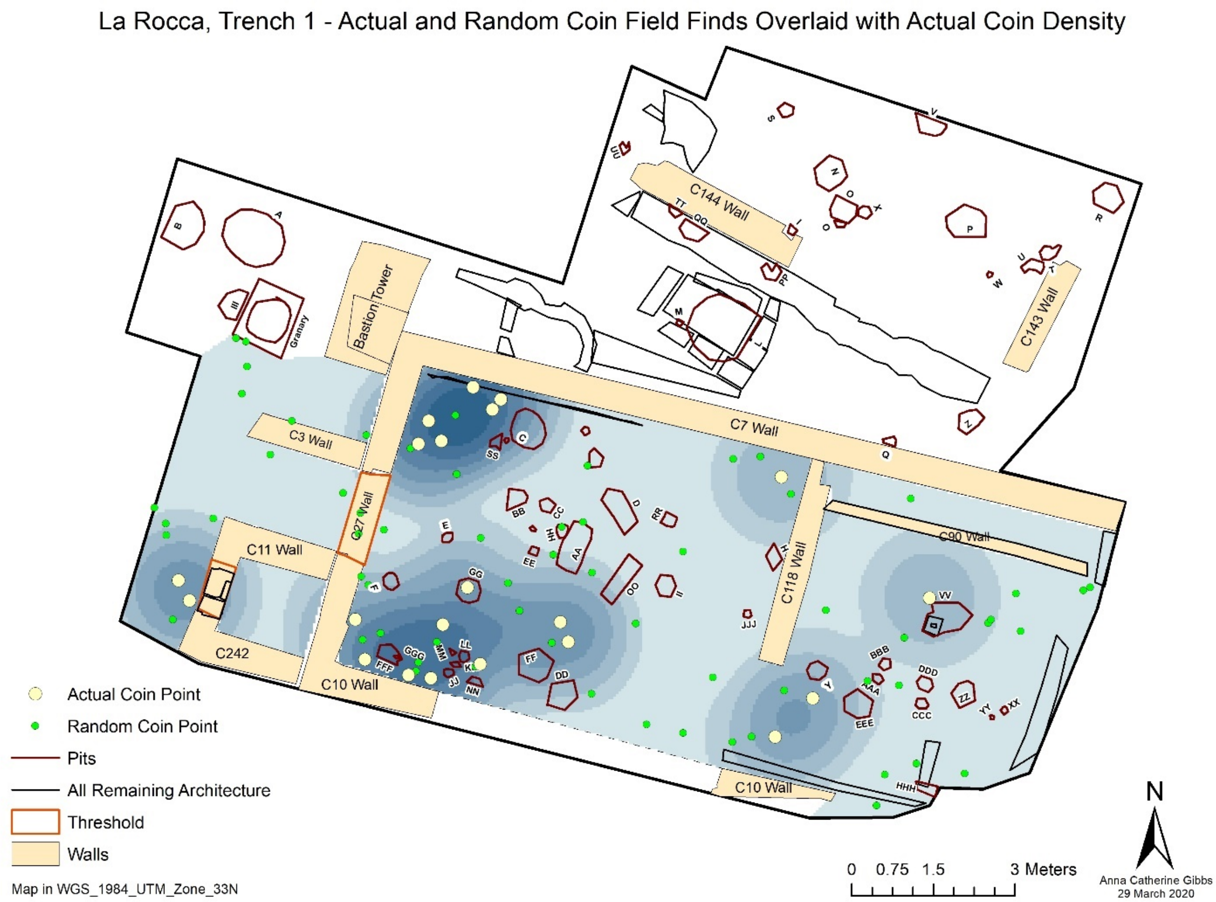


Figure 16: Results of a "Randomly Generated Coins" field, overlaid with actual coin finds and actual coin find density, displaying a contrast between the actual and random distribution. Analysis is isolated to areas of "high density" within Trench 1 to observe specific regions of density in more concentrated areas.

The high-density areas that were included in this map were selected based upon the comprisal of all the highest density hot spots in the total artifact kernel density raster. This narrowing of field find area will allow for a more precise understanding of not just whether artifacts are non-randomly distributed within all of Trench 1, which appears to have been confirmed by both previous KS-tests, but whether the distribution within the most concentrated areas is also random, or displaying a pattern. Figure 17 displays the graphed curves of both the sample and expected coin distributions.

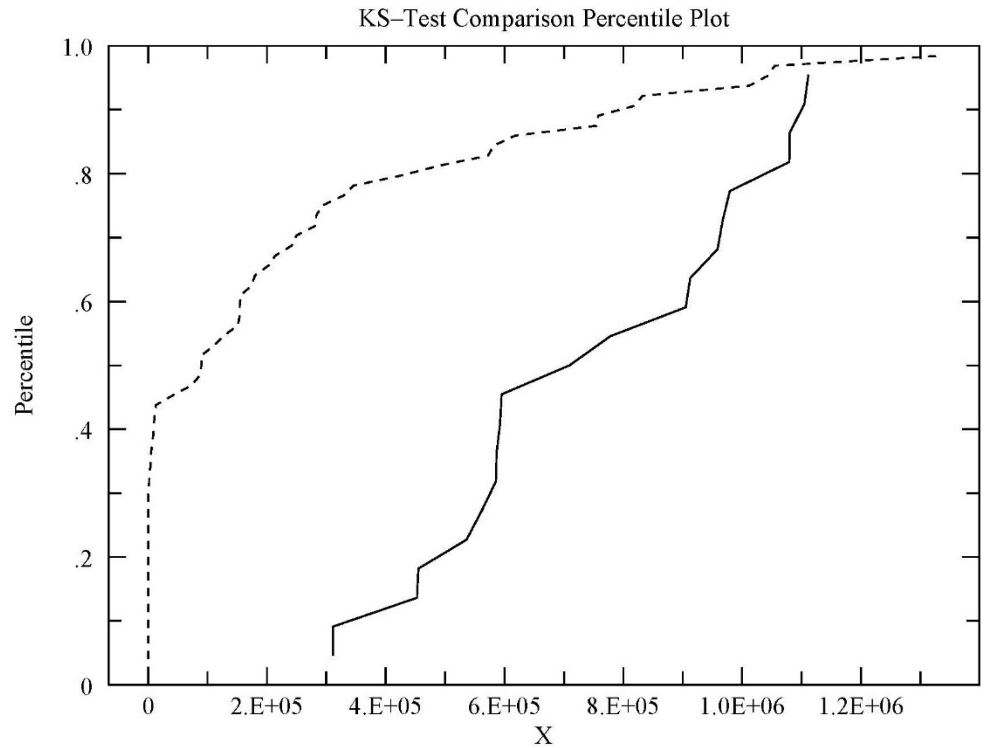


Figure 17, KS-Test for the Coin Field Find Data in Trench 1: Solid curve – actual data, *n*; Dashed curve – extrapolated data, *m; x*-axis – dataset's numerical values, $\frac{n}{d}$ *and* $\frac{m}{d}$, *y*-axis – *D* values, probability of value occurrence.

The x-axis labeled "X," and the y-axis labeled "Percentile" have the same functions as in both the Figures 13 and 15 graphs, except that the values for the "Percentile" axis have changed from are now $\frac{1}{21}$ for the sample values and $\frac{1}{63}$ for the expected values. The x-axis still represents the numerical values $\frac{n}{d}$ and $\frac{m}{d}$, and the y-axis still displays the *D* values.

The statistical output for this coin artifact distribution KS-test produced a measured D_{max} of .7619. The D_{max} is then once again set against the critical value, *d,* to determine whether to reject or fail to reject our second null hypothesis, regarding specific artifact distribution: H_0 – that *x* artifact type is distributed irrespective of the clear architectural boundaries of the site. Our critical value can be calculated by inputting *n* our value of 21 into the equation below:

$$d \approx \frac{1.3581}{\sqrt{n = 21}}$$

(Wheatley 1995: 174)

The resulting *d* critical value is .2964. The D_{max} exceeds the *d* critical value, meaning that the sample distribution is sufficiently different from the expected distribution, and H_0 may be rejected. Once again, the significance level, α, for determining the critical value, *d,* was .05, based upon the selected confidence interval of 95%. Therefore, we can be 95% confident that the coins are not distributed irrespective of the clear architectural boundaries of the site. While this test has slightly different spatial constraints than the previous two KS-tests, the results remain similar, indicating that even within the high-density areas, there is a non-random distribution of coins, and potentially other artifacts.

The Coin distribution in this test and in the cluster analysis, evidences a clear and interpretable level of non-random dispersal. The ability to conduct this test isolated to "high density" areas of the site already makes the assertion that the coin distribution is patterned and limited to areas that appear to be high-traffic and highly defensible regions. In addition to being isolated to interiors and thresholds, the coins also appear to be most densely clustered in the western corners of the interior, indicating that there were specific areas within the main structure were coins were used more frequently. The KS-test deemed coins to not be distributed irrespective of clear spatial boundaries within the "high-density" area of Trench 1, but with the foundational principle of a smaller test-extent, these clustered corners are proved to be not just observable, but statistically relevant.

4.4 Application of Theory

By applying archaeological theory to all of these statistical results, more concrete conclusions can be drawn, not just over what is or is not statistically significant, but over what interpretations may be drawn concerning human use of space and object find locations, connecting the inanimate with the animate. Both the hotspots and clusters analyzed in section 2 of this chapter and the KS-tests run in section three reveal data that is best correlated with spatial usage through the archaeological theory of Behavioral Archaeology. Behavioral Archaeology allows for a connection between observable patterns in the material record and assumptions about how that might be produced by human behavior, functioning through a type of "null hypothesis: a behavioral generalization specifies how we think behavior works" (LaMotta 2012: 66). This theoretical framework supports intuitive observations of an archaeological site, such as observing artifact deposition patterns where assumptions may be easy to draw, but verification can further the archaeological investigation. The null hypothesis provides a deductive method, avoiding inductively fitting data to an assumption, but simply working to "formulate generalizations that codify our assumptions and our provisional knowledge about behavior, as tools for determining if, and to what extent, specific instances of past behavior deviate from our expectations" (LaMotta 2012: 66). This framework is clearly effective in the case of statistical tests where null hypotheses are literally part of the process, as seen in the KS-test. The two null hypotheses in those tests were: 1) H_0 – that the artifacts are distributed irrespective of the clear architectural boundaries of the site; and 2) H_0 – that x artifact type is distributed irrespective of the clear architectural boundaries of the site. While these null hypotheses are not serving to conclusively prove the who, what, when, why how of Trench 1, they do offer insight into the scientifically deductive process of understanding cultural deposition and how things accumulated. By comparing what a random distribution of artifact scatter, it becomes clear that the artifact scatter provided in the San Giuliano fortification was not random. Even within the non-random areas of the fortification, it became clear in the coin KS-test that artifact distribution was significant.

Another theory purported by Behavioral Archaeology is the McKellar Principle. The McKellar Principle is useful in interpreting activity-area based on artifact distribution and suggests that evidence of activity is more likely to be found on high activity surfaces in the form of small items (LaMotta 212: 81). In general, the theory argues that items are dropped or discarded during activity, and if they are small, they remain where they were left. All of the finds of interest, especially finds noted as more diagnostic, in this study – coins, dice, bodkin points, and spindle whorls – are small, easily discarded finds. The McKellar principle is supported both in the cluster analyses results and the KS-test results. Both these studies support the findings that finds are non-randomly distributed, as found in the fact that coins, dice, bodkin points, and spindle whorls were repeatedly clustered together in the Grouping Analysis tool, and in the rejection of the null hypotheses in the KS-tests.

Lastly when interpreting the statistical results provided from these tests, simply observing patterns and applying context can present possible spatial function. As mentioned before, coins and dice are always clustered in their own groups in the cluster analyses outputs, are spatially isolated to high-density area interiors and thresholds, and coins were deemed non-randomly distributed by the KS-test. Furthermore, upon examining coin and dice clusters in relation to one another, both are often clustered in similar locales. At this time, gambling was a well-practiced activity for medieval Italians, evidenced in a business contract in 1403 drawn in Padua, Italy, stipulating the "exclusive supply of all […] ready-to-use gambling dice" (Pigozzo 173). Art at this time also depicted gambling seen in a piece from 1283 at the Library of the Monasterio de El Escorial (Figure 18). The painting illustrates workers squaring bone, slicing bone, sanding the bone, and drilling the circular marks onto each face of the cubic dice.

Figure 18, Painting of Die Production from: Pigozzo, Federico. The manufacturing of playing dice at the end of the Middle Ages. *Ludica* 17-18: 2011-12. Pp. 174.

The gambler in this painting is shown to be naked and disheveled, symbolically marking him as the dishonest individual (Pigozzo 2011: 174). With knowledge that dice were being made specifically for the function of gambling and their spatial correlation within the San Giuliano fortification, this model of space is well within the realm of possibility.

4.4 Future Analysis

Overall, the application of inter-site statistical analyses to intra-site studies does come with certain difficulties. As seen in the arbitrary groupings on the cluster analysis, and the inability to evaluate such small groups as dice and spindle whorls with the KS-test. Ideally in the future, the KS-test may be effectively applied to all find groups to better analyze the relationship between the wide variety of field find types. Furthermore, tests that can manage the dilution effect of glass and iron field finds would allow for a more holistic picture of how field finds are in relationship within the fortification, because while their dispersal may seem arbitrary, glass and iron were found in the same contexts and were utilized in large quantities, arguably making them just as relevant, if not more so, to coins, dice, bodkin points and spindle whorls.

CHAPTER FIVE

Conclusions

The understanding of "space" on the San Giuliano plateau requires a connection between the observable material record and the human agency that led to its deposition. Inherent in these archaeological remains is a culture that orders the resultant data. Through understanding the spatial layout of the San Giuliano fortification as rational constraints on the dispersal and clustering of the collected field finds, an interpretative framework for the statistical significance of distributed data can be accessed. The spatial layout of the fort - walls, thresholds, and structures – indicate spatial boundaries that limit and define how field find data is studied and understood.

The field find data was statistically analyzed according to these spatial boundaries and was found to be significantly distributed in diagnostic artifact clusters, non-diagnostic artifact dispersal, and clustered in the main structure interior. All of these likely clusters and densities indicate "high-traffic" areas within the site, where because of the dense deposits of agent-objects: coins, dice, bodkin points and spindle whorls, the space acted as a social setting. The frequency and density of individual artifacts, in tandem with Behavioral Archaeology's principle of small discarded objects remaining in their place of original abandonment, points toward a region of high social interaction and persistent usage, isolated to the areas of high artifact density.

The statistically significant material record also correlates with the supposed system of the *incastellamento* process, where large populations shift from high levels of dispersal to dense concentration within defensible sites, as seen in the heavily fortified San Giuliano fortress. The social transformation and political transitioning of the Italian landscape at this time connects well with the indication that even within the fortress, interaction was isolated within the most central and defensible portions, with little to no artifact density or key diagnostic finds in the exterior areas or outskirts of the fort. This concentration shows an extreme non-random favoring of secure centralized locales, signaling a high priority on spatial isolation but social collectivity.

Using key markers of space to understand the fragmented nature of the material record presents a rational framework for observing seemingly miscellaneous and randomly distributed artifacts by their spatial similarities. It also allows for a method of connecting theories of "place" and "space," as place simply defines a "spot in which something is located," while space "refers to the physical reality of where things are not located" and the implicit human element of activity and meaning imbued in a locale (Orser 1996: 136). By using an understanding of "place," as in where artifacts are, and connecting that to an understanding of "space," as in where things are situated socially, naturally, and historically.

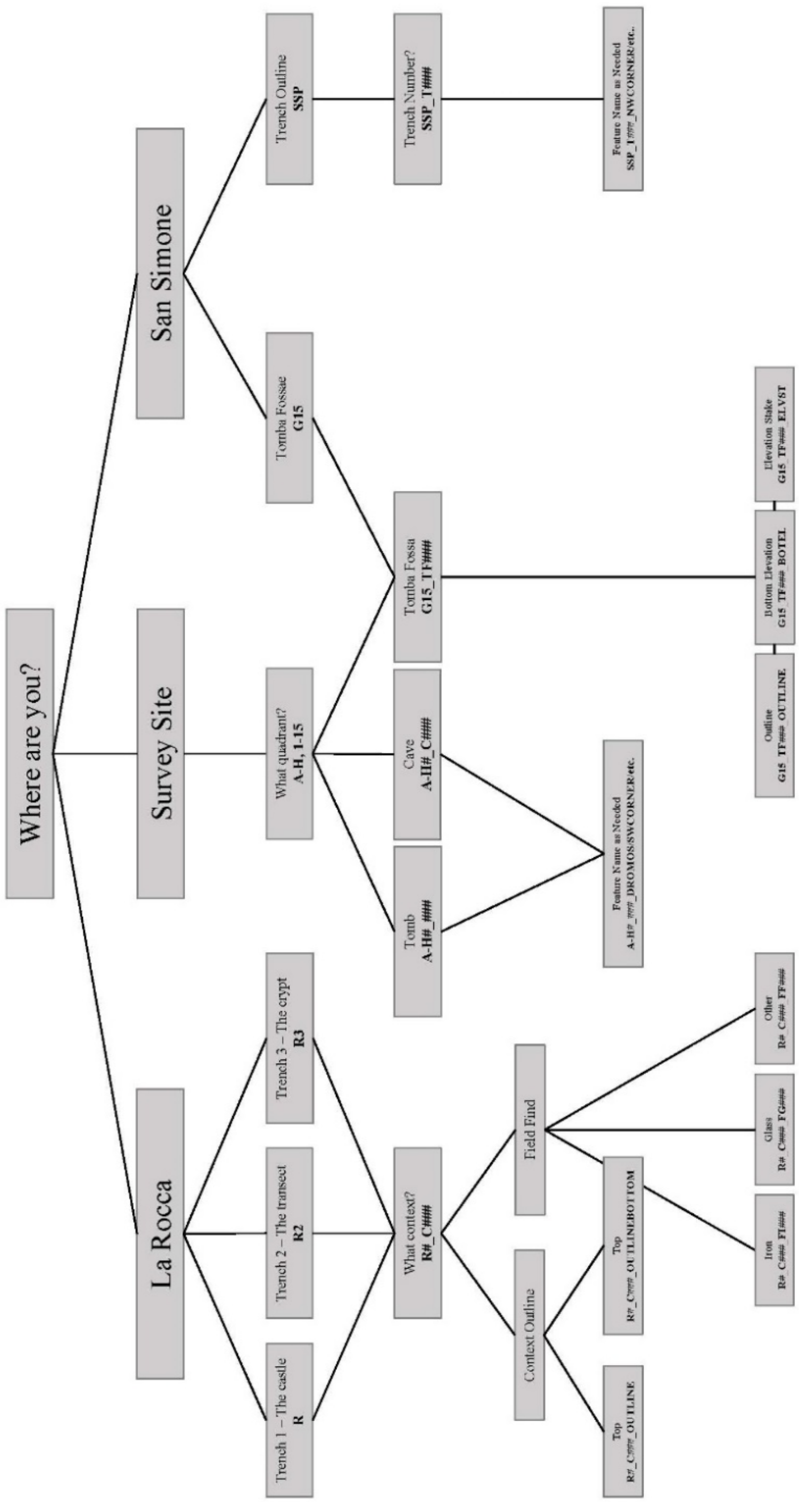
These investigations will become effective with increased excavation of the site. For items such as spindle whorls and dice, which have been found in very low quantities, their clustering and dispersal is hard to quantify, because low quantities correlates to low likelihood of patterning. In the future, ideally more diagnostic artifact types may become available to identify patterns and solidify observed significance.

In addition, observing concrete artifact relationships may expand and deepen an understanding of how artifacts are distributed throughout space. While it appears that patterns do arise from understanding field finds as isolated entities, utilizing a taxonomy coined by Maria Zendeño may allow for enriched understanding of artifacts. Zendeño (2009:419) suggests that “a critical element of artifact classification […] is the focus on sets of objects rather on single artifact classes or types.” It would be interesting to apply this concept to the Grouping Analysis feature by creating fields where artifacts areas are evaluated by their union with another type of find, for instance, quantifying the areas where coins are within a meter of dice, or bodkin points are within a meter of miscellaneous iron. This analysis would go beyond the initial investigation of whether or not artifacts are statistically significantly clustered with each other and within key structures and would begin to investigate the likelihood that artifacts are consistently in relationship with other types, identifying relational patterns within artifact clusters, and not just between them.

APPENDICES

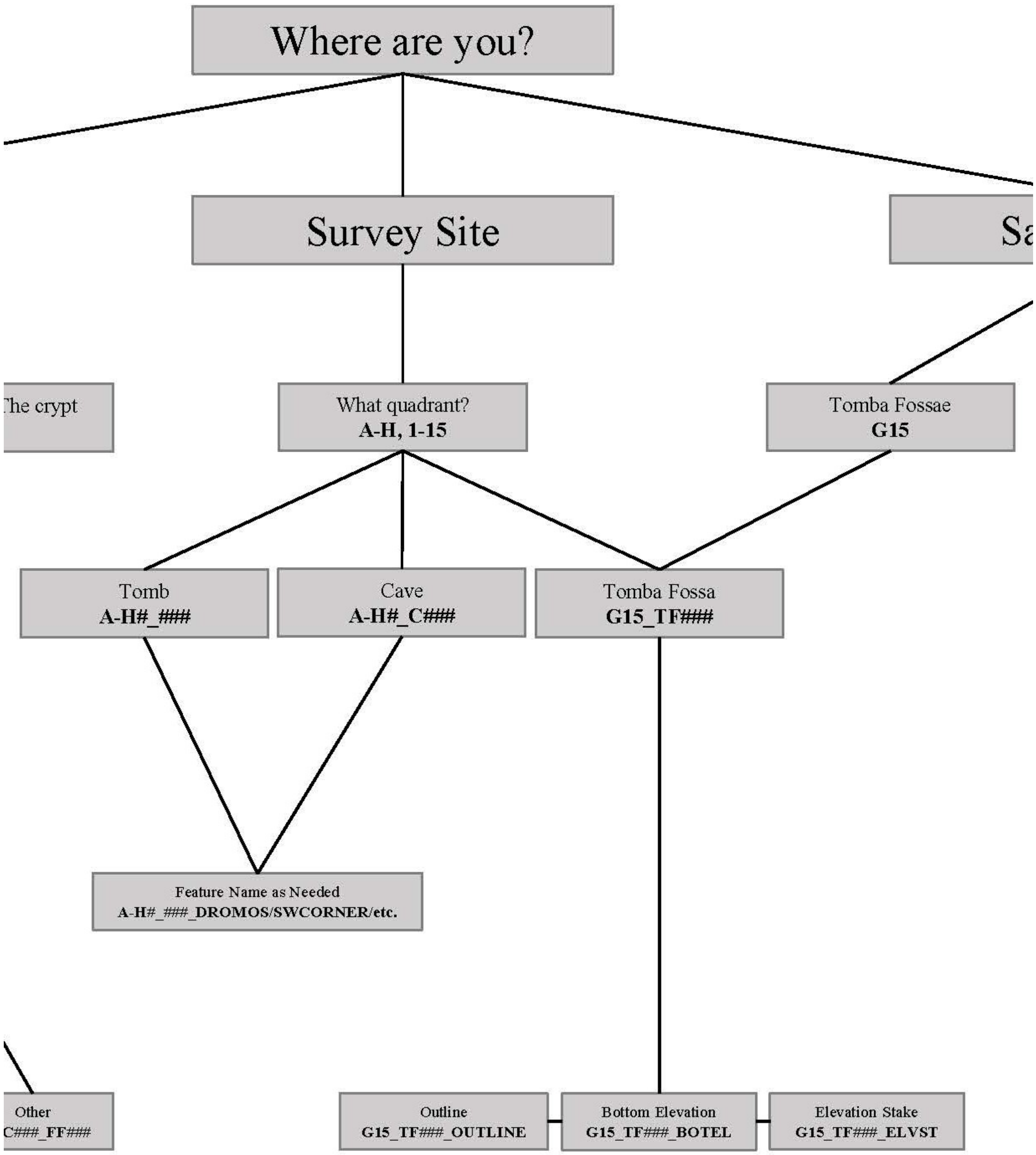
APPENDIX A

Full Flow Chart for Determining In-Field Nomenclature for Total Station Point Data



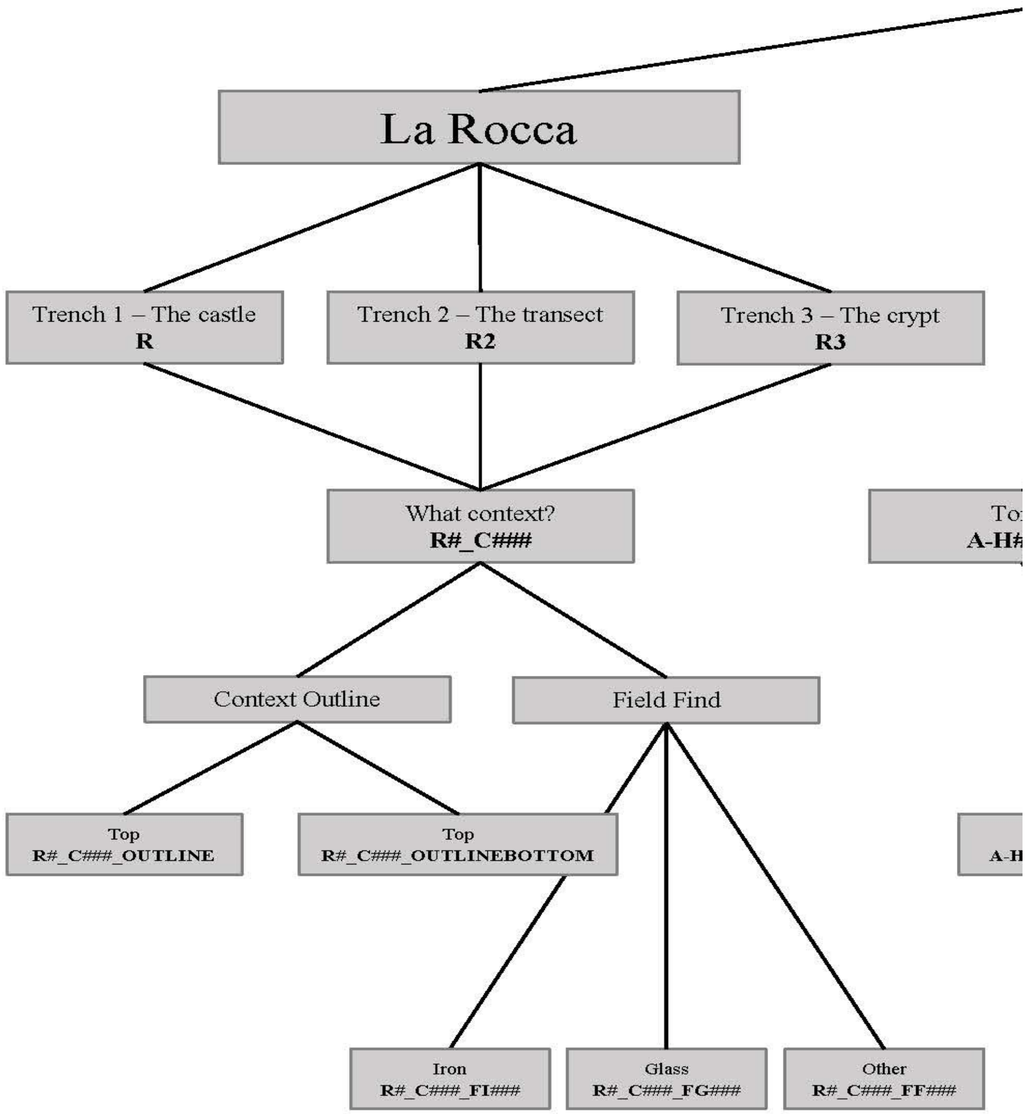
APPENDIX B

Part 1: Center Panel of Flow Chart for Determining In-Field Nomenclature for Total Station Point Data



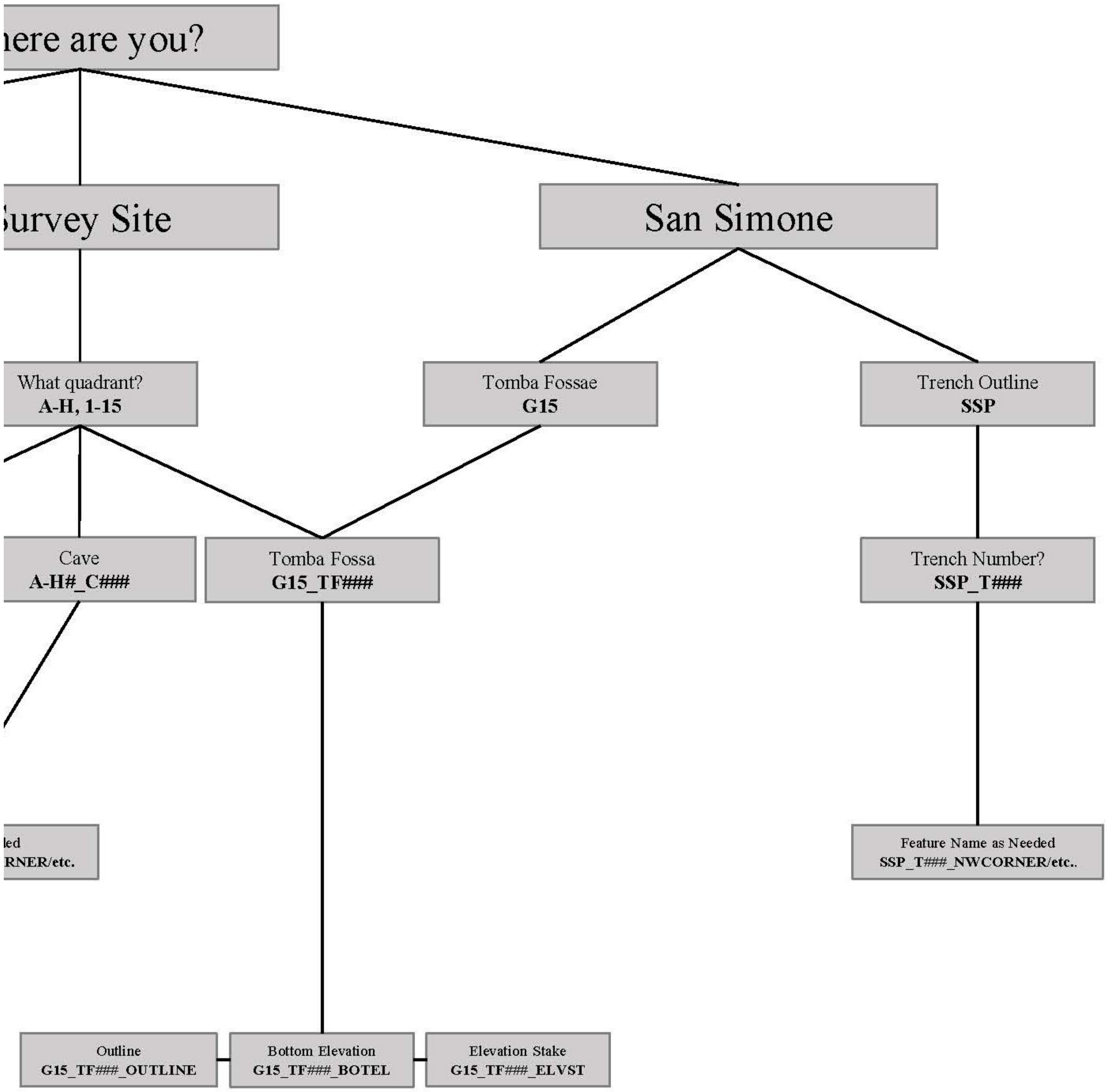
APPENDIX C

Part 2: Left Panel of Flow Chart for Determining In-Field Nomenclature for Total Station Point Data



APPENDIX D

Part 3: Right Panel of Flow Chart for Determining In-Field Nomenclature for Total Station Point Data



APPENDIX E

Full ArcGIS Attribute Table Depicting Complete Selection of Field Find Attributes

Table

In Situ Field Finds

Shape *	Field1	Field2	Field3	Field4	Field5	Uniform_Nomenclature	UniqueID	Description	ShortType	Nail	Bodkin	Bronze	Iron	Glass	Coin	Dice	Whorl	Pits	Area
Point Z	SS2909	4682779.4292	258957.3543	395.2455	R_C246_FI539	R_C246_FI539	539	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	1
Point Z	SS1320	4682788.4688	258968.4758	395.8666	R_C156_FG356	R_C155_FI356	356	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	2
Point Z	SS1843	4682781.2667	258971.0082	395.1532	R_C212_FI458	R_C212_FI458	458	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	5
Point Z	SS1808	4682781.0952	258972.6401	395.1325	R_C212_FI455	R_C212_FI455	455	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	5
Point Z	SS1805	4682781.4106	258970.9245	395.1799	R_C212_FI453	R_C212_FI453	453	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	5
Point Z	SS1584	4682784.4539	258971.8514	395.5224	R_C176_FI420	R_C176_FI420	420	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	2
Point Z	SS1583	4682784.3514	258971.9237	395.5607	R_C176_FI418	R_C176_FI418	418	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	2
Point Z	SS1429	4682780.1765	258971.2796	395.1047	R_C165_FI390	R_C165_FI390	390	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	6
Point Z	SS1428	4682780.4517	258971.2254	395.1004	R_C165_FI389	R_C165_FI389	389	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	6
Point Z	SS1241	4682785.4475	258970.9671	395.876	R_C148_FI307	R_C148_FI307	307	Iron Bodkin Point	Bodkin	0	1	0	1	0	0	0	0	0	2
Point Z	SS1178	4682783.2129	258970.7698	396.1218	R_C142_FI290	R_C142_FI290	290	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	2
Point Z	SS1147	4682784.6146	258972.8664	396.1849	R_C139_FI281	R_C139_FI281	281	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	2
Point Z	SS1806	4682781.4179	258971.0271	395.1841	R_C212_FI452	R_C212_FI452	452	Iron Horse Shoe	Iron	0	0	0	1	0	0	0	0	0	5
Point Z	SS1477	4682785.545	258971.3272	395.5987	R_C162_FI383	R_C162_FI383	383	Iron Artifact	Iron	0	0	0	1	0	0	0	0	0	2
Point Z	SS1809	4682780.9097	258973.2964	395.1943	R_C212_FI448	R_C204_FI448	448	Iron Spike	Iron	0	0	0	1	0	0	0	0	0	5
Point Z	SS1810	4682780.6666	258973.5413	395.1735	R_C212_FI447	R_C204_FI447	447	Iron Strap	Iron	0	0	0	1	0	0	0	0	0	5
Point Z	SS1596	4682788.4207	258969.3083	395.632	R_C180_FI412	R_C180_FI412	412	Iron Nail Head	Nail	1	0	0	1	0	0	0	0	0	2
Point Z	SS1595	4682788.2321	258969.4237	395.6116	R_C180_FI411	R_C180_FI411	411	Iron Bar	Iron	0	0	0	1	0	0	0	0	0	2
Point Z	SS1427	4682779.8264	258971.2419	395.1263	R_C165_FI388	R_C165_FI388	388	Iron Ring	Iron	0	0	0	1	0	0	0	0	0	6
Point Z	SS1426	4682780.6874	258971.1063	395.1096	R_C165_FI385	R_C165_FI385	385	Iron Artifact	Iron	0	0	0	1	0	0	0	0	0	6
Point Z	SS1807	4682781.0915	258972.1467	395.1684	R_C212_FG454	R_C212_FG454	454	Glass Shard	Glass	0	0	0	0	1	0	0	0	0	5
Point Z	SS1412	4682778.05	258969.2101	395.1605	R_C161_FF376	R_C161_FG376	376	Glass Shard	Glass	0	0	0	0	1	0	0	0	0	6
Point Z	SS1411	4682777.9534	258969.0108	395.1321	R_C161_FF374	R_C161_FG374	374	Glass Shard	Glass	0	0	0	0	1	0	0	0	0	6
Point Z	SS1424	4682784.5565	258971.2007	395.5958	R_C162_FG369	R_C162_FG369	369	Glass Shard	Glass	0	0	0	0	1	0	0	0	0	2
Point Z	SS1403	4682777.7978	258969.4954	395.1425	R_C161_FG355	R_C161_FG355	355	Glass Shard w353	Glass	0	0	0	0	1	0	0	0	0	6
Point Z	SS1402	4682777.8849	258969.3738	395.1458	R_C161_FG354	R_C161_FG354	354	Glass Shard	Glass	0	0	0	0	1	0	0	0	0	6
Point Z	SS1401	4682777.9353	258969.5447	395.1131	R_C161_FG353	R_C161_FG353	353	Glass Shard w355	Glass	0	0	0	0	1	0	0	0	0	6
Point Z	SS1347	4682787.9325	258968.7674	395.7232	R_C156_FG348	R_C156_FG348	348	Glass Shard	Glass	0	0	0	0	1	0	0	0	0	2
Point Z	SS1346	4682787.3873	258968.1348	395.7172	R_C156_FG347	R_C156_FG347	347	Glass Shard	Glass	0	0	0	0	1	0	0	0	0	2
Point Z	SS1301	4682783.0243	258971.4697	395.8065	R_C153_FG317	R_C153_FG317	317	Glass Body Shard	Glass	0	0	0	0	1	0	0	0	0	2
Point Z	SS1267	4682787.3277	258968.9585	396.0222	R_C148_FG312	R_C148_FG312	312	Glass Handle	Glass	0	0	0	0	1	0	0	0	0	2
Point Z	SS1266	4682787.3386	258968.3797	396.0446	R_C148_FG311	R_C148_FG311	311	Glass Body Shard	Glass	0	0	0	0	1	0	0	0	0	2
Point Z	SS1263	4682778.0473	258969.1608	395.4246	R_C151_FG308	R_C151_FG308	308	Glass Shard	Glass	0	0	0	0	1	0	0	0	0	6
Point Z	SS1197	4682787.5257	258970.1719	396.1462	R_C148_FG303	R_C148_FG303	303	Glass Rim	Glass	0	0	0	0	1	0	0	0	4	2
Point Z	SS1177	4682784.2434	258969.3609	396.0707	R_C142_FG291	R_C142_FG291	291	Glass Rim	Glass	0	0	0	0	1	0	0	0	0	2
Point Z	SS1179	4682786.1161	258970.3552	396.1448	R_C140_FG289	R_C140_FG289	289	Glass Rim	Glass	0	0	0	0	1	0	0	0	0	2
Point Z	SS1425	4682786.9025	258969.2356	395.6214	R_C162_FF370	R_C162_FF370	370	Rock	Other	0	0	0	0	0	0	0	0	0	2
Point Z	SS1345	4682786.8995	258973.6927	395.9456	R_C155_FF339	R_C155_FI339	339	Iron Bodkin Point	Bodkin	0	1	0	1	0	0	0	0	0	2
Point Z	SS1344	4682779.147	258972.8887	395.2441	R_C157_FF338	R_C157_FF338	338	Bronze	Bronze	0	0	1	0	0	0	0	0	0	6
Point Z	SS1265	4682786.6689	258970.0212	395.9194	R_C148_FF310	R_C148_FF310	310	Smooth Basalt Rock	Other	0	0	0	0	0	0	0	0	5	2
Point Z	SS118	4682786.3817	258959.5914	394.364	R_FF184C57glass	R_C57_FG184	184	Glass Stopper or Base	Glass	0	0	0	0	1	0	0	0	1	1
Point Z	SS117	4682786.0226	258959.1059	394.4049	R_FF183C53glass	R_C53_FG183	183	Glass Chalice	Glass	0	0	0	0	1	0	0	0	1	1
Point Z	SS339	4682784.9027	258966.949	395.665	R_C104_FF259_glass	R_C104_FG259	259	Large Piece of Glass	Glass	0	0	0	0	1	0	0	0	0	2
Point Z	SS270	4682779.9485	258961.4449	395.0517	FF250_C79_Glass	R_C79_FG250	250	Base of Glass Vessel	Glass	0	0	0	0	1	0	0	0	0	3
Point Z	SS214	4682778.0703	258962.5615	394.9455	R_C71_FF226_nail	R_C71_FI226	226	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	3
Point Z	SS217	4682783.2107	258963.4382	395.1823	R_C65_FF233_NAIL	R_C65_FI233	233	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	3
Point Z	SS651	4682781.7263	258969.0079	395.1632	R_C128_FF268_ironnail	R_C128_FI268	268	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	3
Point Z	SS323	4682786.5702	258957.9893	394.1102	FF_255_C88_iron_nail	R_C88_FI255	255	Iron Nail	Nail	1	0	0	1	0	0	0	0	2	1
Point Z	SS183	4682782.4558	258965.5341	395.349	R_C66_FF202_ironnail	R_C66_FI202	202	Iron Point	Iron	0	0	0	1	0	0	0	0	0	3
Point Z	SS187	4682781.5197	258965.3944	395.2647	R_C65_FF209_NAIL	R_C65_FI209	209	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	3
Point Z	SS188	4682783.4642	258963.8039	395.2536	R_C65_FF210_NAIL	R_C65_FI210	210	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	3
Point Z	SS185	4682782.8772	258963.3857	395.2303	R_C65_FF207_nail	R_C65_FI207	207	Iron Nail	Nail	1	0	0	1	0	0	0	0	0	3
Point Z	SS166	4682778.2402	258962.1341	395.0473	R_C66_FF197_nail	R_C66_FI197	197	Iron Nail T Shaped	Nail	1	0	0	1	0	0	0	0	0	3

1 (0 out of 302 Selected)

In Situ Field Finds

APPENDIX F

Part 1: Left Panel of ArcGIS Attribute Table Depicting Complete Selection of Field Find Attributes

Table

In Situ Field Finds

Shape *	Field1	Field2	Field3	Field4	Field5
Point Z	SS2909	4682779.4292	258957.3543	395.2455	R_C246_FI539
Point Z	SS1320	4682788.4688	258968.4758	395.8666	R_C156_FG356
Point Z	SS1843	4682781.2667	258971.0082	395.1532	R_C212_FI458
Point Z	SS1808	4682781.0952	258972.6401	395.1325	R_C212_FI455
Point Z	SS1805	4682781.4106	258970.9245	395.1799	R_C212_FI453
Point Z	SS1584	4682784.4539	258971.8514	395.5224	R_C176_FI420
Point Z	SS1583	4682784.3514	258971.9237	395.5607	R_C176_FI418
Point Z	SS1429	4682780.1765	258971.2796	395.1047	R_C165_FI390
Point Z	SS1428	4682780.4517	258971.2254	395.1004	R_C165_FI389
Point Z	SS1241	4682785.4475	258970.9671	395.876	R_C148_FI307
Point Z	SS1178	4682783.2129	258970.7698	396.1218	R_C142_FI290
Point Z	SS1147	4682784.6146	258972.8664	396.1849	R_C139_FI281
Point Z	SS1806	4682781.4179	258971.0271	395.1841	R_C212_FI452
Point Z	SS1477	4682785.545	258971.3272	395.5987	R_C162_FI383
Point Z	SS1809	4682780.9097	258973.2964	395.1943	R_C212_FI448
Point Z	SS1810	4682780.6666	258973.5413	395.1735	R_C212_FI447
Point Z	SS1596	4682788.4207	258969.3083	395.632	R_C180_FI412
Point Z	SS1595	4682788.2321	258969.4237	395.6116	R_C180_FI411
Point Z	SS1427	4682779.8264	258971.2419	395.1263	R_C165_FI388
Point Z	SS1426	4682780.6874	258971.1063	395.1096	R_C165_FI385
Point Z	SS1807	4682781.0915	258972.1467	395.1684	R_C212_FG454
Point Z	SS1412	4682778.05	258969.2101	395.1605	R_C161_FF376
Point Z	SS1411	4682777.9534	258969.0108	395.1321	R_C161_FF374
Point Z	SS1424	4682784.5565	258971.2007	395.5958	R_C162_FG369
Point Z	SS1403	4682777.7978	258969.4954	395.1425	R_C161_FG355
Point Z	SS1402	4682777.8849	258969.3738	395.1458	R_C161_FG354
Point Z	SS1401	4682777.9353	258969.5447	395.1131	R_C161_FG353
Point Z	SS1347	4682787.9325	258968.7674	395.7232	R_C156_FG348
Point Z	SS1346	4682787.3873	258968.1348	395.7172	R_C156_FG347
Point Z	SS1301	4682783.0243	258971.4697	395.8065	R_C153_FG317
Point Z	SS1267	4682787.3277	258968.9585	396.0222	R_C148_FG312
Point Z	SS1266	4682787.3386	258968.3797	396.0446	R_C148_FG311
Point Z	SS1263	4682778.0473	258969.1608	395.4246	R_C151_FG308
Point Z	SS1197	4682787.5257	258970.1719	396.1462	R_C148_FG303
Point Z	SS1177	4682784.2434	258969.3609	396.0707	R_C142_FG291
Point Z	SS1179	4682786.1161	258970.3552	396.1448	R_C140_FG289
Point Z	SS1425	4682786.9025	258969.2356	395.6214	R_C162_FF370
Point Z	SS1345	4682786.8995	258973.6927	395.9456	R_C155_FF339
Point Z	SS1344	4682779.147	258972.8887	395.2441	R_C157_FF338
Point Z	SS1265	4682786.6689	258970.0212	395.9194	R_C148_FF310
Point Z	SS118	4682786.3817	258959.5914	394.364	R_FF184C57glass
Point Z	SS117	4682786.0226	258959.1059	394.4049	R_FF183C53glass
Point Z	SS339	4682784.9027	258966.949	395.665	R_C104_FF259_glass
Point Z	SS270	4682779.9485	258961.4449	395.0517	FF250_C79_Glass
Point Z	SS214	4682778.0703	258962.5615	394.9455	R_C71_FF226_nail
Point Z	SS217	4682783.2107	258963.4382	395.1823	R_C65_FF233_NAIL
Point Z	SS651	4682781.7263	258969.0079	395.1632	R_C128_FF268_ironnail
Point Z	SS323	4682786.5702	258957.9893	394.1102	FF_255_C88_iron_nail
Point Z	SS183	4682782.4558	258965.5341	395.349	R_C66_FF202_ironnail
Point Z	SS187	4682781.5197	258965.3944	395.2647	R_C65_FF209_NAIL
Point Z	SS188	4682783.4642	258963.8039	395.2536	R_C65_FF210_NAIL
Point Z	SS185	4682782.8772	258963.3857	395.2303	R_C65_FF207_nail
Point Z	SS166	4682778.2402	258962.1341	395.0473	R_C66_FF197_nail

1 (0 out of 302 Selected)

In Situ Field Finds

Part 2: Center Panel of ArcGIS Attribute Table Depicting Complete Selection of Field Find Attributes

Uniform_Nomenclature	UniqueID	Description	ShortType
R_C246_FI539	539	Iron Nail	Nail
R_C155_FI356	356	Iron Nail	Nail
R_C212_FI458	458	Iron Nail	Nail
R_C212_FI455	455	Iron Nail	Nail
R_C212_FI453	453	Iron Nail	Nail
R_C176_FI420	420	Iron Nail	Nail
R_C176_FI418	418	Iron Nail	Nail
R_C165_FI390	390	Iron Nail	Nail
R_C165_FI389	389	Iron Nail	Nail
R_C148_FI307	307	Iron Bodkin Point	Bodkin
R_C142_FI290	290	Iron Nail	Nail
R_C139_FI281	281	Iron Nail	Nail
R_C212_FI452	452	Iron Horse Shoe	Iron
R_C162_FI383	383	Iron Artifact	Iron
R_C204_FI448	448	Iron Spike	Iron
R_C204_FI447	447	Iron Strap	Iron
R_C180_FI412	412	Iron Nail Head	Nail
R_C180_FI411	411	Iron Bar	Iron
R_C165_FI388	388	Iron Ring	Iron
R_C165_FI385	385	Iron Artifact	Iron
R_C212_FG454	454	Glass Shard	Glass
R_C161_FG376	376	Glass Shard	Glass
R_C161_FG374	374	Glass Shard	Glass
R_C162_FG369	369	Glass Shard	Glass
R_C161_FG355	355	Glass Shard w353	Glass
R_C161_FG354	354	Glass Shard	Glass
R_C161_FG353	353	Glass Shard w355	Glass
R_C156_FG348	348	Glass Shard	Glass
R_C156_FG347	347	Glass Shard	Glass
R_C153_FG317	317	Glass Body Shard	Glass
R_C148_FG312	312	Glass Handle	Glass
R_C148_FG311	311	Glass Body Shard	Glass
R_C151_FG308	308	Glass Shard	Glass
R_C148_FG303	303	Glass Rim	Glass
R_C142_FG291	291	Glass Rim	Glass
R_C140_FG289	289	Glass Rim	Glass
R_C162_FF370	370	Rock	Other
R_C155_FI339	339	Iron Bodkin Point	Bodkin
R_C157_FF338	338	Bronze	Bronze
R_C148_FF310	310	Smooth Basalt Rock	Other
R_C57_FG184	184	Glass Stopper or Base	Glass
R_C53_FG183	183	Glass Chalice	Glass
R_C104_FG259	259	Large Piece of Glass	Glass
R_C79_FG250	250	Base of Glass Vessel	Glass
R_C71_FI226	226	Iron Nail	Nail
R_C65_FI233	233	Iron Nail	Nail
R_C128_FI268	268	Iron Nail	Nail
R_C88_FI255	255	Iron Nail	Nail
R_C66_FI202	202	Iron Point	Iron
R_C65_FI209	209	Iron Nail	Nail
R_C65_FI210	210	Iron Nail	Nail
R_C65_FI207	207	Iron Nail	Nail
R_C66_FI197	197	Iron Nail T Shaped	Nail

Part 3: Right Panel of ArcGIS Attribute Table Depicting Complete Selection of Field Find Attributes

Nail	Bodkin	Bronze	Iron	Glass	Coin	Dice	Whorl	Pits	Area
1	0	0	1	0	0	0	0	0	1
1	0	0	1	0	0	0	0	0	2
1	0	0	1	0	0	0	0	0	5
1	0	0	1	0	0	0	0	0	5
1	0	0	1	0	0	0	0	0	5
1	0	0	1	0	0	0	0	0	2
1	0	0	1	0	0	0	0	0	2
1	0	0	1	0	0	0	0	0	6
1	0	0	1	0	0	0	0	0	6
0	1	0	1	0	0	0	0	0	2
1	0	0	1	0	0	0	0	0	2
1	0	0	1	0	0	0	0	0	2
0	0	0	1	0	0	0	0	0	5
0	0	0	1	0	0	0	0	0	2
0	0	0	1	0	0	0	0	0	5
0	0	0	1	0	0	0	0	0	5
1	0	0	1	0	0	0	0	0	2
0	0	0	1	0	0	0	0	0	2
0	0	0	1	0	0	0	0	0	6
0	0	0	1	0	0	0	0	0	6
0	0	0	0	1	0	0	0	0	5
0	0	0	0	1	0	0	0	0	6
0	0	0	0	1	0	0	0	0	6
0	0	0	0	1	0	0	0	0	2
0	0	0	0	1	0	0	0	0	6
0	0	0	0	1	0	0	0	0	6
0	0	0	0	1	0	0	0	0	6
0	0	0	0	1	0	0	0	0	2
0	0	0	0	1	0	0	0	0	2
0	0	0	0	1	0	0	0	0	2
0	0	0	0	1	0	0	0	0	2
0	0	0	0	1	0	0	0	0	2
0	0	0	0	1	0	0	0	0	6
0	0	0	0	1	0	0	0	4	2
0	0	0	0	1	0	0	0	0	2
0	0	0	0	1	0	0	0	0	2
0	0	0	0	0	0	0	0	0	2
0	1	0	1	0	0	0	0	0	2
0	0	1	0	0	0	0	0	0	6
0	0	0	0	0	0	0	0	5	2
0	0	0	0	1	0	0	0	1	1
0	0	0	0	1	0	0	0	1	1
0	0	0	0	1	0	0	0	0	2
0	0	0	0	1	0	0	0	0	3
1	0	0	1	0	0	0	0	0	3
1	0	0	1	0	0	0	0	0	3
1	0	0	1	0	0	0	0	0	3
1	0	0	1	0	0	0	0	2	1
0	0	0	1	0	0	0	0	0	3
1	0	0	1	0	0	0	0	0	3
1	0	0	1	0	0	0	0	0	3
1	0	0	1	0	0	0	0	0	3
1	0	0	1	0	0	0	0	0	3

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