Multivariate Analysis and Geographic Modeling of Archaeological Landscapes

J. Christopher Gillam
University of South Carolina

Follow this and additional works at: http://scholarcommons.sc.edu/etd

Part of the Geography Commons

Recommended Citation

This Open Access Dissertation is brought to you for free and open access by Scholar Commons. It has been accepted for inclusion in Theses and Dissertations by an authorized administrator of Scholar Commons. For more information, please contact SCHOLARC@mailbox.sc.edu.
Multivariate Analysis and Geographic Modeling of Archaeological Landscapes

by

J. Christopher Gillam

Bachelor of Arts
University of South Carolina, 1991

Master of Arts
University of Arkansas, 1995

Submitted in Partial Fulfillment of the Requirements
For the Degree of Doctor of Philosophy in
Geography
College of Arts and Sciences
University of South Carolina
2016

Accepted by:
Michael E. Hodgson, Major Professor
David J. Cowen, Committee Member
John A. Kupfer, Committee Member
David G. Anderson, Committee Member
Cheryl L. Addy, Vice Provost and Dean of the Graduate School
DEDICATION

In loving memory of my father, David E. Gillam, my “adopted” father, Billy G. Lee, and mentors, John J. Winberry and Ted A. Rathbun, for sharing their knowledge, wisdom and friendship with me and so many others.
ACKNOWLEDGEMENTS

I would like to express my profound gratitude to my major professor, Dr. Michael Hodgson, for sharing his knowledge, support and friendship with me over the many years leading to this degree. Dr. Hodgson’s contributions to knowledge are exceptional and I am honored to have had the opportunity to learn from and receive his guidance throughout the development of my academic career.

I would also like to thank my committee members, Drs. David Cowen, John Kupfer, and David Anderson for keeping me engaged through thought-provoking discussions, suggestions and guidance in kind support and mentorship. Drs. Caroline Nagel and Jean Ellis, Director of Graduate Studies, were invaluable in getting me through the university bureaucracy. Mr. Capers Stokes and Mrs. Elizabeth Belcher (ret.) kept me optimistic, humble and smiling through thick-and-thin. Messrs. Lynn Shirley (ret.), Kevin Remington and Geoff Schwitzgebel provided much-needed technical support and friendship.

I owe a tremendous debt of gratitude to Dr. Mark J. Brooks, retired Program Director of the Savannah River Archaeological Research Program (SRARP), for his many years of support, encouragement and friendship that enabled this study to be conducted. I also thank the many members of the SRARP, both past and present, whom contributed to this research in the field, lab and office.
Finally, and most of all, I’d like to acknowledge the love, care and support received from my dear wife, Holly, and daughters, Catherine and Alyssa, while pursuing my ambitions all these many years.
ABSTRACT

Advances in Geographic Information Science (GISci), archaeological databases and statistics enable the development and refinement of spatial applications of multivariate statistics and other quantitative methods for modeling ancient and historical cultural landscapes. Along the Central Savannah River of South Carolina, this research on prehistoric and historic site distributions, their environmental, temporal and cultural context, and geographic modeling explored methodologies for predicting site locations and modeling cultural landscapes to gain a better understanding of the distant and recent past. Methods for testing extant models, detecting changes in land-use through time, and for developing time-sliced and adaptation-based landscape models were demonstrated using archaeological data from the Department of Energy’s Savannah River Site (DOE-SRS), in Aiken, Barnwell and Allendale counties, South Carolina.

Multivariate Analysis of Variance (MANOVA) tests of cultural- and time-sliced datasets using 32 variables surprisingly revealed that only two models were needed to characterize the cultural landscape: a prehistoric and a historic model, respectively. Of the 32 variables available for Binary Logit Model (BLM) development, a knowledge-based approach was used to select seven variables for the prehistoric era plus one additional variable for the historic era. The seven common variables included: elevation, percent slope, profile- and plan-curvature, caloric cost distance to water, relative
elevation to streams, and elevation range (plus, caloric cost-distance to 1951 historic roads, for the historic model).

Both the prehistoric and historic BLM models were reclassified into high, moderate and low probability areas and tested with an independent validation sample and nonparametric ($X^2$) statistics for significance. The prehistoric model was highly significant, beyond the 0.001 probability level, and illustrates the importance of ecologically-rich edge environs to prehistoric cultures. Surprisingly, waterways and wetlands, long considered the most significant factors in prehistoric land use, were coincidental to these edge environs.

Conversely, the historic BLM model demonstrates the importance of the rolling hills between the flat upland terraces and bottomland forests to farming and livestock during the historic era. The surprise for the historic era was that historic roads were not the most significant contributor to the model and this was interpreted as a skewed result. With socio-economics likely yielding to the advantages of dispersed farmsteads, roads were crucial to historic settlement and should have made a significant contribution to the model. While significant ($p < 0.05$), the historic model was comparatively weak statistically and visually it demonstrated low probability values in a few historically-populated areas, particularly in the vicinity of the small town of Dunbarton.
# TABLE OF CONTENTS

DEDICATION ............................................................................................................................ iii

ACKNOWLEDGEMENTS .......................................................................................................... iv

ABSTRACT ............................................................................................................................... vi

LIST OF TABLES ..................................................................................................................... x

LIST OF FIGURES ................................................................................................................ xii

CHAPTER 1: INTRODUCTION ............................................................................................... 1

CHAPTER 2 BACKGROUND ................................................................................................. 8

  2.1 GEOGRAPHIC INFORMATION SCIENCE AND ARCHAEOLOGY .......................... 9

  2.2 ARCHAEOLOGICAL PREDICTIVE MODELING AND VALIDATION TESTING .......... 37

  2.3 CULTURAL RESOURCE MANAGEMENT AND RESEARCH ON THE SRS .......... 43

CHAPTER 3 METHODOLOGY .............................................................................................. 49

  3.1 ENVIRONMENTAL AND HISTORIC DATASETS ...................................................... 49

  3.2 ARCHAEOLOGICAL DATASETS ............................................................................... 53

  3.3 HYPOTHESES AND STATISTICAL ANALYSES ...................................................... 60

  3.4 PREDICTIVE MODELING ......................................................................................... 73

CHAPTER 4 RESULTS .......................................................................................................... 77

  4.1 VALIDATION TESTING OF THE 1989 MODEL ....................................................... 78

  4.2 MULTIVARIATE ANALYSIS OF VARIANCE (MANOVA) TESTS ......................... 84

  4.3 BINARY LOGIT MODELING AND VALIDATION TESTING ..................................... 97
CHAPTER 5 CONCLUSIONS ......................................................................................................................... 127

5.1 ANTHROPOLOGICAL THEORY TO THE INTERPRETIVE RESCUE ........................................... 128

5.2 THERE AND BACK AGAIN: PLANNING AHEAD TO (RE) MODEL ........................................... 130

5.3 ADVANCING ARCHAEOLOGICAL GEOGRAPHIC INFORMATION SCIENCE .......... 135

REFERENCES ........................................................................................................................................ 137
LIST OF TABLES

Table 2.1 Scales of Analysis .................................................................................. 27
Table 2.2 1989 Sensitivity Zones ....................................................................... 45
Table 3.1 Analytical Grids .................................................................................. 50
Table 3.2 Archaeological Grids .......................................................................... 60
Table 3.3 Intensive Survey Grids ........................................................................ 60
Table 3.4 Percent Cover of Intensive Surveys ..................................................... 63
Table 4.1 $X^2$ Statistics for Site Type 1 .............................................................. 80
Table 4.2 $X^2$ Statistics for Site Type 2 .............................................................. 81
Table 4.3 $X^2$ Statistics for Site Type 3 .............................................................. 81
Table 4.4 Statistics for Prehistoric sites .............................................................. 83
Table 4.5 Statistics for Historic sites ................................................................. 84
Table 4.6 MANOVA of Sites .............................................................................. 87
Table 4.7 Archaeological Grids .......................................................................... 88
Table 4.8 MANOVA of All Sites ....................................................................... 91
Table 4.9 MANOVA of Prehistoric Sites ............................................................ 92
Table 4.10 MANOVA of Historic Sites .............................................................. 93
Table 4.11 MANOVA of Adaptations ................................................................. 95
Table 4.12 MANOVA of Prehistoric Adaptations ............................................. 96
Table 4.13 Prehistoric BLM Global Null Hypothesis ....................................... 99
<table>
<thead>
<tr>
<th>Table</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.14</td>
<td>Prehistoric BLM Coefficients</td>
<td>99</td>
</tr>
<tr>
<td>4.15</td>
<td>Prehistoric BLM Odds Ratio</td>
<td>99</td>
</tr>
<tr>
<td>4.16</td>
<td>Prehistoric BLM Observed/Predicted</td>
<td>100</td>
</tr>
<tr>
<td>4.17</td>
<td>Prehistoric BLM AUC Curve</td>
<td>101</td>
</tr>
<tr>
<td>4.18</td>
<td>Prehistoric BLM ROC/Youden’s Index</td>
<td>102</td>
</tr>
<tr>
<td>4.19</td>
<td>Prehistoric Water/Curvature Correlation</td>
<td>107</td>
</tr>
<tr>
<td>4.20</td>
<td>1989 Prehistoric Model Validation Test</td>
<td>109</td>
</tr>
<tr>
<td>4.21</td>
<td>2016 Prehistoric Model Validation Test</td>
<td>109</td>
</tr>
<tr>
<td>4.22</td>
<td>2016 Prehistoric Model Secondary Validation Test</td>
<td>110</td>
</tr>
<tr>
<td>4.23</td>
<td>Historic BLM Global Null Hypothesis</td>
<td>115</td>
</tr>
<tr>
<td>4.24</td>
<td>Historic BLM Coefficients</td>
<td>115</td>
</tr>
<tr>
<td>4.25</td>
<td>Historic BLM Odds Ratio</td>
<td>115</td>
</tr>
<tr>
<td>4.26</td>
<td>Historic BLM Observed/Predicted</td>
<td>116</td>
</tr>
<tr>
<td>4.27</td>
<td>Historic BLM AUC Curve</td>
<td>117</td>
</tr>
<tr>
<td>4.28</td>
<td>Historic BLM ROC/Youden’s Index</td>
<td>118</td>
</tr>
<tr>
<td>4.29</td>
<td>2016 Historic Model Validation Test</td>
<td>120</td>
</tr>
<tr>
<td>4.30</td>
<td>2016 Historic Model Secondary Validation Test</td>
<td>120</td>
</tr>
<tr>
<td>4.31</td>
<td>Historic Roads/Curvature Correlation</td>
<td>126</td>
</tr>
<tr>
<td>5.1</td>
<td>Model Gain Statistics</td>
<td>134</td>
</tr>
</tbody>
</table>
LIST OF FIGURES

Figure 2.1 Spatio-Temporal Queries ................................................................. 31
Figure 2.2 GIS and Archaeological Time ......................................................... 33
Figure 2.3 Timeline of Geographic Influence .................................................... 36
Figure 2.4 1989 SRS Prehistoric Model ............................................................ 48
Figure 3.1 Hypothetical Site Map ................................................................. 55
Figure 3.2 Pre-GPS Site Problems Map ............................................................ 57
Figure 4.1 ROC for Prehistoric BLM Model ......................................................... 101
Figure 4.2 2016 Prehistoric BLM Model ............................................................ 104
Figure 4.3 Prehistoric Sites on Plan Curvature ...................................................... 105
Figure 4.4 Prehistoric Sites on Cost to Water ....................................................... 106
Figure 4.5 Prehistoric Sites Water/Curvature Scatterplot ..................................... 107
Figure 4.6 1989 Prehistoric Model Site Overlay ................................................... 111
Figure 4.7 2016 Prehistoric Model Site Overlay ................................................... 112
Figure 4.8 ROC for Historic BLM Model .......................................................... 117
Figure 4.9 2016 Historic BLM Model ............................................................... 122
Figure 4.10 2016 Historic Model Overlay ........................................................... 123
Figure 4.11 Historic Sites on Plan Curvature ....................................................... 124
Figure 4.12 Historic Sites on Cost to Roads ......................................................... 125
Figure 4.13 Historic Sites Roads/Curvature Scatterplot ....................................... 126
Figure 5.1 Prehistoric Cultural Landscape ................................................................. 131

Figure 5.2 Historic Cultural Landscape ..................................................................... 132
CHAPTER 1

INTRODUCTION

Geographic Information Science (GISci) has had great influence on the field of archaeology in recent years, particularly in the areas of mapping, analytical cartography, and predictive modeling of archaeological landscapes (Kvamme 2012; Mehrer and Wescott 2006), the latter being the focus of this research. The primary purpose of an archaeological predictive model is to minimize the amount of fieldwork required to accurately assess the cultural resources of a locality threatened by physical impacts from land development (Kvamme 1983). However, due to widespread adoption in the subfield of landscape archaeology, archaeological predictive modeling has become increasingly common in problem-oriented research (Chapman 2006; Ullah 2011; Verhagen and Whitley 2012; Whitley 2004, 2005, 2010a), though these approaches are more deductively oriented than their data-driven, inductive counterparts.

A traditional archaeological site prediction model is developed by analyzing empirical data to define the relationship between known archaeological sites, locations of past human activity or habitation, and their environmental context, or the nature and attributes of those locations. This model is then extended to predict the probability of site occupation for other un-surveyed locations. The basic approach is to statistically compare the environmental contexts of known archaeological site locations to known non-site locations, places with no evidence of human activity or habitation, to produce a prediction surface representing the probability of encountering archaeological materials
on the landscape. Environmental data are commonly modeled and extracted using a Geographic Information System (GIS) and tested with a statistical software package (e.g. SAS, SPSS). The resulting maps depict the probability of each location to contain archaeological remains. The final map represents the probability a location will contain archaeological deposits often reclassified into indices (e.g. low, moderate, and high). This probability map aids in site management, fieldwork planning, and research. The reclassification of the raw probability scores into three ordinal levels provides a basis for statistical evaluation in research, as a guide for different levels of archaeological field testing, as a well as, providing a visual aid to non-technical staff and land-use managers on federal properties where such models are common; a fundamental purpose of thematic mapping is to turn raw geographic data into a more meaningful map.

These site occupation predictive models are developed using a variety of statistical techniques. In the Southeastern U. S., univariate statistical techniques have been the dominant method used (Anderson et al. 1988; Anderson and Smith 2003; Beasley et al. 1996; Brooks and Scurry 1978; O’Donoughue 2008; Scurry 2003, 2015; SRARP 1989). As these models have witnessed decades of use, many are now undergoing re-evaluation. These efforts attempt to improve model-building techniques using new or more refined methods (Whitley and Moore 2008). Multivariate techniques established three decades ago (Kvamme 1983) have been infrequently used in the Southeast, although this trend is currently changing and new methodologies to improve both outcomes and interpretations are now appearing (e.g., Cable 1996; Johanson 2011; Whitley 2004, 2005, 2010a, 2010b, 2013; Whitley and Moore 2008, 2012).
Multivariate techniques offer advantages over univariate techniques. Most significantly is the ability of multivariate techniques to evaluate the overall importance of the environmental variables jointly, instead of on an individual basis. Additionally, it was demonstrated in this research that time and cultural lifeway provide a third-dimension to a technology that is otherwise characterized as having two-and-a-half-dimensions, such as time and culture each provide additional dimension or depth to x-, y-, and z-geographic space (e.g., Goodchild 2010).

Archaeological predictive modeling at the Department of Energy’s (DOE) Savannah River Site (SRS) in the Central Savannah River Area (CSRA) of South Carolina has paralleled efforts elsewhere in the Southeast. First published in 1989, the extant archaeological sensitivity model was developed by the Savannah River Archaeological Research Program (SRARP) to aid cultural resource management of prehistoric sites on the SRS (SRARP 1989). Generated prior to the availability of a GIS at the SRS, formerly Savannah River Plant (SRP), the model was understandably based upon only three environmental variables including, elevation in meters above mean sea level (m amsl), relative elevation to streams in meters (m) and distance to streams (m), and the use of univariate statistics. Similar to other predictive models, it provided three zones of relative archaeological sensitivity including low, moderate, and high probability areas, plus an indeterminate zone representing wetland areas typically avoided by land-use planners on the SRS (and therefore not archaeologically tested on a regular basis).

Since its development, the model has served as a guide for fieldwork enabling archaeologists to focus testing and minimize the cost of archaeological surveys (e.g., Cabak et al. 1996; Sassaman et al. 1990; Stephenson et al. 1993).
Typical problems with archaeological predictive models in the Southeast include a reliance on only a few environmental variables, the use of univariate statistics, and the aggregation of archaeological sites into a single sample that were occupied at different times and by different cultures over a period of at least 14,000 years. The use of multiple environmental variables in combination with multivariate statistics should enable greater predictive discrimination over the traditional univariate techniques that incorporate fewer environmental variables.

Separating the overall archaeological sample based upon temporal and cultural classes may increase the research potential of the models (e.g. Gusick and Faught 2011; Mlekuž 2010; Verhagen and Whitley 2012) and enables other forms of analyses, such as change detection, to be developed for future research. Over the past 14,000 years, environmental fluctuations have significantly changed the character of flora, fauna, and surface water available for past cultures to exploit. Cultures themselves changed significantly over time, from early hunter-gatherers exploiting now-extinct Pleistocene megafauna, then to Holocene hunter-gatherers exploiting modern flora and fauna, and finally to horticulturists and agriculturists planting and harvesting crops in the most recent past. These changes were likely related to the stabilization of the Holocene environment and to cultural factors such as migration, group interaction and exchange, and other social activities (e.g., Anderson and Sassaman 2012; Sassaman et al. 1990).

This research was based upon the following assumptions regarding the archaeological record and its corresponding cultural landscapes:
• Long-term cultural trajectories are reflected in the cultural landscape as relatively continuous patterns of land-use and discard of material culture (i.e., archaeological sites and artifacts).
• Cultural trajectories periodically change due to cultural transformations, or fundamental changes in cultural lifeway.
• Cultural transformations typically result in new long-term cultural trajectories that are likewise reflected in a new cultural landscape by changes in land-use patterns and material culture (i.e., site locations and artifact types).
• Cultural reversions (i.e., those similar to a prior lifeway) may occur when transformations are non-sustainable due to environmental change, degradation, or long-term cultural resistance.
• It is possible to model the long-term trajectories, transformations, and reversions of cultural landscapes by statistical and spatial analyses of archaeological site location.

The purpose of this research was to develop GIS-based methods to test extant models, evaluate sample bias, examine temporal and cultural variability and, based on those results, generate multivariate predictive models for the SRS, specifically, that are applicable throughout the Interior Coastal Plain of the South Atlantic Slope, generally, and methodologically, worldwide. Assumptions regarding the use of univariate versus multivariate statistics and the influence of time, culture, and sample bias on the development of archaeological predictive models were likewise tested. In order to
accomplish these goals, the following abbreviated hypotheses were evaluated (p < 0.05 level):

- Archaeological site types are not significantly associated with the 1989 SRS predictive model (i.e., the current model performance is poor when the number of components per site are considered).
- Archaeological sites are not significantly associated with the 1989 SRS predictive model (i.e., the current model performance is poor when the number of components per site are not considered).
- Sample bias is not significant in the archaeological records of the SRARP.
- The environmental context of archaeological sites does not vary significantly over time.
- The environmental context of archaeological sites does not vary significantly by culture type or adaptation.

The resulting statistical evaluations of these hypotheses illustrated the need for multivariate predictive models based upon temporal and cultural classes represented in the archaeological record, primarily along prehistoric and historic temporal and cultural lines. The degree of association of sites to the extant 1989 model was examined first, as this provided the basis for revision and new model development. Examination of sample bias in the archaeological record of the SRARP indicated that the different site samples recorded during the history of the program could not be aggregated to improve sample size. Early sampling techniques were simply too biased for new model development.
Using only the intensive survey sample, two binary multiple logistical regression models, hereafter termed Binary Logit Models (BLM), were produced for the SRS locality, a prehistoric model and an historic model. While the prehistoric model is a good predictor of site occupation, the BLM modeling technique was deemed insufficient for characterizing the historic landscape for reasons elaborated upon in the results chapter. This outcome was not unexpected due to the assumption that historic site distribution was more closely related to the built environment (wells, roads, rails, etc.) than nature. That assumption was clearly challenged by the results (see Chapter 4).

Extending GIS beyond its traditional 2.5 dimensions (cf., Goodchild 2010), while remaining graphically represented in 2-dimensions on a map (cf., Berry 1964), is key to GISci applications in archaeological research and Cultural Resource Management (CRM). That is, the use of cultural- and time-sliced archaeological data, each representing a third dimension in geographical space, is critical to discerning past cultural landscapes that have otherwise been hidden or obliterated by subsequent natural and cultural processes. As such, the hypothesis tests, outcomes, and landscape models presented within may all be valued contributions of this research.
CHAPTER 2

BACKGROUND

The interpretation of archaeological distributions has been an integral part of the field throughout its scholarly history of development. Initially, maps provided the means for examining artifact patterns and regional site distributions. However, more sophisticated methods of recording, visualization, and analysis have been developed over the past few decades. Archaeological predictive modeling has been particularly beneficial to the field, enabling researchers to target specific areas for archaeological deposits and thus minimizing the costs of fieldwork.

The 1960’s witnessed the quantitative revolution in the social sciences and corresponded to the application of mathematical models to archaeological distributions. These models, however, were soon criticized for their inability to demonstrate clear cultural significance or consider aspects of human agency and history (Kroll and Price 1991). The resulting replacement of the ‘new archaeology’ or processual approach by post-processual and ‘processual plus” approaches led to the adoption of a wide range of approaches, including social theory and ethnographic analogy, to move the field forward (Bentley et al. 2008; Hegmon 2003).

Nonetheless, the development of CRM laws in the late 1960’s and early 1970’s resulted in a need to advance quantitative methods for site management purposes. The subfields of quantitative and spatial archaeology continued to prosper, resulting in early efforts to predict archaeological distributions on government reservations. Even
computerized, such analyses were tedious and most early examples contained few landscape variables. Kvanme (1983) led the way by using multivariate logistic regression to develop predictive models of archaeological site location that GIS would, in turn, assist in automating. The 1990’s through 2010’s witnessed considerable advancement in GISci in archaeology, a growing archaeological subfield in America and abroad. The pages that follow outline and critique the development of GISci in archaeology, the need for archaeological predictive modeling, reviews the extant 1989 SRS sensitivity model, the need for testing and revision of existing models, and provides a synopsis of the major issues at hand leading to the methodology and results in the chapters that follow. [Not very clear]

2.1 Geographic Information Science and Archaeology

2.1.1 Common Roots

Many of today’s social sciences share a common background in the Antiquarian pursuits of the 15th through 19th centuries. Antiquarians in Europe were most concerned with historical monuments that were, at least in part, documented in writing. In America, antiquarian research was primarily concerned with the origins of the “mound builders” (Brose 1993; Squier and Davis 1848). Although narrowly focused and subjective, this restricted form of inquiry led to the development of methods that would become the building blocks of modern, scientific archaeology. The antiquarians learned the basics of excavation, mapping, documentation, description, dating, and classification (Trigger 1989).
The dawn of modern American archaeology began with Cyrus Thomas’ 1894 publication of the *Report on the Mound Explorations of the Bureau of Ethnology* (Smith 1985). Thomas’ research went beyond the antiquarian obsession with objects, offering explanation in addition to description. He ended the notion that the prehistoric mounds of eastern North America were constructed by a race other than the Native Americans.

Surveying and mapping were key components of early archaeological research. In America, the distribution of the mounds was geographically constrained and knowledge of this pattern soon formed the basis for the notion of a “culture area” (Thomas 1894). The culture area concept had a gradual and empirical development and would be solidified by later research integrating stratigraphic sequences and regional distributions (Kroeber 1939). Mapping and surveying would remain the primary links between archaeology and geography until the advancement of spatial science in the 1960’s.

2.1.2 Remote Sensing

Remote sensing is often defined as the science, art, and technology of acquiring information about an object without being in direct contact with it (Avery and Berlin 1992; Jensen 2004, 2006; Lillesand and Kiefer 1987). Archaeological sites are commonly large in spatial dimension and severely weathered, resulting in problems with ground-level differentiation from the local landscape. In such instances, remote sensing, particularly aerial photography, imagery and LiDAR (i.e., Light Detection and Ranging), provide valuable information on overall site dimensions and integrity (Parcak 2009). However, sites only represent a small part of a larger regional settlement strategy. Therefore, an understanding of regional resource structure and environmental condition is
key to developing models of past human adaptations. Satellite imagery provides a wealth of data for such modeling efforts (Parcak 2009).

Sites have been photographed from the air for nearly a century (Reeves 1936). Aerial photography facilitates the discovery of new sites and the mapping of sites and other cultural features that are too large or remotely located to be mapped with ease from the ground. Shadow marks, soil marks, and crop marks represent the landscape features most often used to identify site loci and extent (Agapiou et al. 2014; Davidson and Hughes 1986; Edis et al. 1989; Featherstone et al. 1995; Lasaponara and Masini 2007; Lepper 1995; Myers and Myers 1993, 1995). Methods of obtaining aerial photographs vary widely, ranging from light airplanes, tethered balloons and, most recently, remote-controlled drones (Avery and Berlin 1992; Ebert and Lyons 1980; Gojda and Hejcman 2012; Myers and Myers 1993, 1995; Palmer 1988; Smith et al. 2014; Ware and Gumerman 1977; Verhoeven 2009, 2012). Likewise, research applications vary from simple site mapping to studies of site destruction through time (Banerjee and Srivastava 2013; Gillam 1993; Lepper 1995; Newson and Young 2015; Tinney et al. 1977).

Archaeological remote sensing has continued to evolve with the technology over the years (Wiseman and El-Baz 2007). The improved resolution of aerial imagery over that of space platforms has permitted its use in delineating actual site boundaries and other cultural features (Breeze et al. 2015; Ebert 1978). One of the newest technologies, aerial laser scanning, or LiDAR, is capable of producing sub-meter accurate digital terrain models useful for natural and cultural resource management (cf., Reutebuch et al. 2005; Hodgson and Bresnahan 2004; Hodgson et al. 2003, 2005).
Likewise, non-photographic satellite imagery has played an increasing role in the examination of regional settlement systems (Cox 1992; Custer et al. 1986; Sever 1995; Ur 2003; Wendorf et al. 1987; Wiseman 1996). A common use of such digital imagery is in archaeological predictive modeling (Custer et al. 1986; Ebert 1988; Garrison et al. 2008). The image basically becomes a variable in a mapped regression analysis. Landsat MSS, Thematic Mapper, and SPOT imagery are the most common data used in such analyses, however high resolution imagery from more recent platforms, such as ALOS, ASTER and IKONOS, are seeing increased usage (see Agapiou et al. 2014; Banerjee and Srivastava 2013).

The call for incorporation of new forms of remotely sensed data in archaeological research has been heard for nearly four decades in North America (Wiseman and El-Baz 2007). In 1977, Gumerman and Kruckman discussed the "unrealized potential" of remotely sensed data to this very subject. In subsequent years, other technologically adventurous archaeologists and related specialists heralded the cause by reiterating the utility of this blossoming technology (Ebert 1978; Lyons and Scovill 1978). A review of the literature indicated a steady rise in applications as the technology of GISci has become more readily available, accessible, and integrated into anthropology and archaeology academic departments, worldwide (e.g. Comer and Blom 2007; Verhoeven 2012; Wendorf et al. 1987).

2.1.3 Spatial Analysis

The quantitative revolution of the 1950’s and 60’s brought with it new linkages between archaeology and geography. Whereas past decades had witnessed a shared
interest in mapping and description, the 1960’s brought about the development of quantitative models of location (Haggett 1966). Archaeologists were quick to adapt these developments in geography toward problems of prehistory (Clarke 1968, 1972; Hodder and Orton 1976).

Theoretically, Christaller’s (1966) Central Place Theory (CPT) was most influential in the examination of chiefdom- and state-level societies in the Americas. Losch (1954) and Haggett (1966) further advanced CPT, with the majority of archaeological references demonstrating the influence of Haggett’s research. Basically, CPT has been used in archaeological research to examine spatial relationships between permanent settlements of varying size and their regional resources (Butzer 1982).

In contrast, General Gravity Models (GGM) have been applied to hunter-gatherer studies. The mobile lifestyle and overall adaptive flexibility of hunter-gatherers make them a particular challenge to model. Jochim (1976) developed a gravity model to understand the functional organization of hunter-gatherers. His model essentially predicted relative distance to resources based upon a three-tier hierarchy of immobile, dense, and clustered resources.

Clarke (1968, 1972) applied many established geographical principles and techniques to archaeological research. Goudie (1987) was the first to highlight this relationship. Clarke’s works were particularly patterned after those of Peter Haggett. *Analytical Archaeology* was published in 1968 following Haggett’s (1966) publication of *Locational Analysis in Human Geography*. Likewise, his 1972 publication of *Models in Archaeology* holds many similarities with Chorley and Haggett’s (1967) volume, *Models in Geography*.
Willey (1953) heralded settlement pattern analysis in archaeology with the seminal work, *Prehistoric Settlement Patterns in the Viru Valley*. The birth of this field of study established the interest in cultural distributions that would foster the adoption of locational analysis in archaeology in the 1960’s and 70’s. An understanding of settlement patterns is so fundamental today, that few students understand the developmental history of this perspective. The development of GISci in the past four decades has fostered great interest in the development of regional syntheses of prehistoric cultural developments.

### 2.1.4 Geographic Information Systems

The interest in settlement patterns resulted in an early interest in GIS. A GIS can be conceptualized as a spatial database capable of data collection, automation, storage, retrieval, analysis, tabulation, and graphic output (Aronoff 1989; Huxhold 1991; Jensen and Jensen 2012; Starr and Estes 1990). These basic components are common to all modern GIS regardless of data structure. There are two basic data structures, raster and vector, each having separate strengths and weaknesses for archaeological applications.

Raster data structures store information on a cell-by-cell basis as a series of numbers. This structure permits the data to be mathematically manipulated, yielding a powerful tool for cartographic modeling (Tomlin 1990). This data structure facilitates the development of continuous surface models, such as predictive models of prehistoric and historic land use. A good example of archaeological predictive modeling is Kvamme and Jochim’s (1990) study of Mesolithic sites in Germany. They used elevation, slope, aspect, local relief, viewshed, shelter potential, and distance to water data to model landscape
preferences during the Mesolithic Period. Such applications yield insight to why sites are located where they are, in addition to where unknown sites are likely to be.

Vector data structures also offer advantages to archaeological applications. First, vector systems enable sites to be recorded as polygons that closely resemble traditional map elements. This capability results in the production of more appealing map output from the GIS and more accurate measurement of site area. Second, individual components of sites (artifacts, physical features, and sample units) can be represented as points, lines, or polygons, further refining the spatial representation of key cultural features (Cabak et al. 1996, 1998). Third, linear features (e.g. historic roads) can be represented as lines connecting sites (e.g. towns) which enables network analysis of the flow of goods or people over time. Finally, vector data structures efficiently store temporal data sets, effectively reducing requirements on hardware space and processing time (Burrough 1986).

Most current GIS systems offer both vector and raster data structures in an inter-operable, working environment (Jensen and Jensen 2012). The advantages of the vector and raster data structures can be exploited by these integrated systems, effectively offsetting the limitations of each data structure on its own. Problems typical of the raster data structure that are overcome by vector systems include that raster data require large amounts of disk space, topological relationships (connectedness and other spatial relationships within a layer) are difficult to represent, and output is less aesthetically pleasing. Shortcomings of vector data structures that are overcome by the raster data structure include that vector systems have a complex structure, are difficult to conduct
overlay analysis with, do not represent high spatial variability efficiently, and cannot manipulate images effectively (Aronoff 1989).

In America, archaeologists have primarily used GIS to manage data and to develop predictive models of archaeological site location (Allen et al. 1990; Anderson and Horak 1995; Conolly and Lake 2006; Judge and Sebastian 1988; Kvamme 1983, 1986, 1989, 1992; Limp and Farley 1986; Wandsnider and Dore 1995a, b; Westscott and Brandon 2000; Wheatley and Gillings 2002). Raster-based data analysis has dominated the use of GIS by American archaeologists, due to the use of environmental data for predictive modeling of site location. Unfortunately, much of the American literature on archaeological GIS has been “gray” literature, though this trend is not as pronounced in recent years. That is, many CRM applications have been reported in government publications more often than refereed journals in the U.S. (e.g., Hudak et al. 2002; Harris et al. 2015; Judge and Sebastian 1988). This was initially due to the repetitive, technical, inductive, and environmentally deterministic character of predictive modeling.

Understanding cultural significance is rarely the purpose of such analyses and is therefore deemed inappropriate for the greater anthropological literature.

There were two early, groundbreaking volumes on archaeological applications of GIS in America. The first, Quantifying the Present and Predicting the Past (Judge and Sebastian 1988), represents one of the most widely distributed “gray” literature volumes on the topic. Published by the Bureau of Land Management (BLM), this edited volume detailed the process of predictive modeling from its theoretical basis to its application. Kvamme was a major contributor to the volume, having developed the basic
methodology for GIS predictive modeling in his 1983 dissertation at the University of California.

The second volume, *Interpreting Space: GIS and Archaeology* (Allen et al. 1990), was an academic publication that had an international impact. Although applications again focused primarily on predictive modeling, it nonetheless raised considerable academic interest in America and abroad. Notable applications not concerned with predictive modeling include Allen’s (1990) model of historic trade, Savage’s (1990) Late Archaic territories (see critique, Anderson 1989), and Green’s (1990) landscape approach to archaeological GIS. Subsequent edited volumes in the Americas have sought to broaden the scope of archaeological GIS and to raise its academic merit (Lock and Molyneaux 2006; Maschner 1996; Mehrer and Wescott 2006; Reid 2008).

In Europe and elsewhere, the evolution of archaeological GIS applications has been markedly different (Lock and Stancic 1995). Archaeological applications developed slightly later than in America and have been directed more towards problem-oriented research in landscape archaeology than predictive modeling of site location (e.g. Anschuetz et al. 2001; Burg 2016; Chapman 2006; Bevan and Conolly 2004; Fernández et al. 2016; Hritz 2014; Lindholm et al. 2015; Sampson et al. 2015). However, the automation of archaeological data with GIS followed a similar development for cultural resource management.

The edited volume, *Archaeology and Geographical Information Systems: A European Perspective* (Lock and Stancic 1995), clearly demonstrates the differences in the European and American schools of GIS and archaeology. The complexity and different approaches to management of the archaeological record in Europe compared to
that in the US required a very different approach to archaeological GIS. Instead of raster-based models of site location, European studies typically concern territoriality, movement, and interaction. These applications rely more on vector data models and landscape theory, than environmental data and inductive analysis (Harris and Lock 1995). Subsequent volumes on archaeological GIS have demonstrated greater interaction between the American and European schools, paralleling the maturation of GIS worldwide (Aldenderfer and Maschner 1996; Lock and Molyneaux 2006; Maschner 1996; Mehrer and Wescott 2006).

Refereed journals have witnessed a growing number of contributions since the turn of the century, particularly journals with a focus on applied methods (e.g. Duke and King 2014; Kosiba and Bauer 2013; Leroy et al. 2016; Llobera 2001). Applications also range widely. Notable examples include improved site-catchment studies (Hunt 1992), non-site landscape approaches (Cabak et al. 1996, 1998), migration analyses (Anderson and Gillam 2000), eco-cultural niche modeling (Banks et al. 2006; Gillam et al. 2007) and site inter-visibility (Waldron and Abrams 1999). The literature indicates that GISci has been a maturing sub-field in anthropology/archaeology for three decades (Aldenderfer 1992; Conant 1992; Duke and King 2014; Goodchild 1992; Mehrer and Wescott 2006).

As previously mentioned, predictive models have witnessed considerable use by government agencies beginning in the late 1980’s and continuing right to the present (e.g., Anderson et al. 1988; Anderson and Smith 2003; Harris et al. 2015; Hudak et al. 2002; Johanson 2011; Judge and Sebastian 1988; ). The roots of predictive modeling developed in the 1970’s, but it was Kvamme’s 1983 dissertation, “New Methods for
Investigating the Environmental Basis of Prehistoric Site Locations,” that opened the door for more widespread application. Kvamme used 12 environmental variables and logistic regression to provide an empirical test of archaeological site location. The analysis resulted in site predictions that were from 70 to 90% accurate. The GIS was used to extract the environmental data and to produce maps of the predictive model. Following his dissertation, Kvamme continued to advance the application of predictive models and GIS in the field of archaeology, but has focused more on ground-based remote sensing in recent decades (Kvamme 1986, 1989, 1992, 2012).

Subsequent studies containing predictive models have either applied the extant methodology or sought to refine it to gain a better understanding of prehistoric landuse. Estrada (1998) extended the use of predictive models for territory delineation by first developing the predictive model and then using Thiessen polygons to delineate Middle and Late Classic (A.D. 400-900) Mayan territories around cultural centers along the Pacific Coast of Guatemala. This extension of predicting group territories is particularly suitable for application to agricultural societies throughout the world.

Another interesting application is Williams’ (1997) use of GIS to reconstruct canals in Peru for subsequent environmental modeling of water availability during prehistory. Williams used the GIS to model likely routes of the canals based upon the location of archaeological remnants. Subsequently, ice core data were used as a proxy for precipitation and integrated into a water transport cost equation to evaluate water availability across the landscape. The modeling helped define the role of natural disasters, such as earthquakes and weather change, on the rise and decline of agricultural societies in the Andes.
The major criticisms of archaeological GIS relate to the reliance on environmental data and quantitative methods. As anthropologists, many archaeologists shy away from methods that rely heavily on environmental factors. The stigma of environmental determinism still weighs heavily on the minds of scholars in the field [e.g., Sassaman and Randall 2012]. However, with an appropriate theoretical basis, there is no reason that environmental study should be shunned. The environment was important to past cultures and understanding such relationships remains an important aspect of prehistoric study (e.g., Anderson et al. 2007; Binford 2001; Kelly 2013; Redman 1999). In fact, human ecology and geoarchaeology are strong sub-fields in anthropology and archaeology due to the importance of the environment in the development of culture and the preservation of cultural remains (e.g., Goldberg et al. 2001; Kelly 2013).

The criticisms of quantitative methods date back to the late 1960’s and 1970’s. Soon after the quantitative revolution, some anthropologists began to reject complex quantitative models that did not take human agency and cultural behavior into account. Descriptive statistics remain an integral part of the field, but complex models demonstrating association, interaction, and exchange have been less common. These activities are typically demonstrated based on artifact similarities, rather than quantitative geographic methods.

The challenge to archaeologists is to expand uses of GIS in data storage, visualization, and predictive modeling of site location in innovative studies that lead to a better understanding of human agency that defines the cultural landscape, as well as, an understanding of where sites might be located (e.g. Ruggles and Medyckyj-Scott 1996). Site discovery methods, such as Sever (1990), have limited applications as the majority
of human prehistory did not result in the building of permanent structures or pathways that may be detected through remote sensing. Conversely, continental-scale models provide great insight into the changes of the past and help explain the movement and interaction of people over great distances (Anderson and Gillam 2000; Anderson et al. 2010; Banks et al. 2006; Gillam et al. 2006, 2007, 2008). More GISci research needs to be done on defining ancient group territories (e.g. Dahl et al. 2011; Gillam and Tabarev 2004). Thiessen polygons are a simple method of evaluating potential territory size, but these polygons are based upon distance between polities alone and do not represent cultural boundaries reliably. Kinship, language, natural resources, and polity strength tend to shape (and re-shape) such boundaries over time.

2.1.5 The Need for Archaeological Predictive Models

The archaeological record can be conceptualized as a continuous surface across the landscape. The majority of this record is represented by small, discarded artifacts; not the remains of highly visible, physical structures. This makes discovery of archaeological remains particularly challenging as most artifacts are only a few centimeters in length, often buried, occur in relatively low densities and are frequently associated with small numbers of artifacts with similar characteristics. Physically digging test pits is often the only means of discovery. Sampling a continuous landscape with a low occurrence of artifacts can therefore be very costly in both time and money.

For example, let’s assume that a telecommunications company wants to build a cellular tower on a 1-acre square footprint of land located above a perennial stream on one side. For an intensive survey of the entire footprint, approximately 49 shovel test pits
(STP) would have to be excavated using a 30-m interval survey grid. Assuming each STP costs $5 to excavate and record. The cost to survey the area, if no STP has cultural remains requiring additional time to record and process, would be $245. If a predictive model were available indicating that only a single transect of 7 STPs needed excavation, the cost would be $35. That’s a savings of $210 in this simplified hypothetical example, so imagine the savings for a larger survey, such as a new waste processing facility requiring 100-acres under similar survey parameters. That would be $21,000 in cost savings!

By using a sample of known archaeological locations to predict where remains may be found at un-tested locations, a predictive model enables archaeologists to minimize the cost and time required to recover archaeological remains. A predictive model also enables land planners to avoid areas likely to contain a high probability of archaeological sites early in the planning stage of projects. This minimizes the potential of encountering significant archaeological remains and also reduces the chance that an alternative project area will need to be selected late in the project, resulting in significant cost savings.

2.1.6 The Role of GIS in Archaeological Predictive Models

While archaeological predictive modeling does not require the use of a GIS, no other method of extracting environmental data associated with archaeological sites is as expedient, accurate, or replicable. Archaeological site locations are stored as coordinates in the GIS and used to extract environmental data from numerous data layers. These data are in turn used for statistical analyses, the coefficients of which are incorporated into a
cartographic model to generate the prediction model in map form. Factors critical to performing such analyses successfully include the scale of analysis, the resolution and accuracy of the data, the temporal and cultural variation of the archaeological record, and the cartographic modeling process.

2.1.7 Scales of Analysis

Archaeological inquiry concerns analyses at a variety of spatial scales (Mathieu and Scott 2004). Traditionally, these include the area, region, locality, site, and artifact scales of analysis. However, with the availability of global environmental datasets, it is now possible to consider archaeological problems at even greater continental, hemispheric and global scales of analysis. Willey and Phillips (1958) defined the area, region, locality, and site scales of analysis in the classic volume, *Method and Theory in American Archaeology*. The artifact, or non-site, scale of analysis was later defined due to the inherent limitations of the site concept in American archaeology (Thomas 1975). It is the one-dimensional focus on geographic extent that remains the primary weakness in traditional definitions of archaeological scales of analysis. In the following discussion, I review these traditional definitions and highlight resolution, accuracy, time and culture as other factors influencing relevant scales of analysis in archaeological inquiry (see also, Lock and Molyneaux 2006).

The area is typically the largest scale of archaeological analysis (Willey and Phillips 1958). It is conceptually equivalent to a major physiographic province of a continent, such as the North American Southeast. Such areas often have homogenous cultural adaptations due to group proximity and environmental factors. Although
traditionally the largest scale of analysis, powerful GIS workstations and the development of global environmental and cultural data sets are leading to continental, hemispheric, and global scales of archaeological analysis (Anderson and Gillam 2000; Anderson et al. 2010; Banks et al. 2006, 2008; Field and Lahr 2005; Field et al. 2007; Gillam et al. 2006, 2007; 2008; Wells et al. 2014).

At the regional scale, archaeologists define the spatial extent of a given cultural expression across the landscape. The region reflects the range of influence of a given culture over time (Willey and Phillips 1958). Often, a cultural region corresponds to a river basin or other minor physiographic province. The spatial arrangement and complexity of sites across a given cultural region can be further studied to examine hypotheses of social structure. Interaction, movement, and exchange are often focuses of regional archaeological research (e.g. Gillam and Tabarev 2004; Gillam et al. 2010; Iriarte et al. 2008, 2013).

A locality may refer to a single, large site, a group of inter-related sites or even an arbitrary project location (Willey and Phillips 1958), such as the SRS. At this scale, the organizational framework of sites may yield information about social and/or political structure within that ancient community. Particularly among agricultural communities, the spatial arrangement of ceremonial centers yields a wealth of data on the culture that created it. The organization of space is a powerful tool for obtaining insight into the organizational complexity of a culture (e.g., Grøn 1991; Wright 1986).

At the site scale, the spatial distribution of artifacts, structures, and features provide data on site function and organization (Willey and Phillips 1958). Where certain activities were carried out (and where they were not) provides information on the
longevity of the occupation, the number of individuals present, and social organization. Excavation is unfortunately a destructive process. The maps, photographs, and descriptions of site content remain the only record of the distribution of cultural materials after fieldwork is completed. Accuracy and quality of these records must be of primary concern in the process of data acquisition.

The artifact, or non-site, scale of analysis concerns the distribution of the physical remains a culture left behind (Thomas 1975). No attempt is made to scribe a boundary around artifact clusters to define a “site”, rather each artifact is treated independently to gain an understanding of past activity and land use. Activity areas may be defined based upon cluster analysis of related artifacts, whereas unrelated and temporally distinct artifact types are treated independently in such cases.

Although all of these scales remain relevant, the area, region, and locality scales are often generalized in discussion to the regional scale in the literature. This generalization is likely due to the erroneous perception that digital data are scale-less, as well as, the inherently qualitative character of the original definitions. Discussions of spatial scale in archaeology are also often confusing. Archaeologists often refer to a large-scale analysis, when they mean a large area of analysis. Although this is technically correct, it is confusing when the discussion of large-scale maps (small areas) and small-scale maps (large areas) appear in the same text. Given recent developments in environmental and archaeological data sets, the archaeological scales of analysis now include the global, hemispheric, continental, area, region, site and non-site spatial scales. Selecting the proper spatial scale of analysis is driven largely by quantitative factors (i.e.
sampling, resolution, accuracy and time) and the theoretical assumptions of a given study.

2.1.8 Resolution and Accuracy of the Data

The one-dimensional focus on geographic extent remains one of the primary weaknesses in traditional definitions of archaeological scales of analysis. Resolution and accuracy are other factors influencing relevant scales of analysis. Resolution refers to the minimum mapping unit (MMU) or the smallest object represented at a given scale (Aronoff 1989). In qualitative terms, non-site scales of analysis have the artifact as the MMU. The site scale of analysis can also have the artifact as an MMU, however the artifacts are mapped within the bounds of the site and outlying data may be ignored. Test units are also acceptable MMUs at the site scale of analysis. At the locality and regional scales, sites typically are the MMUs, though a group of related sites might also be an MMU. For area, continent, hemispheric, and global scales of analysis, a set of dispersed sites, localities, or regions may represent the MMUs. In quantitative terms, based upon my own analytical observations and experience, site and non-site scales of analysis should have ancillary data with a resolution of 1 m or less, localities should have a resolution of 30 m or less, regions should have a resolution of 90 m or less, and all other scales should have resolution of 10 km or less (Table 2.1). It should be noted that these resolutions were defined here based upon spatial data sets commonly available (e.g. Anderson et al. 2010; Wells et al. 2014), rather than purely cultural considerations of the ancillary data.
Table 2.1: The analytical scales, minimum mapping units (MMU), and resolutions relevant to archaeological research.

<table>
<thead>
<tr>
<th>Scale of Analysis</th>
<th>Minimum Mapping Unit</th>
<th>Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site or Non-Site</td>
<td>Artifact or Test Unit</td>
<td>≤ 1 m</td>
</tr>
<tr>
<td>Locality</td>
<td>Site</td>
<td>≤ 30 m</td>
</tr>
<tr>
<td>Region</td>
<td>Site or Site Group</td>
<td>≤ 90 m</td>
</tr>
<tr>
<td>Area, Continent, Hemisphere, or Global</td>
<td>Dispersed Sites, Locality or Region</td>
<td>≤ 10 km</td>
</tr>
</tbody>
</table>

The positional accuracy of mapped archaeological data is also often difficult to determine. Fieldwork often begins with a survey to establish a record of the topographic setting and spatial extent of sites. Likewise, all archaeological site locations are recorded using an established geographic coordinate system, such as the UTM or State Plane (Dills 1970; Edwards 1969). While site maps are often accurate to within a few centimeters relative to a site datum and grid system, rarely do maps identifying site locations meet defined map accuracy standards (see USGS 1999). Sites drafted on USGS 7.5-minute quadrangles, or other standardized base maps prior to the use of Global Positioning System (GPS) receivers in the past decade, commonly do not meet the standards of the base map due to recorder error and/or insufficient measurement techniques.

The incorporation of GPS into the archaeological tool kit has changed this trend (cf., Fitts 2005; Luo et al. 2014; Spennemann 1992). However, the majority of sites found prior to the past two decades were recorded before this technology was readily available (from August 1995 on the SRS; Gillam 1998). Thus, many sites are inaccurately located on base maps with typical errors measuring from a few hundred meters to extreme examples of more than a kilometer (Wandsnider and Dore 1995). This is a serious problem when considering analysis at the region, locality, site, or non-site scale. This
point cannot be overlooked, as these are the most common scales of analysis in archaeology. Without logical consistency and comparable accuracy between archaeological and ancillary data sets, analysis of the data may yield incorrect and meaningless results.

Given the accessibility and accuracy of GPS technology, most state and federal agencies now require GPS use in mapping cultural remains. Even inexpensive units not capable of differential correction or real-time beacon reception are a significant improvement over traditional mapping techniques. Most consumer-grade Differential GPS (DGPS), such as Wide Area Augmentation System (WAAS)-enabled, handheld units costing around $100 can obtain horizontal positions at less than 10-m average Root Mean Square Error (RMSE) in leaf-on conditions (Danskin et al. 2009), e.g. Garmin eTrex 10 ($109 retail/$85 wholesale. This exceeds national map accuracy standards at 1:24,000-scale of 12-m horizontal accuracy (USGS 1999). Without a DGPS signal, consumer-grade GPS units can still obtain positions under 12-m average. RMSE in leaf-on conditions (Danskin et al. 2009), a significant improvement over manual hardcopy recording methods.

The greatest hazard of electronic data sets remains that small resolution/high accuracy and large resolution/low accuracy data sets can be analyzed together to produce results that appear to be based strictly on small resolution/high accuracy data. This is true because data entered into a GIS can be presented at any scale. For instance, sites mapped from 1:24,000 scale base maps may be analyzed with environmental data derived from 1:100,000 scale base maps. Generalizations made from the analysis would be presented relative to the sites and thus incorrectly reflect the lower resolution and accuracy of the
environmental data. Models developed in this manner will represent extant generalization in ancillary data rather than trends relevant to the archaeological problem under scrutiny.

2.1.9 Representation of Temporal and Cultural Data

As a data extraction and cartographic modeling tool, GIS provides an expedient means of sub-setting archaeological data into a variety of samples for testing and model development. Archaeological sites can typically be broken down into both temporal and cultural components based upon the artifacts each site contains. The database capabilities of a GIS allows the user to quickly extract site locations based upon time and cultural affiliation by simply querying the associated database to create sub-samples of archaeological locations. Environmental data for these sub-sampled locations can be extracted from the GIS layers, resulting values fed into a statistical software package for testing, and coefficients in turn used in a cartographic model to produce maps of past land-use or site prediction.

The representation of temporal data in a GIS is not a new avenue of research (Armstrong 1988; Frank et al. 1992; Langran 1989; Snodgrass 1992; Periodo 2016; Wells et al. 2014). In fact, a broad range of fields have dealt with the representation of time in digital format. A few examples of non-archaeological applications include forest management (Kautz et al. 2011; Osborne and Stoogenke 1989; Yuan 1994), historic geomorphology (James et al. 2012), lightning strike patterns (Matsangouras et al. 2016; Wells and McKinsey 1993), remote sensing (Prabaharan et al. 2010; Xiao et. al. 1989), spatial decision support systems (Lolonis and Armstrong 1993; Van Orshovan et al.
The ability of a GIS to manipulate the temporal components of spatial data is not as straightforward as it might seem. Langran’s (1988, 1989, 1992, 1993) seminal works define the potential functions of a temporal GIS as inventory, analysis, scheduling, quality control, display, and updates. The inventory maintains a description of the area and any changes that might occur within it or within its database representation (see Mouat and Kelmelis 1993). Analyses summarize, take advantage of, and predict processes at work in a region. Scheduling permits the anticipation of system or external maintenance needs. Display capabilities are for the production of maps, on-screen visualizations, and report tables (see Slocum et al. 1993). Updates enable previous versions of geographic information to be replaced when new data becomes available. Finally, there should be quality control methods for evaluating the logical consistency of the new data (see Ward and Zheng 1993).

In addition, Langran (1992) identifies five technical requirements of a temporal GIS. The first of these, the conceptual model, defines what is to be depicted in the temporal GIS. In the following archaeological application, the conceptual model’s entities are sites, the attributes are artifacts, and the relationships are time slices of occupation and cultural affiliation. Second, the treatment of non-spatial attributes should maximize retrieval and storage of the data, in this case a related table of artifact classes is stored separately from the coverage. Third, data processing logistics, such as updates, must also be considered in the development of the temporal GIS. Fourth, the data access method is highly flexible in GIS due to a variety of query commands that can be used to
create the sub-samples. The final technical requirement is a set of efficient algorithms to manipulate the data.

Langran (1993) also provided a useful discussion of what she refers to as, "the dimensional dominance of spatio-temporal queries." Space dominant queries are those concerned with spatial distributions at a given moment, whereas time dominant queries are concerned with the spatial distributions of historical attributes (Figure 2.1). Archaeological queries are typically time dominant applications.

| Retrieve a snapshot of an area at a given moment | space dominant | time dominant |
| Retrieve snapshot(s) of an area at even intervals during a given timespan | | |
| Retrieve all data in an area within a timespan | | |
| Retrieve all features that have ever held certain attributes | | |
| Retrieve snapshot(s) of an area at the moment(s) when a feature holds certain attributes | | |
| Retrieve the history of a given feature | | |

Figure 2.1: The dimensional dominance of spatio-temporal queries (after Langran 1993).

Germane to any discussion of temporal GIS is how to represent temporal features. From an archaeological perspective, the features that will be represented most often are occupation areas commonly referred to as sites. Sites are scattered across the landscape in a non-contiguous fashion. The representation of non-contiguous elements as a single temporal and spatial feature with large voids in between is particularly important to
archaeological applications because sites are widely scattered across the landscape (Figure 2.2). In a GIS, sites are represented as points, polygons, or grid cells, depending upon the application. In predictive modeling, sites are typically represented as grid cells mirroring the resolution of the associated environmental data that will be extracted for statistical analysis.

Archaeologists have always been concerned with the spatial distribution and environmental context of sites. Historically, data such as elevation, soil type, landform category, distance to water, stream rank, and so on have been manually derived from USGS 7.5' quadrangles, county soils maps, and the like. A GIS has the ability to automate the majority of these tasks saving massive amounts of data extraction and input time. The benefits of incorporating archaeological data with GIS outweigh most potential problems, such as start-up costs, personnel and the availability of environmental datasets (Peregrine 1988; Anderson and Smith 2003).

GIS in general has already revolutionized the way archaeologists derive site-level data, while temporal GIS has the potential to revise the way in which archaeologists summarize that data. The temporal order of the archaeological record is derived through a variety of methods. Most frequently, artifacts from sealed stratigraphic contexts that are associated with carbon-dated cultural deposits are used to develop culturally relevant temporal periods. The artifacts can be used for comparison to other sites that lack good stratigraphic and organic context to gain a general perception of cultural extent, while dates from numerous sites having good context provide information on the duration of the cultural expression.
Figure 2.2: Temporal character of archaeological datasets in a GIS (shaded areas represent archaeological sites).

The environmental context of sites for a given time period has traditionally been costly to determine and nearly impossible to derive for all but the smallest of sub-regions. A temporal GIS enables the derivation of these variables at even greater continental and global scales (Banks et al. 2006; Gillam et al. 2007; Wells et al. 2014). Regional scale analyses are already possible for most areas using 1:100,000 scale data and many areas currently have larger scale 1:24,000 data available. The potential for temporal GIS applications in archaeology worldwide is certainly high.

The manipulation of cultural data in an archaeological dataset mimics that of temporal data as it is commonly based upon the artifact inventories of archaeological sites. The major difference being that cultural affiliation in prehistoric contexts often extends over greater periods of time due to similarities in cultural adaptations over time.
and inherent limitations of the archaeological record to reveal minor changes in cultural adaptation. Thus, in this dissertation cultural affiliation was limited to fewer classes than the temporal datasets (e.g. hunter-gatherer, horticulturist, agriculturist, and so on).

2.1.10 Cartographic Modeling

To this point, I have argued that GIS provides the archaeologist with access to geographic data at a variety of scales, these data have a definable accuracy and resolution, and the database and query capabilities enable easy sub-sampling of temporally and culturally variable datasets. Perhaps the most significant capability of GIS for archaeologists is in cartographic modeling. Cartographic modeling is the ability to mathematically manipulate mapped data in the GIS (Tomlin 1990). This capability enables a map to move beyond being a descriptive representation of the earth’s surface by representing map features as numeric values. The map becomes prescriptive, permitting mathematical operations and models to be developed (Berry 1993). In the research undertaken here, logistic regression was used to develop predictive models of past land-use. Basically, the coefficients from statistical analyses were used as map data to produce a probability surface representing the likelihood of encountering archaeological materials across the landscape. The cartographic model is discussed in greater detail in the methodology chapter.

2.1.11 Discussion

The influence of geographic methods on archaeological inquiry has a long and diverse history (Figure 2.3). Surveying and cartography have been the primary links
between archaeology and geography throughout recent history. The mapping and
description of cultural features will perhaps remain the strongest relationship in the
current century. Increasingly automated and accurate, maps remain one of the most
consistently useful heuristics in archaeology.

The applications of central place theory and general gravity models to
archaeological problems have only been partially successful. Unfortunately, ethnographic
analogy cannot provide all of the information necessary to modify these models for
optimal application to prehistoric cultures. Ethnographic analogy and social theory have
been most influential to problem-oriented archaeological research in recent decades.

In contrast, the anthropological concepts of cultural and historical process were a
significant contribution to cultural geography in the 1930’s (Platt 1959). Heralded by
Sauer (Sauer and Brand 1930), these concepts provided a viable alternative to
environmental determinism. The Sauer, or Berkeley, tradition was pluralistic in method
and theory and examined the interaction of people and environment (Price and Lewis
1993). Anthropologists now need to advance theory concerning the cultural use of space
and interaction with the environment. As new spatial theories are also developed in
geography, their application may improve our ability to understand prehistoric settlement
systems.
Figure 2.3: Timeline of geographic influence on archaeological inquiry.

The most promising link between archaeology and geography is in the realm of automated, spatial technology or GISci (Dobson 1983, 1993; Goodchild 1992a, b, 1995, 2006, 2009, 2010). The components of GISci continue to become more and more accessible to archaeologists. This is facilitating a greater understanding of the distribution of cultural remains at all scales. Likewise, the use of DGPS is ensuring the accuracy of site location for future applications.

Improvements in remote sensing technology are encouraging greater use of this data in survey planning and regional research. Affordability has also improved due to the growing competition within the commercial market. Site-level applications are developing due to improvements in accessibility, affordability and spatial resolution. Whereas aerial photography and imaging were once thought to become obsolete as satellite platforms producing 1-m resolution imagery became available (Jensen 1996), the
appearance of affordable drones and imaging solutions on the consumer market are making expedient aerial reconnaissance and mapping accessible to the masses (e.g. Sabina et al. 2015).

The past forty years have witnessed considerable progress in the application of GISci towards archaeological problems. In the future, archaeologists will continue to benefit from the developments in geographic methods. Anthropology programs need to incorporate GIS, GPS, and remote sensing into degree programs to facilitate the use of new technologies toward cultural problems. Likewise, geographers should continue their role as developers of the technology. It is up to archaeologists, anthropologists and cultural geographers to think of new innovative forms of analysis. Predictive modeling, data management, and visualization will remain important, with theoretical foundations and analyses focusing on cultural interaction, exchange, cosmology, and migration further advancing the field.

2.2 Archaeological Predictive Modeling and Validation Testing

2.2.1 Predictive Modeling Approaches

As discussed previously, archaeological predictive modeling is not a new venue of research (e.g., Judge and Sebastian 1988) and there have been many different applications and approaches presented over three decades of use. These range from inductive, CRM applications (e.g., Harris et al. 2015) to more deductive, academic research (e.g., Vogel et al. 2016). However, and as evidenced in this dissertation, the two approaches of “inductive” and “deductive” modeling are not mutually exclusive (cf., Verhagen and Whitley 2012). Multivariate logistic regression or Binary Logit Modeling
(BLM), as applied in this research, remains one of the most widely-accepted methods used (cf., van Leusen et al. 2005).

In the “gray” CRM literature, “Mn/Model,” developed for the state of Minnesota (Hudak et al. 2002), was one of the first state-wide efforts at modeling prehistoric site location, while the Pennsylvania Department of Transportation’s (PA DOT) “Archaeological Predictive Model Set” (Harris et al. 2015) was one of the most recent. Mn/Model’s (Hudak et al. 2002) goal was to use BLM to predict 85-percent of known sites within less than 33-percent of land area classified as high- and moderate site probability, resulting in a gain statistic of 0.6118 or higher (see Section 2.2.2 below). Additionally, model stability was measured by comparing two preliminary models with the Kappa coefficient of agreement (cf., Bonham-Carter 1994).

In academic circles, problem-oriented predictive modeling research has increasingly appeared in peer-reviewed articles and edited volumes on the subject (e.g., Kamermans et al. 2009; Vogel et al. 2016). While many applications in CRM treat archaeological data synchronically without explicit consideration of temporal or cultural variation, most research applications attempt to model cultural landscapes with specific temporal and/or cultural traits and/or diachronically over time and across cultures (Gusick and Faught 2011; Mlekuž 2010; Scurry 2003, 2015; Verhagen and Whitley 2012). The latter is the approach of this research, through hypothesis testing of temporal and cultural data subsets prior to predictive model development (see Chapters 3 and 4).

Other approaches that have gained merit recently include Bayesian and Dempster-Shafer Theory (DST) models that integrate expert judgement and archaeological data more directly (cf., Verhagen et al. 2009). This is made possible by direct input of expert-
weighted categorical datasets into the analyses. In Bayesian models, the formulas for total and conditional probability offer a summation of the weighted variables within a probabilistic framework (Whitley 2016). Unlike Bayesian and other probability models, a DST model is based upon the theory of uncertainty in addition to probability theory. In models based upon DST, “Dempster’s Rule of Combination” is used to compute the degree of agreement between two variables for multiple hypotheses (van Leusen et al. 2009; after, Shafer 1976). Probabilities may be computed for as many variables as desired, resulting in measures of “belief” and “plausibility” that yield measures of uncertainty. Although promising and sophisticated, Bayesian and DST methods of predictive modeling are complex and have not received widespread adaptation in archaeology.

Eco-Cultural Niche Modeling (ECNM) is another alternative approach to predictive modeling that uses machine-learning techniques instead of best subset selection in BLM or expert selection in Bayesian and DST methods (e.g., Banks et al. 2006; Gillam et al. 2007). ECNM is an application of the Genetic Algorithm for Rule-Set Production (GARP) that was designed to predict species distributions in the biological sciences (e.g., Peterson 2003; Sobek-Swant et al. 2012; Stockwell 1999). Its primary weaknesses are replicability of results, due to the unique character of machine-learning calculations, and the potential for biased model selection, as it outputs a series of probability surfaces for the expert to either choose from or combine in an additive fashion. Nevertheless, the DesktopGARP PC program developed by the University of Kansas Biodiversity Research Center is freely available for download and includes small-
scale, global climate and environmental data for expedient application (http://www.lifemapper.org/desktopgarp/).

2.2.2 Validation Testing Approaches

Model performance measures have traditionally taken several forms: measures of gain statistics, measures of classification error, and statistical inference (cf., Verhagen 2009a, b). Gain measures, most notably the Gain Statistic (Kvamme 1988), simply use the percent area of probable site presence (i.e., model accuracy) and the percentage of observed sites (i.e., model precision) to provide a relative measure of model performance (e.g., Hudak et al. 2002). More specifically:

\[
\text{Gain Statistic} = 1 - \left( \frac{\text{Percent Area}}{\text{Percent Sites}} \right)
\]

Where the Percent Area is typically that of high and/or moderate probability areas, and Percent Sites is the actual percentage of known sites found within those areas (Kvamme 1988). However, this is a problematic measure of model performance, since the same gain value may be obtained using different values for accuracy and precision (cf., Ebert 2000). Nonetheless, it is one of the simplest performance measures to calculate without needing a separate validation sample and also permits trial-and-error model optimization through repeated application (cf., Verhagen 2009a).

The use of Deletion/Substitution/Addition (DSA) modeling with Receiving Operator Characteristic (ROC) curves effectively overcomes the limitations of stepwise selection in BLM models (Fernandes et al. 2011). ROC curves are used to both compare the relative performance of alternative models (i.e., environmental vs. cultural-
environmental models) and to examine the contribution of each variable in a model using their corresponding coefficients, calculated for the Area Under the Curve (AUC) value. The AUC values therefore serve a similar purpose to the traditional Gain Statistic in BLM and the variable coefficients can be similarly used in BLM for interpretive purposes or causality. In place of DSA, this dissertation used an expert knowledge approach to select variables for BLM modeling to bypass issues with automated stepwise and best subset selection. ROC curves and AUC values were also used here to evaluate the BLM models and evaluate breakpoints for high probability classification (see Chapters 3 and 4).

Other statistically robust measures of model performance require either complex resampling techniques (i.e., bootstrapping), split sampling (i.e., 50-percent withheld) or, optimally, an independent validation sample similar to the one used in this study. While resampling and split sampling techniques are useful, they are limited by not being fully independent of the model sample and underperform in comparison to independent samples (Muñoz and Felicísimo 2004; Verhagen 2009a). Optimally, an independent validation sample collected separately from the dataset used for model building and evaluated with a nonparametric statistic, that makes no assumption of a normal distribution, will provide the best measure of model performance. The independent validation sample strategy was selected for this research and evaluated with the Chi-Square ($X^2$) nonparametric statistic with overall performance calculated with the Gain Statistic (cf., Earickson and Harlin 1994; Kvamme 1988; see Chapters 3 and 4).
2.2.3 Discussion

As acclaimed statistician George Box (1976) stated, “Since all models are wrong the scientist cannot obtain a ‘correct’ one by excessive elaboration.” Ultimately, the methods used to develop and test a model should mirror the goals of modeling itself; that is, the methods and model should be simple, elegant and replicable. In this regard, inductive BLM modeling has garnered the greatest adoption rate of all multivariate modeling techniques and has withstood the test of time over some three decades of use (e.g., Kvamme 1988; Harris et al. 2015).

However, deductive approaches have their merits as well. The most relevant to this dissertation and the Inner Coastal Plain of the Central Savannah River is the Brooks-Scurry Model (Brooks and Scurry 1978) that has been elaborated upon in recent decades by Scurry (2003, 2015). Their model relied upon a simple GIS overlay approach of four environmental variables and was validated with the Chi-Square statistic for observed versus expected frequencies of sites, the latter similar to this dissertation’s approach. The dependent variables were prehistoric sites in three cultural subsets: Archaic, Woodland and Mississippian. The independent variables of the multicomponent model included low slopes (2 – 15 percent), ecotones (100-m buffers from wet soils), well- to moderately-well drained soils, and southwest facing aspects (136 - 236 degrees) defining high probability areas as those were all four variables overlapped. Remarkably, Scurry found that site locations did not vary significantly over time or by cultural adaptation, a finding that is corroborated using quite different methods and many more environmental variables in this dissertation. Even more remarkably, calculating the Gain Statistic from Scurry’s table (Scurry 2015: 93; Table 6) yields a range of 0.52 to 0.73 for
multicomponent sites; these were higher than the Gains for the 1989 SRARP Sensitivity Model and models in this dissertation (see Chapter 4).

While it is rather arbitrary and unnecessary to reclassify a probability surface into high, moderate and low probability areas, it remains a common product of such modeling efforts in archaeology. This classification provides data for nonparametric statistical evaluation of independent site samples and themes for communication to non-technical map readers. It is the purpose of such thematic mapping to present complex phenomena into easily-grasped categories or themes (Kraak and Ormeling 2011). One objective of this research was to present methods of producing and testing multivariate predictive models that can be replicated and understood by non-specialists in GIScience and statistics. That is, the methods should be accessible to anyone with a basic knowledge of GIS and statistics.

2.3 Cultural Resource Management and Research on the SRS

2.3.1 The 1989 SRS Sensitivity Zone Map

Archaeological predictive modeling at the Department of Energy’s Savannah River Site (DOE-SRS) has paralleled efforts elsewhere in the southeast. First published in 1989, the extant archaeological sensitivity model was developed by the Savannah River Archaeological Research Program (SRARP) to aid cultural resource management of prehistoric sites on the SRS (SRARP 1989). Generated prior to the availability of a GIS at the SRARP, there were nonetheless others developing GIS on the SRS at that time (e.g., Cowen et al. 1995). Given the limited technology at hand, the model was understandably based upon only three environmental variables and univariate statistics.
Similar to other predictive models, it provided three zones of relative archaeological sensitivity including low, moderate, and high probability areas, plus an indeterminate zone representing wetland areas typically avoided by land-use planners on the SRS (and therefore not archaeologically tested on a regular basis).

The terms used to describe the 1989 model were slightly different from the norm. The Probability Areas were referred to as Sensitivity Zones in the model, with Zone 1 corresponding to High Probability areas, Zone 2 corresponding to Moderate Probability areas, and Zone 3 corresponding to Low Probability areas. There was also a Zone 0 that corresponded to areas of unknown probability; more specifically, to inundated floodplains and upland wetlands that had not received extensive archaeological testing (see also, Anderson et al. 1988).

Likewise, it was proposed that three archaeological site types roughly correlate to the three primary “sensitivity zones” (i.e. probability areas) of the predictive model. These site types include Type 1 sites that consist of more than 3 cultural components, Type 2 sites that consist of 1 to 3 cultural components and Type 3 sites that consist of non-diagnostic cultural materials (e.g. debitage, plain sherds).

The corresponding Sensitivity Zones of the 1989 archaeological sensitivity model attempt to define those locations most likely to contain the various site types defined by the SRARP (Figure 2.4). The first, Zone 1, is defined as all areas within 400-m of streams Rank 3 or greater using the Strahler system, less than 83-m amsl, and less than 31-m above the nearest stream Rank 3 or greater (SRARP 1989). Zone 1 represents only 17% of the total SRS land cover (Table 2.2). This zone is presented as the most likely to contain significant, multi-component Type 1 prehistoric sites. Zone 2 is defined as all
areas within 400-m of Rank 1 and 2 streams and within 401-m to 800-m of streams Rank 3 or greater. Zone 2 represents a full 44% of the SRS land cover, frequently containing small, Type 2, multi-component prehistoric sites and Type 3, non-diagnostic prehistoric sites. Zone 3 represents 25% of the SRS land cover, has the lowest probability of containing significant prehistoric sites, and consists of areas outside of Zones 0, 1, and 2. Finally, Zone 0 consists of all wetland areas as these do not receive regular archaeological reconnaissance due to their protected status from land-use development. Zone 0 represents only 14% of the total SRS land cover.

<table>
<thead>
<tr>
<th>Archaeology Zones</th>
<th>SRS Hectares</th>
<th>SRS % Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zone 0</td>
<td>10146</td>
<td>13</td>
</tr>
<tr>
<td>Zone 1</td>
<td>13113</td>
<td>17</td>
</tr>
<tr>
<td>Zone 2</td>
<td>34933</td>
<td>44</td>
</tr>
<tr>
<td>Zone 3</td>
<td>20332</td>
<td>26</td>
</tr>
<tr>
<td>Totals</td>
<td>78524</td>
<td>100</td>
</tr>
</tbody>
</table>

2.3.2 Discussion

The SRS is located in the Upper Coastal Plain of South Carolina along the Middle Savannah River, representing an area of 78,524 hectares that is currently dominated by pine silviculture. The major landforms of the SRS include the modern Holocene floodplain of the Savannah River, the Pleistocene terraces of that river, and the Aiken Plateau in the sandy uplands (Brooks et al. 1986). Several major tributaries of the
Savannah River dissect the upland sand hills, including Upper Three Runs, Fourmile Branch, Pen Branch, Steele Creek, and Lower Three Runs.

At the end of the 2015 fiscal year, the SRARP had recorded 1,998 prehistoric and historic archaeological sites. The majority of these have been recorded during the normal compliance activities of the SRARP. These activities include a range of sampling techniques used over the years including surface survey of roads, firebreaks, and clear-cut forests, shovel test surveys in wooded areas, and a limited number of block excavations at mitigation sites. Most recently, both the 1989 sensitivity model and intensive surveys have dominated these site discovery activities.

The primary weaknesses of the extant model are related to the fact that the SRARP developed the model without the benefit of a GIS and therefore used a limited number of variables for analysis. These variables included only distance to nearest stream, elevation, and relative elevation to nearest stream. While the model is effective for targeting areas of prehistoric site use, new assumptions regarding the significance of single component sites versus their multi-component counterparts and the desire to predict a higher percentage of sites in the highest probability zone of the model warrants the development of a new model that is not based upon the number of components per site.

In practice, the 1989 model has been used mainly as a guide for fieldwork. Fieldwork has not been restricted to only the highest probability area of the model. For example, in Moderate Probability (Zone 2) areas, the terraces edges along Strahler Rank 1 and 2 streams have been consistently tested using systematic 30-m interval transect surveys. Likewise, in Low Probability (Zone 3) upland areas the edges of upland
wetlands and Carolina Bays have witnessed systematic survey when encountered during compliance and research projects. Historic sites have been targeted, independent of the 1989 sensitivity model, using historic maps and 1951 aerial photographs and, most recently, 2004 LiDAR imagery of the SRS. The continued use of these alternative data sources will be demonstrated to be the most effective means of determining historic site potential. The consistent effort to systematically sample areas outside of the highest probability area of the 1989 model has resulted in a very robust site sample within the SRS bounds.

Despite the recognized weaknesses of the 1989 sensitivity model, it has been invaluable as a tool for limiting the scale of survey projects and for communicating potentially sensitive areas to non-archaeologists involved with land-use planning on the SRS. Given that the 1989 model was developed before the availability of GIS at the SRARP, significant improvements should be realized incorporating more numerous environmental data sets, multivariate statistical evaluations of the data, and time-slice samples of the archaeological distributions. This will further enhance both the CRM-related and archaeological research activities on the SRS.
Figure 2.4: The 1989 Sensitivity Zone Model for the SRS (SRARP 1989).
CHAPTER 3

METHODOLOGY

The purpose of this research was to develop statistical, GIS-based methods to test extant archaeological predictive models, evaluate archaeological sample bias, examine temporal and cultural variability in archaeological site distribution and, based on those results, generate a multivariate predictive model(s) for the SRS. This chapter presents the methodological framework including its data, hypotheses, analyses, and modeling techniques. The first section highlights the archaeological and environmental datasets that are used to test the research hypotheses and to develop the archaeological predictive model(s). The second section provides the research hypotheses and a discussion of the analytical techniques used in their evaluation. Finally, the third section discusses the analyses and describes the archaeological predictive model(s) to be developed from the outcome of the hypothesis tests.

3.1 Environmental and Historic Datasets

A series of environmental and analytical datasets form the basis of the revised predictive models for the SRS (Table 3.1). These data were used to derive the independent variables for statistical analyses in this research. The primary environmental datasets consist of (1) a digital elevation model (DEM) and (2) a Carolina Bays and upland wetlands layer converted to grids. Secondary environmental data derived from
Table 3.1: Environmental/Analytical Grid Datasets (n=32).

<table>
<thead>
<tr>
<th>Grid</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>dem_ned30</td>
<td>Elevation (DEM) 30-m resolution</td>
</tr>
<tr>
<td>slp_ned30p</td>
<td>Slope percent rise</td>
</tr>
<tr>
<td>facc_ned30</td>
<td>Flow accumulation</td>
</tr>
<tr>
<td>cal_ned30</td>
<td>Cumulative calories per 30-m cell</td>
</tr>
<tr>
<td>curv_ned30</td>
<td>Curvature at center</td>
</tr>
<tr>
<td>prof_ned30</td>
<td>Curvature direction of slope</td>
</tr>
<tr>
<td>plan_ned30</td>
<td>Curvature perpendicular to slope direction</td>
</tr>
<tr>
<td>annglb00</td>
<td>Annual Solar Potential</td>
</tr>
<tr>
<td>solglb00</td>
<td>Summer solstice solar potential</td>
</tr>
<tr>
<td>solglb01</td>
<td>Winter solstice solar potential</td>
</tr>
<tr>
<td>solglb02</td>
<td>Equinox solar potential</td>
</tr>
<tr>
<td>elev_rng900</td>
<td>Elevation Range (450-m radius)</td>
</tr>
<tr>
<td>rel_strm900</td>
<td>Relative Elevation to water (streams or upland bays)</td>
</tr>
<tr>
<td>rel_strm3k</td>
<td>Relative Elevation to streams</td>
</tr>
<tr>
<td>strm_c4</td>
<td>Caloric cost distance to nearest stream</td>
</tr>
<tr>
<td>strm3_c4</td>
<td>Caloric cost distance to nearest Strahler Rank 3+ stream</td>
</tr>
<tr>
<td>srfp_c4</td>
<td>Caloric cost distance to Savannah River floodplain</td>
</tr>
<tr>
<td>fluv_c4</td>
<td>Caloric cost distance to fluvial wetland</td>
</tr>
<tr>
<td>bays_c4</td>
<td>Caloric cost distance to Carolina bay wetland</td>
</tr>
<tr>
<td>wet_c4</td>
<td>Caloric cost distance to nearest wetland (fluvial or upland)</td>
</tr>
<tr>
<td>fs_c4</td>
<td>Caloric cost distance to nearest fluvial wetland or stream</td>
</tr>
<tr>
<td>fbs_c4</td>
<td>Caloric cost distance to nearest fluvial wetland, bay, or stream</td>
</tr>
<tr>
<td>edge_c4</td>
<td>Caloric cost distance to edge environment</td>
</tr>
<tr>
<td>trls2_c4</td>
<td>Caloric cost distance to prehistoric trail model</td>
</tr>
<tr>
<td>qry_c4</td>
<td>Caloric cost distance to chert quarry (southeast)</td>
</tr>
<tr>
<td>sed_c4</td>
<td>Caloric cost distance to South Fork Edisto (northeast)</td>
</tr>
<tr>
<td>pdm_c4</td>
<td>Caloric cost distance to Piedmont (northwest)</td>
</tr>
<tr>
<td>bri_c4</td>
<td>Caloric cost distance to Brier Creek, Georgia (southwest)</td>
</tr>
<tr>
<td>mills_c4</td>
<td>Caloric cost distance to historic primary roads</td>
</tr>
<tr>
<td>roads_c4</td>
<td>Caloric cost distance to all modern roads</td>
</tr>
<tr>
<td>roads51_c4</td>
<td>Caloric cost distance to 1951 roads</td>
</tr>
<tr>
<td>rails_c4</td>
<td>Caloric cost distance to historic rail lines</td>
</tr>
</tbody>
</table>
these include percent-slope, flow accumulation, hydrography, caloric cost to traverse each 30-m cell, local elevation range, relative elevation to water, curvature of each cell (center curvature, profile curvature, and plan curvature), solar potential (annual, summer solstice, winter solstice, and equinox), and the various (n=18) caloric cost distance measures (Table 3.1). These derived environmental data were created by common raster processing and modeling techniques. Transportation networks consisting of historic roads, rails, navigable streams and a model of potential upland trail locations, are also incorporated as grids.

Without a GPS record of individual artifact or test unit locations available for analysis, the use of high resolution LiDAR (2-m and 5-m) and 10-m National Elevation Dataset (NED10) data on the SRS was determined to be unwarranted. For this reason and for replicability of the analyses in other regions of the U.S., the use of the 30-m National Elevation Dataset (NED) Digital Elevation Model (DEM) was selected. The NED 30-m DEM was derived from multi-source elevation data and is the numerical equivalent of a series of USGS 7.5’ quadrangle topographic maps for the SRS facility (Gesch et al. 2002, 2009). These data are freely available online at the USGS Seamless Data Warehouse website (http://viewer.nationalmap.gov). With similar 30-m resolution Shuttle Radar Topography Mission (SRTM) data available worldwide (Guth 2006), successful predictive models based upon derivative datasets of NED (e.g. stream networks, slope, etc.) have even broader applicability. These methods and global SRTM GIS datasets have been similarly applied to archaeological research in South America and East Asia by the author (cf., Gillam and Tabarev 2006; Dahl et al. 2011).
Elevation is an important factor in the model due to the topographic variation of the dissected landforms on the SRS. Archaeological sites are known to commonly occur along topographic breaks across the landscape. Thus, elevation and derivatives of elevation (e.g. percent-slope, elevation range) are believed to be potentially significant in relation to archaeological site distributions. Likewise, solar potential is a key factor in vegetation cover exploited by prehistoric populations and also a likely factor in seasonal habitation selection.

The remaining data were derived from a variety of sources. The hydrography layer represents a hydrologic model of the NED 30-m DEM. This was chosen over other hydrologic data sources for replicability purposes, as well as control over modern natural and cultural hydrologic features (i.e., removing man-made 20th century lakes). The hydrography layer also includes Strahler rank data. Streams have potential significance for many reasons. First, streams are a source of potable water. Second, streams are a source of fish and a variety of other aquatic fauna and flora. Third, avian and terrestrial species also frequent potable water sources providing an ideal setting for hunting game. Fourth, major streams (Strahler rank 3 or greater on the SRS; cf. Strahler 1957) provide a transportation network via simple watercraft (e.g. canoes). Thus, the minimum cost distance to streams and the Savannah River floodplain are potentially significant to past cultures.

The Carolina Bays/upland wetlands layer was developed using aerial photography and field surveys by various SRS-related agencies including the U. S. Forest Service and the University of Georgia’s Savannah River Ecology Lab (cf. Schalles et al. 1989). These upland wetlands share the potential significance of streams as potable water sources and
provide ready access to fauna and flora. Carolina Bays and other upland wetlands likely served as resource patches throughout much of prehistory in the resource-poor, pine-dominant upland Sandhills of the SRS. As such, these landscape features may have served as resource oases along trail networks in the inter-riverine uplands.

Transportation networks included primary historic roads from 1951 aerial photos, the 1825 Mills Atlas (Mills 1825) and a model of potential upland trails for the prehistoric analyses. The cartographic error in the Mills’ Atlas was found to exceed 600-m and therefore precluded a direct digitizing of the Barnwell District map for incorporation in the analyses (Gillam 2000). Instead, modern roads that are known to correspond to those in the Mills’ Atlas will be used to estimate the location of the historic roads. Similarly, there are no known prehistoric trail locations known for the SRS, but potential upland trail locations were modeled using least-cost paths analysis. The cost distance of sites from historic roads and upland trails were calculated for historic and prehistoric sites, respectively.

3.2 Archaeological Datasets

The archaeological datasets used in the analyses that follow consist of a total of 1,218 prehistoric and 903 historic archaeological site locations, maintained by the author and curated by the SRARP (SRARP-SCIAA-USC, 1321 Pendleton Street, Columbia, SC 29208). The majority of these have been recorded during the normal compliance activities of the SRARP. These activities include a range of site discovery and sampling techniques including surface survey of roads, firebreaks, and clear-cut forests, shovel test surveys in wooded areas, and a limited number of block excavations at mitigated sites.
This variation in site discovery techniques and sampling highlights the need for statistical testing before the various samples are combined for additional hypothesis tests and predictive model development. The sites are represented in the GIS as x-y coordinate pairs and 30-m grid cells. A database containing temporal and cultural (component) data is linked to the GIS layer and queried to make time-slice and cultural sub-sets of the geographic data.

The site concept in archaeology has witnessed considerable debate in recent years (Bevan and Connolly 2004; Bintliff and Snodgrass 1988; De Haas 1012; Sassaman et al. 1996). The debate typically centers on the problem associated with scribing a boundary around an area that contains artifacts. The problem is that most “sites” have been occupied during multiple time periods in the past. Therefore, they contain multiple components or artifacts from those different periods. Site boundaries are defined based upon clusters of artifacts, but typically do not reflect the temporal variation of artifact distribution (there are not separate boundaries overlapping to represent the separate occupations, rather a single boundary defines a generalized site area).

Figure 3.1 illustrates the point. The bold polygon represents a typical site boundary that would be recorded in the South Carolina state archaeological site files. However, the three remaining polygons (T1, T2, and T3) represent distinct temporal components of the site. Unfortunately, a component-based map is not required for the state site files of South Carolina, nor is this a common practice anywhere in the United States at present (Anderson and Horak 1995; Wells et al. 2014).

Site polygons are thus arbitrary boundaries that do not take into account variation in the temporal periods of site use or level of disturbance of cultural remains. Site
polygons thus vary significantly from one site to the next and do not produce a reliable basis for locational analyses. On the SRS, site polygons range in shape from simple circles, rectangles and squares to complex amorphous shapes (Figure 3.2). In addition, sampling by surface survey and/or 35-cm by 35-cm shovel test pits (STP) at 10-m to 30-m intervals introduces considerable sample error. With so much potential for error, a centrally or selectively located (i.e., based on artifact density, an intact feature, etc.) site datum or unit location recorded in the field is deemed a more reliable estimate of general site context than the arbitrarily-bounded site polygon.

Figure 3.1: A hypothetical archaeological site map.

Site datums at the SRS have only been recorded with differentially-corrected GPS since fiscal year 1996 (i.e., from mid-August 1995; cf., Gillam 1998), with 839 sites
having GPS records of the 1,995 total sites (42-percent with GPS). Problems associated with pre-GPS site locations and with site polygon variation in shape and size are illustrated in Figure 3.2. My own experience at the SRS indicates non-GPS site locations recorded on 1:24,000-scale USGS topographic maps typically have horizontal position errors of approximately 50-m on average, with extreme examples being those sites that are accurately located and those in excess of 1-km error (Figure 3.2). This knowledge, in addition to changes in site discovery methods over the decades, provided additional justification for the site sample bias analyses.

Defining site type is another problem in the interpretation of the archaeological record. There are few sites that have been excavated to the extent necessary to define a distinct type. Type is also a problem due to the limited number of artifacts that are preserved at sites. That is, archaeologists typically recover stone, ceramics, and other durable goods, but rarely recover wood, bone, cloth, and other non-durable goods. In the prehistoric record, there are often no structural remains at sites to offer information on the length of habitation or season of use. Sites traditionally recorded as “seasonal base camps” due to their comparatively high density of artifacts may in fact be sites that were simply revisited more often than others, rather than being inhabited for a longer period of time. Similarly, sites in archaeological databases that seem to have a high density of artifacts are commonly those that have witnessed the greatest amount of excavation, thus skewing the dataset based upon recovery type rather than site type.

Due to the problems inherent in the archaeological record, the recorded site datums were used to define the location of sites in the analyses presented here. On the SRS, the topography and environment typically have gradual transitions across the
Figure 3.2: Typical problems with pre-GPS archaeological site locations and typical high variation in site polygon shape and area that disregard time, sample error and disturbance.
landscape. Therefore, the generalization of occupations to a single coordinate pair or 30x30m pixel is acceptable for the scale of analysis involved in this research. Likewise, site type will not be defined due to the limitations of the record. Instead, presence or absence of artifacts will be used to separate the data into temporally and culturally discreet datasets. The only exception to this approach herein are the component-based, site type designations used to test the 1989 Sensitivity Model (see Hypothesis I, this chapter).

The archaeological data were used to develop time-sliced and cultural datasets resulting in a total of 12 archaeological samples (Table 3.2). The intensive survey sample was expanded to include sites recorded during clear-cut surveys from 1990 to present. Using these clear-cut survey data increased the intensive survey archaeological sub-sample to 295 sites. The intensive survey sites, pre-1990 sites, and 1989 model-derived sites were split into their respective prehistoric and historic categories. The remaining six test samples included the 1973-1989 prehistoric sites, post-1990 prehistoric sites recorded using the 1989 model, post-1990 prehistoric sites recorded during intensive surveys, 1973-1989 historic sites, post-1990 historic sites recorded using the 1989 model and post-1990 historic sites recorded during intensive surveys. Finally, there are three model validation samples that consist of intensive survey sites excluded from the test samples: all validation sites, prehistoric validation sites and historic validation sites, respectively.

Attribute data for each site location is included the artifact inventory database. The artifact attributes enabled the data to be separated into distinct samples based on time of occupation and cultural affiliation.
3.2.1 Intensive Archaeological Site Samples

A total of 295 archaeological sites were included in the analytical sample from the systematic, intensive surveys (Table 3.3). Of these, 199 contain prehistoric components and 183 contain historic components (87 sites have both prehistoric and historic components in their assemblages). A separate validation sample consisted of 152 sites for model testing (Table 3.3). The sites were again represented in the GIS as x-y coordinate pairs and 30-m grid cells. A database containing temporal and cultural (component-level) data was linked to the GIS layer for querying to make time-slice and cultural sub-sets of the geographic data.

Table 3.2: Archaeological Grid Datasets (n=12).

<table>
<thead>
<tr>
<th>Grids</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Pre-1990 Sample Sites</td>
<td>559</td>
</tr>
<tr>
<td>Total Post-1990 Model Sample Sites</td>
<td>817</td>
</tr>
<tr>
<td>Total Intensive Survey Sites</td>
<td>295</td>
</tr>
<tr>
<td>Total Validation Sample Sites</td>
<td>152</td>
</tr>
<tr>
<td>Prehistoric Pre-1990 Sample Sites</td>
<td>427</td>
</tr>
<tr>
<td>Prehistoric Post-1990 Model Sample Sites</td>
<td>478</td>
</tr>
<tr>
<td>Prehistoric Intensive Survey Sites</td>
<td>199</td>
</tr>
<tr>
<td>Prehistoric Validation Sample Sites</td>
<td>89</td>
</tr>
<tr>
<td>Historic Pre-1990 Sample Sites</td>
<td>256</td>
</tr>
<tr>
<td>Historic Post-1990 Model Sample Sites</td>
<td>473</td>
</tr>
<tr>
<td>Historic Intensive Survey Sites</td>
<td>183</td>
</tr>
<tr>
<td>Historic Validation Sample Sites</td>
<td>110</td>
</tr>
</tbody>
</table>
Table 3.3. Intensive Survey Archaeological Grid Datasets (n=6).

<table>
<thead>
<tr>
<th>Grids</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Intensive Survey Sites</td>
<td>295</td>
</tr>
<tr>
<td>Prehistoric Intensive Survey Sites</td>
<td>199</td>
</tr>
<tr>
<td>Historic Intensive Survey Sites</td>
<td>183</td>
</tr>
<tr>
<td>Total Validation Sample Sites</td>
<td>152</td>
</tr>
<tr>
<td>Prehistoric Validation Sample Sites</td>
<td>89</td>
</tr>
<tr>
<td>Historic Validation Sample Sites</td>
<td>110</td>
</tr>
</tbody>
</table>

3.3 Hypotheses and Statistical Analyses

There are five primary hypotheses tested in this research, as discussed in the Introduction, as well as a number of secondary hypotheses and explanations derived from them, discussed in the Results chapter. The first hypothesis targets the validity of the extant model currently adopted by the SRS. It tests the 1989 model’s ability to predict the three archaeological site types defined in the original analyses using an independent site sample. This evaluates the relative strengths and potential weaknesses of the extant model when sites are classified based upon the number of components at each site.

The second test examines all prehistoric sites and historic sites, respectively, without a classification of the data based on the number of components per site. This latter test provides a basis for new model development as it reflects changes in our assumptions about the significance of single component sites as opposed to the multi-component sites used in the 1989 model.

The third hypothesis tests the validity of combining archaeological data recorded by various sampling strategies during the four decades of archaeological research on the
Savannah River Site. The research hypothesis is that all sites recorded by the different sampling strategies of the SRS over the past 38 years have the same spatial distribution. If this hypothesis is true then all sites can be lumped in the same population allowing for a much larger sample size.

The fourth hypothesis examines if statistically important environmental factors vary between prehistoric and historic populations at the component level (Early Archaic, Middle Archaic, Late Archaic, etc.). This hypothesis examines what archaeological periods or components need to be modeled separately to assess changes in the environmental factors over time.

The fifth hypothesis also evaluates the cultural variation in environmental factors by these prehistoric and historic peoples, but is based upon a more generalized classification of sites than the previous component-level analysis (e.g. prehistoric hunter-gatherers vs. prehistoric horticulturists vs. historic agriculturists). The classification of sites by culture type will determine what life-ways need to be modeled separately to examine changes in environmental factors by cultural type.

Together, these five hypotheses provide the basis for the archaeological predictive modeling that follows. The expectations are that the extant model will require refinement, that archaeological datasets can be combined to improve overall sample size, and there are indeed differences in the temporal and cultural distributions of sites on the SRS. If these expectations are correct, then multiple models of the cultural landscape are needed for the SRS.
3.3.1 HYPOTHESIS I – 1989 Model Component-Level Test

H₀: Archaeological site types are not significantly associated (p < 0.05) with the sensitivity zones of the 1989 Archaeological Predictive Model of the SRS.

The first test of the 1989 model determines if there is a significant association of the frequency of prehistoric archaeological site types to the sensitivity zones of the 1989 Sensitivity Model of the Savannah River Site. This was tested using an intensive, systematically derived site sample and GIS overlay analysis to identify the frequency of sites by archaeological sensitivity zone of the 1989 predictive model. This involved testing the model using the number of components (temporally distinct occupations) per prehistoric site to characterize the site sample into the three prehistoric site types defined by the SRARP (1989).

The systematic intensive surveys consisted of timber stands distributed throughout the SRS facility. In all, over 4,300 hectares were covered in the surveys resulting in a sample of 5.6-percent of the entire SRS landscape (78,524 hectares). Careful selection of survey areas resulted in a proportional sample of predictive model zones that closely approximates that of the entire SRS as well (Table 3.4).
Table 3.4: Percent cover for predictive model zones by SRS-wide coverage and the systematic, intensive survey sub-sample.

<table>
<thead>
<tr>
<th>Archaeology Zonal Zones</th>
<th>Survey Hectares</th>
<th>SRS Hectares</th>
<th>Survey % Area</th>
<th>SRS % Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zone 0</td>
<td>218</td>
<td>10146</td>
<td>5</td>
<td>13</td>
</tr>
<tr>
<td>Zone 1</td>
<td>944</td>
<td>13113</td>
<td>21</td>
<td>17</td>
</tr>
<tr>
<td>Zone 2</td>
<td>2216</td>
<td>34933</td>
<td>51</td>
<td>44</td>
</tr>
<tr>
<td>Zone 3</td>
<td>995</td>
<td>20332</td>
<td>23</td>
<td>26</td>
</tr>
<tr>
<td>Totals</td>
<td>4373</td>
<td>78524</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

A total of 199 sites containing prehistoric components were selected from the surveys. These sites provide the observed frequencies ($f_o$) for each prehistoric site type within the zones of the 1989 model. Expected frequencies ($f_e$) for each zone are calculated using the sub-sample totals and area of each zone:

$$f_e = \left( \frac{\text{#sites}}{\text{total area}} \right) \times \text{zone area}$$

The prehistoric archaeological site type samples are queried by archaeological zone. Significance between zonation and observed site frequencies are then evaluated using Yates’ Correction for Continuity for $X^2$ tests of two or more small independent samples (i.e. samples with an expected frequency of less than or equal to 5; Yates 1934):

$$\text{Yates’ corrected } X^2 = \sum_{i=1}^{k} \left( \frac{\left( |f_o - f_e| - 0.5 \right)^2}{f_e} \right)$$

Where $k$ is equal to the number of zones, $f_o$ is the observed frequency in type $i$ of zone $j$, and $f_e$ is the expected frequency in type $i$ of zone $j$, and -0.5 is Yates’ correction factor. The $X^2$ values are evaluated at the 0.05 probability level and degrees of freedom ($v$) calculated as:

$$v = k - 1$$
Overall, it is expected there will be significant differences in the frequency of sites by site type in the zones of the 1989 model. For Type 1 sites, it is expected that significantly more sites than expected by chance alone occur in Zone 1 and significantly fewer sites occur than expected by chance alone in all other zones. For Type 2 sites, it is expected that significantly more sites than expected by chance alone occur in Zones 1 or 2 (or these sites may simply be randomly distributed within these two zones) and significantly fewer sites occur than expected by chance alone in Zone 3. It is expected that Type 3 sites are randomly distributed throughout Zones 1 through 3, representing short-term extraction activities over time throughout the landscape.

If patterns of site distribution are found to deviate from this ideal described above, then there will be justification for a new model development that is in addition to the changed assumptions regarding the relative significance of multi-component versus single-component sites. Also, the validity test of the extant model is independent of the other objectives of this research, which are to test for variability in the cultural landscape and to provide temporally and culturally distinct models, as necessary, in addition to any necessary refinements to the extant combined prehistoric model for land-use planners. The latter models may provide greater archaeological and anthropological research potential than the combined model that is intended for use by non-archaeologists.

3.3.2 HYPOTHESIS II – 1989 Model Site-Level Test

H₀: Archaeological sites (prehistoric and historic) are not significantly associated (p < 0.05) with the sensitivity zones of the 1989 Archaeological Predictive Model of the SRS.
The second test examined all prehistoric sites and historic sites, respectively, without a classification of the data based on the number of components per site. This latter test provides the basis for new model development as it reflects changes in assumptions about the significance of single component sites as opposed to the multi-component sites used in the 1989 model. The validity of the 1989 model without a classification of sites based upon the number of components is questionable and the association of sites to the sensitivity zones is not expected to be significant for all zones. Likewise, it is expected that historic sites are randomly distributed in relation to the zones of the 1989 prehistoric model, highlighting the need for further analyses of historic site locations on the SRS.

The extant model was again tested using the intensive survey sample. A total of 295 archaeological sites were selected from the systematic, intensive surveys. Of these, 199 contain prehistoric components and 183 contain historic components (87 sites have both prehistoric and historic components in their assemblages).

Similar to the first test, the area of each zone and number of recorded sites in the prehistoric and historic samples was used to calculate expected frequencies of sites and statistically compared to the actual (observed) frequency of sites within each zone using the $X^2$ statistic. The GIS was used to query the prehistoric and historic archaeological site samples by archaeological zone in a simple point-in-polygon operation. These data represent the observed frequencies ($f_o$) for prehistoric and historic sites within the zones of the 1989 model, respectively. Expected frequencies ($f_e$) for each zone were calculated using the sample totals and area of each zone:
fe = (#sites / total area) * zone area

These in turn were used to calculate the $X^2$ statistic to test for significant frequencies of sites by archaeological sensitivity zone; Yates’ correction was not needed since expected frequencies are demonstrated to be greater than 5 (Earickson and Harlin 1994; Norcliffe 1977):

$$X^2 = \sum_{i=1}^{k} \frac{(fo - fe)^2}{fe}$$

The $X^2$ values were evaluated at the 0.05 probability level and degrees of freedom are:

$$\nu = k - 1$$

To reject the null hypothesis for the prehistoric sample, Zone 1 of the model should demonstrate significantly higher frequencies of prehistoric sites than expected by chance alone and Zones 0, 2, and 3 of the model should have significantly fewer prehistoric sites than expected by chance alone. In this scenario, if the null hypothesis is accepted the development of a new archaeological predictive model for prehistoric sites will be warranted. For the historic sample, no significant relationship (positive or negative) between site frequency and the prediction zones is expected as historic sites were not included in that model’s development. Historic sites are known to occur in more upland settings than their prehistoric counterparts. The uplands were made habitable in the historic era by the use of wells and a subsistence shift to agriculture and livestock farming.
3.3.3 *HYPOTHESIS III – Sample Bias Multivariate Test*

$H_0$: The environmental context (variable means) of archaeological site locations are not significantly affected ($p < 0.05$) by different archaeological sampling methods on the SRS.

The evaluation of archaeological sample bias presented here is a test for the hypothesis there is no significant difference in the values of environmental variables of archaeological sites ($n=1,671$) recorded using different field sampling techniques on the SRS. For example, this hypothesis determines the validity of combining archaeological data recorded by various field-sampling strategies during the four decades of archaeological research at this locality. These include sites recorded in intensive surveys without the use of the 1989 predictive model ($n=295$), archaeological data derived using the 1989 predictive model as a field survey guide ($n=817$), and archaeological data that predates the model's development recorded from the years 1973 to 1989 ($n=559$). The validation sample sites ($n=152$) were excluded from these site totals. The premise here was that if no significant differences in the environmental variables are found, then the various datasets can be combined to improve the sample size and the robustness of the resulting models.

The differences in environmental context of the sites were examined using the Multivariate Analysis of Variance (MANOVA) technique (Bray and Maxwell 1985). The MANOVA tests the hypothesis that the environmental variable means are not affected by different sample strategies on the SRS. This provided information regarding the overall
environmental context of the site samples and thus, the validity of combining the samples to improve sample size for subsequent analyses and model development. Hypothetically:

\[ \mu_{\text{pre-1989 surveys}} = \mu_{\text{1989 model surveys}} = \mu_{\text{intensive surveys}} \]

If the overall environmental characteristics of the sites are the same as the intensive survey site sample, then there is little bias represented in the location of sites from the other two samples. If this occurs, the samples may be combined for the analyses that follow. However, if significant differences are found to exist, then only the intensive survey site sample should be used, as it is the only systematic site sample unbiased by intuitive and predictive model sampling strategies.

The MANOVA tests were run with the SPSS statistics program. Although a univariate analysis of variance (ANOVA) alone would be useful, the multivariate approach of MANOVA was more appropriate as we are interested in comparing the overall environmental contexts of the site samples. This objective can only be met through a multivariate technique. While MANOVA assumes multivariate normality and archaeological data deviate from that ideal, the robustness of the multivariate approach and large archaeological samples of the SRS alleviate typical concerns of a lower significance threshold.

The overall or omnibus (MANOVA) significance was evaluated using the Pillai’s Trace estimation of the F statistic (Bray and Maxwell 1985). Pillai’s Trace is generally viewed as the most robust statistic and the most appropriate when using small or unequal samples, both are common problems in archaeological samples and reflected in the analyses that follow. If the F test is significant at 0.05 probability, then the null hypothesis was rejected and only the intensive sample data, recorded independent of the
1989 model, was used to test subsequent hypotheses and to develop the prediction models. If it is not rejected, then the data from the various samples were combined to improve the overall site sample size.

3.3.4 HYPOTHESIS IV – Temporal Change Multivariate Test

H₀: The environmental context (variable means) of archaeological site locations are not significantly affected (p < 0.05) by the time period of occupation.

The first analysis tests if there is no significant difference in the environmental variables of archaeological sites through time (cf. Langran 1988, 1989, 1992, 1993). The archaeological sites were sub-sampled using artifact data to separate them based upon time of occupation (n=295 sites; n=452 occupations at those sites over time). Eight separable time periods were possible, including the Paleoindian and Early Archaic (ca. 14,000-8,000 years B.P.; n=26), Middle Archaic (ca. 8,000-6,000 years B.P.; n=21), Late Archaic (ca. 6,000-3,000 years B.P.; n=34), Early Woodland (ca. 3,000-2,000 years B.P.; n=34), Middle Woodland (ca. 2,000-1,500 years B. P.; n=61), and Late Woodland and Mississippian (ca. 1,500-300 years B.P.; n=37), 18th century to mid-19th century historic (n=76), and mid-19th century to early 20th century historic (n=163). These eight periods were clearly separable using diagnostic artifacts such as stone tools and decorated pottery wares.

The differences in environmental context of the sites were then examined using the MANOVA technique. The MANOVA tests the hypothesis that the means of the site
samples are equal to one another for all environmental variables (Bray and Maxwell 1985). This provided information regarding the overall environmental context of the sites. Hypothetically:

$$\mu_{PEA} = \mu_{MA} = \mu_{LA} = \mu_{EW} = \mu_{MW} = \mu_{LWM} = \mu_{19th} = \mu_{20th}$$

If the overall environmental characteristics (n=32 variables; Table 3.1) of the sites are the same for each sample, then the sites reflect great continuity in land and resource use through time. This would likely equate to a generalized forager adaptation to local resources (cf. Binford 1980), despite environmental changes and developments in gardening and agriculture over time expected for this locality. Conversely, if differences in the environmental means occur, then land-use practices changed significantly over time.

The MANOVA tests were run with the SPSS statistics program. MANOVA was used in this analysis to enable the examination of the mean differences between environmental variables of the site samples. Although a univariate analysis of variance (ANOVA) alone would be useful, the multivariate approach of MANOVA is more appropriate as we are interested in comparing the overall environmental contexts of the sites. This objective can only be met through a multivariate technique. Again, while MANOVA assumes multivariate normality and archaeological data deviate from that ideal, the robustness of the multivariate approach and large archaeological samples of the SRS alleviate typical concerns of a lower significance threshold.

In regard to the possibility of co-occurrence sites exhibiting all three adaptations, the omnibus or overall significance evaluation minimizes the error introduced by the co-occurrences by maintaining the site sample size (instead of artificially inflating it and
introducing repeated values to the opposing means under evaluation). The overall or omnibus (MANOVA) significance was evaluated using the Pillai’s Trace estimation of the $F$ statistic (Bray and Maxwell 1985). Pillai’s Trace is generally viewed as the most robust statistic and the most appropriate when using small or unequal samples, both are common problems in archaeological samples and reflected in the analyses that follow.

If the $F$ test is significant at 0.05 probability, then the null hypothesis were rejected and the development of separate predictive models based upon time period were warranted. It was expected that the environmental factors will vary significantly over time as changes in human adaptation occurred over many generations and potentially numerous cultures. If the null hypothesis is accepted, this would indicate great continuity over the millennia in human adaptations along the Savannah River.

3.3.5 HYPOTHESIS V – Cultural Change Multivariate Test

$H_0$: The environmental context (variable means) of archaeological site locations are not significantly affected ($p < 0.05$) by culture type or lifeway.

The second analysis tests if there is no significant difference in the environmental variables of archaeological sites based upon cultural adaptation. The archaeological sites were again sub-sampled using artifact data to separate them based upon cultural adaptation (n=295 sites; n=352 occupations at those sites by adaptation). These include prehistoric hunter-gatherers (n=53), prehistoric horticulturists (n=119), and historic agriculturists (n=180). Similar to the temporal analysis in the previous example, this
analysis differs in that the classification of sites is more generalized, reflecting hypothesized changes in adaptation rather than changes in artifact types over time. More specifically, prehistoric hunter-gatherers represent the Paleoindian through Late Archaic periods (ca. 14,000-3,000 years B.P.), prehistoric horticulturists represent the Woodland through Mississippian periods (ca. 3,000-300 years B.P.), and historic agriculturists represent the 18\textsuperscript{th} through the early 20\textsuperscript{th} centuries.

While this analysis is more generalized on the temporal scale than the prior analyses, it highlights environmental variation brought about by changes in overall adaptation through time (as opposed to examining that variation based upon changes in technology reflected by artifact types). Likewise, the more generalized site samples provide for higher frequencies of sites in each sample. The increased site sample size helped to verify the results from the time-sliced analyses given previously.

The differences in environmental context of the sites were again examined using MANOVA. This tested the hypothesis that the means of the site samples are equal for all environmental variables (n=32; Table 3.1; Bray and Maxwell 1985).

\[
\mu_{\text{preh}-\text{h-g}} = \mu_{\text{preh}-\text{hort}} = \mu_{\text{hist}-\text{agri}}...
\]

The overall or omnibus (MANOVA) significance was again evaluated using the Pillai’s Trace estimation of the $F$ statistic (Bray and Maxwell 1985). Pillai’s Trace is the most robust statistic and the most appropriate for unequal samples, such as those presented here.

If the null hypothesis is rejected, the use of different environmental factor weights for each cultural lifeway class was warranted. It was expected that the environmental factors will vary significantly over time corresponding to changing cultural systems in the
Central Savannah River locality. If the null hypothesis is accepted, then there is greater continuity in cultural systems along the Savannah River than is expected from the archaeological record.

3.4 Predictive Modeling

It was expected that the development of new archaeological predictive models will be warranted by the results of the hypothesis testing mentioned above. At a minimum, a revised prehistoric model is needed to fulfill future Cultural Resource Management (CRM) objectives on the SRS. Statistical evaluation consisting of multivariate logistic regression, hereafter Binary Logit Model (BLM), analyses were conducted using the SAS statistics program, with data extraction and cartographic modeling using ArcGIS software. BLM regression was used to predict the probability that a given site type will exist at an un-sampled location (Kvamme 1983, 1988, 1992). In this scenario, the archaeological site was the dependent variable and the greater environment (elevation, slope, etc.) represented the independent variables.

Following Tomlin’s terminology for cartographic modeling (Tomlin 1990), the BLM model can be implemented in a GIS as a simple local operation. The coefficients of the regression analyses were mapped in the GIS software. Once the BLM regression coefficients were calculated, a map of the predicted values for sites was produced using simple map algebra techniques:

\[
P\text{rediction\_map}=\frac{1}{1+\exp(-(a_0+a_1x_1+a_2x_2+ \ldots)))}
\]
Where \(a_0, a_1, a_2, \text{etc.}\) are the coefficients of regression and \(x_1, x_2, \text{etc.}\) are the independent data (environmental variables; \(n=7\)) from which the coefficients were derived.

The resulting raster grids depicted the probability of each cell to contain archaeological remains, from 0.0 to 1.0 probability. The final maps were reclassified data layers representing low, moderate, and high probabilities containing archaeological deposits. The breakpoints for the reclassification were from 0.5 to 1.0 for High Probability, 0.5 to 0.5 minus 1 standard deviation for Moderate Probability, and 0.0 to 0.5 minus 1 standard deviation for Low Probability.

These breakpoints were chosen based on the “Empirical Rule” or “Three Sigma Rule” (Pukelsheim 1994) that in a normal distribution, 50-percent of sites will theoretically fall above the mean, and an additional 34-percent will fall within 1 standard deviation below it. Therefore, 84-percent of sites will theoretically fall within the high and moderate probability zones. This method provides a replicable, theoretical basis for reclassification that is not entirely arbitrary in nature, though the assumption of a normal distribution is a caveat.

The assumption of normalcy primarily affects the less critical low- to moderate-probability breakpoint, since the 0.5 probability breakpoint was simply based on high probability being locations with greater than 50-percent chance (no concern for normalcy). An alternate method was three-level classification using natural breaks (Jenks 1967), however this method too is a parametric (also called goodness of variance fit) and can adversely affect the breakpoint for high probability above or below 0.5 \(p\) and was therefore avoided.
Receiving Operator Curves (ROC), Area Under the Curve (AUC) and Youden’s Index (YI) values were calculated to evaluate each unclassified BLM model’s performance and to confirm that the high probability breakpoint of 0.5 was appropriate for the model reclassifications. ROC curves are used to test the performance of the model by its ability to discriminate between sites and non-sites. This is accomplished by plotting the true positive rate (sensitivity) as a function of the false positive rate (1-specificity); the closer the curve arcs toward the upper left corner of the graph, the closer the model is to a perfect discrimination and the higher is its accuracy (Zweig and Campbell 1993).

The performance of the model is measured for significance by calculating the AUC and the corresponding Z test statistic ($p < 0.05$). The AUC value ranges from 0 to 1, where 0.5 is random and 1 is an ideal predictor. In general, the AUC values of an effective model will always be above 0.5 (Zweig and Campbell 1993).

Finally, the breakpoint for reclassifying the model at 0.5 $p$ was compared to the theoretical “optimum” breakpoint by calculating Youden’s Index (Youden 1950). In short, Youden’s Index is calculated as:

$$\text{Youden’s Index} = \text{Sensitivity} + \text{Specificity} - 1$$

The optimum breakpoint is the model’s value of $p$, where Youden’s Index is closest to 0. Youden’s Index for the prehistoric and historic BLM models were found to be at or near 0.5, justifying the use of the 05 breakpoint and the Empirical Rule for model reclassification.

As discussed in the background chapter, such models are invaluable as a CRM and research tool, providing a means to communicate avoidance areas to non-archaeologists involved in SRS land-use planning, allowing the SRARP staff to reduce
labor-hours when evaluating cultural resources in the field, and enabling researchers to
target specific locations for field study. The SRS predictive model(s) will also serve as a
knowledge base for future modeling efforts by the Office of the State Archaeologist at the
South Carolina Institute of Archaeology and Anthropology (OSA-SCIAA), the State
Historic Preservation Office (SHPO), and private CRM firms conducting fieldwork in
South Carolina and adjacent states.
CHAPTER 4

RESULTS

Results of this research demonstrate the utility of GIS- and statistically-based methods to test extant models, evaluate sample bias, examine temporal and cultural variability and, based on those results, generate multivariate predictive models for the SRS, specifically, that are applicable to any locality or region. Assumptions regarding the use of univariate versus multivariate statistics and the influence of time, culture, and sample bias on the development of archaeological predictive models were tested. In order to accomplish those goals, the following abbreviated hypotheses were evaluated (p < 0.05):

- Archaeological site types are not significantly associated with the 1989 SRS predictive model (i.e., the current model performance is poor when the number of components per site are considered).
- Archaeological sites are not significantly associated with the 1989 SRS predictive model (i.e., the current model performance is poor when the number of components per site are not considered).
- Sample bias is not significant in the archaeological records of the SRARP.
- The environmental context of archaeological sites does not vary significantly over time.
- The environmental context of archaeological sites does not vary significantly by culture type or adaptation.
The resulting statistical findings of these hypotheses illustrate the need for multivariate predictive models based upon temporal and cultural classes represented in the archaeological record, primarily along prehistoric and historic temporal and cultural lines. The degree of association of sites to the extant 1989 model was examined first, as this provided the basis for revision and new model development. Examination of sample bias in the archaeological record of the SRARP indicated that the different site samples recorded during the history of the program could not be aggregated to improve sample size. Early sampling techniques were simply too biased for new model development.

Using only the intensive survey sample, two binary multiple logistical regression models, hereafter Binary Logit Models (BLM), were produced for the SRS locality, a prehistoric model and an historic model. Validation testing using separate intensive survey archaeological samples demonstrate the strengths and weaknesses of the resulting models. The prehistoric model was statistically valid, whereas the historic model’s statistical validity is questionable. Notably, the historic model demonstrates that historic site distributions on the SRS are too variable for meaningful prediction and highlight the need for continued manual use of historic aerial photos, maps and LiDAR data, and in field “ground-truthing” to target those resources.

4.1 Validation Testing of the 1989 Model

4.1.1 Component-Level Test of the 1989 Model

The first test of the 1989 model evaluated if there was a significant association of prehistoric archaeological site types to the sensitivity zones of the 1989 Sensitivity Model of the Savannah River Site. This was tested using an intensive, systematically derived site
sample and simple overlay GIS analysis to identify the frequency of sites by archaeological sensitivity zone of the 1989 predictive model. This involved testing the model using the number of components (temporally distinct occupations) per prehistoric site to characterize the site sample into the three prehistoric site types defined by the SRARP (1989).

A total of 199 sites contained prehistoric components were recorded in the surveys. These sites provide the observed frequencies \( f_o \) for each prehistoric site type within the zones of the 1989 model. Expected frequencies \( f_e \) for each zone were calculated using the sub-sample totals and area of each zone:

\[
fe = (\#\text{sites} / \text{total area}) \times \text{zone area}
\]

The prehistoric archaeological site type samples were queried by archaeological zone. Significance between zonation and observed site frequencies were evaluated using Yates’ Correction for Continuity for \( X^2 \) tests of two or more small independent samples (i.e. samples with expectancy less than or equal to 5; Yates 1934).

4.1.1.1 HYPOTHESIS I

\( H_0 \): Archaeological site types are not significantly associated \( (p < 0.05) \) with the sensitivity zones of the 1989 Archaeological Predictive Model of the SRS.

The results illustrate that the 1989 Model was effective at predicting significantly more Type 2 \( (n=85) \) and Type 3 \( (n=98) \) sites (those with fewer than four cultural components) in the highest probability areas, Zone 1 (Tables 4.1, 4.2 and 4.3). However, the Type 1 sites \( (n=16) \) that the model was specifically designed to predict are randomly
distributed overall in relation to the model’s probability zones (Table 4.1). Likewise, Type 2 and Type 3 sites are randomly distributed in relation to the indeterminate and moderate probability areas (Zones 0 and 2) of the model. Optimally, significantly fewer sites than expected by chance alone would occur in Zones 0, 2, and 3 and significantly more sites would occur in Zone 1 for all site types. Thus the results are somewhat mixed.

While the extant model is effective for predicting likely locations of sites with fewer than four components, fieldwork based upon the model will likely miss numerous Type 2 and 3 sites in Zones 0, 2, and 3. More importantly, the model did not reliably predict the locations of the most temporally significant Type 1 sites, those containing four or more cultural components. The 1989 model failed to meet its primary goal of predicting the locations of these multi-component sites and therefore warrants revision.

Table 4.1: Yates’ Corrected $X^2$ Statistics for Site Type 1 by Prediction Zone.

| Zone | Area | Expected Sites | Observed Sites | $((|fo - fe| - 0.5)^2 / fe)$ | df |
|------|------|----------------|----------------|--------------------------|----|
| 0    | 5    | 1              | 0              | 0.250                    | 1  |
| 1    | 21   | 3              | 7              | 4.083                    | 1  |
| 2    | 51   | 8              | 8              | 0.031                    | 1  |
| 3    | 23   | 4              | 1              | 1.563                    | 1  |
| Total| 100  | 16             | 16             | 5.927                    | 3  |

where $X^2 \geq 7.82$ at 0.05 probability and 3 degrees of freedom.
Table 4.2: Yates’ Corrected $X^2$ Statistics for Site Type 2 by Prediction Zone.

| Zone | % Area | Expected Sites | Observed Sites | $(|f_o - f_e| - 0.5)^2 / f_e$ | df |
|------|--------|----------------|---------------|-----------------------------|----|
| 0    | 5      | 4              | 1             | 1.563                      | 1  |
| 1    | 21     | 18             | 39            | 23.347                     | 1  |
| 2    | 51     | 44             | 36            | 1.278                      | 1  |
| 3    | 23     | 19             | 9             | 4.750                      | 1  |
| Total| 100    | 85             | 85            | 30.938                     | 3  |

where $X^2 \geq 7.82$ at 0.05 probability and 3 degrees of freedom.

Table 4.3: Yates’ Corrected $X^2$ Statistics for Site Type 3 by Prediction Zone.

| Zone | % Area | Expected Sites | Observed Sites | $(|f_o - f_e| - 0.5)^2 / f_e$ | df |
|------|--------|----------------|---------------|-----------------------------|----|
| 0    | 5      | 5              | 1             | 2.450                      | 1  |
| 1    | 21     | 21             | 35            | 8.679                      | 1  |
| 2    | 51     | 50             | 43            | 0.845                      | 1  |
| 3    | 23     | 22             | 19            | 0.284                      | 1  |
| Total| 100    | 98             | 98            | 12.258                     | 3  |

where $X^2 \geq 7.82$ at 0.05 probability and 3 degrees of freedom.

4.1.2 Site-Level Test of the 1989 Model

The second series of tests examined all prehistoric sites and historic sites, respectively, without a classification of the data based on the number of components per site. This latter test provides the basis for new model development as it reflects changes in assumptions about the significance of single component sites as opposed to the multi-component sites used in the 1989 model. The validity of the 1989 model without a classification of sites based upon the number of components is questionable and the association of sites to the sensitivity zones was not expected to be significant for all
zones. Likewise, it was expected that historic sites would be randomly distributed in relation to the zones of the 1989 prehistoric model, highlighting the need for further analyses of historic site locations on the SRS. The extant model was again tested using the intensive survey sample. A total of 295 archaeological sites were encountered during the systematic, intensive surveys. Of these, 199 contained prehistoric components and 183 contained historic components (87 sites had both prehistoric and historic components in their assemblages).

Similar to the first test, the area of each zone and number of recorded sites in the prehistoric and historic samples was used to calculate expected frequencies of sites and statistically compared to the actual (observed) frequency of sites within each zone using the $X^2$ statistic. The GIS was used to query the prehistoric and historic archaeological site samples by archaeological zone. These data represented the observed frequencies ($f_o$) for prehistoric and historic sites within the zones of the 1989 model, respectively. Expected frequencies ($f_e$) for each zone were calculated using the sample totals and area of each zone:

$$f_e = \frac{\text{#sites}}{\text{total area}} \times \text{zone area}$$

These in turn were used to calculate the $X^2$ statistic to test for significant frequencies of sites by archaeological sensitivity zone (Earickson and Harlin 1994; Norcliffe 1977).

4.1.2.1 HYPOTHESIS IIa

$H_0$: Prehistoric archaeological sites are not significantly associated ($p < 0.05$) with the sensitivity zones of the 1989 Archaeological Predictive Model of the SRS.
Prehistoric sites once again presented mixed results (Table 4.4). Whereas, Zone 1 (High Probability) is a good predictor of where sites are located, the sites were randomly distributed in relation to Zone 2 (Moderate Probability). A stronger model would demonstrate significantly fewer sites than expected by chance alone in the three remaining zones. While Zone 2 was the only zone with sites randomly distributed in relation to the model, it consisted of nearly 44-percent (n=87) of the total sample. Improvements may be realized by revision of the model, although the overall significance was high for the extant model when prehistoric sites are treated as a whole and not separated by their number of components.

Table 4.4: 1989 Model X^2 statistics for Prehistoric sites.

<table>
<thead>
<tr>
<th>Zone</th>
<th>% Area</th>
<th>Expected Sites</th>
<th>Observed Sites</th>
<th>(fo - fe)^2 / fe</th>
<th>df</th>
<th>Gain</th>
<th>% of Sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>5</td>
<td>10</td>
<td>2</td>
<td>6.32</td>
<td>1</td>
<td>N/A</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>21</td>
<td>43</td>
<td>81</td>
<td>33.69</td>
<td>1</td>
<td>0.49</td>
<td>41</td>
</tr>
<tr>
<td>2</td>
<td>51</td>
<td>101</td>
<td>87</td>
<td>1.90</td>
<td>1</td>
<td>N/A</td>
<td>44</td>
</tr>
<tr>
<td>3</td>
<td>23</td>
<td>45</td>
<td>29</td>
<td>5.85</td>
<td>1</td>
<td>N/A</td>
<td>15</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>199</td>
<td>199</td>
<td>47.76</td>
<td>3</td>
<td>N/A</td>
<td>100</td>
</tr>
</tbody>
</table>

where X^2 ≥ 7.82 at 0.05 probability and 3 degrees of freedom.

4.1.2.2 HYPOTHESIS IIb

H_0: Historic archaeological sites are not significantly associated (p < 0.05) with the sensitivity zones of the 1989 Archaeological Predictive Model of the SRS.
Historic sites as a whole are randomly distributed in relation to 1989 model’s prediction zones (Table 4.5). The exception is Zone 0 (Indeterminate Probability) that has significantly fewer (n=2) sites than expected by chance alone. This was likely due to the wetlands character of the zone, precluding long-term habitation by historic-era households. Note that the summed chi-square score was not significant; therefore a need for a separate historic predictive model is suggested.

Table 4.5: 1989 Model $X^2$ statistics for Historic sites.

<table>
<thead>
<tr>
<th>Zone</th>
<th>% Area</th>
<th>Expected Sites</th>
<th>Observed Sites</th>
<th>$(fo - fe)^2 / fe$</th>
<th>df</th>
<th>Gain</th>
<th>% of Sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>5</td>
<td>9</td>
<td>2</td>
<td>5.61</td>
<td>1</td>
<td>N/A</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>21</td>
<td>40</td>
<td>39</td>
<td>0.01</td>
<td>1</td>
<td>0.0</td>
<td>21</td>
</tr>
<tr>
<td>2</td>
<td>51</td>
<td>92</td>
<td>98</td>
<td>0.24</td>
<td>1</td>
<td>N/A</td>
<td>54</td>
</tr>
<tr>
<td>3</td>
<td>23</td>
<td>42</td>
<td>44</td>
<td>0.11</td>
<td>1</td>
<td>N/A</td>
<td>24</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>183</td>
<td>183</td>
<td>5.97</td>
<td>3</td>
<td>N/A</td>
<td>100</td>
</tr>
</tbody>
</table>

where $X^2 \geq 7.82$ at 0.05 probability and 3 degrees of freedom.

4.2 Multivariate Analysis of Variance (MANOVA) Tests

Given the mixed results of the 1989 model’s validation testing, what model or models need to be developed? The test of the 1989 model indicated that at a minimum, separate prehistoric and historic predictive models would be needed. However, the SRS has an archaeological record that stretches back over 14,000 years in the past, representing numerous cultures and adaptations from Pleistocene hunter-gatherers that hunted now-extinct megafauna to early-20th Century farmers. Clearly, further separation of the archaeological record needs evaluation before final model development. The following MANOVA tests reveal quite a few surprises, the most significant may be the
great continuity in land-use through time by prehistoric cultures. It was revealed that only two models are needed for the SRS: one for prehistoric sites and one for historic sites, respectively.

4.2.1 Multivariate Test for Archaeological Sample Bias

The evaluation of archaeological sample bias presented here tests the hypothesis that there is no significant difference in the values of environmental variables (n=32) of archaeological sites recorded using different field sampling techniques on the SRS. This hypothesis thus determines the validity of combining archaeological data recorded by various field-sampling strategies during the four decades of archaeological research at this locality. These include sites recorded in intensive surveys without the use of the 1989 predictive model (n=295, excluding the validation sample), archaeological data derived using the 1989 predictive model as a field survey guide (n=817), and archaeological data that predates the model's development recorded from the years 1973 to 1989 (n=559). The premise here is that if no significant differences in the environmental variables occurring in each dataset are found, then the various datasets can be combined to improve the sample size and the robustness of the resulting models.

4.2.1.1 HYPOTHESIS III

H₀: The environmental context (variable means) of archaeological site locations are not significantly affected (p < 0.05) by different archaeological sampling methods on the SRS.
The differences in environmental context of the sites were examined using the MANOVA technique (Bray and Maxwell 1985). The MANOVA tests the hypothesis that the environmental variable means are not affected by different sample strategies on the SRS. This provides information regarding the overall environmental context of the site samples and thus, the validity of combining the samples to improve sample size for subsequent analyses and model development. Hypothetically:

\[ \mu_{\text{pre-1989 surveys}} = \mu_{1989 \text{ model surveys}} = \mu_{\text{intensive surveys}} \]

If the overall environmental characteristics of the sites are the same as the intensive survey site sample, then there is little bias represented in the location of sites from the other two samples. If this occurs, the samples may be combined for the analyses that follow. However, if significant differences are found to exist, then only the intensive survey site sample should be used, as it is the only systematic site sample unbiased by intuitive and predictive model sampling strategies.

The MANOVA tests were run with the SPSS statistics program. Although a univariate analysis of variance (ANOVA) alone would be useful, the multivariate approach of MANOVA is more appropriate as we are interested in comparing the overall environmental contexts of the site samples. This objective can only be met through a multivariate technique. While MANOVA assumes multivariate normality and archaeological data deviate from that ideal, the robustness of the multivariate approach and large archaeological samples of the SRS alleviate typical concerns of a lower significance threshold.

The overall or omnibus (MANOVA) significance was evaluated using the Pillai’s Trace estimation of the F statistic (Bray and Maxwell 1985). Pillai’s Trace is generally
viewed as the most robust statistic and the most appropriate when using small or unequal samples, both are common problems in archaeological samples and reflected in the analyses that follow.

The overall environmental characteristics of the three archaeological site samples were significantly different with a probability less than 0.001 (Table 4.6). This indicates that sample bias was present in the samples derived from intuitive landscape surveys and surveys based upon the 1989 predictive model. Therefore, the intensive systematic survey sample of 295 prehistoric and historic sites were the only sample used in subsequent analyses and model development.

Table 4.6: Multivariate Analysis of Variance (MANOVA) Table with \( F \) test of archaeological site samples (3 samples; \( n=1671 \) total sites).

<table>
<thead>
<tr>
<th>Effect</th>
<th>Value</th>
<th>( F )</th>
<th>Hypothesis df</th>
<th>Error df</th>
<th>Sig.</th>
<th>Partial Eta Noncent.</th>
<th>Observed Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>Pillai’s Trace</td>
<td>1.000 54516101.977(b)</td>
<td>25</td>
<td>1644 0.000</td>
<td>1.000 1.4E+09</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Wilks’ Lambda</td>
<td>0.000 54516101.976(b)</td>
<td>25</td>
<td>1644 0.000</td>
<td>1.000 1.4E+09</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Hotelling’s Trace</td>
<td>829016.149 54516101.976(b)</td>
<td>25</td>
<td>1644 0.000</td>
<td>1.000 1.4E+09</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Roy’s Largest Root</td>
<td>829016.149 54516101.976(b)</td>
<td>25</td>
<td>1644 0.000</td>
<td>1.000 1.4E+09</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Sample</td>
<td>Pillai’s Trace</td>
<td>0.140 4.966</td>
<td>50</td>
<td>3290 0.000</td>
<td>0.070 248.291</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Wilks’ Lambda</td>
<td>0.863 5.008(b)</td>
<td>50</td>
<td>3288 0.000</td>
<td>0.071 250.414</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Hotelling’s Trace</td>
<td>0.154 5.051</td>
<td>50</td>
<td>3286 0.000</td>
<td>0.071 252.536</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Roy’s Largest Root</td>
<td>0.115 7.597(c)</td>
<td>25</td>
<td>1645 0.000</td>
<td>0.104 189.919</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

a  Computed using alpha = .05
b  Exact statistic
c  The statistic is an upper bound on \( F \) that yields a lower bound on the significance level.
d  Design: Intercept+Sample

4.2.2 Intensive Archaeology Site Sample

The MANOVA revealed significant differences in the archaeological samples of the SRS, highlighting the need for use of only the intensive archaeological sample for subsequent tests and the development of archaeological predictive models for the SRS. As discussed previously, a total of 295 archaeological sites were from the systematic,
intensive surveys (Table 4.7). Of these, 199 contained prehistoric components and 183 contained historic components (87 sites had both prehistoric and historic components in their assemblages). The sites were again represented in the GIS as x-y coordinate pairs and 30-m grid cells. A database containing temporal and cultural (component-level) data was linked to the GIS layer and queried to make time-slice and cultural sub-sets of the geographic data.

<table>
<thead>
<tr>
<th>Grids</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Intensive Survey Sites</td>
<td>295</td>
</tr>
<tr>
<td>Prehistoric Intensive Survey Sites</td>
<td>199</td>
</tr>
<tr>
<td>Historic Intensive Survey Sites</td>
<td>183</td>
</tr>
<tr>
<td>Total Validation Sample Sites</td>
<td>152</td>
</tr>
<tr>
<td>Prehistoric Validation Sample Sites</td>
<td>89</td>
</tr>
<tr>
<td>Historic Validation Sample Sites</td>
<td>110</td>
</tr>
</tbody>
</table>

4.2.3 Multivariate Test for Temporal Changes in Land Use

The first analysis tested for significant differences in the environmental variables of archaeological sites through time. The archaeological sites were sub-sampled using artifact data to separate them based upon time of occupation (n=295 sites; n=452 occupations at those sites over time). Eight separable time periods were possible, including the Paleoindian and Early Archaic (ca. 14,000-8,000 years B.P.; n=26), Middle Archaic (ca. 8,000-6,000 years B.P.; n=21), Late Archaic (ca. 6,000-3,000 years B.P.; n=34), Early Woodland (ca. 3,000-2,000 years B.P.; n=34), Middle Woodland (ca. 2,000-
1,500 years B.P.; n=61), and Late Woodland and Mississippian (ca. 1,500-300 years B.P.; n=37), 18th century to mid-19th century historic (n=76), and mid-19th century to early 20th century historic (n=163). These eight periods were clearly separable using diagnostic artifacts such as stone tools and decorated pottery wares.

The differences in environmental context of the sites were examined using the MANOVA technique (Bray and Maxwell 1985). The MANOVA tested the hypothesis that the environmental variable means are not affected by different time periods of occupation. This provides information regarding the overall environmental context of the sites. Hypothetically:

$$\mu_{PEA} = \mu_{MA} = \mu_{LA} = \mu_{EW} = \mu_{MW} = \mu_{LWM} = \mu_{19th} = \mu_{20th}$$

If the overall environmental characteristics (Table 3.1) of the sites are the same for each sample, then the sites reflect great continuity in land and resource use through time. This would likely equate to a generalized forager adaptation to local resources (cf., Binford 1980), despite environmental changes and developments in gardening and agriculture over time expected for this locality. Conversely, if differences in the environmental means occur, then occupation site practices changed significantly over time.

The MANOVA tests were run with the SPSS statistics program. MANOVA was used in this analysis to enable the examination of the mean differences between environmental variables of the site samples. Although a univariate analysis of variance (ANOVA) alone would be useful, the multivariate approach of MANOVA is more appropriate as we are interested in comparing the overall environmental contexts of the sites. This objective can only be met through a multivariate technique. Again, while
MANOVA assumes multivariate normality and archaeological data deviate from that ideal, the robustness of the multivariate approach and large archaeological samples of the SRS alleviate typical concerns of a lower significance threshold.

In regard to the possibility of the co-occurrence of sites exhibiting all three adaptations, the omnibus or overall significance evaluation minimizes the error introduced by the co-occurrences by maintaining the site sample size (instead of artificially inflating it and introducing repeated values to the opposing means under evaluation). The overall or omnibus (MANOVA) significance was evaluated using the Pillai’s Trace estimation of the F statistic (Bray and Maxwell 1985). Pillai’s Trace is generally viewed as the most robust statistic and the most appropriate when using small or unequal samples, both are common problems in archaeological samples and reflected in the analyses that follow.

4.2.3.1 HYPOTHESIS IVa
H₀: The environmental context (variable means) of archaeological site locations are not significantly affected (p < 0.05) by the time period of occupation (prehistoric and historic periods included).

The overall environmental characteristics of the eight samples spanning the prehistoric and historic periods were significantly different with a probability of 0.001 the environmental characteristics are the same (Table 4.8). We know from the prior analysis of the 1989 model that the historic data were statistically different than the prehistoric, so this test confirms prior expectations. The question remains whether the six prehistoric
periods and two historic periods represented in the samples were significant from one
another, consecutively. MANOVA was again used to examine these relationships.

Table 4.8: Multivariate Analysis of Variance (MANOVA) Table with $F$ test of
prehistoric and historic periods (8 samples; n=295 sites).

<table>
<thead>
<tr>
<th>Effect</th>
<th>Value</th>
<th>$F$</th>
<th>Hypothesis df</th>
<th>Error df</th>
<th>Sig.</th>
<th>Partial Eta Noncent. Observed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.000</td>
<td>26564670.336(b)</td>
<td>25</td>
<td>420</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Wilks' Lambda</td>
<td>0.000</td>
<td>26564670.336(b)</td>
<td>25</td>
<td>420</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Hotelling's Trace</td>
<td>1581230.377</td>
<td>26564670.336(b)</td>
<td>25</td>
<td>420</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Roy's Largest Root</td>
<td>1581230.377</td>
<td>26564670.336(b)</td>
<td>25</td>
<td>420</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Sample</td>
<td>0.524</td>
<td>1.379</td>
<td>175</td>
<td>2982</td>
<td>0.000</td>
<td>0.075</td>
</tr>
<tr>
<td>Wilks' Lambda</td>
<td>0.552</td>
<td>1.498</td>
<td>175</td>
<td>2853.09</td>
<td>0.000</td>
<td>0.081</td>
</tr>
<tr>
<td>Hotelling's Trace</td>
<td>0.685</td>
<td>1.637</td>
<td>175</td>
<td>2928</td>
<td>0.000</td>
<td>0.089</td>
</tr>
<tr>
<td>Roy's Largest Root</td>
<td>0.473</td>
<td>8.060(c)</td>
<td>25</td>
<td>426</td>
<td>0.000</td>
<td>0.321</td>
</tr>
</tbody>
</table>

a  Computed using alpha = .05
b  Exact statistic
c  The statistic is an upper bound on $F$ that yields a lower bound on the significance level.
d  Design: Intercept+Sample

4.2.3.2 HYPOTHESIS IVb

$H_0$: The environmental context (variable means) of archaeological site locations are not
significantly affected ($p < 0.05$) by the prehistoric time period of occupation (historic
periods excluded).

The overall environmental characteristics (see Table 3.1) of the prehistoric sites
(n=199) were similar for the six samples (Table 4.9). No significant differences exists
between them. These sites reflect great continuity in land- and resource-use despite
hypothesized changes in culture and environment over time. This likely equates to a
generalized forager adaptation to local resources during prehistory (cf., Binford 1980).
Despite the developments in gardening and agriculture through time expected for this locality, people continued to position themselves similarly on the landscape over time to maximize the use of natural resources. These results suggested that the prehistoric time-sliced samples can be merged into a single sample for predictive modeling of prehistoric site locations. Also, see Hypothesis V that follows which tests the prehistoric and historic samples in a slightly different way. That is, based upon adaptation rather than time-slices derived from artifact typology.

Table 4.9: Multivariate Analysis of Variance (MANOVA) Table with F test of prehistoric periods, exclusively (6 samples; n=199 sites).

<table>
<thead>
<tr>
<th>Effect</th>
<th>Value</th>
<th>F</th>
<th>Hypothesis df</th>
<th>Error df</th>
<th>Sig.</th>
<th>Partial Eta Noncent.</th>
<th>Observed Effect Value</th>
<th>Hypothesis df</th>
<th>Error df</th>
<th>Sig.</th>
<th>Partial Eta Noncent.</th>
<th>Observed Effect Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.000</td>
<td>18239391.662(b)</td>
<td>25</td>
<td>183</td>
<td>0.000</td>
<td>1.000</td>
<td>4.6E+08</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wilks’ Lambda</td>
<td>0.000</td>
<td>18239391.662(b)</td>
<td>25</td>
<td>183</td>
<td>0.000</td>
<td>1.000</td>
<td>4.6E+08</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hotelling’s Trace</td>
<td>2491720.172</td>
<td>18239391.662(b)</td>
<td>25</td>
<td>183</td>
<td>0.000</td>
<td>1.000</td>
<td>4.6E+08</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Roy’s Largest Root</td>
<td>2491720.172</td>
<td>18239391.662(b)</td>
<td>25</td>
<td>183</td>
<td>0.000</td>
<td>1.000</td>
<td>4.6E+08</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wilks’ Lambda</td>
<td>0.640</td>
<td>0.688</td>
<td>125</td>
<td>935</td>
<td>0.995</td>
<td>0.084</td>
<td>86.16</td>
<td>0.991</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hotelling’s Trace</td>
<td>0.474</td>
<td>0.688</td>
<td>125</td>
<td>907.524</td>
<td>0.995</td>
<td>0.085</td>
<td>84.643</td>
<td>0.99</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Roy’s Largest Root</td>
<td>0.202</td>
<td>1.509(c)</td>
<td>25</td>
<td>187</td>
<td>0.065</td>
<td>0.168</td>
<td>37.733</td>
<td>0.957</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

a  Computed using alpha = .05
b  Exact statistic
c  The statistic is an upper bound on F that yields a lower bound on the significance level.
d  Design: Intercept+Sample

4.2.3.3 HYPOTHESIS IVc

H0: The environmental context (variable means) of archaeological site locations are not significantly affected (p < 0.05) by the historic time period of occupation (prehistoric periods excluded).
Similarly, the overall environmental characteristics of the historic sites (n=183) were similar for the two historic samples (Table 4.10). No significant difference existed between these two historic samples. These results also indicated that the historic samples can be treated as a single sample for predictive modeling.

Table 4.10: Multivariate Analysis of Variance (MANOVA) Table with $F$ test of historic periods, exclusively (2 samples; n=183 sites).

<table>
<thead>
<tr>
<th>Effect</th>
<th>Value</th>
<th>$F$</th>
<th>Hypothesis df</th>
<th>Error df</th>
<th>Sig.</th>
<th>Partial Eta</th>
<th>Power(a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.000</td>
<td>18377936.567(b)</td>
<td>25</td>
<td>213</td>
<td>0.000</td>
<td>1.000</td>
<td>4.6E+08</td>
</tr>
<tr>
<td>Wilks' Lambda</td>
<td>0.000</td>
<td>18377936.567(b)</td>
<td>25</td>
<td>213</td>
<td>0.000</td>
<td>1.000</td>
<td>4.6E+08</td>
</tr>
<tr>
<td>Hotelling's Trace</td>
<td>2157034.808</td>
<td>18377936.567(b)</td>
<td>25</td>
<td>213</td>
<td>0.000</td>
<td>1.000</td>
<td>4.6E+08</td>
</tr>
<tr>
<td>Roy's Largest Root</td>
<td>2157034.808</td>
<td>18377936.567(b)</td>
<td>25</td>
<td>213</td>
<td>0.000</td>
<td>1.000</td>
<td>4.6E+08</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sample</th>
<th>Value</th>
<th>$F$</th>
<th>Hypothesis df</th>
<th>Error df</th>
<th>Sig.</th>
<th>Partial Eta</th>
<th>Power(a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample</td>
<td>0.050</td>
<td>.451(b)</td>
<td>25</td>
<td>213</td>
<td>0.990</td>
<td>0.050</td>
<td>11.276</td>
</tr>
<tr>
<td>Wilks' Lambda</td>
<td>0.950</td>
<td>.451(b)</td>
<td>25</td>
<td>213</td>
<td>0.990</td>
<td>0.050</td>
<td>11.276</td>
</tr>
<tr>
<td>Hotelling's Trace</td>
<td>0.053</td>
<td>.451(b)</td>
<td>25</td>
<td>213</td>
<td>0.990</td>
<td>0.050</td>
<td>11.276</td>
</tr>
<tr>
<td>Roy's Largest Root</td>
<td>0.053</td>
<td>.451(b)</td>
<td>25</td>
<td>213</td>
<td>0.990</td>
<td>0.050</td>
<td>11.276</td>
</tr>
</tbody>
</table>

a Computed using alpha = .05
b Exact statistic
c The statistic is an upper bound on $F$ that yields a lower bound on the significance level.
d Design: Intercept+Sample

4.2.4 Multivariate Test for Adaptive Changes in Land Use

The second analysis tests if there is no significant difference in the environmental variables of archaeological sites based upon cultural adaptation. The archaeological sites were again sub-sampled using artifact data to separate them based upon cultural adaptation (n=295 sites; n=352 occupations at those sites by adaptation). These include prehistoric hunter-gatherers (n=53), prehistoric horticulturists (n=119), and historic agriculturists (n=180). Similar to the temporal analysis in the previous example, this analysis differs in that the classification of sites is more generalized, reflecting
hypothesized changes in adaptation rather than changes in artifact types over time. More specifically, prehistoric hunter-gatherers represent the Paleoindian through Late Archaic periods (ca. 14,000-3,000 years B. P.), prehistoric horticulturists represent the Woodland through Mississippian periods (ca. 3,000-300 years B.P.), and historic agriculturists represent the 18th through the early 20th centuries.

While this analysis is more generalized on the temporal scale than the prior analyses, it highlights environmental variation brought about by changes in overall adaptation through time (as opposed to examining that variation based upon changes in technology reflected by artifact types). Likewise, the more generalized site samples provide for higher frequencies of sites in each sample. The increased site sample size will help to verify the results from the time-sliced analyses given previously.

The differences in environmental context of the sites were again examined using MANOVA (Bray and Maxwell 1985). The MANOVA tests the hypothesis that the environmental variable means are not affected by cultural lifeway:

\[ \mu_{\text{preh-h}} = \mu_{\text{preh-hort}} = \mu_{\text{hist-agri}} \]

The overall or omnibus (MANOVA) significance was again evaluated using the Pillai’s Trace estimation of the \( F \) statistic (Bray and Maxwell 1985). Pillai’s Trace is again the most robust statistic and the most appropriate for unequal samples, such as those presented here.
4.2.4.1 HYPOTHESIS Va

H$_{0}$: The environmental context (variable means) of archaeological site locations are not significantly affected (p < 0.05) by culture type or lifeway (prehistoric and historic cultures included).

The overall environmental characteristics of the three site samples spanning the prehistoric and historic adaptations were significantly different with a probability less than 0.001 (Table 4.11). We know from prior analyses that the historic data were significantly different than the prehistoric, so this test supports the prior results. The question remains whether the two prehistoric adaptations represented in the site samples are significant from one another. MANOVA was used to examine this relationship.

Table 4.11: Multivariate Analysis of Variance (MANOVA) Table with $F$ test of prehistoric and historic adaptations (3 samples; n=352 sites).

<table>
<thead>
<tr>
<th>Effect</th>
<th>Value</th>
<th>$F$</th>
<th>Hypothesis df</th>
<th>Error df</th>
<th>Sig.</th>
<th>Squared</th>
<th>Parameter Power(a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.000</td>
<td>25292680.831(b)</td>
<td>25</td>
<td>325</td>
<td>0.000</td>
<td>1.000</td>
<td>6.3E+08</td>
</tr>
<tr>
<td>Wilks' Lambda</td>
<td>0.000</td>
<td>25292680.831(b)</td>
<td>25</td>
<td>325</td>
<td>0.000</td>
<td>1.000</td>
<td>6.3E+08</td>
</tr>
<tr>
<td>Hotelling's Trace</td>
<td>1945590.833</td>
<td>25292680.831(b)</td>
<td>25</td>
<td>325</td>
<td>0.000</td>
<td>1.000</td>
<td>6.3E+08</td>
</tr>
<tr>
<td>Roy's Largest Root</td>
<td>1945590.833</td>
<td>25292680.831(b)</td>
<td>25</td>
<td>325</td>
<td>0.000</td>
<td>1.000</td>
<td>6.3E+08</td>
</tr>
<tr>
<td>Sample</td>
<td>0.280</td>
<td>2.119</td>
<td>50</td>
<td>652</td>
<td>0.000</td>
<td>0.140</td>
<td>105.956</td>
</tr>
<tr>
<td>Wilks' Lambda</td>
<td>0.729</td>
<td>2.229(b)</td>
<td>50</td>
<td>650</td>
<td>0.000</td>
<td>0.146</td>
<td>111.474</td>
</tr>
<tr>
<td>Hotelling's Trace</td>
<td>0.361</td>
<td>2.34</td>
<td>50</td>
<td>648</td>
<td>0.000</td>
<td>0.153</td>
<td>117.002</td>
</tr>
<tr>
<td>Roy's Largest Root</td>
<td>0.327</td>
<td>4.258(c)</td>
<td>25</td>
<td>326</td>
<td>0.000</td>
<td>0.246</td>
<td>106.45</td>
</tr>
</tbody>
</table>

a  Computed using alpha = .05  
b  Exact statistic  
c  The statistic is an upper bound on F that yields a lower bound on the significance level.  
d  Design: Intercept+Sample
4.2.4.2 HYPOTHESIS Vb

H₀: The environmental context (variable means) of archaeological site locations are not significantly affected (p < 0.05) by culture type or lifeway (historic cultures excluded).

The overall environmental characteristics of the prehistoric sites were similar for the two samples (Table 4.12). No significant difference existed between the two prehistoric samples. These sites reflect great continuity in land- and resource-use despite hypothesized changes in cultural adaptation over time. This again equates to a generalized forager adaptation to local resources during prehistory (cf., Binford 1980), despite the developments in gardening and agriculture over time expected for this locality. With no significant difference between the prehistoric samples, we have also confirmed that it is the historic sample that is significantly different from the two prehistoric samples. Thus, there are two predictive models needed for the SRS: one for the combined prehistoric sites and one for the combined historic sites, respectively.

Table 4.12: Multivariate Analysis of Variance (MANOVA) Table with F test of prehistoric adaptations, exclusively (2 samples; n=172 sites).

<table>
<thead>
<tr>
<th>Effect</th>
<th>Value</th>
<th>F</th>
<th>Hypothesis df</th>
<th>Error df</th>
<th>Sig.</th>
<th>Partial Eta Noncent.</th>
<th>Observed Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.000</td>
<td>13292427.805(b)</td>
<td>25</td>
<td>146</td>
<td>0.000</td>
<td>1.000</td>
<td>3.3E+08</td>
</tr>
<tr>
<td>Wilks' Lambda</td>
<td>0.000</td>
<td>13292427.805(b)</td>
<td>25</td>
<td>146</td>
<td>0.000</td>
<td>1.000</td>
<td>3.3E+08</td>
</tr>
<tr>
<td>Hotelling's Trace</td>
<td>2276100.652</td>
<td>13292427.805(b)</td>
<td>25</td>
<td>146</td>
<td>0.000</td>
<td>1.000</td>
<td>3.3E+08</td>
</tr>
<tr>
<td>Roy's Largest Root</td>
<td>2276100.652</td>
<td>13292427.805(b)</td>
<td>25</td>
<td>146</td>
<td>0.000</td>
<td>1.000</td>
<td>3.3E+08</td>
</tr>
</tbody>
</table>

Sample

<table>
<thead>
<tr>
<th>Effect</th>
<th>Value</th>
<th>F</th>
<th>Hypothesis df</th>
<th>Error df</th>
<th>Sig.</th>
<th>Partial Eta Noncent.</th>
<th>Observed Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pillai's Trace</td>
<td>0.079</td>
<td>.502(b)</td>
<td>25</td>
<td>146</td>
<td>0.977</td>
<td>0.079</td>
<td>12.554</td>
</tr>
<tr>
<td>Wilks' Lambda</td>
<td>0.921</td>
<td>.502(b)</td>
<td>25</td>
<td>146</td>
<td>0.977</td>
<td>0.079</td>
<td>12.554</td>
</tr>
<tr>
<td>Hotelling's Trace</td>
<td>0.086</td>
<td>.502(b)</td>
<td>25</td>
<td>146</td>
<td>0.977</td>
<td>0.079</td>
<td>12.554</td>
</tr>
<tr>
<td>Roy's Largest Root</td>
<td>0.086</td>
<td>.502(b)</td>
<td>25</td>
<td>146</td>
<td>0.977</td>
<td>0.079</td>
<td>12.554</td>
</tr>
</tbody>
</table>

a Computed using alpha = .05
b Exact statistic

c The statistic is an upper bound on F that yields a lower bound on the significance level.
d Design: Intercept+Sample
4.3 Binary Logit Modeling and Validation Testing

4.3.1 Prehistoric Binary Logit Model

Following a knowledge-based approach for the current study, seven environmental variables were selected for prehistoric model production based on extant knowledge of significant elements of the prehistoric cultural landscape. This method is preferred to other approaches, such as stepwise or best subset variable selection, due to archaeology’s focus on selective, agent-based human systems, processes and decisions that are not necessarily dependent on environment. That is, an expedient “shotgun” approach might yield a statistically valid model that does not correlate meaningfully to cultural decisions and activities that the resulting model attempts to represent. The anthropologically-relevant variables chosen for analysis include: elevation, relative elevation to streams, local elevation range, caloric cost-distance to wetlands, streams and bays, percent slope, and landform plan- and profile-curvature (land curvature perpendicular- and parallel to slope direction, respectively).

The values were extracted in ArcGIS, exported to tabular format and analyzed statistically in SAS to derive binary, multivariate logistic regression (hereafter, binary logit) coefficient estimates for model generation. The global test of the null hypothesis (Table 4.13) for the prehistoric model discloses if all model effects together influence the success probability of the binary response (site/non-site). The test was significant (p < 0.05), indicating that at least one of the model effects significantly influences the probability of observing an event.

Examination of the parameter estimates (Table 4.14) and odds ratios (Table 4.15) reveals that all but the plan curvature effect, plan_ned30, have large p-values and
therefore one or more of the other model effects may not be needed. Likewise, the intercept estimate was not significant, indicating weakness in the model overall that might be improved with an inductive approach (i.e. best subset). That was a central issue going into this research; that is, will a more statistically valid model necessarily be a more meaningful one? From a problem-oriented and cultural perspective, the deductive approach was chosen. As this was a deductive model based upon anthropologically meaningful effect variables, there was no need to attempt a “best subset” through trial-and-error or automated means.

Examining the association of predicted probabilities and observed responses (Table 4.16) there was good concordance (66.4%) and a relatively high score for Somers’ D (0.332), further supporting the effectiveness of the prehistoric model. Somers’ D reflects how many more concordant than discordant pairs are present divided by the sum frequency of pairs (Somers 1962). The scores range from -1 (all pairs disagree) to 1 (all pairs agree); the larger the value, the greater the predictive power. Further testing with the validation sample and a visual examination of site distribution in comparison to the model confirmed its utility. The prehistoric binary logit model was generated in the GIS using the equation, grid layers and associated coefficient estimates below (see Table 3.1 for grid descriptions):

\[
\text{preh_mod16} = 1 \div (1 + (\exp(-0.499 + (-0.013 * \text{dem_ned30}) + (0.014 * \text{elev_rng900}) + (-0.005 * \text{fbs_c4}) + (6.853 * \text{plan_ned30}) + (-2.238 * \text{prof_ned30}) + (-0.009 * \text{rel_strm3k}) + (0.064 * \text{slp_ned30p}))))
\]
Table 4.13: Prehistoric model test of the global null hypothesis.

<table>
<thead>
<tr>
<th>Test</th>
<th>Chi-Square</th>
<th>DF</th>
<th>Pr &gt; ChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Likelihood Ratio</td>
<td>29.6955</td>
<td>7</td>
<td>0.0001</td>
</tr>
<tr>
<td>Score</td>
<td>28.1755</td>
<td>7</td>
<td>0.0002</td>
</tr>
<tr>
<td>Wald</td>
<td>25.6032</td>
<td>7</td>
<td>0.0006</td>
</tr>
</tbody>
</table>

Table 4.14: Coefficient estimates for the binary logit model (n=199 prehistoric sites; n=200 random, non-sites).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>DF</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>Wald Chi-Square</th>
<th>Pr &gt; ChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1</td>
<td>0.4987</td>
<td>0.3983</td>
<td>1.5681</td>
<td>0.2105</td>
</tr>
<tr>
<td>dem_ned30</td>
<td>1</td>
<td>-0.0133</td>
<td>0.00857</td>
<td>2.4275</td>
<td>0.1192</td>
</tr>
<tr>
<td>slp_ned30p</td>
<td>1</td>
<td>0.0642</td>
<td>0.052</td>
<td>1.5268</td>
<td>0.2166</td>
</tr>
<tr>
<td>prof_ned30</td>
<td>1</td>
<td>-2.238</td>
<td>1.8672</td>
<td>1.4365</td>
<td>0.2307</td>
</tr>
<tr>
<td>plan_ned30</td>
<td>1</td>
<td>6.8526</td>
<td>2.8276</td>
<td>5.8733</td>
<td>0.0154</td>
</tr>
<tr>
<td>fbs_c4</td>
<td>1</td>
<td>-0.0046</td>
<td>0.00744</td>
<td>0.377</td>
<td>0.5392</td>
</tr>
<tr>
<td>rel_strm3k</td>
<td>1</td>
<td>-0.0086</td>
<td>0.0175</td>
<td>0.2428</td>
<td>0.6222</td>
</tr>
<tr>
<td>elev_rng90</td>
<td>1</td>
<td>0.0138</td>
<td>0.0139</td>
<td>0.9768</td>
<td>0.3230</td>
</tr>
</tbody>
</table>

Table 4.15: Prehistoric model odds ratio estimate effect statistics.

<table>
<thead>
<tr>
<th>Odds Ratio Est. Effect</th>
<th>Point Estimate</th>
<th>95% Wald Conf. Lim.</th>
<th>Pr &gt; ChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td>dem_ned30</td>
<td>0.987</td>
<td>0.97</td>
<td>1.003</td>
</tr>
<tr>
<td>slp_ned30p</td>
<td>1.066</td>
<td>0.963</td>
<td>1.181</td>
</tr>
<tr>
<td>prof_ned30</td>
<td>0.107</td>
<td>0.003</td>
<td>4.144</td>
</tr>
<tr>
<td>plan_ned30</td>
<td>946.304</td>
<td>3.709</td>
<td>&gt; 999.999</td>
</tr>
<tr>
<td>fbs_c4</td>
<td>0.995</td>
<td>0.981</td>
<td>1.010</td>
</tr>
<tr>
<td>rel_strm3k</td>
<td>0.991</td>
<td>0.958</td>
<td>1.026</td>
</tr>
<tr>
<td>elev_rng90</td>
<td>1.014</td>
<td>0.987</td>
<td>1.042</td>
</tr>
</tbody>
</table>
Table 4.16: Prehistoric model observed response and predicted probabilities.

<table>
<thead>
<tr>
<th>Association of Predicted Probabilities and Observed Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent Concordant</td>
</tr>
<tr>
<td>Percent Discordant</td>
</tr>
<tr>
<td>Percent Tied</td>
</tr>
<tr>
<td>Pairs</td>
</tr>
</tbody>
</table>

Receiving Operator Curves (ROC), Area Under the Curve (AUC) and Youden’s Index values were calculated to evaluate the unclassified prehistoric BLM model’s performance and to confirm that the high probability breakpoint of 0.5 was appropriate for the model reclassification. The ROC curve for the prehistoric BLM is uniform in the shape of its arc (Figure 4.1), but does not get near the upper left corner of the chart which would be ideal. However, the AUC value is 0.67 and is significant ($p < 0.05$; Table 4.17). Finally, Youden’s Index indicates the optimum breakpoint for reclassification is 0.5 (Table 4.18), precisely the value chosen based upon the Empirical Rule classification.

The resulting raster grid layer, containing values from 0.0 to 1.0 probability, was then reclassified to create zones for high probability areas at 0.5 to 1.0 probability, moderate probability at 0.5 to 0.37 (0.5 minus 0.13; 1-standard deviation), and low probability at 0.37 to 0.0 probability. There were also subtractive and additive landscape elements used to produce the final prehistoric predictive model. Wetland areas that are typically inaccessible set-asides at the SRS were reclassified as indeterminate probability areas (though there is likely a high probability of wet and deeply buried sites in
Figure 4.1: Receiving Operator Curve (ROC) for Prehistoric BLM Model.

Table 4.17: Prehistoric BLM Area Under the Curve (AUC) values.

<table>
<thead>
<tr>
<th>AUC</th>
<th>Predicted Probability</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area</td>
<td>Std. Error</td>
<td>Significance</td>
</tr>
<tr>
<td>0.66583</td>
<td>0.02714</td>
<td>0.00000</td>
</tr>
</tbody>
</table>
Table 4.18: Prehistoric BLM ROC table for determining optimum $p$ breakpoint using Youden’s Index.

<table>
<thead>
<tr>
<th>$p$</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Youden's Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00000</td>
<td>1.00000</td>
<td>1.00000</td>
<td>1.00000</td>
</tr>
<tr>
<td>0.13930</td>
<td>0.99495</td>
<td>1.00000</td>
<td>0.99495</td>
</tr>
<tr>
<td>0.16537</td>
<td>0.98990</td>
<td>1.00000</td>
<td>0.98990</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>0.50045</td>
<td>0.63131</td>
<td>0.37500</td>
<td>0.00631</td>
</tr>
<tr>
<td>0.50126</td>
<td>0.63131</td>
<td>0.37000</td>
<td>0.00131</td>
</tr>
<tr>
<td>0.50196</td>
<td>0.63131</td>
<td>0.36500</td>
<td>-0.00369</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>0.88724</td>
<td>0.01010</td>
<td>0.00000</td>
<td>-0.98990</td>
</tr>
<tr>
<td>0.90956</td>
<td>0.00505</td>
<td>0.00000</td>
<td>-0.99495</td>
</tr>
<tr>
<td>1.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>-1.00000</td>
</tr>
</tbody>
</table>

floodplains). Carolina Bays were under-represented in the archaeological sample and are known to have significant prehistoric resources, so previously recorded Carolina Bay sites were used to determine an appropriate buffer for Bay rims. A histogram of distance to Carolina Bays indicated typical site occupations peaked within 70-m of wetland edges; these areas were then added to the high probability zones resulting in the final predictive model (Figure 4.2). Examination of the coefficient estimates (Table 4.14) revealed that plan curvature was the significant variable ($p < 0.05$), while elevation, profile curvature, cost to water and relative elevation to streams have negative coefficients.

Plan curvature as a variable represents ridges and valleys in slope data, being the curvature of the landform perpendicular to the direction of slope. In the prehistoric model, its dominance highlights the importance of edge environs to the prehistoric cultural landscape. It was clear from the map of all prehistoric sites on the plan curvature grid (Figure 4.3) that sites are often associated with areas having a wide range of
curvature values, such as edge environs. Perhaps more importantly, the negative
coefficient for cost to water sources and relative elevation to streams suggested that
proximity to water was likely related to water sources having diverse edge environs (e.g.
ridge noses). So it was the ecological diversity of edge environs that was critical to
prehistoric lifeways.

Examining all prehistoric sites on the caloric cost-distance grid to fluvial soils,
bays or streams, sites occur at a range of distances from these features but tend to be
nearby (Figure 4.4). To see if there is a statistical correlation between cost-distance to
water and plan curvature, a Pearson Correlation analysis was conducted (Table 4.19). The
score was very close to being significant at $p = 0.051$ but with a weak $R = 0.139$, so a
scatterplot was graphed of the two variables revealing some clustering, but no linear
relationship (Figure 4.5). What was intriguing about the graph was that the cluster
indicates that sites tend to occur at slightly excurvate ridges and within 35 calories (kCal)
of water. This would appear to be a close match to the Brooks-Scurry model described
Figure 4.2: The 2016 Prehistoric Multivariate Predictive Model for the SRS.
Figure 4.3: Prehistoric site distribution over plan curvature.
Figure 4.4: Prehistoric site distribution over caloric cost-distance to water/wetland (Fluvial Soil, Carolina Bay or Stream).
Table 4.19: Water/wetland cost-distance and plan curvature correlation for prehistoric sites.

<table>
<thead>
<tr>
<th>Prehistoric Correlations</th>
<th>fbs_c4</th>
<th>plan_ned30</th>
</tr>
</thead>
<tbody>
<tr>
<td>fbs_c4</td>
<td>Pearson Correlation</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>199</td>
</tr>
<tr>
<td>plan_ned30</td>
<td>Pearson Correlation</td>
<td>0.139</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.051</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>199</td>
</tr>
</tbody>
</table>

Figure 4.5: Scatterplot of water/wetland cost-distance and plan curvature for prehistoric sites.
To test the model, a validation sample was used to statistically evaluate the probability zones. This sample includes 89 prehistoric sites recorded during independent, intensive archaeological surveys that were specifically excluded from all prior tests and the new model’s development for validation purposes. As the 1989 SRARP Model yielded mixed results using the 2016 model’s intensive survey sample for validation purposes, it was further evaluated here with the separate validation sample so the relative effectiveness of the 1989 and 2016 models can be compared directly.

Using the validation sample of 89 prehistoric sites, it is more clearly demonstrated here that the distribution of prehistoric sites are not significantly associated with the 1989 SRARP Model. That is, prehistoric sites do not significantly correlate to the probability zones of the prior 1989 SRARP Model. The $X^2$ tests revealed that observed verses expected frequencies of sites for each probability zone lack significance at 0.05 probability, individually and overall (Table 4.20). Also, only 26-percent of sites (n=23) occurred in the Zone 1, High Probability areas (21-percent of surveyed area). How then, does the newly developed prehistoric binary logit model compare?

For the revised prehistoric predictive model, the overall model was significant at much less than the 0.05 probability level (i.e., $p < 0.005$), as was the observed frequency of sites in the highest probability areas of Zone 1 (Table 4.21). High probability areas, Zone 1, contain some 51-percent of sites (n=46) in only 34-percent of the surveyed area. Although fewer sites were observed than expected by chance alone for the lower probability areas (Zones 0, 2, and 3), these were not significantly low frequencies. This
likely reflects limitations of the relatively small validation sample size, as the expected and observed sub-sample sizes for each zone ranged from only 8 to 30 expected sites.

Table 4.20: 1989 Model tested with Independent, Intensive Prehistoric Site Sample (n=89).

<table>
<thead>
<tr>
<th>Zone</th>
<th>% Area</th>
<th>Expected Sites</th>
<th>Observed Sites</th>
<th>(O-E)²</th>
<th>df</th>
<th>Gain</th>
<th>% Sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>6</td>
<td>5</td>
<td>4</td>
<td>0.336</td>
<td>1</td>
<td>N/A</td>
<td>5</td>
</tr>
<tr>
<td>1</td>
<td>21</td>
<td>19</td>
<td>23</td>
<td>0.994</td>
<td>1</td>
<td>0.19</td>
<td>26</td>
</tr>
<tr>
<td>2</td>
<td>54</td>
<td>48</td>
<td>52</td>
<td>0.323</td>
<td>1</td>
<td>N/A</td>
<td>58</td>
</tr>
<tr>
<td>3</td>
<td>19</td>
<td>17</td>
<td>10</td>
<td>2.824</td>
<td>1</td>
<td>N/A</td>
<td>11</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>89</td>
<td>89</td>
<td>4.477</td>
<td>3</td>
<td>N/A</td>
<td>100</td>
</tr>
</tbody>
</table>

where $X^2 \geq 7.82$ at 0.05 probability and 3 degrees of freedom.

Table 4.21: 2016 Model tested with Independent Intensive Prehistoric Site Sample (n=89)

<table>
<thead>
<tr>
<th>Zone</th>
<th>% Area</th>
<th>Expected Sites</th>
<th>Observed Sites</th>
<th>(O-E)²</th>
<th>df</th>
<th>Gain</th>
<th>% Sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>9</td>
<td>8</td>
<td>6</td>
<td>0.500</td>
<td>1</td>
<td>N/A</td>
<td>7</td>
</tr>
<tr>
<td>1</td>
<td>34</td>
<td>30</td>
<td>46</td>
<td>8.533</td>
<td>1</td>
<td>0.33</td>
<td>51</td>
</tr>
<tr>
<td>2</td>
<td>33</td>
<td>30</td>
<td>23</td>
<td>1.633</td>
<td>1</td>
<td>N/A</td>
<td>26</td>
</tr>
<tr>
<td>3</td>
<td>24</td>
<td>21</td>
<td>14</td>
<td>2.333</td>
<td>1</td>
<td>N/A</td>
<td>16</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>89</td>
<td>89</td>
<td>13.0</td>
<td>3</td>
<td>N/A</td>
<td>100</td>
</tr>
</tbody>
</table>

where $X^2 \geq 7.82$ at 0.05 probability and 3 degrees of freedom.

To illustrate this point, a second validation sample (n=1078) from the excluded, non-intensive surveys was analyzed. This much larger prehistoric sample of independent, non-intensive survey sites demonstrates that the model is much more significant, and therefore effective, than indicated by the small, intensive validation sample alone. Indeed, it indicates a pattern of significance that is nearly ideal. That is, there were significantly
more sites observed than expected by chance alone for the highest probability areas (Zone 1), and significantly fewer sites than expected for all other, lower probability, areas (Zones 0, 2, and 3; Table 4.22). Indeed, Zone 1 high probability areas contained some 56-percent of sites (n=606) in only 28-percent of the SRS area.

Distribution maps of prehistoric sites along Upper Three Runs Creek illustrate the increased effectiveness of the multivariate predictive model. The 1989 model displayed a weak correlation between sites and its corresponding probability zones (Figure 4.6). In contrast, the probability zones of the new multivariate predictive model demonstrated a high correlation with prehistoric site distributions (Figure 4.7). That is, most of the documented sites occurred within the highest probability zone of the model, Zone 1.

Table 4.22: The 2016 Model tested with Independent Non-Intensive Prehistoric Site Sample (n=1078)

<table>
<thead>
<tr>
<th>Zone</th>
<th>%</th>
<th>Area</th>
<th>Expected Sites</th>
<th>Observed Sites</th>
<th>(O-E)²/E</th>
<th>df</th>
<th>Gain</th>
<th>% Sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>19</td>
<td>19</td>
<td>205</td>
<td>85</td>
<td>70.095</td>
<td>1</td>
<td>N/A</td>
<td>8</td>
</tr>
<tr>
<td>1</td>
<td>28</td>
<td>28</td>
<td>302</td>
<td>606</td>
<td>306.498</td>
<td>1</td>
<td>0.50</td>
<td>56</td>
</tr>
<tr>
<td>2</td>
<td>27</td>
<td>27</td>
<td>291</td>
<td>245</td>
<td>7.289</td>
<td>1</td>
<td>N/A</td>
<td>23</td>
</tr>
<tr>
<td>3</td>
<td>25</td>
<td>25</td>
<td>270</td>
<td>142</td>
<td>60.320</td>
<td>1</td>
<td>N/A</td>
<td>13</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>100</td>
<td>1078</td>
<td>1078</td>
<td>444.202</td>
<td>3</td>
<td>N/A</td>
<td>100</td>
</tr>
</tbody>
</table>

where $X^2 \geq 7.82$ at 0.05 probability and 3 degrees of freedom.
Figure 4.6: The distribution of recorded prehistoric sites demonstrate the limitations of the 1989 Prehistoric Sensitivity Model of the SRS.
Figure 4.7: The distribution of recorded prehistoric sites demonstrate the effectiveness of the 2016 Prehistoric Multivariate Predictive Model of the SRS.
4.3.2 Historic Binary Logit Model

Again following a knowledge-based approach, eight environmental variables were selected for historic logit model production based on extant knowledge of significant elements of the historic cultural landscape. The anthropologically-relevant variables chosen for analysis include: historic (primary) roads, elevation, relative elevation to streams, local elevation range, caloric cost-distance to wetlands/streams/bays, percent slope, and landform plan- and profile-curvature (land curvature parallel and perpendicular to slope direction, respectively). The values were extracted in ArcGIS, exported to tabular format and analyzed statistically in SAS to derive binary, multivariate logistic regression (binary logit) coefficient estimates for model generation.

The global test of the null hypothesis (Table 4.23) for the historic model discloses if all model effects together influence the success probability of the binary response (site/non-site). The test was significant ($p < 0.05$), indicating that at least one of the model effects significantly influenced the probability of observing an event. However, this does not mean that the model is necessarily going to meet its intended goals.

Examination of the parameter estimates (Table 4.24) and odds ratios (Table 4.25) revealed that all but the plan curvature effect, plan_ned30, have large p-values and therefore one or more of the other model effects may not be needed. Likewise, the intercept estimate was not significant, indicating weakness in the model overall that might be improved with an inductive approach (i.e. best subset). Again, that was a central issue going into this research; that is, will a more statistically valid model necessarily be a more meaningful one? From a problem-oriented and cultural perspective, the deductive
approach was chosen. As this is a deductive model based upon anthropologically meaningful effect variables, there was no need to attempt a “best subset” through trial-and-error or automated means.

Examining the association of predicted probabilities and observed responses (Table 4.26) there was good concordance (62.5%) and a slightly lower positive score for Somers’ D (0.256) than the prehistoric model, but suggested an effective historic model. Again, Somers’ D reflects how many more concordant than discordant pairs are present divided by the sum frequency of pairs (Somers 1962). The scores range from -1 (all pairs disagree) to 1 (all pairs agree); the larger the value, the greater the predictive power. However, despite these positive indicators, testing with the validation sample and a visual examination of site distribution in comparison to the historic model highlight some serious limitations. The historic binary logit model was generated in the GIS using the equation, grid layers and associated coefficient estimates below (see Table 3.1 for grid descriptions):

\[
\text{hist_mod16} = 1 \div (1 + (\exp(-(-0.1576 + (-0.00917 \times \text{dem}_{\text{ned30}}) + (-0.00216 \times \text{slp}_{\text{ned30p}}) + (-2.6164 \times \text{prof}_{\text{ned30}}) + (5.5071 \times \text{plan}_{\text{ned30}}) + (0.00822 \times \text{fbs}_{\text{c4}}) + (0.0202 \times \text{rel}_{\text{strm3k}}) + (-0.00024 \times \text{elev}_{\text{rng900}}) + (-0.00011 \times \text{roads51}_{\text{c4}}))))
\]
Table 4.23: Historic model test of the global null hypothesis.

<table>
<thead>
<tr>
<th>Test</th>
<th>Chi-Square</th>
<th>DF</th>
<th>Pr &gt; ChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Likelihood Ratio</td>
<td>17.6941</td>
<td>8</td>
<td>0.0236</td>
</tr>
<tr>
<td>Score</td>
<td>17.1852</td>
<td>8</td>
<td>0.0282</td>
</tr>
<tr>
<td>Wald</td>
<td>16.1961</td>
<td>8</td>
<td>0.0397</td>
</tr>
</tbody>
</table>

Table 4.24: Coefficient estimates for the historic binary logit model (n=184 historic sites; n=200 random, non-sites).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>DF</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>Wald Chi-Square</th>
<th>Pr &gt; ChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1</td>
<td>-0.1576</td>
<td>0.457</td>
<td>0.119</td>
<td>0.7301</td>
</tr>
<tr>
<td>dem_ned30</td>
<td>1</td>
<td>-0.0092</td>
<td>0.00809</td>
<td>1.2825</td>
<td>0.2574</td>
</tr>
<tr>
<td>slp_ned30p</td>
<td>1</td>
<td>-0.0022</td>
<td>0.0574</td>
<td>0.0014</td>
<td>0.9699</td>
</tr>
<tr>
<td>prof_ned30</td>
<td>1</td>
<td>-2.6164</td>
<td>2.0116</td>
<td>1.6918</td>
<td>0.1934</td>
</tr>
<tr>
<td>plan_ned30</td>
<td>1</td>
<td>5.5071</td>
<td>3.0594</td>
<td>3.2402</td>
<td>0.0719</td>
</tr>
<tr>
<td>fbs_c4</td>
<td>1</td>
<td>0.00822</td>
<td>0.00686</td>
<td>1.4372</td>
<td>0.2306</td>
</tr>
<tr>
<td>rel_strm3k</td>
<td>1</td>
<td>0.0202</td>
<td>0.0164</td>
<td>1.5122</td>
<td>0.2188</td>
</tr>
<tr>
<td>elev_rng90</td>
<td>1</td>
<td>-0.0002</td>
<td>0.0153</td>
<td>0.0003</td>
<td>0.9874</td>
</tr>
<tr>
<td>roads51_c4</td>
<td>1</td>
<td>-0.0001</td>
<td>0.00152</td>
<td>0.0051</td>
<td>0.9429</td>
</tr>
</tbody>
</table>

Table 4.25: Historic model odds ratio estimate effect statistics.

<table>
<thead>
<tr>
<th>Odds Ratio Est. Effect</th>
<th>Point Estimate</th>
<th>95% Wald Conf. Lim.</th>
<th>Pr &gt; ChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td>dem_ned30</td>
<td>0.991</td>
<td>0.975</td>
<td>1.007</td>
</tr>
<tr>
<td>slp_ned30p</td>
<td>0.998</td>
<td>0.892</td>
<td>1.117</td>
</tr>
<tr>
<td>prof_ned30</td>
<td>0.073</td>
<td>0.001</td>
<td>3.767</td>
</tr>
<tr>
<td>plan_ned30</td>
<td>246.429</td>
<td>0.613</td>
<td>&gt; 999.999</td>
</tr>
<tr>
<td>fbs_c4</td>
<td>1.008</td>
<td>0.995</td>
<td>1.022</td>
</tr>
<tr>
<td>rel_strm3k</td>
<td>1.02</td>
<td>0.988</td>
<td>1.054</td>
</tr>
<tr>
<td>elev_rng90</td>
<td>1</td>
<td>0.97</td>
<td>1.030</td>
</tr>
<tr>
<td>roads51_c4</td>
<td>1</td>
<td>0.997</td>
<td>1.003</td>
</tr>
</tbody>
</table>
Table 4.26: Historic model observed response and predicted probabilities.

<table>
<thead>
<tr>
<th>Association of Predicted Probabilities and Observed Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent Concordant</td>
</tr>
<tr>
<td>Percent Discordant</td>
</tr>
<tr>
<td>Percent Tied</td>
</tr>
<tr>
<td>Pairs</td>
</tr>
</tbody>
</table>

Receiving Operator Curves (ROC), Area Under the Curve (AUC) and Youden’s Index (YI) values were calculated to evaluate the unclassified historic BLM model’s performance and to confirm that the high probability breakpoint of 0.5 was appropriate for the model reclassification. The ROC curve for the historic BLM was less uniform in the shape of its arc than the prehistoric model and did not get near the upper left corner of the chart which would be ideal (Figure 4.8). However, the AUC value of 0.63 was significant ($p < 0.05$; Table 4.27). Youden’s Index indicated the theoretical optimum breakpoint for reclassification was 0.47 (Table 4.28), close enough to justify the chosen breakpoint of 0.5 based upon the Empirical Rule.
Figure 4.8: Receiving Operator Curve (ROC) for Historic BLM Model.

Table 4.27: Historic BLM Area Under the Curve (AUC) values.

<table>
<thead>
<tr>
<th>AUC Area</th>
<th>Predicted Probability</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.62745</td>
<td>0.02827</td>
<td>0.00002</td>
</tr>
</tbody>
</table>
Table 4.28: Historic BLM ROC table for determining optimum $p$ breakpoint using Youden’s Index.

<table>
<thead>
<tr>
<th>$p$</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Youden's Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00000</td>
<td>1.00000</td>
<td>1.00000</td>
<td>1.00000</td>
</tr>
<tr>
<td>0.18972</td>
<td>0.99457</td>
<td>1.00000</td>
<td>0.99457</td>
</tr>
<tr>
<td>0.19523</td>
<td>0.99457</td>
<td>0.99500</td>
<td>0.98957</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>0.46967</td>
<td>0.57609</td>
<td>0.43000</td>
<td>0.00609</td>
</tr>
<tr>
<td>0.46997</td>
<td>0.57609</td>
<td>0.42500</td>
<td>0.00109</td>
</tr>
<tr>
<td>0.47008</td>
<td>0.57065</td>
<td>0.42500</td>
<td>-0.00435</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>0.78595</td>
<td>0.00543</td>
<td>0.00500</td>
<td>-0.98957</td>
</tr>
<tr>
<td>0.80653</td>
<td>0.00000</td>
<td>0.00500</td>
<td>-0.99500</td>
</tr>
<tr>
<td>1.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>-1.00000</td>
</tr>
</tbody>
</table>

The resulting raster grid layer, containing values from 0.0 to 1.0 probability, was reclassified to create zones for high probability areas at 0.5 to 1.0 probability, moderate probability at 0.5 to 0.38 (0.5 minus 0.12; 1-standard deviation), and low probability at 0.38 to 0.0 probability. There were also subtractive landscape elements used to produce the final historic predictive model. Wetland areas that are typically inaccessible set-asides at the SRS were reclassified as indeterminate probability areas. (Figure 4.9).

Examination of the coefficient estimates (Table 4.24) revealed that plan curvature was again the only significant variable ($p < 0.05$), while elevation, slope, profile curvature, elevation range and 1951 roads had negative coefficients. Plan curvature as a variable again represents ridges and valleys, being the curvature of the landform perpendicular to the direction of slope. In the historic model, its dominance highlights the importance of upland gently rolling hills, as well as, edge environs to the historic cultural landscape. Perhaps more importantly, the negative coefficient for primary historic roads...
was a surprise. This may indicate that the economic benefits of dispersed farmsteads for livestock and agriculture outweighed direct access to primary roadways. This was likely further facilitated by horseback carriage on secondary roads prior to the early 20th century, a mode of transport not accessible by prehistoric cultures of the region.

To test the historic model, a validation sample of 110 historic sites recorded during independent, intensive archaeological surveys that were excluded from the model’s development for validation purposes. Validation demonstrated that the model is somewhat of a successful failure. That is, the overall model was significant at slightly less than the 0.05 probability level, but failed to have significantly greater or fewer sites than expected by chance alone for each of the model’s prediction zones (Table 4.29). While high probability areas, Zone 1, contain some 41-percent of sites (n=45) in 31-percent of the surveyed area (Gain of only 0.24), this was not a significantly high frequency of observed sites. Moderate probability, Zone 2, areas also had more sites than expected by chance alone, but not in significant numbers. Although fewer sites were observed than expected by chance alone for the lower probability areas (Zones 0 and 3), these too were not significantly low frequencies.

To illustrate this point, a second validation sample (n=724) from the excluded, non-intensive surveys was analyzed (Table 4.30). This much larger historic sample of independent, non-intensive survey sites demonstrates that the model was statistically significant, but not very effective with a Gain of only 0.30. Zone 1, high probability areas only contained 43-percent of sites (n=309) in 30-percent of the SRS area.
Distribution maps of historic sites along Fourmile Creek illustrate the problems with the historic BLM predictive model. The historic model displays a weak correlation between sites and its corresponding probability zones (Figure 4.10). While there is agreement between the model and sites in some places, a greater share occur within the moderate and low probability zones.

Table 4.29: 2016 Historic Model tested with Independent Intensive Historic Site Sample (n=110)

<table>
<thead>
<tr>
<th>Zone</th>
<th>% Area</th>
<th>Expected Sites</th>
<th>Observed Sites</th>
<th>(O-E)²/E</th>
<th>df</th>
<th>Gain</th>
<th>% Sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>9</td>
<td>10</td>
<td>6</td>
<td>1.536</td>
<td>1</td>
<td>N/A</td>
<td>5</td>
</tr>
<tr>
<td>1</td>
<td>31</td>
<td>34</td>
<td>45</td>
<td>3.484</td>
<td>1</td>
<td>0.24</td>
<td>41</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>55</td>
<td>54</td>
<td>0.018</td>
<td>1</td>
<td>N/A</td>
<td>49</td>
</tr>
<tr>
<td>3</td>
<td>10</td>
<td>11</td>
<td>5</td>
<td>3.273</td>
<td>1</td>
<td>N/A</td>
<td>5</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>110</td>
<td>110</td>
<td>8.311</td>
<td>3</td>
<td>N/A</td>
<td>100</td>
</tr>
</tbody>
</table>

where \( X^2 \geq 7.82 \) at 0.05 probability and 3 degrees of freedom.

Table 4.30: 2016 Historic Model tested with Independent Non-Intensive Historic Site Sample (n=724)

<table>
<thead>
<tr>
<th>Zone</th>
<th>% Area</th>
<th>Expected Sites</th>
<th>Observed Sites</th>
<th>(O-E)²/E</th>
<th>df</th>
<th>Gain</th>
<th>% Sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>19</td>
<td>138</td>
<td>51</td>
<td>54.468</td>
<td>1</td>
<td>N/A</td>
<td>7</td>
</tr>
<tr>
<td>1</td>
<td>30</td>
<td>217</td>
<td>309</td>
<td>38.799</td>
<td>1</td>
<td>0.30</td>
<td>43</td>
</tr>
<tr>
<td>2</td>
<td>43</td>
<td>311</td>
<td>323</td>
<td>0.438</td>
<td>1</td>
<td>N/A</td>
<td>45</td>
</tr>
<tr>
<td>3</td>
<td>8</td>
<td>58</td>
<td>41</td>
<td>4.943</td>
<td>1</td>
<td>N/A</td>
<td>6</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>724</td>
<td>724</td>
<td>98.649</td>
<td>3</td>
<td>N/A</td>
<td>100</td>
</tr>
</tbody>
</table>

where \( X^2 \geq 7.82 \) at 0.05 probability and 3 degrees of freedom.

Visual observation of the historic model at smaller scale revealed some obvious shortcomings. Particularly apparent were the low probability areas in the central portion
of the SRS, including the historic town of Dunbarton (Figure 4.9). Most other areas of the site appear to meet general expectations, that is, that high probability areas fall on the upland terraces, in stark contrast to the prehistoric model’s emphasis of wetland edge environs. The fact that statistical evaluations of the historic model were largely inconclusive, reflects the nearly random distribution of historic sites relative to the natural environment.

It was worth another look at the historic roads data that essentially fell out of the BLM analysis. First, maps were made of the dominant variable, plan curvature, and the historic roads grid. Examination of the plan curvature map (Figure 4.11) indicated that historic sites also occurred near edge environs, similar to the prehistoric sites but with slightly more variation in their distribution. Examining the caloric cost distance to primary roads (Figure 4.12), it was immediately apparent that the BLM analysis might have missed a significant variable due to the exaggerated influence of plan curvature. Historic sites seem to parallel many primary roads from a sizable distance. Checking for a correlation with plan curvature again yielded insignificant results (p =0.755; Table 4.31). A scatterplot of plan curvature vs. roads revealed another cluster of sites, this time at slightly excurvate curvature scores and within 200 kCal of roads (Figure 4.13).

Ultimately, exploitation of the upland areas was enabled by the use of wells, instead of natural surface water sources, throughout the historic period. Prehistoric hunting, gathering, fishing and gardening gave way to historic-era cattle grazing and agricultural crop production. Overall, the historic logit model is unsuitable for targeting historic cultural resources on the SRS and it is recommended that geo-referenced historic maps, 1951 aerial photos and LiDAR imagery be used to target historic sites on the SRS.
Figure 4.9: The 2016 Historic Multivariate Predictive Model yielded weak results and is not recommended for CRM compliance on the SRS.
Figure 4.10: Historic site distribution over 2016 Historic BLM Model
Figure 4.11: Historic site distribution over plan curvature.
Figure 4.12: Historic site distribution over caloric cost-distance to primary historic roads.
Table 4.31: Primary roads cost-distance and plan curvature correlation for historic sites.

<table>
<thead>
<tr>
<th>Historic Correlations</th>
<th>plan_ned30</th>
<th>roads51_c4</th>
</tr>
</thead>
<tbody>
<tr>
<td>plan_ned30</td>
<td>Pearson Correlation</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.755</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>183</td>
</tr>
<tr>
<td>roads51_c4</td>
<td>Pearson Correlation</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.755</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>183</td>
</tr>
</tbody>
</table>

Figure 4.13: Scatterplot of primary roads caloric cost-distance and plan curvature for historic sites.
CHAPTER 5
CONCLUSIONS

There were some surprises revealed by the analyses of the prehistoric cultural landscape and initial concerns regarding the difficulties of modeling the historic landscape were largely confirmed in this research. It was expected that the prehistoric cultural landscape witnessed significant changes in land use practices over nearly 14,000 years. With six clearly discernable sub-periods, it was thought that each might need a separate model to represent the prehistoric cultural landscape. Yet, that was not evidenced in the analyses.

At a minimum, then, it was expected that separate models would be needed based upon primary lifeway, i.e. hunter-gatherers vs. horticulturists/agriculturists. However, the hypothesis tests revealed that environmental context of prehistoric sites did not vary significantly over time or by lifeway. This reveals a surprising level of continuity in the cultural landscape during the prehistoric period. This was not an artifact of sample size or distribution, as evidenced by the significant shift in environmental context at the beginning of historic European settlement.

Likewise, the “early” and “late” historic samples did not significantly vary from one another. This was surprising too, as early historic sites were expected to be similar to the late prehistoric, due to the common theme of subsistence agriculture. The most likely cause of this difference was the use of wells for water during the historic period, which
enabled home sites to be located in the uplands instead of adjacent to active waterways and bays.

Now that the hypothesis tests and modeling processes are completed, what has been learned about the underlying assumptions driving this research and what interpretations may be gleaned from those results? That is, what has been learned about the long-term cultural trajectories, transformations and reversions as reflected in the cultural landscape? Did the behavior of individual actors shape that landscape through influence of the aggregate whole or was some form of environmental determinism placing limits on cultural expression?

5.1 Anthropological Theory to the Interpretive Rescue

Results of the hypothesis tests indicated that long-term cultural trajectories are the norm and rather linear for the Central Savannah River, particularly during the prehistoric era. Despite the fact that significant transformations in lifeway occurred in this region, as evidenced by the artifacts they left behind, from simple hunter-fisher-gatherers to complex agriculturists, the locational choices for habitation, resource extraction and landscape maintenance apparently changed little over time. This is intriguing considering that over those 14,000 years, the environment changed radically from the extreme oscillations of the Pleistocene to the warmth and stability of the Holocene.

Nevertheless, no significant variation in site location occurred over time until the radical cultural change of the historic European diaspora and colonization of recent centuries. This suggests that late prehistoric agriculturists had as balanced an approach to subsistence and settlement as their hunter-fisher-gatherer forbearers. They likely valued
and maintained the long-term traditions of exploitation and management of nut-bearing forest stands, herbaceous plants and wild game, in addition to their fields and gardening plots. Perhaps this pattern of relative continuity is best explained by Rational Choice Theory (Boudon 2009), where group behavior follows the rational decisions of individuals as actors on the landscape, that in turn serve to provide sustenance, care and shelter in a reliable and predictable way to the greater social group, as opposed to the risk of radically or randomly changing subsistence and settlement strategies.

Thus cultural transformations of hunter-gatherers and early agriculturists were likely more ideological or cosmological in nature and not clearly reflected in the cultural landscape, at least at the local level of the SRS study area. Garden plots were likely adjacent to habitations for ease of maintenance and habitations themselves were distributed in the same settings throughout prehistory. Longer-term habitation construction and the cost of building garden plots were therefore additive behaviors and elements of the cultural landscape that enabled beneficial change, while minimizing risk. Therefore, while environmental setting was important, so too were the actions of cultural selection and the continuity of cultural traditions.

The cultural landscapes of the Central Savannah River had very long temporal trajectories. This is evidenced by the apparent 14,000-year duration of prehistoric site location preference and a similar occurrence of a few hundred years for the historic era. For the prehistoric cultures, the edge environs adjacent to wetlands provide both habitation space and sustenance (Figure 5.1). Nut-bearing trees and fertile soils provided for hunter-fisher-gatherers and horticulturists alike. In the secondary areas, foraging and
agriculturally-productive soils were likewise available. In the tertiary upland terraces, large game migrated and trails that crossed into adjacent river systems were abundant. After the arrival of Europeans, a radical shift in landuse and lifeway occurred (Figure 5.2). Homesteads dotted the upland landscape in a nearly inverse manner to that of the prehistoric era before it. This was facilitated by the digging of wells for water and the building of roads for transportation, where only rough trails once crisscrossed the landscape. Bottomlands served as additional transport by boat, provided hydrologic power for mills, and animal pelts for trade. Much of the landscape was open-canopy forest and pasture, suitable for livestock and agriculture. Since 1951, the SRS landscape has undergone additional radical changes as the Cold War raged-on for decades, cooled for a while, and now shows signs of heating up once again. The role of this landscape has changed, however, from that of nuclear production to nuclear waste management.

5.2 There and Back Again: Planning Ahead to (Re)Model

As the menu of New Orleans’ famous Antoine’s Restaurant states, “Faire de la bonne cuisine demande un certain temps. Si on vous fait attendre, c'est pour mieux vous servir, et vous plaire. (Good cooking takes time. If you are made to wait, it is to serve you better, and to please you.)” So too has the modeling effort at the SRS progressed in recent years, i.e. slowly and with thoughtful care. When initial plans to test the 1989 Archaeological Sensitivity Model began in the year 2000, it was immediately apparent that there was a significant problem. Not with the research problem itself, but with the SRARP’s archaeological site data. That is, there was no independent sample available to
Figure 5.1: The Prehistoric Cultural Landscape of the Central Savannah River.
Figure 5.2: The Historic Cultural Landscape of the Central Savannah River.
test the extant model, nor to develop a new one. There had simply been no independent archaeological survey strategy planned to test the 1989 model after its adoption.

It took another five years to acquire a sample sufficient for the tasks of testing the extant model and developing a more statistically rigorous one to replace it, then another decade to record a validation sample sizable enough to test the revised and improved predictive model. That’s a long wait indeed and at times it felt as if there would need to be two more sub-periods added to the analyses: Cold War SRS and post-Cold War SRS. Those landscapes too will need to be characterized in the future, as the modern built environment has seen significant shifts from its nuclear production era of the Cold War to the decommissioning of those facilities and nuclear waste processing today.

Nevertheless, there should be an ongoing plan to test a significant portion of the landscape using full-coverage, high-intensity landscape surveys. Like the surveys used in this study, these should consist of a 30-m grid of shovel test pits in Phase 1 CRM testing. A goal of 10 sites per year recorded in this method would be ideal, as that would enable a sample size of 100 sites after 10 years for further model testing and refinement. That goal may not be cost-effective in the current budget climate, but should be considered as an objective. Likewise, new and existing sites encountered in the full-coverage surveys should be archaeologically tested more extensively to permit testing and modeling of site and landscape multi-componency in the future.

Last, but not least, there’s the rather average results of the validation testing of the new models. The Gain scores, in particular, were underwhelming (Table 5.1). Is it possible that the statistically-robust multivariate methodologies are more fallible than a simple deductive map-overlay approach, such as the Brooks-Scurry model (Brooks and
Scurry 1978; Scurry 2003, 2015)? With Gain scores ranging from 0.52 to 0.73, Scurry’s (2015) model for the Interior Coastal Plain outperformed those presented in this dissertation.

Table 5.1: Gain Statistics for the various models and samples,

<table>
<thead>
<tr>
<th>Model/Sample</th>
<th>% Area</th>
<th>% Sites</th>
<th>Gain</th>
</tr>
</thead>
<tbody>
<tr>
<td>1989 Prehistoric/Validation</td>
<td>21</td>
<td>26</td>
<td>0.19</td>
</tr>
<tr>
<td>2016 Prehistoric/Validation</td>
<td>34</td>
<td>52</td>
<td>0.35</td>
</tr>
<tr>
<td>2016 Historic/Validation</td>
<td>31</td>
<td>41</td>
<td>0.24</td>
</tr>
<tr>
<td>1989 Prehistoric/Non-Intensive*</td>
<td>17</td>
<td>36</td>
<td>0.53</td>
</tr>
<tr>
<td>2016 Prehistoric/Non-Intensive</td>
<td>28</td>
<td>56</td>
<td>0.50</td>
</tr>
<tr>
<td>2016 Historic/Non-Intensive</td>
<td>30</td>
<td>43</td>
<td>0.30</td>
</tr>
</tbody>
</table>

*Sample not independent of model.

Part of the reason for this underwhelming performance was due to the dominance of a single variable, plan curvature, in both the prehistoric and historic models. For the highly-dissected sandhills of the Interior Coastal Plain, the plan-, profile- and combined-curvature variables are always dominant when used. For example, when a purely inductive, best subset BLM model is performed, both the prehistoric and historic models are dominated by the combined-curvature variable. That doesn’t mean it’s a bad variable, but it may skew results adversely, as was likely the case in the historic model here.

Interestingly, the bivariate scatterplots suggest an overlay of plan-curvature with 35-calorie buffers from wetland edges, similar to Scurry’s model, and buffers of 200-calories from historic roads, may provide two simple, elegant and useful models without all of the multivariate statistics. Such models will definitely be worth exploring further in the future.
5.3 Advancing Archaeological Geographic Information Science

Like most bodies of work, this study was not without a few surprises along the way. It was largely successful in reaching its goals, and in the process confirmed the difficulties in modeling and understanding cultural landscapes of the past from the limited samples available to archaeologists. Ideally, one would have data from numerous sites with extensive excavations to examine, but such extensive samples are rare at the present time, given how few sites locally have been subject to extensive excavation. Given the scarcity of diagnostic cultural materials revealed in 30-m interval shovel test surveys, it is remarkable that greater variation in their context and distribution was not experienced as an artifact of the recovery method alone. This indicates that the sample strategy is not as limiting as presumed and the significant locational differences between prehistoric and historic samples, respectively, demonstrates the cultural data are robust.

Whereas, prehistoric and historic sites varied significantly from one another, samples tested within these greater sub-periods did not. That is, prehistoric sites did not vary significantly over time or by culture type, nor did historic sites. This indicates great cultural continuity and land use over time, on the order of some 14,000 years for the prehistoric era, and over the last three centuries for the historic era. The advent of horticulture and agriculture in the prehistoric era were thus apparently additive forms of subsistence. That is, gardening added additional foodstuffs to already diverse local resources, such as stream fisheries, terrestrial and avian game, and stands of nut-bearing trees. The most significant finding related to the prehistoric cultural landscape was that distance to streams, long believed to be the most significant factor in local settlement,
may be coincidental to the ecological diversity of ridge noses and other edge environs that happen to be near local water sources.

Historically, the use of wells opened the uplands for dispersed homesteads and farms, enabling year-round habitation. The greatest surprise of the historic analyses is that historic roads were not the most significant contributor to the model of historic land use. Like the prehistoric era, the rolling hills and diverse edge environs above local watercourses were dominant features of the historic landscape. These locations offered rich, well-drained soils for crops, as well as open-canopy grazing with nearby water sources for livestock.

Application of GISci methods and technology will likely remain a significant contribution to archaeological research and CRM practices in the future. Future research on the cultural landscapes of the Central Savannah River may benefit from established methodologies in landscape ecology (e.g., Kupfer 1995, 2011). In particular, Geographically-Weighted Regression (GWR) may offer improved predictive performance and resolution over the BLM procedures employed here (Kupfer and Harris 2007).

This research extended GIS beyond its traditional 2.5 dimensions by using cultural- and time-sliced archaeological data, each representing a third dimension in geographical space, to discern past cultural landscapes that have otherwise been obscured by subsequent natural and cultural processes. As such, it is hoped that the hypothesis tests, outcomes, and landscape models herein are perceived as valuable contributions to our knowledge of the past and present, within and beyond the Central Savannah River.
REFERENCES


Brooks, Mark J. and James D. Scurry. 1978. *An Intensive Archaeological Survey of Amoco Realty Property in Berkeley County, South Carolina with a Test of Two Subsistence-Settlement Hypotheses for the Prehistoric Period*. Research Manuscript Series 149, Columbia, SC: South Carolina Institute of Archaeology and Anthropology, University of South Carolina


145


Inventory Data: The Digital Index of North American Archaeology (DINAA). 


———. 2012. A Paleoeconomic Approach to Predictive Modeling in the Lower Mississippi River Region (Southern Arkansas, Northern Louisiana, and Western Mississippi, USA). A paper prepared for the *Computer Applications in Archaeology Conference (2012)*, Southampton, UK.


