ABSTRACT

Title of Thesis:	RECENT TIMBERING ACTIVITY AS A VARIABLE IN PREDICTIVE MODELING
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This thesis explores how the presence of recent timbering activities affects the predictive power of predictive models in regard to precontact archaeological sites. Predictive models have been used to assess the likelihood of identifying cultural resources in a given area for decades. A county-wide predictive model has not been created for any county in the state of Georgia. This research applies what is known about predictive modeling to Henry County, Georgia and assesses its accuracy. It then seeks to test predictive power of another environmental variable in order to further refine the process of predicting the location of precontact archaeological sites.

The thesis focuses its efforts in Henry County, Georgia, which has multiple instances of pine silviculture areas that have been surveyed for cultural resources after being harvested. Timber has been an important natural resource in Georgia since the nineteenth century. The management of forests for the timber industry began in 1875 with the establishment of the American Forestry Association. The timbering and replanting of these areas can occur as often as every 15 to 30 years. This process can disturb soils and buried resources.

Elevation, soil, and hydrology data was collected from multiple public sources including the United State Geological Survey (USGS) and the United States Department of Agriculture Natural Resources Conservation Service (USDA, NRCS). Archaeological site and previous survey data was taken from the Georgia Natural Archaeological and Historic Resources Geographic Information Systems (GNAHRGIS). The environmental data was combined to create a set of predictive models for predicting the likelihood of an area to contain a precontact archaeological site using Geographic Information Systems (GIS). Each predictive model was tested for accuracy using previously collected archaeological data. The predictive model found to be most accurate was analyzed within multiple areas containing recent timbering activities that have been previously surveyed for cultural resources.

It appears that the presence of recent timbering activities does not negatively affect the predictive power of a predictive model regarding precontact archaeological sites. This is demonstrated by showing that a predicative model for the entirety of Henry County, Georgia does not lose accuracy when applied to multiple areas that have been timbered prior to survey for cultural material.

Predictive models can be powerful tools in the Cultural Resource Manager's toolkit. However, many may be reticent to apply these tools to areas that have seen large-scale industrial ground disturbing activities. This thesis has demonstrated that predictive models can still be useful tools in areas recently affected by large-scale timbering activities. While systematic survey is still necessary, this can be helpful in matters of scoping, budgeting, and planning.

RECENT TIMBERING ACTIVITY AS A VARIABLE IN PREDICTIVE MODELING

by

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Chapter 1: Introduction

Predictive models can be a useful tool in the archaeologist's arsenal. Using the environmental variables that precontact people selected for when choosing locations, archaeologists can judge a given area's relative attractiveness to a precontact group. However, modern developments in industry have altered the physical environment in a myriad of ways. The silviculture industry, in particular, has affected large portions of the state of Georgia along with the rest of the American Southeast. Multiple steps in the silviculture process are known to be ground disturbing, including the timbering process. This thesis intends to answer the question: Does the presence of recent timbering activities negatively affect the predictive power of predictive models in regard to precontact archaeological sites?

Predictive Modeling in Cultural Resource Management

Predictive modeling has been making a transition from an innovation solely used in academia to a valuable tool in the kit of archaeologists working in the Cultural Resource Management (CRM) industry. Advancements in software and processing power are likely to blame for this change. Predictive modeling has become more affordable and time efficient. This thesis presents a methodology for creating and testing predictive models using the common software ESRI's ArcMap and free, publicly available environmental data. The speed and low cost at which predictive models can now be constructed is ideal for the CRM industry which operates on slim budgetary margins and short timeframes. Predictive models have begun to see usage

in the CRM industry for a multitude of uses. With the application of a systematic approach to creation and testing of predictive models, it is likely that they will begin to be a more common fixture in the survey process.

Silviculture in the State of Georgia

Silviculture is the practice of growing trees for the purpose of cultivation. Timbering is the process by which these trees are cultivated. Many of the processes of silviculture can be ground disturbing. The tilling and planting process often includes digging troughs and mounding up soil to create alternating troughs and furrows. Trees are planted along the furrows while water pools and drains through the troughs. During the life cycle of the trees, properly managed forests are often subjected to a controlled burn. This eliminates underbrush and weeds that might divert some of the available nutrients from the soil while preserving the larger heartier trees. Finally, the trees are cultivated in the timbering process. A recently timbered forest can be compared to a World War I battlefield crisscrossed with splintered wood, fresh stumps, and massive tire tracks. It stands to reason that Cultural Resource Managers might feel that this area cannot be modeled for precontact sites with any kind of effectiveness. But, would they be correct in this assumption?

The manipulation of the pine forests of Georgia for human purposes has been recorded as far back as the first contact with the native people by European settlers. The American Indians would regularly stage controlled burns. The burns would result in an open park-like forest of long leaf pines that was ideal for hunting. Europeans began logging the vast pine forests of Georgia soon after colonization. After depleting

the soil with cotton farming and erosion from the initial deforestation, the Piedmont had become the ideal environment for the loblolly pine. Silviculture, mainly of pine, became one of Georgia's top industries. By the 1960s, Georgia was the nation's leading producer of lumber. Currently, Georgia is the location of more timberland than any other state in the US. The industry is worth $36.3 billion annually and employs over 55,000 Georgia residents. It is essential that Cultural Resource Managers better understand the effects of this industry on cultural resources. This thesis examines one dimension of these effects, the relative power of predictive modeling in contexts of silviculture development.

Below, the chapters that make up this thesis are listed along with a summary which explains their contents and importance in answering the research question.

Summary of Following Chapters

Theoretical Background

The theoretical background is presented in order to establish a theoretical basis on which to build the thesis. The review begins with a brief history of predictive modeling in Cultural Resource Management as well as in academic archaeology. Through the early history of predictive modeling, the basic understandings and assumptions that the practice is built upon are better understood. From here, the chapter introduces the two basic theoretical models through which predictive modeling is understood: the inductive method, and the deductive model. The inductive method of predictive modeling is presented along with case studies. The case studies both reveal the theoretical underpinnings of the inductive method as well

as present the utility of these models in a variety of different environments. The deductive method is presented mostly in opposition to the inductive method.

The presentation of deductive models flows well into the theoretical issues that scholars hold against the practice of predictive modeling. Lastly, the chapter presents three case studies of predictive modeling being used on small scales in the Piedmont physiographic region of Georgia and one set of models on created across the entirety of the state of Georgia.

Historical Background and Context

This chapter lays out a short cultural history and context of Henry County, Georgia. The chapter begins with a description of the general physiography of the County. This is relevant to the environmental factors that were used to construct the predictive models. The cultural history is laid out sequentially by cultural group. The cultural history focuses specifically on precontact cultures as they are responsible for the sites which the predictive models in this thesis attempt to predict. Each era and cultural group is laid out in order to best understand the how the cultural group would be represented in the archaeological record. Special attention has been paid to the environmental factors that most effected these cultural groups. This helps to give context as to how a model based on environmental factors could be useful in predicting the presence or absence of precontact archaeological sites. Lastly, a short history of silviculture is presented. This is done in order to better understand the effect that the industry has had on the county over the course of centuries.

Data and Methodology

The methodology describes the data sources and how they are manipulated to create the environmental data used to create and test the predictive models. The sources of the four types of environmental data, slope, aspect, soils, and distance to water, are discussed. The source of the previous sites and surveys is also discussed.

The chapter goes on to describes how the model was built from the available environmental data. The methods of testing the predictive models for relative accuracy in order to choose the most accurate predictive model is discussed. The chapter then presents the equations used to produce accuracy scores. Next, the author describes how the same tests were then applied to the two case studies in order to determine if the predictive model was less, more, or as accurate when applied to the two case studies that contain surveys conducted entirely within recently timbered areas. This is done with the understanding that the predictive model performing less accurately within the case studies will indicate that the presence of recent timbering will negatively affect the predictive power of a predictive model. If the model performs as effectively or more effectively within the two study areas, then the presence of recent timbering within an area will not negatively affect the predictive power of a predictive model.

Results

The results chapter begins by graphically presenting the results of manipulating the data described in the Methods Chapter. The chapter then shows how each of the nine predictive models were created by weighting the four sets of

environmental data at different weights. These weights are presented in Table 1. The Chapter goes on to describe how each of the nine models was tested for accuracy and assigned scores. The accuracy scores are presented in Table 2.

Model 9, the most accurate predictive model, is presented graphically in Figure 6. Next, the chapter describes how Predictive Model 9 was applied to each of the two case studies and the accuracy scores produced.

Analysis

Here, the results given in the last chapter are analyzed. The thought process behind building the nine predictive models and the weights given to each environmental factor are described. The scores given to the models are described in greater detail and the real meaning behind each is discussed. The equation developed by the author and used to evaluate the accuracy of each model is analyzed in order to better understand its inputs and the value of its outputs. Once a reasonably accurate predictive model is created using the major environmental variables, it is possible to isolate the variable of recent timbering activity. The end of this chapter analyses the results acquired from isolating this variable and testing it in two case studies.

Conclusion

The final chapter of the thesis distills and discusses the major accomplishments of the thesis. After revisiting the research question, the research process is summarized and considered. Recommendations and courses of action for future work are presented. Then, three major takeaways from the research are

established as foundations on which to build further research and tools to be applied elsewhere.

Chapter 2: Theory of Predictive Modeling

Introduction

Predictive models have become a powerful tool in archaeology throughout the world. While their theoretical basis was developed long before computers, the advent of Geographic Information Systems has propelled them to new levels of usefulness and predictive ability. While finding an early foothold in Cultural Resource Management, predictive modeling has steadily gained traction in the world of academic archaeology as well. The power and potential of predictive models can be seen through its early history, its basic theoretical basis, the issues with and arguments against it, and its practical implementation around the world as well as in the state of Georgia.

A Short History of Predictive Modeling

While predictive modeling has become intrinsically tied to Geographic Information Systems (GIS), basic models mapping probable site locations existed decades before GIS (Kvamme 2005: 4; Branigan 2019: 32-33). Its origins can be traced to Landscape Archaeology and Settlement Archaeology in the 1960s and earlier (Kvamme 2005: 4; Altschul et al. 2016: 196). Through the 1950s and 60s, Gordon Wiley worked to find patterns to the settlement locations chosen by various past cultures. In his 1953 study of the Viru Valley in Peru, Wiley argues that sites are associated with particular environmental factors. He states that social changes and

variations in subsistence strategies can be discovered though the distribution of site locations (Willey 1953; Altschul et al. 2016: 195).

Early predictive models were based largely on the experience of archaeologists and local expertise (Branigan 2019: 31-33; Kvamme 2005). These models often consisted of large polygons labeled with land uses such as valley, grassland, or forest (Kvamme 2005: 8). Simple models based on the common variables of slope, aspect, and distance to water were created by hand computation and represented as a grid of probabilities over a topographic map of an area (Kvamme 2005: 8-10). The exciting possibilities of these early models were realized by the introduction of GIS software in the 1980s. Both Kvamme and Branigan describe their experiences at the forefront of predictive modeling using GIS software. Kvamme describes this as the First Age of Modeling. He recounts entering equations into his TI-59 calculator and mapping probability across large grids (Kvamme 2005: 8-10). He refers to the era beginning with GIS software and continuing into the present as the Second Age of Modeling. This age is characterized by accessible data, GIS software that is increasingly powerful and easy to use, models developed and projected across entire states, a diversity of models within any given region, and models largely being utilized in the world of Cultural Resource Management and Heritage Management (Kvamme 2005: 10-12).

Two Theoretical Methods for Predictive Modeling

At their base, predictive models work under the assumption that settlement location choices made by precontact people were heavily influenced by factors in

their environment. The distribution of sites that can be seen in the archaeological record today is the result of choices made by these people largely based on the world around them (Duncan and Beckman 2000: 33; Dalla Bona 2000: 75). These factors can include factors such as slope, aspect, distance to water, soil type and depth, vegetation, proximity to resources, and a variety of other known data (Kvamme 2005 10-12; Duncan and Beckman 2000: 36; van Dalen 2000: 117; Sebastian and Judge 1988; Ebert and Kobler 1988). These factors can be used as variables in an equation that would calculate the likelihood of discovering archaeological material at a given point in space (Kvamme 2005: 4-5; Altschul et al. 2016: 196-198; van Dalen 2000: 117; Kincaid 1988; Elbert and Kobler 1988). When these probabilities are projected on a map, they create a probability model, a spatial representation of the probability of locating a site across a given area (Kvamme 2005: 14-17; Altschul et al. 2016: 194; van Dalen 2000: 117; Kincaid 1988; Elbert and Kobler 1988; Sebastian and Judge 1988). There are understood to be two methods for creating a predictive model, the inductive method and the deductive method (Kvamme 2005 14-17; Altschul et al. 2016: 196-199).

The Inductive Method

The first method is an inductive method which begins with known archaeological sites. Using these site locations, environmental factors that are common among the sites are extracted and quantified (van Dalen 2000: 117). Duncan and Beckman describe an inductive model in their case study of four areas along river valleys in Pennsylvania and West Virginia. They describe their inductive model as a correlation between known sites locations and background environmental variables.

Multiple layers representing multiple themes are overlayed. They describe how the interplay among these layers can reveal behavioral patterns (Duncan and Beckman 2000: 34-36).

Duncan and Beckman describe the creation of an inductive model in a step-by-step process of twelve steps. The first step involves the collection of primary datasets. This data is easily obtainable and digitized. It can include soil types, elevations, and previous site locations for example. The second step is deriving the secondary data. The secondary data is formed from the primary data. For example, secondary could include slope, which is derived from elevation data. The third step is to sample the environmental variables of site locations. This is where the environmental factors that indicate a favorable location for a site are collected. A random background sample should be sampled in areas that do not have sites as well. The fourth step consists of statistical analysis of the two populations, the two populations being areas with sites and those without. The fifth step is to run a logistical regression (Duncan and Beckman 2000: 34-36).

In Duncan and Beckman's sixth step, the variables that proved to be statistically significant in the location of archaeological sites are identified. These variables will be applied to the model. The seventh step is to create the model's formula. This formula will place the appropriate amount of weight to the more significant variables. This is usually expressed as a separate multiplier applied to each variable. In the eighth step, the formula is applied to each of the 30-meter square parcels. This creates a predictive surface. The ninth step is to test the model against a training sample. The tenth step tests the model against an independent sample. This

independent sample contains data that was not used to create the initial predictive surface. In the eleventh step, the model is reformed based on the results of the two tests. Step twelve has to do with the continual usage of the model and its intention to be ever growing and adapting. The step dictates that the model is continually updated as future archaeological sites are identified (Duncan and Beckman 2000: 34-36). This model represents a very utilitarian, strictly statistical and practical model meant only for the identification of new archaeological sites. However, Duncan and Beckman point out that the relationships between variables discovered by this statistical method could potentially teach archaeologists something about location selection by precontact people (Duncan and Beckman 2000; 33).

Tilton and Comer have leaned heavily into the inductive method of building models by isolating anomalies in vegetative cover. The authors plot known site locations against very high-definition satellite imagery of Santa Catalina Island. The pixels within the satellite imagery that correspond with the known sites are then run through a series of analyses. These analyses attempt to quantify the spectrum of color contained within these individual pixels, indicating variables in existing vegetation. They also work to determine difference in color and value between these pixels and their nearest neighbors (Tilton and Comer 2013: 242-244). The authors proposed to use this data to analyze more satellite images to identify areas with pixels that fall within the discovered value ranges (Tilton and Comer 2013: 244-248).

Archaeologists within the processualist school have historically been very tough on inductive predictive models (Kvamme 2005: 4). Processual archaeologists demand that hypotheses be explanatory of the behavior of past people (Binford 1965:

203-204). Binford described using ethnographic examples to form hypotheses about cultural systems. These systems could then be tested with archaeological data (Binford 1967: 1). For archaeologists of this mind, a statistical methodology to predict the location of archaeological material was not explanatory at all (Kvamme 2005: 12-13). Kvamme actually describes these processual archaeologists and their need for "lawlike behavioral statements" as a hinderance to his early work on models (Kvamme 2005: 4). For the processual archaeologists, inductive models were based purely on correlation. This correlative data had no power for explanation. Kvamme argues that the statistical models are not just correlations though. The very act of selecting variables must be based on experience with archaeological material and theoretical knowledge. Furthermore, good statistical models weight the variables based on importance to site likeliness. The amount of weight added to which variables should be based on theory as well (Kvamme 2005: 12-13). Processual archaeologists far prefer the second method of creating models, the deductive method.

The Deductive Method

The second type of method of modeling is the deductive method. This method bases models on anthropological theory, previous findings, or ethnographic analogies (Kvamme 2005: 14-17). They test general trends in settlement such as are villages forming within a particular culture and how large are the villages? They do not provide probabilistic statements about likely site locations the way inductive models do (Altschul et al. 2016: 196-199; Altschul and Nagle 1988). Kvamme is adamant

that predictive models can be based in deductive methodologies (Kvamme 2005: 12-13; Kvamme 1988). He gives three reasons that archaeologists can pursue predictive models: human behavior follows patterns that are often affected by the natural environment, the archaeological record can be compared to the environment to find the relationships between the two, and GIS allows us to map data that we know (Kvamme 2005: 6; Kvamme 1988).

Theoretical Issues with Predictive Modeling

Branigan argues that models should not just be predictive. They should help to explain why the sites are in their particular locations. At the highest level, they should be used to infer the ideology of the people that lived on and used the landscape in question (Branigan 2019: 33-35). As an example, she offers the occurrence of petroglyphs and rock art. There has been no model that can predict where rock art sites can be found. When using environmental factors that would allow for rock art and petroglyphs to be produced, the results give many locations that have none. For whatever reason, the few places that contain rock art are used for thousands of years. It would be much more useful to understand the cultural ideology behind these locations rather than just the environmental factors (Branigan 2019: 34).

Harrower also discusses the social and cultural dimension issue. Predictive models have often been criticized for not putting enough focus on the agency of people and the cultural factors that play a role in locational decision making. Of course, environmental factors are usually much more easily quantified than cultural factors. Harrower insists that data concerning geospatial analysis cannot be the end all

and be all. It should be a supplement and a part of the greater picture (Harrower 2013: 217).

Altschul et al. also provide discussion on shifting the focus of predictive models from environmental determinism towards agency. The authors term this field as "agent-based modeling" in which the focus is on the human actors as the agents that make decisions like settlement location (Altschul et al. 2016: 197). They credit this concept to landscape theory in archaeology (Altschul et al. 2016: 196-197). This approach leads to the creation of what the authors call "cognitive predictive models" (Altschul et al. 2016: 197). These models represent environmental data as resource patches. This approach allows for agents to make settlement decisions based on resource availability. While these models are innovative, they are hindered by their dependence on the availability of data about the ancient conditions of a particular area (Altschul et al. 2016: 197).

For example, Luke Dalla Bona argues that his predictive model used a deductive based methodology. He describes how the model was tested in three separate stages, starting with small plots and ending with vast swaths of Ontario forest. In his summation, a deductive model must consider the ways humans make choices about location, choose variables that affect these locational decisions, and create a set of predictions that can be compared to archaeological data (Dalla Bona 2000: 75-77). He also stresses the importance of value-weighted variables within a deductive model. This is based on the assumption that each variable contributes in a different way to the choices made about location (Dalla Bona 2000: 76-77; Kvamme 2005: 12-13).

Predictive Modeling in the State of Georgia

There have been a few small-scale attempts at employing predictive modeling in the state of Georgia. Three have been developed in the context of Cultural Resource Management. The subsequent set of models is brand new and was unveiled during the course of writing this thesis. In 1979, Kohler developed a predictive model for use on Fort Benning. The model was built using data collected from the Halloca Creek area. The model included slope, soil type, distance to water, and vegetation as factors. Analysis of survey results of the base determined that slope, distance to water, and soil type were significant variables and were incorporated into the final version of the model (Kohler 1979).

In 2001, Brockington and Associates developed a predictive model for GDOT in preparation for the proposed Northern Arc project along SR 411 north of Atlanta. This model only applied two variables: slope percent and cost distance to water. Both were modeled using logarithmic standardization. The model weighted 25% importance on the variable of slope and 75% importance on cost distance to water (Webb and Bloom 2002; Whitley 2001).

In 2010, Tom Lewis employed a predictive model in the planning of a road project along SR 400 in an archaeologically sensitive area north of Atlanta at the request of the Georgia Department of Transportation (GDOT). The model took into account a relatively small corridor along SR 400. Lewis' model used slope, distance to water, and soil suitability to farming as the environmental variables for the model. The weights given to each environmental variable were adjusted until the predictive

model best fit the data from known archaeological sites in the surrounding area. The model was able to be refined to a 75% accuracy with ten of fifteen known sites falling within high probability areas (Lewis 2010).

In early 2023, the Georgia Department of Community Affairs, Georgia Department of Natural Resources, Georgia Department of Transportation, and the Georgia Archaeological Site File, hosted by University of Georgia, unveiled a new version of Georgia's Natural, Archeological, and Historic Resources GIS (GNAHRGIS). The new version included multiple layers for predictive models of archaeological sites. The layers consist of a heat map indicating the likelihood of an area to contain cultural resources. A separate layer was constructed for each major cultural period.

Post-doctoral researcher Matthew Howland created the models using the methodologies of Lindsey Cochran (Cochran et al. 2022). The models were constructed based on six environmental variables that were weighted subjectively. Each factor was given a score from one to ten based on the likelihood of finding cultural resources from that time period in those conditions. Proximity to freshwater was weighted at 10%, elevation was weighted at 20%, slope was weighted at 20%, soils were weighted at 20%, geology was weighted at 20%, and present-day landcover was weighted at 10%.

The power and potential of predictive modeling are revealed through its early history, theoretical basis, problems, and implementation. Despite much criticism, models have been shown to be very useful in directing the focus of survey time and

resources to locations where they are of most use. These powerful tools have become a major force in modern archaeology around the world.

Chapter 3: Historical Background and Context

Introduction

While the previous chapter discussed the theoretical background necessary to conduct this thesis, this chapter explores the historic and cultural background and context. First, the physiography of the region is discussed. This is in an effort to establish the geographic and geologic features that shape and dominate the Piedmont region as a whole and Henry County, Georgia specifically. The physiography of Henry County is extremely important to the background of this thesis because it encompasses the majority of environmental data that is drawn upon in order to build the predictive model that is instrumental to answering the research question, "do predictive models lose predictive power when applied to a recently timbered area?" Next, the chapter gives a brief precontact cultural history of the county. This is done with special emphasis on the settlement patterns of each culture group and the physical remains they have left in the archaeological record. These two aspects are inextricably tied to how the people of each group interacted with their environment when choosing locations and to the data the left behind that is available to current researchers. Lastly, a brief history of silviculture and the timber industry is discussed in order to explore the effect it has had on Henry County throughout recent history.

Physiography

Henry County is in central northern Georgia just southeast of Atlanta. The physiography is typical of the Georgia Piedmont region, north of the coastal plains

and south of the mountainous North Georgia Ridge and Valley and Blue Ridge regions. Henry county is in the Washington Slope District of the Piedmont region. The district features gently rolling hills and valleys with a general trend of higher elevations in the north towards the mountains and lower elevations to the south as it approaches the coastal plains (Clark and Zisa 1976; Wood and Bowen 1995: 3). Because of these physical attributes, the majority of the County contains less than ten percent slope. This plentitude of relatively flat area likely made slope less of an important factor in choosing locations for precontact groups and individuals. The upland soils tend to be eroded while the hills of the district are dissected by many stream and creek sized drainages. The South River makes up much of the northeastern boundary of the County and the Towaliga River makes up a portion of its southern border. Henry County has no major rivers within its boundaries and the majority of its waters drain eastward toward the Ocmulgee River. These environmental factors heavily influenced where precontact people chose to settle and perform activities that leave an archaeological record.

Paleoindian Period

The earliest reliable evidence of human occupation of the southeastern region of the United States dates to approximately 12,534 BC. Stone tools were discovered along mastodon bones with signs of butchering at the Page-Langdon site in Florida. The people responsible for the butchering are believed to be the earliest colonizers of the American southeast and coexisted with and utilized ice age megafauna for around

2000 years. This is the first Pre-clovis site found in the southeast and the most current start of the Paleoindian Period in the region (Haligan 2016).

The Paleoindian period is understood to begin with the earliest arrival of humans in the region and last until the end of the Pleistocene and beginning of the Holocene around 8000 BC. During the Pleistocene, the climate was notably colder and drier in Georgia. Little is known about these first people due to the lack of archaeological data. It is assumed that they arrived from the West and were highly mobile. It is often theorized that they followed herds of megafauna. They are recognized in the archaeological record by fluted lanceolate style points usually made from very high-quality material. The material is often not local to where it was discovered. Over the course of the Paleo period, projectile points tend to shrink in size. This has been associated with a concentration on smaller game over time. At the end of the Pleistocene, the climate warmed and the massive continental glacier to the north began to melt as the environment approached modern conditions. This led to massive sea level rise as well as widespread extinctions (Anderson et al. 1990).

Archaic Period

The Archaic Period as a whole is generally presented as beginning with the start of the Holocene at approximately 8000 BC and ending in 1000 BC. The Period is traditionally divided into Early, Middle, and Late Archaic Periods. These divisions are largely based on artifact assemblages, settlement patters, and subsistence strategies (Stanyard 2003).

Early Archaic

The Early Archaic Period spans from 8000 BC to 6000 BC. The Period is often seen as transitional. Both the transition of the climate from Pleistocene climatic conditions to more modern ones as well as the transition from a highly mobile paleo lifestyle towards more localized and generalized subsistence strategies are observed during this period (Anderson and Hanson 1988). The Georgia Piedmont was mostly covered in a forest of hardwoods. There were upland stands of pines that are generally less utilized by the Early Archaic people.

Within the hardwood forests of the Piedmont, the Early Archaic people took advantage of increasingly varied types of plants and varied sizes of game (Stanyard 2003: 20, 25). The exploitation of smaller game in comparison to their Paleoindian predecessors is seen in the archaeological record through the abandonment of large lanceolate projectiles for smaller hafted bifacial projectile points. The newer points were notched at the sides or corners for hafting (Stanyard 2003: 20-22).

During the Early Archaic Period, there was an increase in population. This population was largely based around larger drainages and watersheds. Rivers served as a method for travel as well as resource acquisition (Stanyard 2003: 20). The people of this period were still quite mobile and migrated seasonally in order to take advantage of different resources (Stanyard 2003: 26-27). Groups would follow the river drainages to the lowlands and into the warmer coastal plains during the winter and back up into the hills and Piedmont during the summer and warmer times of the year (Anderson and Hanson 1988). Distance to water was an important environmental

factor to the people of the Early Archaic. Because of this, distance to water has proven to have strong predictive power for the location of Early Archaic sites.

The Early Archaic people organized themselves into mobile bands of about 50-150 individuals (Stanyard 2003: 26-27). They would likely remain within a specific river drainage system. Seasonally, these micro-bands would gather at a significant time. This would likely occur during an autumn harvest period of resource abundance. This macro-band gathering would likely consist of 500-1500 individuals. These gathering would likely consist of gift giving and mate exchange between microbands, further strengthening the network of bands (Anderson and Hanson 1988; Stanyard 2003; 26-34).

Middle Archaic

The Middle Archaic Period in Georgia spans from 6000 BC to 3000 BC. At the time, the environment was stabilizing from its transitional warming at the beginning of the Holocene (Stanyard 2003: 35). With this stabilization of the climate, the Middle Archaic people continued to utilize mostly the same resources as the Early Archaic people. White tail deer was the most prevalent animal protein and hardwood nuts made up a large portion of the plant diet (Stanyard 2003: 46-47). The seasonal round movement and micro-band macro-band system continued to be the dominant settlement pattern and community organization. In the archaeological record, a shift towards utilization of more locally available lithic material is evident. This lithic material began to include quartz as well in contrast to the earlier preference for high quality chert (Stanyard 2003: 36).

Late Archaic

The Late Archaic Period spans from 3000 BC to 1000 BC. This period is characterized by an increase in the size and the permanence of habitation sites. This is reflected in the more diverse and extensive archaeological record than seen in previous eras. An increase in social complexity can be seen in the evidence for surplus labor. The appearance of soapstone artifacts and ceramic vessels both indicate a division of labor within groups. The artifact assemblage also reveals an increase in trade and an expansion in the size of trade networks and distance traveled (Stanyard 2003: 51-53).

Woodland Period

The Woodland Period in Georgia began in 1000 BC and lasted until about 900 AD (Stanyard 2003: 51; Wood and Bowen 1995: 8-15). The Woodland Period is similarly divided into the Early, Middle, and Late Woodland Periods. In the Georgia Piedmont, these temporal periods correspond closely to three prominent cultural groups. While there are some gaps and overlaps, the Early Woodland Period corresponds to the Kellog Culture, Middle Woodland corresponds to Cartersville, and the Late Woodland period corresponds to the Swift Creek cultural complex (Wood and Bowen 1995: 8-15). For the sake of usefulness and simplicity, this chapter will look at the Woodland Period in terms of these cultural groups.

Kellog

The Kellog cultural group is prominent in the Georgia Piedmont from around 760 BC to 20 BC (Wood and Bowen 1995: 9). In the archaeological record, this culture is recognized by fabric marked pottery and small triangular projectile points (Wood and Bowen 1995: 8). Settlements tend to occur in two major types: large year-round occupations and smaller seasonal locations. The settlements appear to be located in order to maximize resource potential (Wood and Bowen 1995: 10). At these settlements, archaeologists have discovered large subterranean food storage pits. These pits are evidence of surplus and likely contributed to the ability for year-round habitation sites. Kellog sites contain evidence of a wide variety of plant and animal species utilized and show no evidence of domestication of plant species (Wood and Bowen 1995: 9-10)

Cartersville

The Cartersville culture can be seen in the archaeological record from around 100 BC to 500 AD (Wood and Bowen 1995: 12). The major unique indicators of the culture in the artifact assemblage are seen in ceramics. Checked stamp and simple stamp pottery begin to appear at Cartersville sites in this time period (Wood and Bowen 1995: 13). Cartersville sites often take the form of small sites on terraces overlooking streams (Wood and Bowen 1995:12). Sites such as these have a high potential of being predicted through environmental factors such as elevation, slope, and distance to water. The Cartersville people lived in circular houses that left circular pattern of post holes in the archaeological record. Archaeologists have found

fewer instances of food storage pits which has been linked to the introduction of domesticated plant species. These domesticates include the appearance of maize (Wood and Bowen 1995: 12). The introduction of agriculture indicates a greater ability to predict site locations base on the relative suitability for farming of the soils. Cartersville sites have been found to have ceremonial practices that show influence from Hopwellian culture of the Midwest. Examples include stone and earth mounds that contain burials and exotic artifacts. These ceremonial aspects have been associated with an increase in social stratification (Wood and Bowen 1995: 13).

Swift Creek

The Swift Creek culture is dated to 400 AD to around 900 AD. It is likely that this cultural group spanned from the Middle Woodland into the Late Woodland period. Artifacts from this culture include pottery decorated with complicated stamps. This pottery features paddle stamps carved with geometric elements combined to create complex designs. Archaeologists also note that the lithic tool assemblage seems to be shrink in size and importance in this period (Wood and Bowen 1995: 13-14). Swift Creek settlements appear to be far more concentrated in the broad floodplains of major rivers while upland and tributary areas are more seldom inhabited (Wood and Bowen 1995: 15). These settlements have a high predictability by using environmental factors such as distance to water and slope that constitutes a broad floodplain. Agricultural fields were likely chosen to favor an area with soils that are ideal for farming and a southern aspect to receive more sunlight.

Mississippian Period

The Mississippian Period is also divided into three periods: the Early Mississippian, Middle Mississippian, and the Late Mississippian Periods. The Early Mississippian is dated to approximately 900 AD – 1200 AD and is largely distinguished in the archaeological record by the complex designs used to decorate its ceramics (Hally and Rudolph 1995: 19). The Woodstock culture was prominent in the Georgia Piedmont during the Early Mississippian period. It is often considered transitional between the cultures of the Woodland period and the Mississippian period (Hally and Rudolph 1995: 29). The Etowah culture is known to follow the Woodstock, but it also co-existed with Woodstock. How these two cultures interacted with one another is not well understood. Even more increase in social and political complexity took place during the period. This can be seen in the large ceremonial and political centers emerging across the Piedmont (Hally and Rudolph 1995: 37).

The Middle Mississippian Period dates from 1200 AD to 1350 AD. The most prevalent culture from this time was the Savannah culture. The Savannah complex is similarly recognized in the archaeological record based on their particular ceramic decorations. The culture is known for the Savannah complicated stamp, Etowah complicated stamp, check stamp, and plain pottery. This ceramic assemblage has been demonstrated to have been developed from the Etowah culture (Hally and Rudolph 1995: 51-52).

The Late Mississippian Period dates to about 1350 AD to 1550 AD. The period end with the arrival of DeSoto, the Spanish explorer (Hally and Rudolph 1995: 63). In this period, the Savannah culture transitions into the Lamar culture in the

Georgia Piedmont. The Lamar people practiced maize agriculture along with beans and squash (Hally and Rudolph 1995: 69). White tail deer was still the predominant form of animal protein. Lamar sites include evidence of square domestic structures that were inhabited year-round. The sites also include ceremonial structures such as earthen mounds (Hally and Rudolph 1995: 70).

Planting, Silviculture, and Post-colonization

Early historical accounts report that the native people encountered in the Piedmont, and throughout Georgia, would use fire to strategically shape the long leaf pine forests that covered the state at that time. The fire would leave the massive long leaf pines largely unaffected while clearing the floor of any brush and young growth. The affect was a park-like, open, yet shaded, forest environment that was ideal for hunting deer and other small game. After the burning, young shoots and new growth would attract the game and even provide enough food to grow their populations (Edwards 2004; Kemp 2009).

After European colonization of Georgia, the massive forests of long leaf pine were logged for timber and to make way for agriculture. By the beginning of the nineteenth century, cotton became a valuable cash crop and was planted all across the Georgia Piedmont. Farmers would roll from east to west, planting and harvesting for a few years until the soil was entirely depleted, then move westward. This caused massive amounts of topsoil to be eroded into streams and rivers. It is estimated that an average of 7.5 inches of topsoil was lost from the Piedmont (Clements 1921; Edwards 2004; Kemp 2009).

Cotton farming seriously decreases in 1920 due to the boll weevil outbreak and declining prices and overseas markets. The leftover depleted, acidic, and mostly clay soils in the Piedmont created the perfect environment for the loblolly pine to take over. Silviculture, particularly of the loblolly pine, steadily became one of Georgia's major industries. By the 1960s, Georgia was the nation's leading producer of lumber (Clements 1921; Edwards 2004; Kemp 2009). Currently, Georgia is the location of more timberland than any other state in the US. The industry is worth $36.3 billion and employs over 55,000 Georgia residents (Georgia Forestry Commission 2023).

Conclusion

This chapter explored the physiography, cultural history, and the history of silviculture in Henry County and the Piedmont region in order to better understand the factors that played into site selection for precontact people. With an understanding of the physical setting of the county, the settlement patterns of the people, and the material culture left behind, we can better understand how to predict site locations. This is all done in effort to answer the question, "do predictive models lose predictive power when applied to a recently timbered area?" The next chapter will discuss the methods and data sources used to build a predictive model, test its relative accuracy, and apply the model to two case studies.

Chapter 4: Methods and Data Collection

Research Design

Predictive models can use environmental variables such as slope, aspect, soils, and distance to water in order to give an approximation of which areas would be most attractive to a precontact person. However, the silviculture industry has employed ground disturbing methods of cultivation on a large scale across the American Southeast. The methodology below describes, first, how environmental data was collected and manipulated in order to create predictive models spanning Henry County, Georgia. The methodology then describes how each predictive model was tested for relative accuracy. Lastly, the methodology demonstrates how the most accurate predictive model was used to compare two areas that are known to have been timbered to the data available across the entirety of Henry County, Georgia. This is in effort to answer the question, "do predictive models lose predictive power when applied to a recently timbered area?"

Data Sources

Slope and Aspect

Digital Elevation Models (DEMs) acquired from the United States Geographical Society (USGS) were utilized in order to obtain slope and aspect information. The elevation data was acquired by the Shuttle Radar Topographic Mission (SRTM) carried out aboard the NASA space shuttle Endeavour in 2000. The

mission utilized interferometric C-band Spaceborne Imaging Radar to create 30 m by 30 m resolution topographic data. Some missing areas of data have been interpolated using algorithms and other elevation data sets. Two tiles of elevation data, each one degree by one degree in area, were utilized for this thesis. USGS_1_n34w084, published in 2013, and USGS_1_n34w085, published in 2022, were downloaded from USGS Earth Explorer (USGS 2013; USGS 2022).

The USGS elevation data was manipulated in order to calculate slope over the extent of Henry County. The "Slope" tool within the Spatial Analyst toolset in ArcMap 10 facilitated the calculation. The USGS DEMs were the input raster data sets. The output raster data sets were heat maps representing slope in any given area. The "Reclassify" tool was then used in order to organize the continuous slope data into three categories. The first category contained five percent slope and less. The second category contained slope greater than five percent and less than ten percent. The last category contained slope ten percent and greater. The categories were then assigned a score from one to five to reflect its attractiveness to a precontact individual or group. The category with five percent slope or less was assigned a score of five. The category with greater than five percent and less than ten percent slope was assigned a score of three. The last category, containing slopes of ten percent and greater, was assigned a score of 1.

The USGS elevation data was similarly manipulated in order to calculate aspect of slope. The "Aspect" tool within the Spatial Analyst toolset in ArcMap 10 was used for the calculation. The USGS DEMs were the input raster data sets. The output raster data sets divided the county by aspect using eight general directions:

north, northeast, east, southeast, south, southwest, west, and northwest. The "Reclassify" tool was used to assign every area with a southern aspect a score of five. All southeastern and southwestern aspects were assigned a score of four. All other aspects were assigned a score of one.

Soils

Soil data was downloaded from the United States Department of Agriculture (USDA) Natural Resource Conservation Service (NRCS) as polygon shapefiles. This data was produced by the National Cooperative Soil Survey. The data was converted into raster format with the "Feature to Raster" tool in ArcMap 10. The USDA has classified each soil type as "ideal for farming" or "not ideal for farming" (USDA NRCS 2022). The classification of "ideal for farming" was given to soils by the USDA that would yield crops well before the introduction of modern fertilizer and other agriculture intensification strategies. Each soil type that was considered "ideal for farming," was assigned a score of five. Each soil type that was considered "not ideal for farming," was assigned a score of one. This is meant to give a higher score to areas in which precontact people may have practiced agriculture and left behind cultural material.

Distance to Water

The National Hydrography Dataset (NHD) streamline data was utilized in order to calculate distance to water. The streamline data was collected in the 1990s and upkept since by the United States Environmental Protection Agency. The data was downloaded as line shapefiles from the USGS NHD (USGS NHD 2022). The

line data was then converted to raster data using the “Feature to Raster” tool in ArcMap 10. This raster was used as the input for the “Euclidean Distance” tool within the Spatial Analyst toolset in ArcMap 10. This tool output a raster dataset that gave the distance of each 30 m by 30 m tile to the nearest streamline. This raster file was the reclassified so that every tile fell into three categories: less than 75 m to water, 75-225 m to water, and greater than 225 m to water. Then, based on previous research, the first category was then assigned a score of three, the second was assigned a score of five, and the third was assigned a score of one.

Previous Sites and Surveys

Previous archaeological site and survey data was gathered from Georgia’s Natural, Archeological, Historic Resources Geographic Information Systems (GNAHRGIS). GNAHRGIS catalogs information about archaeological resources in Georgia and makes them accessible through a GIS viewer. It contains archaeological sites that have been recorded in the Georgia Archaeological Site File (GASF) at University of Georgia and has been compiled in collaboration with Gorgia’s State Historic Preservation Division of the Department of Natural Resources (GNAHRGIS 2022).

Previously recorded sites within Henry County were downloaded as polygon shapefiles. Associated site forms were used to determine the cultural affiliation of each site. Only precontact sites were kept. There are currently 315 previously identified precontact sites within Henry County. Polygon shapefiles were downloaded for all previously surveyed areas in Henry County.

Building the Models

The raster data sets containing environmental data described above (slope, aspect, soils, and distance to water) were combined using the "Weighted Overlay" tool within the Spatial Analyst toolset in Arc Map 10. The tool was used to overlay the four input raster data sets over one another. Using the scores assigned to each tile within the input raster data sets, it assigned a new score to each tile of the output raster. A tile with a high score across multiple input raster data sets is given a high score in the output raster data set. This high score in the output raster data set corresponds to the theoretical attractiveness of the area to a precontact individual or group. The weighted overlay tool categorized the output data into three categories, which have been labeled high-probability, medium-probability, and low-probability.

The weighted overlay tool also allows for the placement of variable weights of importance on each of the four input raster datasets. By varying the amount of importance placed on each raster, multiple predictive model maps were produced.

Testing the Models

In order to test which predictive model was most successful at predicting the location of archaeological sites, previously identified sites were used as positive data. Previously survey area that did not contain a site was used as negative data. If a previously identified site fell within or intersected an area categorized as high-probability, this was considered a positive hit. A positive hit accuracy was determined by dividing the number of positive hits by the total number of sites.

Positive Hit Accuracy = Positive Hits / Number of sites

The area of previous survey that is occupied by a site was subtracted from the total area covered by previous survey. The remaining area was then considered negative for archaeological material. The negative cultural area was systematically covered by a grid of points at 100 m by 100 m intervals. There were 5,258 points in total. If one of these points was contained within a low-probability or a medium-probability area, it was considered a negative hit. A negative hit accuracy was calculated by dividing the number of negative hits by the total number of negative data points.

Negative Hit Accuracy = Negative Hits / Number of Negative Data Points

The total accuracy of the model was decided by adding the number of positive hits to the number of negative hits to calculate the number of total hits. The number of total hits was then divided by the total number of data points (number of sites + number of negative data points).

Total Test Accuracy = (Positive Hits + Negative Hits) / (number of sites + number of negative data points)

or

Total Test Accuracy = (Positive Hits + Negative Hits) / (315 + 5,258)

Case Studies

Two previous surveys were chosen as case studies due to the fact that the authors of both survey reports explicitly state that the area had been recently logged previous to the survey. Both surveys were conducted using current Georgia Guideline standards**.** The *Phase I Cultural Resources Survey Proposed Indian Creek Water Reclamation Facility and Holding Pond Henry County Georgia* was conducted in 2009 across 450 acres (181 hectares) (Finney et al. 2009). The *Phase I Cultural Resource Survey and Phase II Testing of Sites 9HY453 and 9HY454 Proposed Walnut Creek Water Reclamation Facility and Holding Pond Henry County, Georgia* in 2008 across 581 acres (235 hectares) (Webb 2008). The most accurate predictive models were tested for accuracy in the same method as given above but bounded by the area of the two surveys. The differences in accuracy between the model with the bounds of the survey areas and the accuracy of the model across the entire county were assessed for statistical significance.

Chapter 5: Results

Introduction

The process of timbering during silviculture is known to have ground disturbing effects. However, it is unclear what effects these ground disturbing activities have on cultural resources. Are the effects so great that the traditional environmental variables used to deduce the location of a precontact site are no longer useful? This thesis intends to answer the question, "do predictive models lose predictive power when applied to a recently timbered area?" In order to answer this question, nine predictive models were built across the extent of Henry County, Georgia. Below, the results of creating these models and testing them for accuracy are given. After the most accurate model was chosen, it was applied to two case studies. The results of these case studies are displayed at the end of this chapter.

Results of Building the Predictive Models

Five sets of data were considered when building the predictive models. The five data sets, slope, aspect, distance to water, soil suitability for farming, and previous sites and surveys, are presented in the maps below.

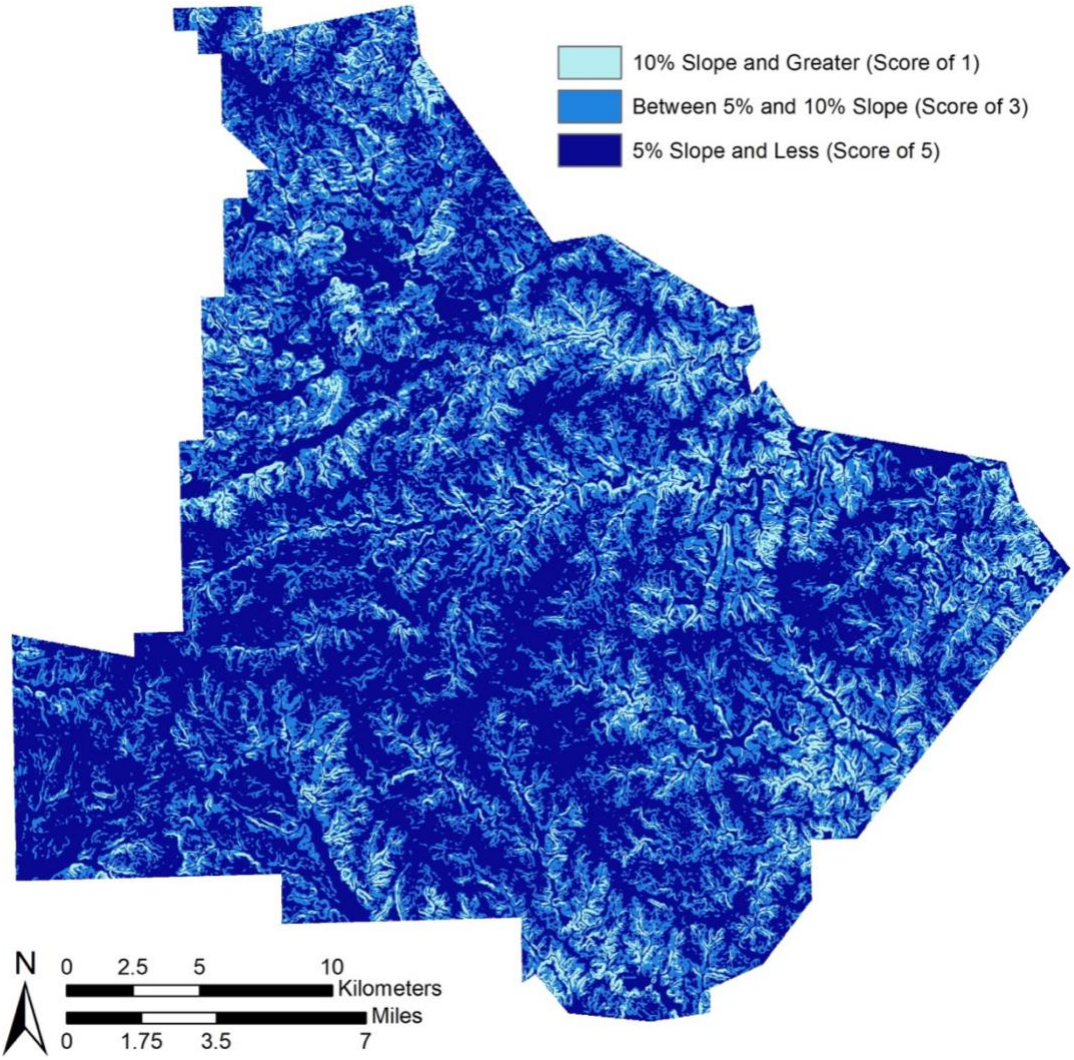

Figure 1. Henry County Slope Map. Created by the author.

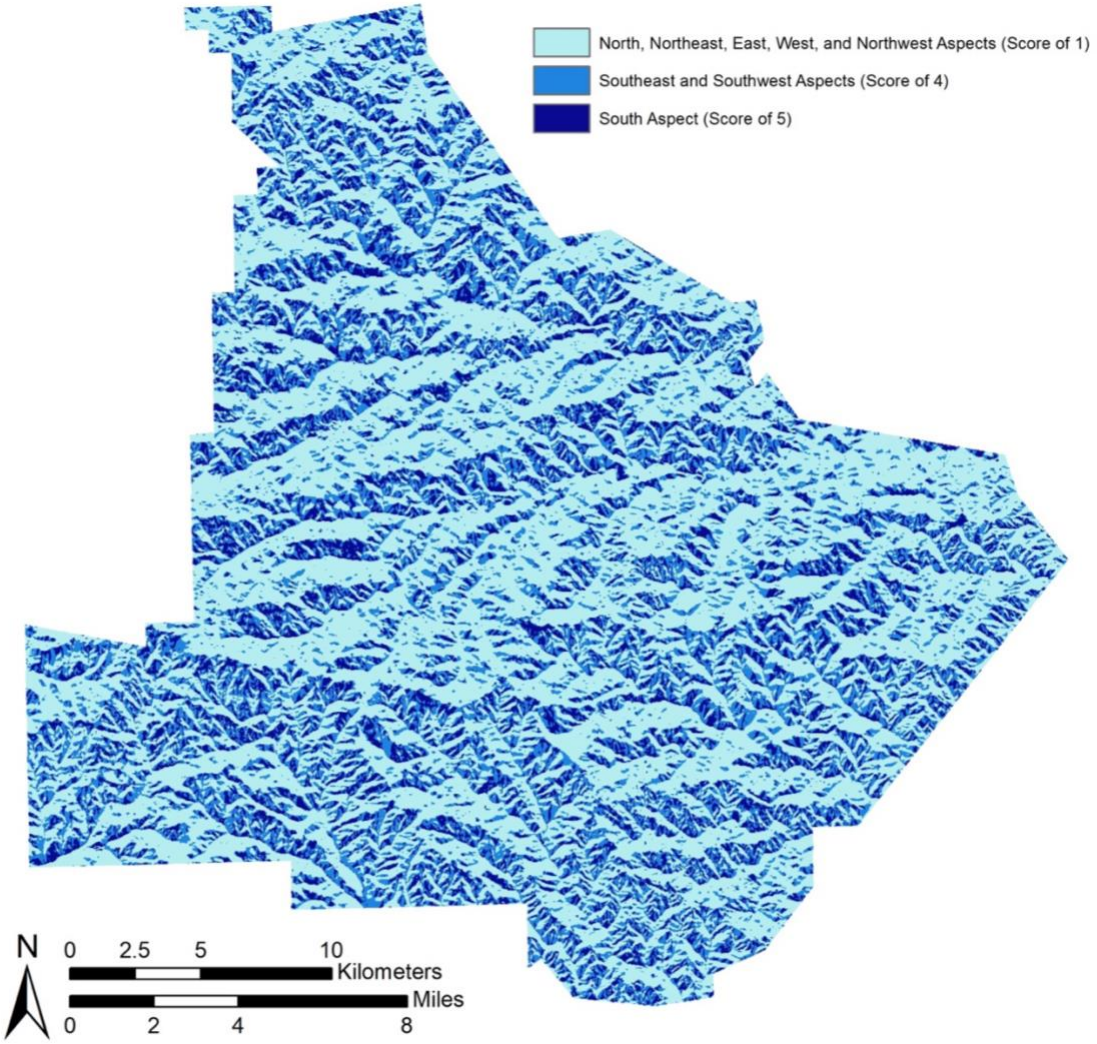

Figure 2. Henry County Aspect Map. Created by the author.

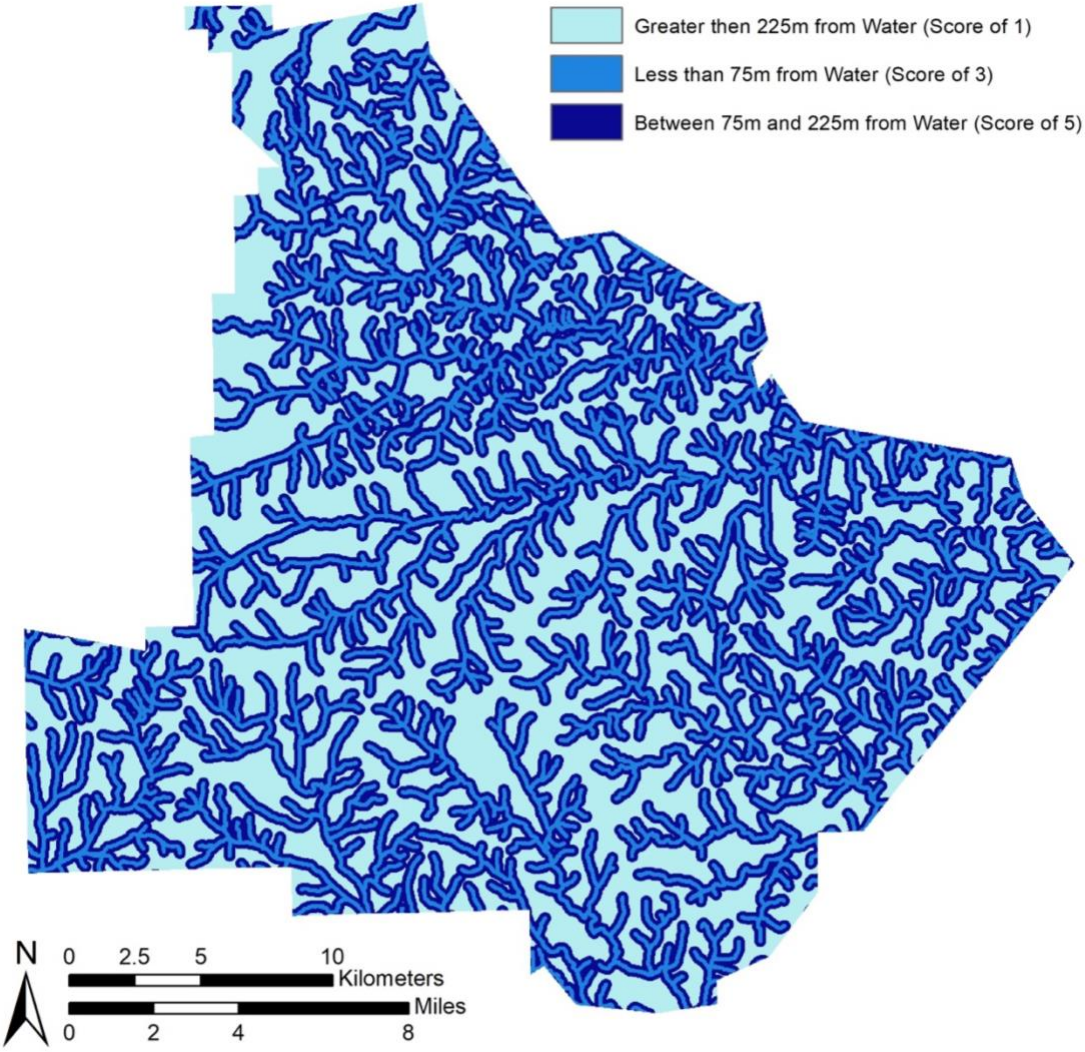

Figure 3. Henry County Distance to Water Map. Created by the author.

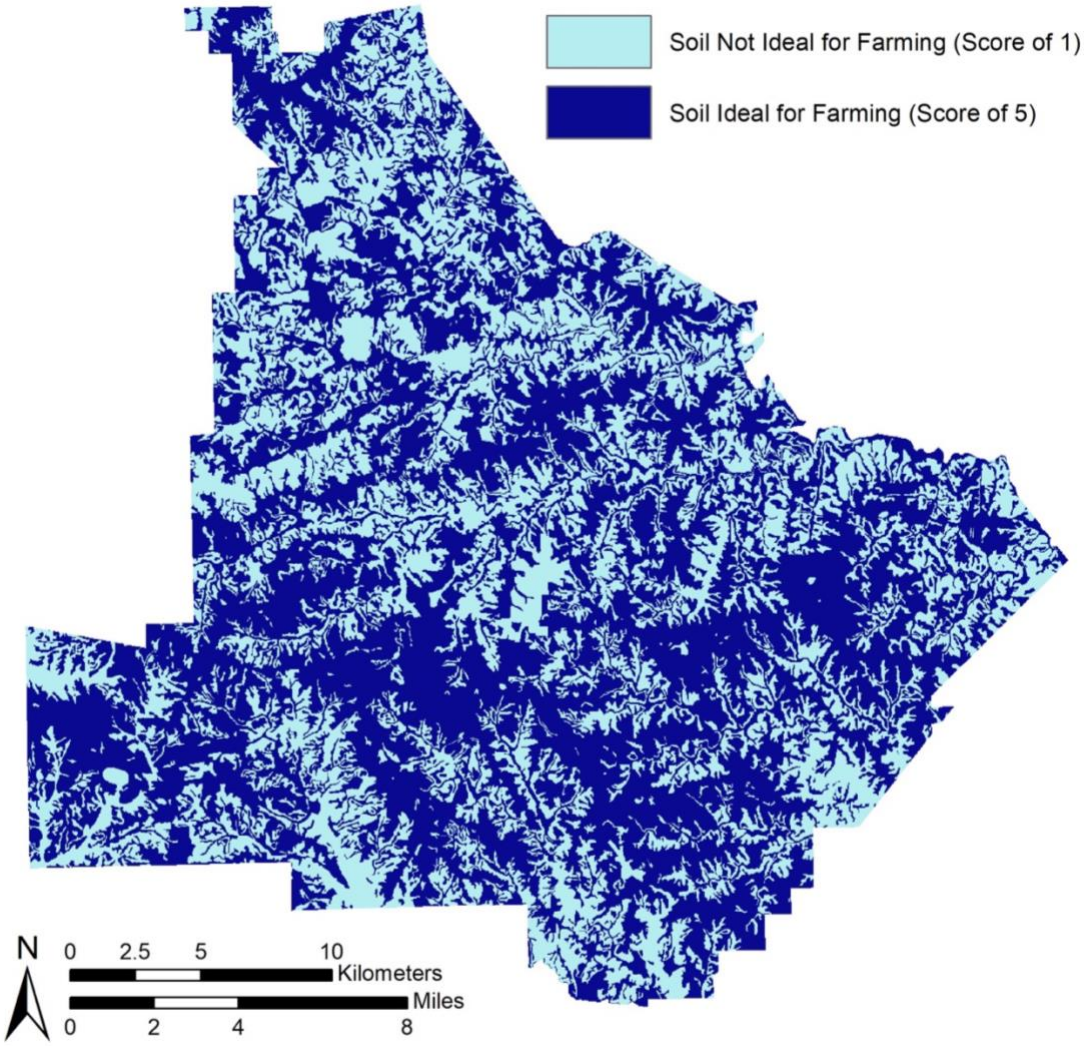

Figure 4. Henry County Soil Suitability for Farming Map. Created by the author.

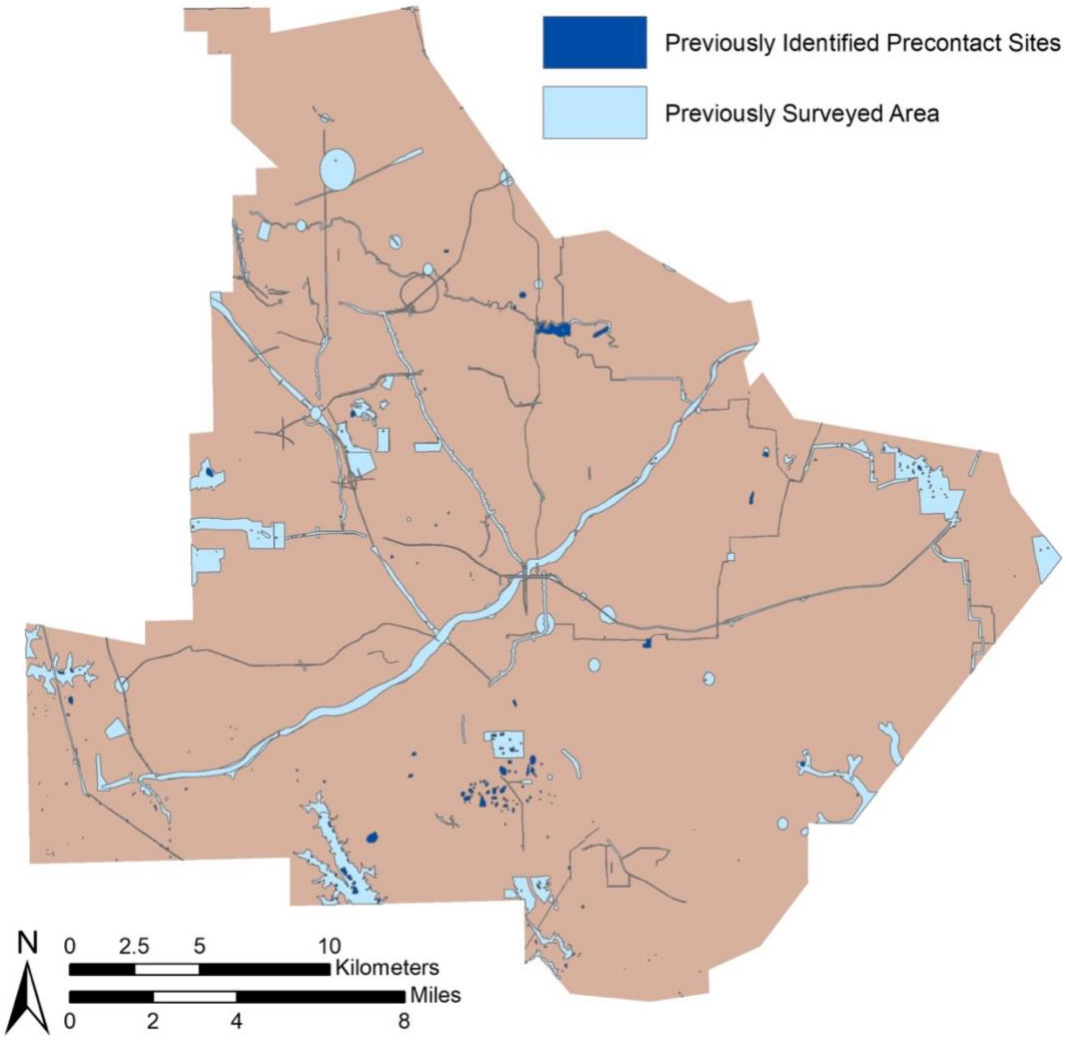

Figure 5. Henry County Previous Sites and Surveys Map. Created by the author.

Results of Testing the Predictive Models

Data from four of the five datasets, slope, aspect, distance to water, and soil suitability for farming, were combined using the Weighted Overlay tool in ArcMap 10. The weighted overlay tool allowed for a weight to be applied to each environmental factor dataset. The table below shows the weight applied to each environmental variable for each predictive model created. Each model divided the County into areas based on three categories. These three categories were named based

on their likelihood to contain precontact archaeological sites. They were given the names “high-probability area,” “medium-probability area,“ and “low-probability area.”

Table 1. Weight given to each environmental variable in order to create each model.

Predictive Model Name	Percent Weight Applied to Slope	Percent Weight Applied to Aspect	Percent Weight Applied to Distance to Water	Percent Weight Applied to Soil Suitability for Farming
Model 1	25%	25%	25%	25%
Model 2	20%	20%	40%	20%
Model 3	20%	20%	20%	40%
Model 4	20%	40%	20%	20%
Model 5	40%	20%	20%	20%
Model 6	11%	11%	67%	11%
Model 7	40%	10%	40%	10%
Model 8	10%	10%	40%	40%
Model 9	10%	30%	50%	10%

Each of these models was tested using the existing data available through previously identified archaeological sites and previously surveyed areas. Previous sites were used as positive data. If a previously identified site intersected with a “high-probability area,” then it was considered a positive hit. A positive hit accuracy was determined by dividing the number of positive hits by the total number of sites. There were 315 total previously identified sites. The table below shows the number of positive hits and the positive hit accuracy of each model.

Any area of previous surveys that was occupied by a site was subtracted from the total area covered by previous surveys. The remaining area was then considered negative for archaeological material. The negative cultural area was systematically covered by a grid of points at 100 m by 100 m intervals. There were 5,258 points in total. If one of these points was contained within a low-probability or a medium-

probability area, it was considered a negative hit. A negative hit accuracy was calculated by dividing the number of negative hits by the total number of negative data points. The table below shows the number of negative hits and the negative hit accuracy of each model.

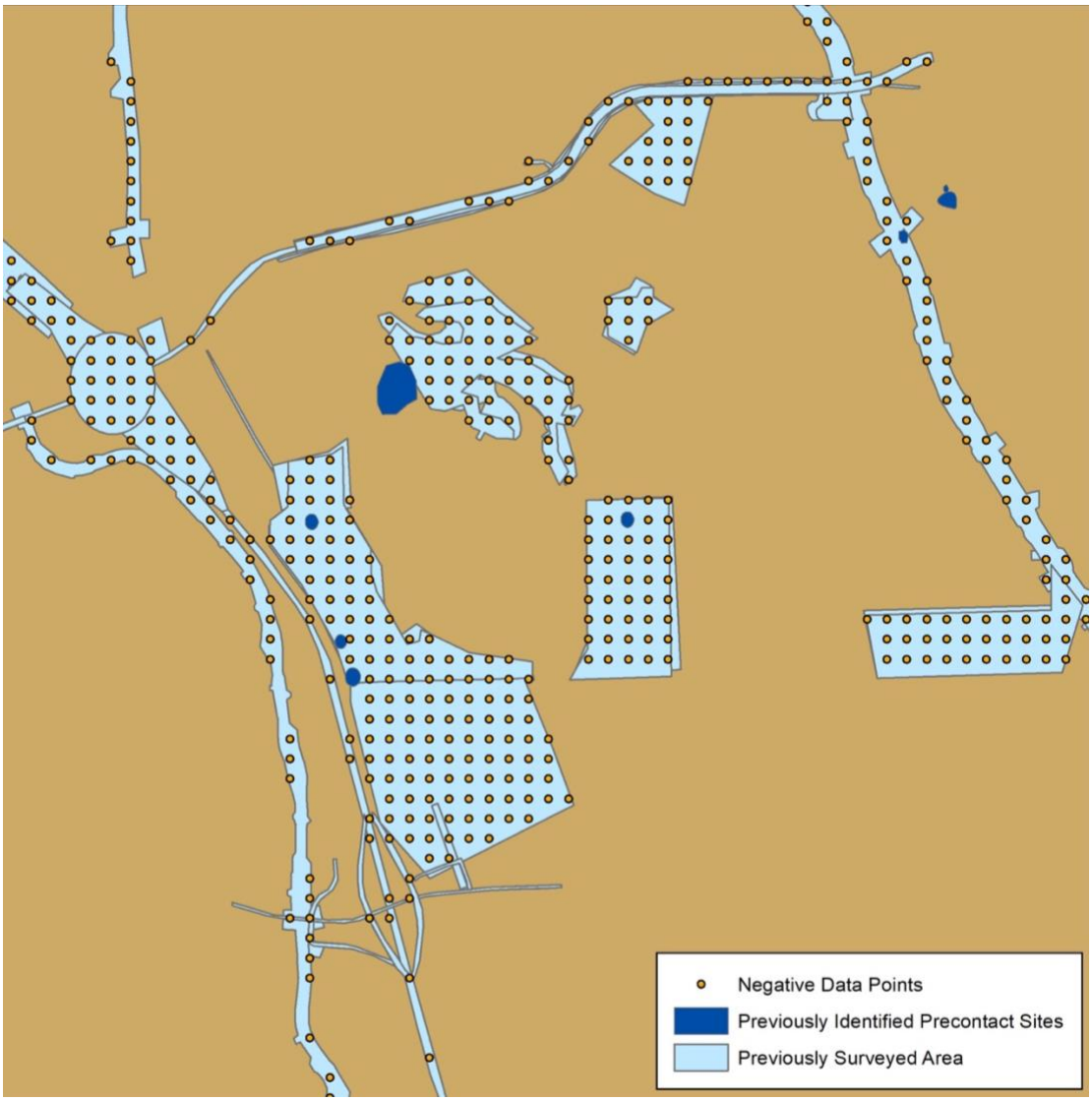

Figure 6. Detail of negative data points constructed on 100m x 100m grid across previously surveyed area. Created by author.

The overall accuracy of the model was decided by adding the number of positive hits to the number of negative hits to calculate the number of total hits. The number of total hits was then divided by the total number of data points. The total number of data points was determined by adding the total number of sites to the total number of negative data points. The table below shows the overall accuracy of each model.

Table 2. Accuracy scores given to each model according to the accuracy equations.

Predictive Model Name	**Number of Positive Hits**	**Positive Hit Accuracy**	**Number of Negative Hits**	**Negative Hit Accuracy**	**Overall Accuracy**
Model 1	196	.6222	3833	.7290	.72295
Model 2	164	.5206	4332	.8239	.80675
Model 3	170	.5397	4006	.7619	.74933
Model 4	173	.5492	4114	.7824	.76925
Model 5	182	.5778	3911	.7438	.73443
Model 6	207	.6571	3826	.7277	.72367
Model 7	181	.5746	4084	.7767	.76530
Model 8	156	.4952	4313	.8202	.80190
Model 9	168	.5333	4388	.8345	.81751

Predictive Model 9 was shown to be the most accurate model and to have the most predictive power. For this reason, it was selected to be used in the testing of the two case studies. An image of Predictive Model 9 is shown below.

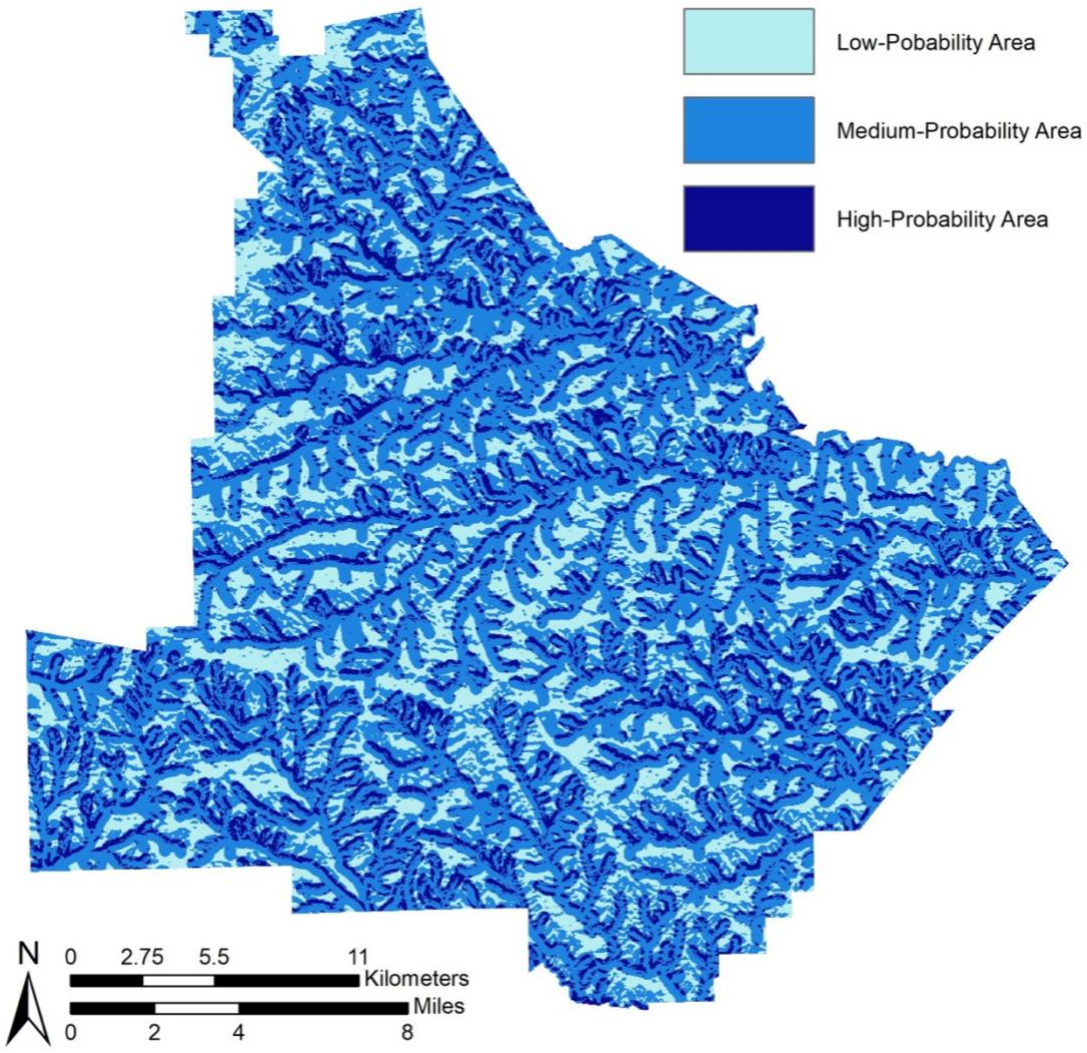

Figure 7. Predictive Model 9. Created by the author.

Results of Testing the Two Case Studies

Case Study 1

Predictive Model 9 was used to test two case studies. Both case studies consist of surveys completed to modern standards contained within area that had been recently logged. The first case study consists of survey number AR 5560, the *Phase I Cultural Resources Survey Proposed Indian Creek Water Reclamation Facility and*

Holding Pond Henry County Georgia (Finney et al. 2009). The survey identified seven new precontact sites. When Predictive Model 9 was applied to the area covered by the survey, six of the seven sites intersected with high-probability areas. This was considered six positive hits out of seven total sites.

The area of the survey not containing sites was systematically covered by a grid of points at 100 m by 100 m intervals. These were considered negative data points. There were 138 total negative data points. 117 of these negative data points fell within medium-probability and low-probability areas. This is considered 117 negative hits out of 138 total negative data points.

The positive hits were added to the negative hits for a total of 123. The total number of sites was then added to the total number of negative data points for a total of 145. The total number of hits (123) was then divided by the total number of data points (145) for an overall accuracy of 0.84828.

Case Study 2

The second case study consists of survey number AR 5808, the *Phase I Cultural Resource Survey and Phase II Testing of Sites 9HY453 and 9HY454 Proposed Walnut Creek Water Reclamation Facility and Holding Pond Henry County, Georgia* (Webb 2008). The survey identified 26 new precontact sites. When Predictive Model 2 was applied to the area covered by the survey, 8 of the 26 sites intersected with high-probability areas. This was considered 8 positive hits out of 26 total sites.

The area of the survey not containing sites was systematically covered by a grid of points at 100 m by 100 m intervals. These were considered negative data points. There were 376 total negative data points. 344 of these negative data points fell within medium-probability and low-probability areas. This is considered 344 negative hits out of 376 total negative data points.

The positive hits were added to the negative hits for a total of 352. The total number of sites was then added to the total number of negative data points for a total of 402. The total number of hits (352) was then divided by the total number of data points (402) for an overall accuracy of 0.87562.

Conclusion

This chapter gives the results of the methods carried out in the previous chapter. First, graphic representations of the data acquired for slope, aspect, soil suitability for farming, and distance to water are displayed in Figures one though four. Each data set has been separated into discreet categories. Each category has been given a score from one to five based on the attractiveness to precontact people. Next, the previously identified precontact sites and the previously survey areas of Henry County are shown in Figure five. The nine predictive models are listed in Table one along with the weights given to each environmental variable in order to create them. Below, the accuracy scores returned from testing each predictive model are displayed in Table two. Figure six shows the Predictive Model nine, the most powerful predictive model. The results of applying Predictive Model nine to the two case studies are given below. These results will be analyzed in the next chapter.

Chapter 6: Analysis

Introduction

This chapter analyses the results given in the last chapter. It describes the thought process behind building the nine predictive models and the weights given to each environmental factor. The scores given to the models are described in greater detail and the real meaning behind each is discussed. The equation used to evaluate the accuracy of each model is analyzed in order to better understand its inputs and the value of its outputs. This is all done in effort to create a predictive model that is reasonably accurate across the extent of Henry County, Georgia. After this is achieved, it is possible to isolate the variable of recent timbering activity. The end of this chapter analyses the results acquired from applying this predictive model to two case studies which were recently timbered previous to their survey for cultural materials. In this way, the chapter intends to answer the question, "do predictive models lose predictive power when applied to a recently timbered area?"

Predictive Model Tests

Data from four of the five datasets, slope, aspect, distance to water, and soil suitability for farming, were combined using the Weighted Overlay tool in ArcMap 10. The weighted overlay tool allowed for a weight to be applied to each

environmental factor dataset. Each time the weighted overlay tool was used to combine the four sets of environmental data, a new predictive model was the result. Each predictive model was then tested for accuracy using the previously identified precontact archaeological sites and previous surveys within Henry County.

Table 3: Weights applied to environmental factors for each predictive model

Predictive Model Name	**Percent Weight Applied to Slope**	**Percent Weight Applied to Aspect**	**Percent Weight Applied to Distance to Water**	**Percent Weight Applied to Soil Suitability for Farming**
Model 1	25%	25%	25%	25%
Model 2	20%	20%	40%	20%
Model 3	20%	20%	20%	40%
Model 4	20%	40%	20%	20%
Model 5	40%	20%	20%	20%
Model 6	11%	11%	67%	11%
Model 7	40%	10%	40%	10%
Model 8	10%	10%	40%	40%
Model 9	10%	30%	50%	10%

The first model applied an equal weight to each of the four environmental factors. This provided a baseline to work from. It resulted in an accuracy of 0.72295. The next four predictive models were created by applying more weight to one of the four factors. This was meant to isolate any one factor that may influence the predictive accuracy of a model. When looking at Models 2 through 5, the clear standout is Model 2. This model placed the most weight on the "Distance to water" environmental factor and received an accuracy score of 0.80675. This indicates that distance to water has the greatest effect on the predictive power of a model. The next most accurate model of Model 2 through 5 is Model 4. This model weights aspect the

heaviest of the four environmental factors. This indicates that aspect has the second most influence on the predictive power of a model.

Model 6 was an attempt to place even more weight on the distance to water factor. However, after placing 67% weight on distance to water and 11% weight on the other three factors, the accuracy fell to about the same as the baseline established by Model 1. This indicates that the distance to water factor must be combined with the other environmental factors in order to elevate its predictive power.

Models 7 through 9 combine a heavy weight on distance to water with a heavy weight on one of the other three environmental factors. This is in an effort to find which environmental factor combines with distance to water best to create the model with the highest accuracy. Of Models 7 through 9, Model 9 scores the highest in accuracy. Model 9 combines a high weight on distance to water with a high weight on aspect. This follows the logic that combining the two factors with the most influence on the accuracy of a model would create the most accurate model overall. As the most accurate model, Model 9 was used to test the two case studies.

Table 4: Results of testing Predictive Models

Predictive Model Name	**Number of Positive Hits**	**Positive Hit Accuracy**	**Number of Negative Hits**	**Negative Hit Accuracy**	**Overall Accuracy**
Model 1	196	.6222	3833	.7290	.72295
Model 2	164	.5206	4332	.8239	.80675
Model 3	170	.5397	4006	.7619	.74933
Model 4	173	.5492	4114	.7824	.76925
Model 5	182	.5778	3911	.7438	.73443
Model 6	207	.6571	3826	.7277	.72367
Model 7	181	.5746	4084	.7767	.76530
Model 8	156	.4952	4313	.8202	.80190
Model 9	168	.5333	4388	.8345	.81751

Accuracy Equation Analysis

Total Test Accuracy = (Positive Hits + Negative Hits) / (number of sites + number of negative data points)

or

Total Test Accuracy = (Positive Hits + Negative Hits) / (315 + 5,258)

Due to the nature of archaeological data and CRM surveys, there is far more negative data than positive data for site locations. This can be seen in the nature of the equation used for accuracy. There are far more negative data points than positive data points. This, in effect, selects for models that are highly accurate at predicting where sites are not as opposed to predicting where sites are.

There is a temptation to transform the data in such a way that the positive hit accuracy of the model is as important, or even more important, than the negative hit accuracy. However, this would be a disservice to the data. Understanding the environmental factors that make a location unattractive to the theoretical precontact person is as important as understanding what makes a location attractive. Knowing where sites are not is as important as knowing where sites are. For these reasons, the data was not artificially weighted towards positive data.

Case Study Tests

Now that a predictive model has been constructed and shown to be reasonably accurate across Henry County, it can be applied to areas that have been documented as recently timbered previous to their survey for cultural resources. If Predictive Model 9 performs less accurately than when applied across the entire county, then this is evidence that recent timbering activities have had a negative effect on the predictive power of Predictive Model 9. If Predictive Model 9 performs as accurately or more accurately than when applied across the entire county, then this is evidence that recent timbering activities have not had a negative effect on the predictive power of Predictive Model 9.

Table 5: Case Study Results

	AR 5560 (Case 1)	**AR 5808 (Case 2)**
Positive Hits	6	8
Negative Hits	117	344
Positive Accuracy	.85714	.30769
Negative Accuracy	.84783	.91489
Overall Accuracy	.84828	.87562

In Case Study 1, Model 9 received an accuracy score of 0.84828. In Case Study 2, Model 9 received an accuracy score of 0.87562. This is in comparison to Model 9 applied to the entirety of Henry County, which received an accuracy score of 0.81751. In both case studies, Predictive Model 9 was shown to have a significantly

higher accuracy than the score given to the model when considering the entire county. This indicates that the existence of recent timbering activity does not negatively affect the predictive power of a predictive model.

Conclusion

This chapter discussed the results given in the previous chapter. It described the thought process behind building the nine predictive models and the weights given to each environmental factor, the scores given to the models, and the equation used to evaluate the accuracy of each model. The chapter discussed the meaning of the results given by the two case studies. The next chapter will discuss the significance of these findings and conclusions that can be drawn from them.

Chapter 7: Conclusion

Introduction

Predictive modeling has largely been relegated to the world of academia. This is likely due to the amount of processing power, specialized programs, and time required to create and utilize them. As computers have become more powerful, predictive modeling has become faster and cheaper. This has made it more available to the Cultural Resource Management industry which is heavily confined by thin budgetary margins. CRM firms are often limited to equipment and technology that is absolutely necessary and justifiable from a business perspective. Currently, predictive models can be created using ESRI's ArcMap or a similar competing program. This is a program that almost every CRM firm has at least one subscription to and uses on a daily basis. This shift has seen CRM firms applying predictive modeling for various purposes on a contract basis. This thesis describes a methodology developed using the Spatial Analyst extension of ESRI's ArcMap. This methodology also utilizes environmental data that is free of cost and readily available from public sources. With the application of a systematic approach, predictive models can be produced and tested at an expedited rate and minimized cost. In this way, predictive models can be used as a regular step in the background research that takes place before each survey. This thesis demonstrates a replicable method for producing and testing predictive models using four environmental variables.

While the previous chapter discussed and analyzed the results returned by the methods of this thesis, this chapter will discuss the impact and relevance of this thesis. First the research question is revisited and answered. Next, the research process and methodology is summarized in review. Recommendations for how the subject should progress in the future as well as some recommended adjustments to the methodology are suggested after this. Then, to conclude the chapter, the three useful aspects that resulted from this thesis are discussed.

Research Question

Silviculture and the timbering process is widespread across the southeastern United States. It is known to have ground disturbing effects. However, the extent of the disturbance created is not entirely understood. The preceding thesis was carried out in effort to better understand silviculture's effects on precontact archaeological sites in the Piedmont region of the state of Georgia. The thesis asked the question, "does the presence of recent timbering activities negatively affect the predictive power of predictive models in regard to precontact archaeological sites?" The answer to this question, based on the methods of this thesis, was clear. The presence of recent timbering activities does not negatively affect the predictive power of a predictive model.

The Research Process

In order to answer the research question, first a large-scale predictive model needed to be constructed that could be shown to be reasonably accurate. Henry County, Georgia was chosen for the extent of the predictive model for ease of access to environmental as well as archaeological data. Nine predictive models were constructed across the county by placing different relative importance on each of the four environmental variables used: slope, aspect, soil suitability for farming, and distance to water. Next, a way of testing relative accuracy of the nine models was needed. A system of deciding positive as well as negative hits was devised. From there, positive and negative hits could be compared to the total available data points in order to derive a relative accuracy score. These scores were used to determine the most accurate of the predictive models.

With a reasonably accurate predictive model for the entirety of Henry County, a baseline was established. This baseline could now be compared to areas in which recent timbering activities were reported prior to their survey for cultural material. This was done with the understanding that if the predictive model performed less accurately within the case studies, that indicates that the presence of recent timbering does have a negative effect on the predictive power of a predictive model. If the predictive model performed more accurately or as accurately within the case studies, that indicates that the presence of recent timbering does not have a negative effect on the predictive power of a predictive model.

In this way, the thesis developed a methodology for determining the relative predictive power of a single variable within a predictive model. A variable can be isolated by finding an area in which the variable is present. This area will be used as a case study. The predictive model can then be applied to the case study. Using the accuracy equation developed by this thesis, the experimenter can determine the relative accuracy performance of the predictive model within the case study. Comparing the accuracy scores received by the case study to the accuracy scores received by the initial predictive model can provide insights to the predictive power of the particular variable. A significantly lower accuracy score can indicate that the variable has a negative effect on the likelihood of discovering a site. A significantly higher score can indicate the opposite.

Future Work and Methodological Changes

Predictive models are meant to be fluid and growing tools. They are meant to be trained on data as more data becomes available. The predictive models built for this thesis are no different. They have been trained with a limited set of data. The accuracy of each model was tested with the location of only 315 known precontact sites and the available survey data in Henry County, Georgia as of 2023. This data is constantly being added to by Cultural Resource Managers. As more surveys take place, new predictive models should be trained using the new data.

Beyond the limited amount of survey data, this thesis is very limited in its location. Henry County is an arbitrary boundary chosen in order to limit the scope of this thesis into a manageable amount of data. While the scale of an entire county is much larger than any previous predictive modeling effort attempted in Georgia, there

is nothing stopping this methodology from being applied across the entire state or the entire Southeast region of the United States. In a region so affected by the silviculture industry, it would be interesting to experiment with timbering activity as a variable in predictive models across different regions of the Southeast.

Another direction that future research may expand is to delve into the other processes involved in silviculture. The timbering process is only one aspect of silviculture. It was used in this thesis largely for the availability of the data. Recent timbering activities are easily visible. Any well written survey report will describe the obvious effects of recent timbering when describing the land use and environmental conditions. This made locating case studies for surveys that had taken place in recently timbered areas relatively easy to find. Information about how many times this land had been timbered and replanted over the last hundred years, however, is far more difficult to find. Further studies including more of this historical silvicultural data could be very enlightening.

One major flaw in the methodology that was revealed upon reflection was the lack of separation of the case study data from the training data. The testing of each of the nine predictive models can be considered the "training phase" of the methodology. In this phase, the data from previous sites and surveys was used to determine which model was most accurate. Both case studies were included in the previous surveys used for this testing and all of the associated sites were included as positive data points. It is possible that these data points affected the results obtained when testing the case studies in isolation. It is possible that the accuracy scores received by the case studies were artificially inflated by this oversight. Best practices

would dictate that the data points associated with the case studies were simply removed from the initial testing of the predictive models. It is recommended that this practice is included in the methodology for future research.

Another improvement in the methodology that could improve future research is the way positive hits and misses were counted. For this thesis, a positive hit was counted as any previous site intersecting with a high-probability area. For negative area, a 100m by 100m grid of points was constructed to represent negative data points. Constructing a 100m by 100m grid across all of the previous site areas in the same way, would more accurately reflect the amount of positive area in a way that is more proportional to the amount of negative area. However, this method was not considered for this thesis because many of the sites were too small to be hit by the 100m by 100m grid. The smaller sites were essentially invisible using this method. The way to combat this would be to create a tighter grid consisting of more points. A grid of 30m by 30m or even 15m by 15m would be a natural scale to work with since this is how the areas are surveyed with a grid of shovel tests. Again, this solution was not available for this thesis due to the sheer size of the shapefile created making it unusable with the processing power available. This method should be considered when working at smaller scales than an entire county or when high levels of computational power are available.

Major Takeaways

There are three useful outcomes of this thesis. The answer to the research question, the predictive models themselves, and the accuracy equation can all find uses by future researchers.

The Research Question

In an attempt to answer the question "does the presence of recent timbering activities negatively affect the predictive power of predictive models in regard to precontact archaeological sites?" the thesis applied a predictive model that was proven to be effective across Henry County to two case study areas. Each case study had been reported to contain recent logging activity throughout prior to survey. When applied to these case studies, the predictive model performed better than it did across the entire county. This should indicate to Cultural Resource Managers that areas of recent logging activity should not be discounted when applying predictive models. They still contain the possibility for the productive use of predictive models. This information could prevent a lapse in judgement during the budgeting phase that would lead to a time or money crunch caused by expected discoveries. A recently timbered area should not be seen as hopelessly disturbed and without the potential for aligning with predictions for the locations of precontact archaeological material. However, it should be noted that while sites may remain sufficiently intact enough to be discovered during Cultural Resource survey, the sites are still disturbed by the timbering activity. Artifacts that are churned and dispersed can still be recovered through shovel testing or surface collection. Features are more likely to be irreparably

damaged though. While the timbering process does not appear to affect the predictive power of a predictive model, it still likely has a negative effect on the integrity of a site.

The Predictive Models

Predictive Model 9, presented in the Results and Analysis chapters of this thesis, is useful in its own right. The model is applicable to anyone conducting desktop research before a survey in Henry County, Georgia. It could also prove useful in planning efforts when attempting to chose an option that is less likely to disturb precontact cultural resources.

The methodology used in the creation of all nine predictive models is easily replicable. It allows for application across other counties or even much smaller areas. Predictive models, in general, can be powerful tools when applied to scoping for CRM projects. Predictive models could be used to assist Cultural Resource Managers in ensuring that a closer approximation of the proper resources are allotted for each project. This would help to alleviate future budgetary strains caused by unexpected discoveries of precontact archaeological sites.

In this particular model, the environmental factor of "distance to water" proved to have the most predictive power. A location having a southern facing aspect was the next most powerful variable. While this may be particular to Henry County, Georgia, it is likely that this pattern holds true to the entire Piedmont physiographic region of the United States. This could be a valuable insight into the lifeways and decision making of the Precontact people of the Southeastern United States.

The Accuracy Equation

This is an original equation devised by the author that provides a replicable index number representing the accuracy in determining positive and negative site locations. While it is only a simple augmentation of a percentage equation, it provides a systematic method of judging the relative accuracy of a predictive model using previously acquired survey data. This simple tool can be applied in order to quickly and efficiently rate predictive models and the relative predictive power of their components.

Conclusion

All archaeologists have dreamed of peering below the surface of the ground to see what is hidden by the soil and earth. Every anthropologist has wished for the ability to see into another person's mind to understand their world view. The practice of predictive modeling brings us, ever so slightly, closer to both unreachable ideals. Through computer assisted recognition of patterns, researchers can better anticipate what lies beneath the surface in regard to cultural material. And, with these patterns, archaeologists can better understand the minds of the people responsible for these sites and the way they saw the world around them. While not a replacement for testing and excavation, predictive models can be immensely practical tools for archaeologists in the Cultural Resource Management industry. Furthermore, in a region that has been heavily affected by the silviculture industry such as the American Southeast, Cultural Resource Managers might be wary of whether

predictive models can still be applicable. This thesis concludes that predictive models retain their predictive power even within recently timbered area. Even when these cultivated forests have been ravaged beyond recognition, predictive models can peer into the past and see something closer to the physical environment that precontact people experienced.

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