2.0 ARCHEOLOGICAL SENSITIVITY

Archaeological site predictive modeling first appears in the literature in the 1970's consequent the theories of the Ecological and Economical schools of the preceding decades (Kohler 1988). In the 1980's computerized models based on earlier methodologies were developed and applied, especially in the Cultural Resource Management (CRM) context (Wescott 2000). The CRM industry in the United States has embraced computerized (GIS) modeling for many reasons. Least of which is the promise of saving time and manpower by having a computer first predict where sites may be before a survey crew ever enters the field. Despite numerous models having been successfully implemented in the process of managing cultural resources (referenced below), a debate continues centered on modeling methodology. The methodology of archaeological locational modeling is divided into two main areas: Deductive/explanatory and Inductive/correlative approaches.

Deductive approaches "begin with some theory predicting human behavior in a systematic context (Kohler 1988)" to produce a working output. This theoretical approach to modeling starts with a hypothesis and then works down to an analytical model through explanation. It is the element of explanation that makes the deductive model very attractive. Being able to use computers to build theoretically informed models that can explain the human influence behind archaeological observations is a high reaching goal of archaeological modeling. Though, this lofty goal is rarely achieved, particularly in the cost consciences CRM industry. Sebastian and Judge (1988:8) sum up Explanatory (Deductive) Models with one sentence, "explanatory models are *extremely* difficult to create and validate (emphasis is original)." These models are difficult to create based on the lack of available fine grain data and difficult to validate because of their theoretical underpinning. If created though, a deductive model would be highly beneficial to archaeological research. Advancements are being forged in the research and application of complex explanatory models, but few have yet proven applicable in a management context.

Inductive modeling builds from the correlation of survey data to some feature (usually environmental) on the landscape and then uses the pattern of the correlation to estimate the spatial distribution of archaeological resources. Therefore, sites are hypothesized to be found in environments similar to those where sites have been found in the past. This process can be done with complex computerized statistical operations and dozens or variables or a simple map, calculator, and two variables; the underlying methods are the same. Termed as correlative models (Sebastian and Judge 1988), empirical models (Kohler 1988), inferential models (Kohler 1988), pattern-recognition point specific models (Altschul 1988), inductive models all build from the data up and generally do not contain appreciable explanatory power. Analytic inductive models, which most are, make hypothesis about the connection of site locations to environmental features, but cannot explain *why* the connection is. This is because the environmental data used to correlate is either modern or imperfectly sampled and extrapolated from paleoenvironmental data. Secondly, the survey data that inductive models rely on are rarely composed of a homogenous and unbiased sample. Modelers simply cannot control for all the variables in the model. On the other hand, systematic inductive models do offer some explanatory power. This is through the rigorous use of paleoenvironmental or ethnographically derived variables applied to high resolution environmental/cultural data and, perhaps more importantly, the consideration of depositional and post-depositional environments to help explain why we find sites where we do. Gathering the data necessary for such models is time consuming, but ultimately beneficial to management and research. In the future, with more research and application, these models could bridge the gap between method and theory. All in all, inductive/correlative models are the most frequently used models in CRM. This is due to their relatively low cost/time, more standardized empirical methodology, relative understandability, and better application to large area resource management as compared to current deductive models.

A review of models that have been applied in CRM contexts similar to US 113 North/South Study Area or to environments similar to Sussex County and Kent County, Delaware turned up a host of inductive/correlative models (Bona 2000; Custer and Melin 1989; Duncan and Beckman 1989, 2000; Heaton, Smith, and Klein, 2003; Westcott and Kuiper, 2000; Warren and Asch 2000). With varying degrees of analytical and systematic sophistication, each model was based on the same general methods and assumptions. These models were studied and appropriate methods and techniques were drawn to derive the approach use in the US 113 North/South Study Area model. In the end, an inductive/correlative model framework was chosen for US 113 North/South Study Area. Due to the time and data available, and the need for a large area model that could assist planners in knowing where potential prehistoric cultural resources are more likely to be found in relation to where they are less likely to be found, this methodology was deemed the most appropriate. As stated by Kincaid (1988; 556), "inductive, correlative models usually have the statistical precision needed to develop quantitative estimates of site populations, densities, and distributions and are currently the better source of such estimates [compared to deductive/explanatory]."

Deviating from the models referenced above, please note that the term "Predictive Model" has been intentionally sidestepped in this discussion thus far. The implication of a "Prediction" is inherently explanatory. A true prediction will tell of what is going to happen in the future by means of special knowledge. The special knowledge is taken as an understanding of the inner workings of the event/system being predicted, such as the reoccurrence of the full moon through knowledge of planetary rotation. In this case, a correlation between sites and streams (or any other environmental feature) does not suffice as special knowledge or knowledge of the inner workings of a settlement system. For this reason, this model is referred to as an archaeological sensitivity model; more specifically/technically an archaeologically sensitive landform model. Because this model defines the correlations between environmental variables and previously recorded archaeological sites, it is the combination of environmental variables (aka landform) that is deemed as being sensitive for archaeological material. References throughout this text to the US 113 North/South Study Area model as a predictive, inductive, or any other type of model refer to the same methodology described above.

Lastly, counter to some of the models previously referenced, this text does not make a statement of assumptions regarding environmental dependence (*not* environmental determinism). Many texts referenced for this project (Warren and Asch 2000; Duncan and Beckman 2000; and Bona 2000) explicitly state that their model is based on two primary assumptions. First is that prehistoric habitation sites were chosen non-randomly. And second, that the prehistoric inhabitants were dependent upon and restricted by their local environment. The former assumption is applicable to all archaeological models, but the latter assumption is not needed here. As stated earlier, the correlations derived from the study area are between recorded prehistoric sites and *modern* environmental features. There are no assumptions in this model that the correlations found are in any way directly linked to prehistoric habitation decisions. In reality, many of the correlations may be linked in some way, but the scores of inconsistencies and biases in the environmental and site location data make it hazardous to state such a claim. When environmental variables are rigorously derived with ethnographic data then the environmental dependence assumption may be warranted. As many models stand, loosely incorporating ethnographic environmental variables or intuitive variables with modern environmental variables simply muddies-up the explanatory waters and creates more room for cross-correlations and collinearity. The US 113 North/South Study Area model is based on the two basic assumptions first stated by Kvamme (1988). Writing about pattern-recognition locational models (such as the US 113 North/South Study Area model), Kvamme (1988:327) states, "…archaeological…models must work if two assumptions can be met. The first assumption requires that the locational patterns exhibited by the initial site (or site-type) sample used to 'train' the pattern classifier (the quantitative model) are reasonably representative of the site population under study. The second assumption is that the site locations are non-randomly distributed with respect to the environmental or social factors under investigation." Kvamme's second assumption, a non-random distribution, is the same as the assumptions stated by other authors, but Kvamme's first assumption is the one that has been interpreted to infer that the environmental variables used in the model must be linked to the environmental variables that conditioned prehistoric habitation. As discussed later in this text, that is untrue. The correlation between *modern* environmental factors and the recorded sites is just that, a correlation without causation. Site locations are correlated to modern environmental features which may or may not be linked to prehistoric environmental conditions; the correlation is relative to the environment that it is found in. Removing the assumption that that modern/prehistoric environmental link must be present frees the model from the pitfall of environmental fluctuation over time. Although this eliminates the very tentative explanatory power of a model that assumes a past/present environmental connection, it revels that this model does not attempt to seek behavioral explanations through measurements of environmental features (one of the main arguments against correlative models.) As stated by Gaffney and van Leusen (1995:379), "statistics can be used to describe patterning in archaeological datasets in a rigorous manner without reference to the cause(s) of those patterns, and if the extrapolation of those patterns yields predictions that are useful in CRM … the method is validated." Given the bias and inaccuracy inherent in archeological survey and the environmental data available, this model is purely inductive/correlative and, as restated from above, the "quantitative estimates of site populations, densities, and distributions are very useful in a land-use/planning capacity (Kincaid 1988:556)." From this general landscape inductive/correlative model, research and/or deductively oriented models can use new field data and test the environmental correlations and patterns to determine what they represent and derive archaeological causes and meaning. It is only through many layers of clearly applied models, with minimal assumptions, that archaeological explanation can begin.

2.1 PREHISTORIC SENSITIVITY

2.1.1 METHODS

Prehistoric Site Data

There are 140 Cultural Resource Survey (CRS) point locations for prehistoric sites used in this model. These point locations are derived from the CRS database that contains all of the US 113 CRS points that were recorded, as of July 2003, in this study area. The 140 prehistoric sites were extracted from the larger CRS database based on the presence of a prehistoric temporal component listed in the "PERIOD" column. Each point location represented the centroid of the site boundary for all 140 prehistoric sites, as they are recorded (hand drawn) on the Delaware State Historic Preservation Office's (SHPO) State Planning Office (SPO) maps (1962 aerial photo mosaics notated by DelDOT in 1964).

During previous work for The Department, JMA transferred the location of the prehistoric site points from the SPO maps to a laptop computer by visually comparing the location on the 1964 map to an on-screen 2002 aerial photograph in the ESRI ArcGIS Geographic Information System (GIS) software. The locations of the transferred prehistoric site points were then recreated using the "Create Centroid" in the "X-tools" add-on for ArcGIS. This method creates a point at the true geometric center of the digitized site boundary, where site boundary information was available. Where site boundaries are unknown, a hypothetical site boundary is drawn around each point at a 30m diameter. The centroid of the prehistoric site CRS point is used as a location to gather environmental variable measures for each site, whereas the entire site within its boundary is used in the testing of the model's performance.

Also, a set of non-sites is used in the construction and analysis of this model. Given that the few previous large cultural resource surveys undertaken within the US 113 North/South Study Area revealed little about the location of non-sites and given that there is contradictory evidence regarding the number of sites found during these surveys, non-site data is best assumed to be equivalent to a random distribution. To create the non-site coverage, 1400 points were randomly placed across the study area using a randomizing script for ArcGIS. This number of random points was used because it is ten times the number of recorded sites and is considered a sufficient sample for this sensitivity model.

Primary Environmental Data Layers

The environmental data used in the creation of this model was gathered from on-line, academic, and governmental sources. The data layers used as primary environmental sources are elevation, rivers, wetlands, and soils. These primary environmental sources have varying error rates and accuracies. In general, these are very reliable data. Actions were taken to mitigate any errors or inaccuracies that were correctable. Beyond the inaccuracy of data collection methods, a second source of error should be discussed, that is the environmental fluctuation.

An unavoidable source of error in this model is the fact that modern environmental data is used to predict for the sensitivity of sites in past environments. Paleoenvironmental studies have shown that the prehistoric environments greatly fluctuated throughout time (Kellogg and Custer 1994). This notion leads to the possibility that using modern environmental data would lead to inaccurate predictions of prehistoric site locations. This line of thought certainly has a strong basis, but is not entirely true for this type of modeling. To better understand this, two different types of environmental fluctuation are discussed: punctuated and continuous.

First, in punctuated change, environmental features can be gained or lost over time. Meaning that during very wet cycles, streams may exist in areas where streams are absent during dry cycles. Like wise, the same goes for marshes, lakes, and biotic communities. Second, continuous change in the environment causes features to shift or change size. An example of shifting continuous change is a soil gradually changing drainage characteristics or an ecological community shift. An example of resizing is the rise and fall of sea level or the contraction of swamp. It is true that both punctuated and continuous changes have modified the environment throughout time, but based on this type of model, the differences in the modern environmental data are not detrimental.

As noted above, continuous change results in environmental features shifting attribute measures and changing in size and shape. If it can be assumed that the shifts and resizes are taking place uniformly across the landscape, then changes will not greatly affect the results of this model. For example, if a change in sea level causes the level the Mispillion Creek to fluctuate, it will not affect the model as long as it is a uniform change across the basin. This is because the model measures the distance from a site to the location of the Mispillion Creek as it is today, not as is was in, for example, 2000 BC. A series of sites that were 20 meters from the water in 2000 BC may be 50m from the water today. It is the area 50m from the Mispillion Creek that the model is predicting as sensitive. The pattern is the same, meaning that the sites are at a fixed point on the landscape and the water level changes relative to those points. An example of a continuous shift in an environmental feature is soil properties. In this study area, there is a high correlation between prehistoric sites and the Evesboro soil association. It is true that in 2000 BC the characteristics of what we call the Evesboro may have been different, but holding the assumption of uniformity in environmental changes, the ancestral soil to Evesboro at one location is probably very similar to what evolved into Evesboro in another location. Therefore, the change in soil properties is again relative and the location of the site is fixed. Continuous and uniform change will not greatly affect the results of this model due to its location specific pattern recognizing nature. The same can not be as confidently stated for punctuated change.

Punctuated change, as stated earlier, refers to the presence and absence of environmental feature such as streams, lakes, or glades. If a small series of 4000 year old sites are located on the banks of a stream that has since disappeared, they will appear as having high distances to water when measured for this model. This will affect the results and effectiveness of the model unless the sites strongly correlate to another environmental feature or if the sample size of sites is large enough to create a significant impact. Neither of these conditions can be assumed for in this modeling technique. Given that up to 10 environmental variables are used in each physiographic setting, the chances that site locations correlate to multiple variables is high. This would lessen the impact of disappearing features. Though, it is not likely in this study area that a site sample would be large enough to make a significant impact in the model. In this case, the sites may be predicted for less effectively than if the stream was present today. Conversely, if a stream was artificially constructed in modern times, some prehistoric sites may erroneously correlate strongly to it even though it was not present in 2000 BC. In this case, the modern stream will be included in the predictive models patterning, which is not entirely bad, but may compete against environmental features which were the true attraction for prehistoric inhabitants. In this case, the model may be “confused” as to what is the true attractor, leading to a specification or generalization of the sensitive areas. Punctuated environmental change can lead to variations in the models effectiveness, which may attach sensitivity to non-sensitive areas or brand sites as “outliers” when truly they are not. Based on the test results of this model, presented later, it does not appear that too many sites are missed or that too much area is included as sensitive. These results diminish the probability that environmental change played a large role in this models error rate. The following are the primary environmental data layers.

- *DIGITAL ELVATION MODEL* - The Digital Elevation Model (DEM) data used in the creation of the prehistoric sensitivity models was calculated from 916,649 SPOT satellite derived elevations points. Using 2003 aerial photographs and Digital Raster Graphics (DRGs) the study area is examined and were applicable, the elevation points on or around obvious modern landscape alterations are removed (e.g. landfill, quarry). The Kriging method of interpolation is used to turn the elevation points into a continuous elevation surface.

- *STREAMS* - The coverage of streams used for both sensitivity models was modified from the original on-line version to achieve a more accurate representation of the prehistoric drainage network. Due to a long history of agriculture, drainage modification, and irrigation, the stream network of the study area has been seriously altered. Using historic USGS topographic quadrangles, aerial photos, and a topographically derived hydrologic model, the modern stream network was edited and modern irrigation ditches and ponds were removed, unless they were noticeably modifications of a natural water course.

- *WETLANDS* - The locations of wetlands in the study area proved to be an important aspect in regards to environmental variables. The GIS coverage used for the wetland locations is from the Statewide Wetlands Mapping Project (SWMP). This data layer was used in an unaltered form for this sensitivity model. It was later discovered that this data layer includes natural as well as manmade wetlands. The wetlands of an unnatural origin are designated in the data table by an “x” following the wetland type. Upon further examination it was established that the inclusion of the manmade wetlands in the sensitivity model did not significantly affect the outcome of the modeling process. The manmade wetlands were generally placed in close proximity to natural wetlands or at least in river floodplains where natural wetlands are in close proximity.

- *SOILS* - The final primary data layer used in this sensitivity model was soil associations. Two soils layers were used in this model due to the time of availability and the completeness of the coverage. At the beginning of this project the only available soils data was gathered from the Soil Survey Geographic Database (SSURGO) website of the United States Department of Agriculture’s (USDA) Natural Resources Conservation Service (NRCS). Updating the SSURGO coverage is an ongoing process. The data received form this site only cover the Southern half of the study area. The attributes included with the spatial data are very in-depth and quite useful, but only for a portion of the study area. Given that this was the only data available, layers of soil association and soil drainage capacity were created for the Southern half of the study area. At a later data, a digital coverage of soils for the entire study area was obtained through the Delaware Department of Agriculture (DDA). The DDA does not contain any of the in-depth soil association specific attributes as did the SSURGO data. When the two layers are compared, soil association outlines and boundaries often do not match and different soil association naming conventions are used. Although the DDA data had far fewer attributes than the SSURGO data, it was eventually used as the primary soils layer because of the full study area coverage. Although, the soil drainage capacity data layer from the SSURGO data was retained in this model, for physiographic settings seven and eight, because of its high significance in discriminating sites and non-sites.

Secondary Environmental Data Layers

Soils, elevation (DEM), streams, and wetlands are the primary data layers from which more analytical environmental data layers were derived. Termed “Secondary Data Layers,” these layers act to find more precise environmental relationships between man and the land, as well as, distinguish the relationships between interacting environmental variables. Secondary variables were created as an attribute of a primary data source or the interaction of two or more primary or secondary variables (Figure 2). Following are the environmental variables names, followed by a description:

- ELEV – (Elevation) This layer represents the surface elevation in meters above mean sea level (MAMSL) for the entire study area. ELEV represents the most basic attribute of a

DEM. As stated above, the DEM is created through the method of Ordinary Kriging. The resulting data layer was then "filled", meaning small depressions or "sinks" are locally averaged out. The filled coverage is used as the elevation data from which the ELEV measurements are taken. Further, this layer was used as the basis to derive the variables of SLOPE and ASPECT.

- SLOPE – (Slope) Calculated as percent slope, this variable is derived directly from the DEM using the ArcGIS Spatial Analyst extension.

Figure 2. Example of how different environmental layers are combined to create a composite layer of predicted sensitivity.

- ASPECT – (Aspect) Also derived from the DEM using the Spatial Analyst extension, ASPECT is the calculated angle of a landform in relation to the compass. This variable had implications of sun angle and solar insolation. This variable was ultimately NOT used in the modeling process because it was found to be statistically insignificant in every watershed and physiographic setting.
- WATER – (Distance to water) The distance to water is calculated as a Euclidian distance, using ArcGIS's Spatial Analyst, to the closest stream. The stream in this case is mapped from the modified stream coverage mentioned above.
- WTLND – (Distance to a wetland) As with the variable WATER, WTLND is a Euclidian distance calculation to the nearest wetland polygon using the unmodified SWMP wetlands data.
- ELEVRNG – (Elevation range) The range in elevation is a measure of local relief. The range for which the maximum and minimum elevation measurement is taken is a 60m diameter buffer around the center point of each mapped prehistoric site. The MAX and MIN measurements are recorded using Spatial Analyst's Zonal Statistics function.
- RIVCOST2 – (Cost distance surface to River_2) Time and effort are both considered "Costs" associated with traveling across a landscape. In this case, the slope of the land is perceived as barrier, increasing the costs of travel. RIVCOST2 is a cost distance surface

that is a calculation, using Spatial Analysts Cost Distance function, of the cumulative costs of traveling from any point to the nearest stream. The paths that travel over very steep slopes have a higher cost than paths that travel over relatively flat ground. Even if the flat path is longer in distance than the steep path, it is considered more desirable because it has a lower cost of travel.

- RIVCOST3 – (Coast distance surface to River_3) Using the same theory as the variable described above, RIVCOST4 is a calculation of the travel cost to water where wetlands are the barrier. It is assumed that walking across a wetland is less desirable than walking across well drained ground to reach a stream. This variable does not consider the valuable resources that are located within a wetland or any other beneficial aspects of the wetland. This variable only considers the elevated effort necessary to walk or carry across poorly drained ground versus well drained ground.
- TEXTURE – (Terrain texture) Adopted from Kvamme (1988:333), terrain texture is a measure of local elevation variance. To calculate texture, Spatial Analyst's Neighborhood Statistics function was used to obtain the variance of elevation measurements in a 3 X 3 cell neighborhood. Given that each cell 30m X 30m, a total of 8100 sq meters of surface area are represented by 9 elevation points located at the center of each cell in the neighborhood. According to Kvamme (1988; 333), "High values suggest variable and dissected terrain, while low values indicate a level, smooth surface."
- DRAINAGE – (Soil drainage capacity) As discussed earlier, the first soil layer used in this model had numerous attributes attached to each soil association, but only covered half of the study area. On of the attributes in the soil database is "Drainage." This measurement ranges from 1 to 6 and can be interpreted as "Excessively Drained" to "Very Poorly Drained" respectively.
- SOILWGHT – (Soils weighted for preference) The SOILWGHT layer is a statistically derived overlay of the soil association polygons that encodes the preference for prehistoric sites to be found, hence established, within each association. The method for developing the weights of each soil association compares the percentage of sites that fall into each association versus the percentage of non-sites (random points) for that association. Basically, higher results are produced when there are more sites within a given area of a particular soil association than chance would allow. The differences in percentage are run through a probability function, returning a value between 0 and 1. Finally, these values are truncated to three significant digits and applied to the GIS soils coverage and mapped.

Statistical Methodology: Univariate

Upon creating the secondary environmental variables, univariate statistics were used to show the significance of each variable. A significant variable is one that can be used to split prehistoric sites into a separate class from non-sites based on the measures of that environmental variable. If a variable is deemed insignificant, it cannot be used to differentiate prehistoric sites as a subset. Meaning that, an insignificant environmental variable does not distinguish a prehistoric site from the environmental background. This is not to say that an insignificant variable is not important to prehistoric decisions concerning habitation locations. Because of the collinearity of nature, the complex interactions of environmental systems, simple statistics can not prove that a particular environmental variable is unimportant to habitation locations. The purpose of this test is to distinguish which of the variables appears to be the most significant within a given environment, in this case each physiographic setting. Ranking the statistical relevance of each variable is important for deciding which variables to enter in to the regression equation and interpreting the regression results. The significance test was run for each variable in each physiographic setting. This was done because a separate model was constructed for each setting based on the particular environmental character of that setting.

For this model, the Mann-Whitney U Test (aka Wilcoxon Test), the Kolmogorov-Sminopov two sample test, and the t-Test for two independent sample was conducted on each variable for each physiographic setting (Figure 3). All of these tests compute the difference in sample means. Concluding whether the diversion from the mean is significant enough to call the sample set a statically distinct set. Multiple tests were used to account for the assumptions made by each statistical measure. The results from each test were very consistent; discrepancies were analyzed. For the final ranking, the T Test for two independent sample statistics was used. The significance of the results is based on a two-tail test at (p = 0.05).

Example of T-test output:

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0.451185	8.666519598
Variance	3.533853915	1250.66226
Observations	60	398
Hypothesized Mean Difference	0	
df	411	
t Stat	-4.591604148	
P(T<=t) one-tail	2.92753E-06	
t Critical one-tail	1.648568286	
P(T<=t) two-tail	5.85506E-06	
t Critical two-tail	1.965754564	

Figure 3. Example of a t-Test.

The interrelations and interactions of environmental variables can be worked into the modeling process to produce a more accurate model with fewer competing, therefore diluting, environmental variables. Co-linearity is a term used, in this context, to describe the complex interactions that different environmental variables have with one another (Rose and Altschul 1988; 215). Co-linearity of environmental variables in the linear modeling process can lead to variables appearing more important that they truly are in the location of prehistoric sites and other variables appearing not significant at all when truly they are significant. In this model, the negative effects of collinearity are lessened by gaining an understanding in the relationships shared by environmental variables, sites, and non-sites (environmental background).

Statistical Methodology: Bivariate

To further understand and utilize the relationships shared between environmental variables, simple bivariate statistics were used. This process includes the variables ELEV, SLOPE, and WATER compared with both sites and non-sites. These three variables were compared in all permutations using cross-correlation. This technique produces a scatter plot where the axis are the variables being compared, the data points are sites and non-sites. A best fit line and the R^2 value is calculated for the sites and non-sites scatter plots. Trend lines indicate the relationship of sites/non-sites to the variables in comparison by showing site/non-site discrimination where the lines do not follow the same pattern. Analyzing the relationship of the scatter clouds, the trend lines, and using the R^2 value as an indicator of confidence, conclusions are drawn about environmental/site relationships, as well as, site/non-site relationships. These conclusions are factored into the modeling process as possible explanations for environmental/site trends and in the inclusion and exclusion of variables in the regression process.

Statistical Methodology: Multivariate

The core procedure for this modeling process is the application of a "Least Squares Multilinear Fit" to the site, non-site, and environmental data. In short, this type of linear regression finds the best fitting correlation between sites and the environment. This method takes into consideration the environmental background and seeks out the most important environmental variables in distinguishing site locations from non-site location. Before the regression, a table was made for each physiographic setting where the first column is coded as '1' for each site and '0' for each non-site. Further, this table contains ten columns that encoded the environmental variable measure for each site and non-site. Using a program named Data Plot from the National Institute for Statistics and Technology, the prepared table was input, using the "READ" command, and the regression was accomplished by a writing a small script which contains the "FIT" command. The parameters for this command include the "Y" or dependant variable (site presence or absence) and the "X" or independent variables, in this case, the environmental variables. The output from this command contains the standard deviation and T-scores for each environmental variable, the residuals standard deviation for the model, and the regression coefficient for each environmental variable. The regression coefficients, or parameter estimates, is the number derived from the regression equation that allows for the "prediction" of the study area. The regression coefficients are numbers that describe how much each environmental variable changes with one unit increase in the predictor, basically the difference between sites and non-sites. From this point, the statistics generated were applied to the GIS.

ArcGIS Rater Calculator

The use of GIS technology allows for not only the visualization of environmental attributes and prehistoric site locations, but also the ability to manipulate known data to create new data and analysis. It is by using ArcGIS Spatial Analyst's Raster Calculator that this modeling procedure is brought from statistics to a visual representation of our modeled reality.

In this process, the GIS layer for an environmental variable is multiplied, using the Raster Calculator, by the regression coefficient that was generated for that variable. Each environmental variable is multiplied by its coefficient and then added or subtracted to/from the next variable, which is multiplied by its coefficient (e.g. Grid_1 = 0.089 + 0.0085 * [elev] - 0.252 * [elevrng] - 0.00161 * [rivcost2] + 3.84 * [texture] + 0.506 * [PHYS5SOILWGHT]).

Linear Regression Model:

$$Y_i = a + \beta_1 * X_1 + \beta_2 * X_2 + ... + \beta_p * X_p$$

Y_i – Score derived from the linear model (Dependant Variable)
a – Y intercept
X_i – Environmental variables (Independent Variables)
β_i – Regression Coefficients

The result of this step is a single grid layer, for each physiographic setting, that is the visualized version of the regression calculation. The data displayed in the single grid layer is the score, based on the regression coefficient, which ranges from negative infinity to positive infinity. To change this ungainly range into something more manageable, the probability scores were run though a probability function to bring them to a range of -1 to 1 (e.g. Grid_2 = 1 / (1 + Exp(-[Grid_1]))).

Probability Function:

$$P_i \quad \frac{1}{1 + \mathit{Exp}\ (-}$$

Y_i – Score derived from the linear model (Dependant Variable)
P_i – Resulting Probability Score

Again, a single grid layer was produced, but this time coded with the new probability values for prehistoric sensitivity. From this point, the model was classified into High, Medium, Low, and Slight sensitivity using user defined natural breaks.

The classification process for this step is subjective, but based on the idea of the “optimal cut-off point.” This method, when practiced quantitatively, plots the percent correct predictions against the percent incorrect predications for a range of probability cut-off points; see Kvamme 1988 (388-389) for a description of this procedure. The optimal cut-off point is the probability at which the highest percentage of sites is correctly predicted for while minimizing the incorrect prediction, or total surface area covered by the prediction. A model may predict correctly 95% of the time, but it is a poor model if 95% of the surface area is considered High Probability. This process allows the modeler to negotiate between including sites in the correct predictions and excluding large volumes of land as predicted for. In this model, the “optimal cut-off” method was not quantitatively applied. Instead, a qualitative approach was used that adjusted the cut-points and visually interpreted the gain and loss of prediction area. The model was considered optimized when the number of sites included in the prediction was maximized and the area predicted for was minimized. Classifying the model to the optimum cut-off did not always produce an acceptable model. Some cut-off classifications showed that the model was not going to produce an acceptable result regardless of what the cut-offs where established at. In these cases, the methodology was taken back to the regression and new environmental variable combinations were utilized. This process was repeated until an acceptable model was produced.

Once the model was classified into High, Medium, Low, and Slight it was saved as a raster file and the multivariate and GIS procedures were repeated for each physiographic setting. Finally, all five models were joined together, using the ArcGIS Spatial Analyst Raster Calculator, to form a project area composite grid of prehistoric sensitivity.

Statistical Model Testing

This model has only been tested internally. Meaning that the results have not yet been field tested, but the model has been evaluated using random points and previously recorded sites. The three internal tests used to credit the validity of this model are counts by sensitivity zone, checks against randomness, and the Kvamme Gain statistic (Kvamme, 1988). The tests and analysis discussed below are completed by using two different units of analysis, individual cells and mapped site boundaries.

First, the mapped site boundary as the unit of analysis was used in all three performance tests. Within the recorded set of 140 prehistoric sites in this project area, 56% of the sites (n = 79) had recorded boundaries. The remaining 44% (n = 61) of the prehistoric sites were buffered with 30m diameter circles to establish an arbitrary boundary. Within these boundaries Neighborhood statistics were used to find the Mode sensitivity value for each sites area. The total area occupied by each sensitivity value (High, Medium, Low, or Slight) was counted for each site area and the one that occurred most is attributed to the site. Used instead of taking the Average sensitivity value for each site area, this method is more accurate at the macro scale of site areas, but subject to variation based on data generalization and site size variation. This method returned a more accurate assessment of the models performance as opposed to using site centroids as the unit of analysis.

Second, individual 30m X 30m cells as a unit of analysis were used in only two performance tests, counts by sensitivity zone and the Kvamme Gain statistic. For this approach each individual grid cell within a prehistoric sites boundary was counted in the results. Therefore, the generalizing effect of the Mode analysis is replaced by an exact count of High, Medium, Low, and Slight grid cells. This analysis is more precise on the micro level of the grid cell, but subject to variation based on data generalization and site size variation.

A limiting factor in the building and testing of this model is the relatively small sample (n = 140) of recorded prehistoric sites, roughly one site per 2 square miles. Because of this limitation, the internal testing of the model had to be conducted using the same site sample (training sample) that was used in the creation of the model; a non-independent sample. Ideally, at the beginning of the modeling process the known site sample would be split into two separate sets. The first sample, the training sample, would be used to create the model whereas the second sample, the test sample, would be used to test the model. This methodology is used to avoid a circular correlation in the results. If a model is built around a certain set of sites, it assumed that the model will perform well in predicating the location of that same set; therefore, they are generally not used in testing. In this case, it was unavoidable to use the training sample as the testing sample. By splitting the sample at the beginning of this model, the resulting two samples would not be representative of the known variation in landscape settings and consequently, not be valid for either training or testing. Therefore, for this model, the same set of sites used to construct the model is being used to test it.

Counts

The simplest test to judge a model's predictability is to count the number of known prehistoric sites that fall within each sensitivity stratum (High, Medium, Low, and Slight). In this model the counts were first completed for each site area as a while, based on the Mode count discussed above. The results (Figure 4) show that 45% (n = 63) of the recorded sites are located in High sensitivity areas, 28% (n = 39) of recorded sites are in Medium sensitivity areas, 20% (n = 28) are in Low sensitivity areas, and 7% (n = 10) are in Slight sensitivity areas. This test was also performed using the grid cell data as a ratio of the counts of cells within site boundaries to the total count cells for each sensitivity strata. The results were multiplied by 100 and truncated to two decimal places to make the results easier to interpret. The test (Figure 5) returned .72 for High, .40 for Medium, .21 for Low, and .07 for Slight. These results are not percentages; they are scores that demonstrate a relative accuracy between sensitivity strata. Closeness to 1 indicates higher prediction accuracy. As compared to the counts by site area, the counts by grid cell show a more exponential distribution. This is due to the fact that not only do a high number of the High sensitivity cells fall within recorded site boundaries but also the total number of High sensitivity cells in the model is smaller in proportion as compared to other sensitivity strata. Admittedly, this test is similar to the Kvamme gain statistic, but does not consider the cell counts as percentages of the whole; these are strictly counts. In all the Counts tests demonstrate that this model predicted the location of more sites and cells within High sensitivity areas that any other area. Following the trend, Medium, Low, and Slight sensitivity accounted for decreasing numbers of sites and cells.

Vs. Random

This test, also based on counts, compares the number of sites that fall within each sensitivity stratum against the number of non-sites (random points) that fall into the same sensitivity stratum. As shown in the count test (Figure 6), 45% (n = 63) of the recorded sites are located in High sensitivity areas, 28% (n = 39) of recorded sites are in Medium sensitivity areas, 20% (n = 28) are in Low sensitivity areas, and 7% (n = 10) are in Slight sensitivity areas. The counts of random points are distributed such that, 7% (n = 99) of the random points are within high sensitivity area, 12% (n = 170) are in Medium sensitivity, 22% (n = 301) are in Low sensitivity, and 59% (n = 830) are in Slight sensitivity areas. As evident in the graph depicting these counts, the random point count increases inversely to the count of sites, for each sensitivity strata. This outcome demonstrates that the distribution of sites within each sensitivity strata is not random and is quite different form the background environment.

Kvamme Gain Statistic

The final performance test performed on this model is the Kvamme Gain Statistic (Kvamme 1988). Unlike counts or percentages, this statistic gives a result that is based on the number of correct site and non-site predictions relative to the area covered by the model (Figure 7). As stated by Kvamme (1988:329) "if the area likely to contain sites is small (relative to the total area of the region) and if the sites found in that area represent a large percentage of the total sites in the region, then we have a fairly good model of site location." The results of this statistic range

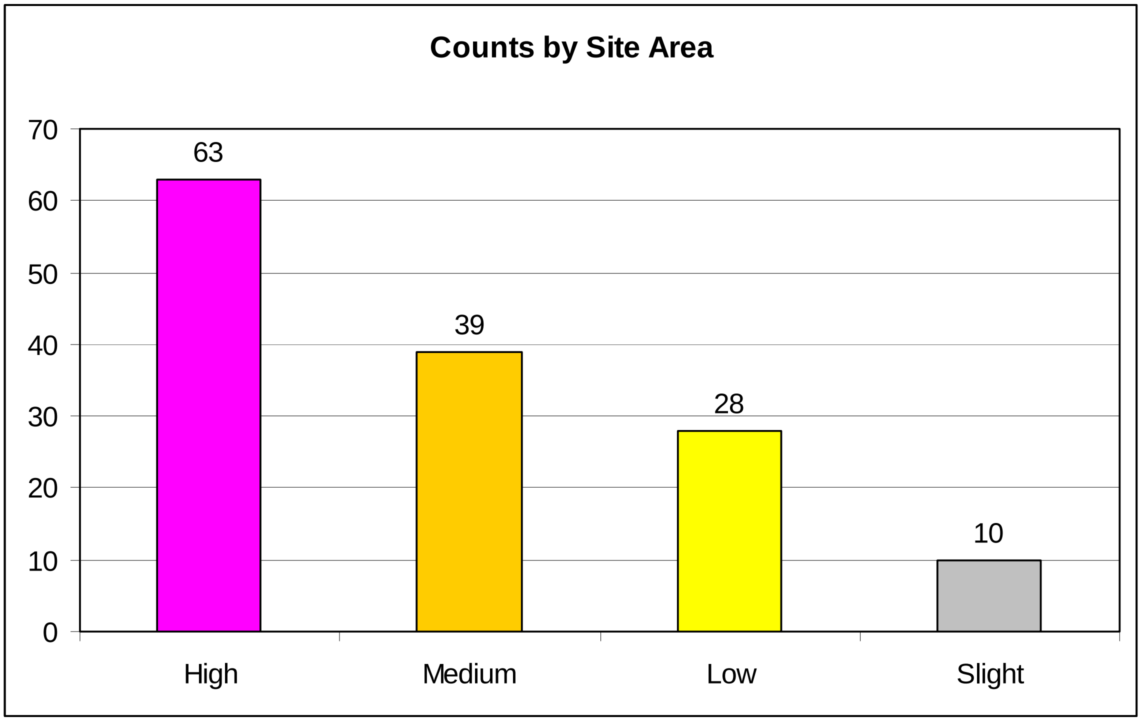

Figure 4. Number of 30 m sensitivity grids that are coincident with the area of a prehistoric site.

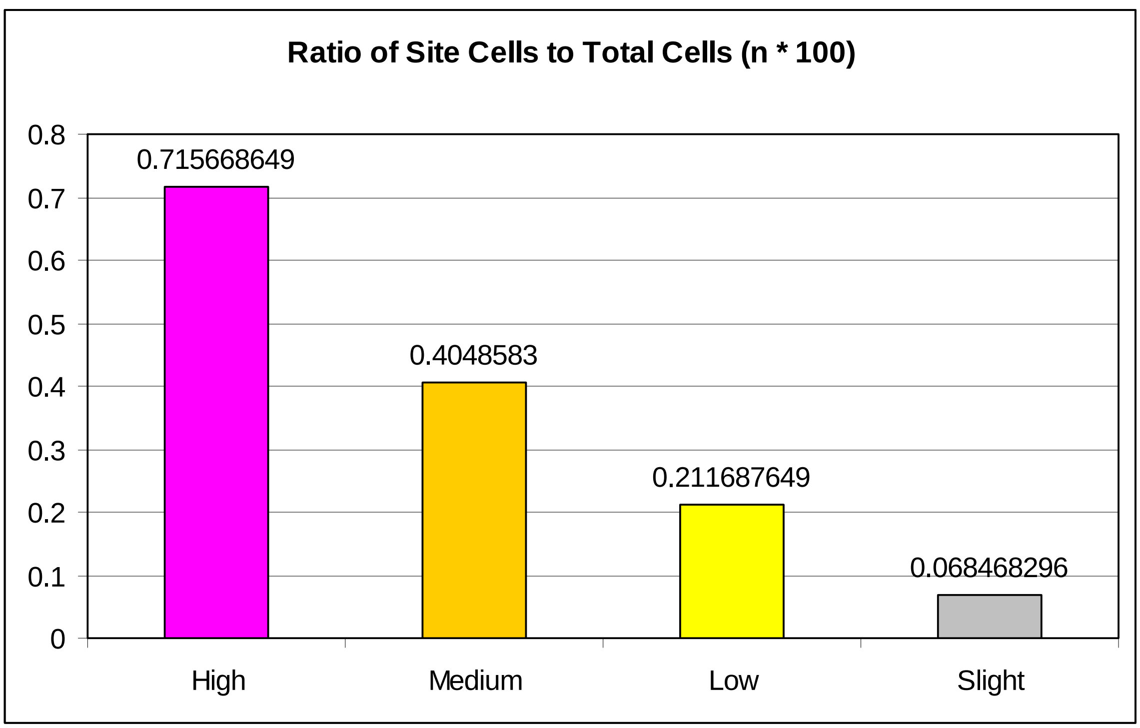

Figure 5. Percent of prehistoric site area within 30 m sensitivity grid units.

from 1 to - ∞. As the Gain statistic approaches 1, it has increased predictive ability, as the Gain statistic drops below zero and approaches -1, the model has reverse predictive utility (Kvamme 1988; 329). The results (Figure 7) of this model will be detailed for sites as units of analysis as well as cells as the unit of analysis. The Gain statistics for sites as the unit of analysis are as follows, 0.83 for High sensitivity, 0.57 for Medium sensitivity, and -0.06 for Low sensitivity. The Gain statistics for cells as the unit of analysis are as follows, 0.73 for High sensitivity, 0.53 for Medium sensitivity, and 0.10 for Low sensitivity. As noted by these figures as well as the graph, the results for both sites and cells are very comparable. The High sensitivity gains of 0.83 and 0.73 are quite good and show that this model has a high predictive utility. Crossing over at the Medium sensitivity points the two analysis return a value of 0.57 and 0.53. These values also have a good predictive utility. At Low sensitivity values, the results for sites and cells reverse with values of -0.08 and 0.1. Whereas the value for sites in the High sensitivity was better, the value for cells in the Low sensitivity is better. Notably, the Gain statistic for the cells in the Low sensitivity stratum stays above zero. The more extreme values demonstrated by the sites Gain statistic for sites may be attributable to the effects of the Mode calculation. Granting that both the cells analysis and the sites analysis have pros and cons, the true Gain is taken to be within the range between the two lines, in this case reported as the average of the two lines. The average is 0.78 for High sensitivity, 0.55 for Medium sensitivity, and 0.02 for Low sensitivity. Viewed another way, the average Gain can be read as the High sensitivity stratum contains 37% of the sites and only covers 0.07% of the map, the Medium sensitivity stratum contains 26% of all sites and covers 12% of the map, and finally the Low sensitivity stratum contains 22% of all sites and covers 21% of the total area. Particularly, the Gain for the High sensitivity stratum of this model

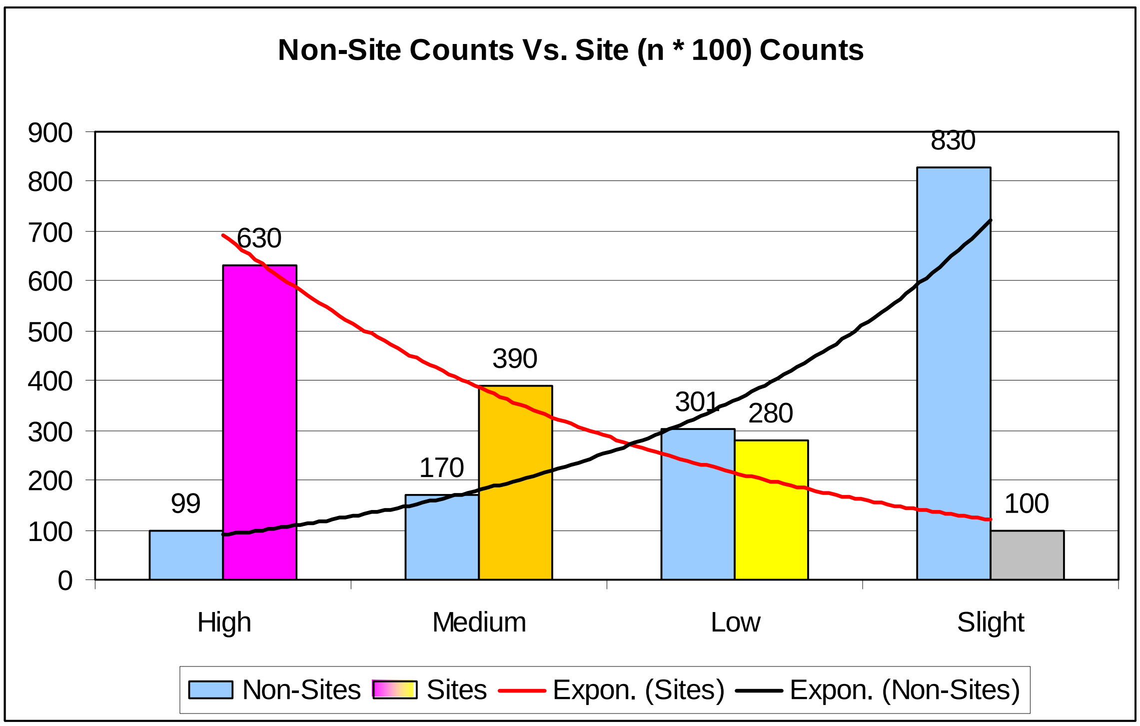

Figure 6. Relationship between known prehistoric site locations and random non-site locations as related to sensitivity.

performs very well, while there is a modest, but expected, decrease in the Medium sensitivity stratum. The Low sensitivity stratum lies just above the zero line, but is not considered a bad result. As will be discussed below, the sites that are found in the Low sensitivity stratum may not fit the same environmental pattern as the majority of the study area, but may be isolated for cultural or functional reasons. Viewed either way, it is apparent that this sensitivity model performs well according to the Kvamme Gain Statistic (1988).

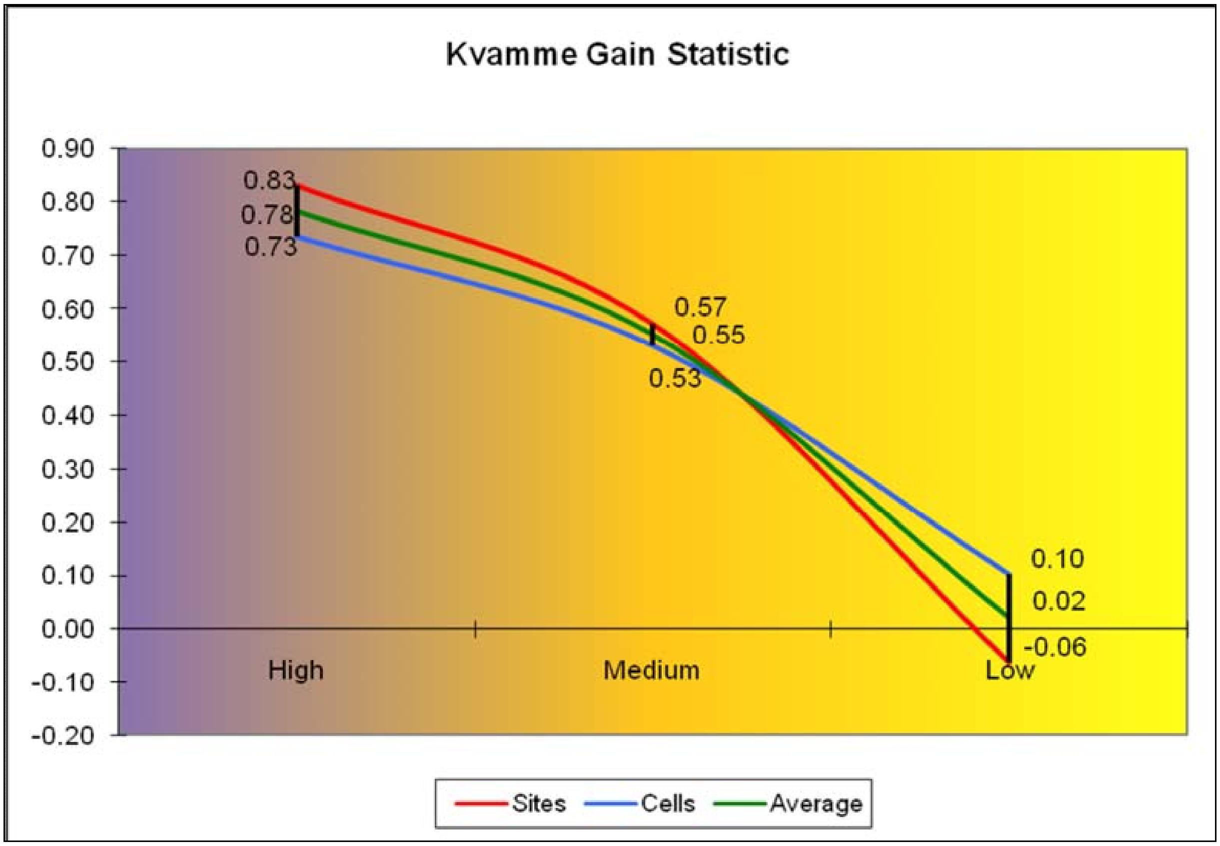

Figure 7. Result of Kvamme Gain Statistics showing that the locations of the existing prehistoric sites conform to the model.

2.1.2 Statistical Test Results

Based on the results of the tests above, two analyses were conducted to try and shed some light on the meaning of the results. First, site size and sensitivity stratum were analyzed to see if there is any correlation. It is hypothesized that variation in site size may lead to the differences between sites and cell analysis in the Kvamme Gain statistic results. Secondly, the temporal components and sensitivity strata for each site were analyzed. There are two hypotheses being tested here. First, because this is an environmentally based model and the environmental data is used in building the model is modern, sites that date to the most recent time period (Woodland II) will be more successfully predicted for. Secondly, the mutually exclusive hypothesis that the Low and Slight sensitivity stratum will contain a set of sites that is temporally distinct from the High and Medium stratum. The results of these analyses are presented below.

Site Size vs. Sensitivity Analysis

The hypothesis that variations in site size correlated to sensitivity stratum was found to be false. Using difference of mean tests, there is no statistical difference in the site size or sensitivity strata when the data are classified into five classes using three different methods; quantiles, standard deviation, and equal interval. Using the different methods protects against the distribution assumptions made by each classification. Accepting the new hypothesis, there is no correlation between site size and sensitivity eliminates this as a viable reason for variation in cell and site results for the Kvamme gain statistic.

Component Analysis

The following analysis is performed on temporal component data attributed to each site. This data was collected from the Delaware SHPO in the summer of 2003. Any information that has been updated since then is not reflected in these results. Also, these analyses are performed with the knowledge that prescribing temporal components is a very subjective process and liable to misinterpretation.

The first hypothesis tested by this temporal component analysis is that more recent time periods will be more successfully predicted because of the time dependent nature of environmental data. This hypothesis could not be statistically proven as true, therefore it is taken that environmental variation through time does not have a major impact in site location. Although no statistically significant results were obtained in this analysis, some interesting observations should be noted. First, while there are only 3 paleoindian components recorded in this study area, all of them are included in High sensitivity areas. This observation runs counter to the initial hypothesis given the climactic conditions of the paleoindian period are very different from those of today. Also, a second observation is that more Woodland II sites (n = 10, 43%) fall into the High sensitivity stratum than any other. Although this is not a statistically significant result, it does show in the favor of the original hypothesis. But conversely, 30% of Woodland II sites are found within the Low sensitivity stratum, which is slightly more than one standard deviation away from the mean for that sensitivity stratum. Given that Woodland II sites seem to be over represented by both percent *in* High sensitivity and percent *of* Low sensitivity, no conclusive results are observed.

The second hypothesis tested by this analysis is that the Low and Slight sensitivity stratum are composed of a distinguishable set of sites. The foundation of this hypothesis is that the sites in these strata do not fit into the environmental pattern observed by the majority of the sites in this study area. Some possibilities for this are that these sites occupy a different environmental niche because of natural resource procurement issues, site function issues, temporal issues, or unknown cultural/social reasons. Given the data attributed to these sites, only temporal issues can be discussed. The data regarding site function and associated artifacts is too sparse to be analyzed. As noted above, 30% of all Woodland II sites are in Low sensitivity. This is one standard deviation more than the mean for Low sensitivity. Although not statistically significant, this is the only noticeable peak in the distribution for the Low sensitivity stratum. A more interesting distribution is noted for in the Slight sensitivity stratum. Each of the 10 sites that comprise the Slight sensitivity stratum is attributed with an "Unknown Prehistoric" component. The chance of this being a small sample size statistical anomaly appears less than likely, but is a possibility. It is difficult to interpret the cause or meaning of this result due to the lack of site attribute data. One possibility, that could be further explored, is that these sites represent special function, nondiagnostic "lithic scatters." Across the Middle Atlantic region "lithic scatters", or generally small sites containing various amounts of lithic debris with no temporally diagnostic bifaces or ceramics, are a prominent issue in CRM due to their general lack of NR eligibility, but ubiquitous distribution. Frequently, prehistoric sites that do not conform to the regional norm for predicted locations fall into the "lithic scatter" site class. The unusual environmental characteristics of these sites could be resultant from cultural normative actions and/or special site functions. From the data available for the "Unknown Prehistoric" sites in the Slight sensitivity stratum it is impossible to confidently speculate on the reason for their location, but it is interesting to note.

Based on the internal testing of this model using the Count test, Counts vs. Random test, and Kvamme Gain statistic (Kvamme, 1988) it is concluded that this model effectively predicts the sensitivity of landforms for prehistoric utilization. Following this conclusion it must be noted that due to a small sample size, the tests used to evaluate performance are calculated using a non-independent sample. This could lead to a circular argument if the test sample is not representative of the entire body of prehistoric sites in the study area. Given that the test sample is comprised of 100% of the prehistoric sites recorded within this study area recorded at the SHPO, it is must be assumed that it is a representative sample. Therefore the chance of error is minimized and the results stand as the best given the available data. Only future field testing can positively confirm or deny the results of this model.

The analysis of the model data were used above to test three hypotheses. The hypotheses were revaluated after analysis and reformulated accordingly; the results are as follows:

1) The total prehistoric site areas, as recorded on the SPO maps at the SHPO, do not correlate to sensitivity strata. Site size did not influence this models predictability.

2) Temporal components do not appear to correlate to sensitivity strata. Therefore, it is unlikely that using modern environmental data had a noticeable affect on predicting for 10,000 + years of human occupation within the study area.

3) It is inconclusive whether the Low and Slight sensitivity strata sites, those that do not closely fit to the environmental or possibly cultural pattern of the majority of the prehistoric sites in the study area, do not make up a statistically exclusive set. Although the Slight sensitivity stratum is composed of 100% "Unknown Prehistoric" components, the site sample size and amount of available attribute data is not large enough to make either conclusion statistically significant.

The next step to test this model will be to conduct archeological testing within areas of potential impact based on the model. The results of the testing can then be integrated into the sensitivity model to further refine the model. At this point, this model is ready for field testing and then further evaluation.

2.2 EARLY HISTORIC SENSITIVITY

Within this project area, the early historic period, designated as 1600 AD to 1770 AD, is scarcely represented by nine recorded cultural resource properties. To model the sensitivity of this time period, a methodology was developed that does not rely on previously recorded sites, resources depicted on historic maps, or environmentally deterministic assumptions. To work around these restrictions, two separate models were created. The first model, termed the "Expert System

Model" (ESM) was created based on the current research of experts working in this area and time period within the region. The second model, termed the "Deductive Model" (DM) was created from an assessment of ground water table depths and the connection between the depth of the water table and areas suitability of habitation. Once complete, these models were coupled to form the early historic sensitivity.

2.2.1 METHODS

The first step in the creation of the Expert System Model (ESM) was to collect the available data on early historic settlement patterns within and around the study area. Due to a lack of excavated sites, little has been written on this time period within the study area and Southern Delaware. Three sources were used in the creation of the "rules" that governed early historic settlement as is currently interpreted from the available archaeological data. De Cunzo and Catts (1990) *Management Plan for Delaware's Historical Archaeological Resources*, Bedell (2002), *Historic Context: The Archaeology of Farm and Rural Dwelling Sites In New Castle And Kent Counties, Delaware 1730-1770 And 1770-1830*, and Fithian (2004) are used to establish the current state of knowledge for this time period. From the literature, specific observations were drawn that could be programmed into the GIS to derive areas of the landscape that are considered by the researchers to be sensitive.

The body of literature was not in total agreement of what constituted a sensitive location for the settlement of early historic inhabitants. The discrepancies were adjusted for by taking a more conservative approach to accepting observations as "rules." An example of a specific observation that was programmed as a "rule" into the GIS is the statement De Cunzo and Catts (1990) citing work of Wise (1980) that "historic sites dating from this time period will be located within 300 ft (100 yd) of the drainage on which they fronted." Based on this observation, all areas within 300 ft of a stream (modern ditches and drainages removed) were parsed out as a part of the potentially sensitive area. Although Bedell (2002) claims that this may not always be true, he does not offer a concise estimation for the preferable distances of early sites to streams. Therefore, in the case of the "distance to water" rule, De Cunzo and Catts (1990) is used. Doubtlessly, early historic colonists in Southern Delaware did not conform to a set of rules when making decisions about farmstead placement, but using this approach to establish guidelines for possible settlement locations is very useful. For the ESM the rules used to govern sensitive landscape locations are:

1. Located within 300 ft of drainage
2. Located within 12 miles of Atlantic coast
3. Located at the head of tide on Eastern flowing rivers
4. Located within Evesboro, Sassafras, and Matapeake soils associations
5. Built on well drained landforms.

With the five rules established, GIS environmental layers were queried to find the areas where all five rules intersect (Figure 8). All of the locations throughout the study area that met the five criteria add up to a total area of 13.8 square miles. This is 5.2 percent of the entire 262.9 square mile study area. Based on the non-ranking nature of this approach, all of the areas designated by the ESM are equal in sensitivity. Meaning, if a location in the study area met the five criteria it is considered sensitive, but not on the High, Medium, or Low scale.

As stated by Bedell (2002:53) "these rules are useful, but hardly iron-clad." The interpretation of this data should keep Bedell's cautionary words in mind. Although the studies that this model are based on are the most current, this area of research is still developing. Without a larger site sample, these results are the best given the available data.

The selection of the depth to ground water dataset in the deductive Model (DM) is based on the hypothesis testing power of Deductive modeling. Based on an observation that early population centers where located on areas of deeper ground water and the fact that some desirable landscape attributes coincided with deeper ground water, the hypothesis was constructed that depth to ground water has some correlation to the attractiveness of landscapes for early European settlement. Based on this hypothesis, the DM is constructed to fill the void of settlement theory for this area. When joined with the research based ESM model, the DM contributes to the "Why" element to illuminate the possible reasons that certain landforms are demeaned sensitive. Using a cultural/environmental approach such as this is a viable alternative to a more cultural/historical approach when time and data are at a premium.

To create the deductive model, the first step was to create a GIS layer from the information contained in the water resources report, *The Availability of Ground Water in Western Sussex County, Delaware*, by Sundstrom R.W. and Pickett T.E (1970). This report, along with the counterpart for Eastern Sussex County, details many attributes of the entire ground water system of Sussex County. Drawn from this report is a map of many hundreds of test wells across Sussex County. Of these test wells, 270 are located in or directly adjacent to the US 113 North/South Study Area. Along with the locations of the test wells, the map also shows the drilled depths to the non-artesian aquifer that provides the near surface water for Southern Delaware. The well locations and depths to ground water are the data that is used to create the deductive model (Figure 9).

Once scanned, the map was geo-rectified based on the locations of major shore line features and streams. Once the map was correctly oriented in the GIS, each of the 270 well locations was mapped with a point symbol, it its depth to ground water was recorded in the layers attribute table. The result is a GIS layer with the same information as the reports map, but only for the US 113 North/South Study Area. Next, the ArcGIS Spatial Analysis extension is used to create a continuous surface of the test well data.

In this procedure, the Spatial Analysis extension was used to predict the depth to ground water for the entire study area based on the depth at the 270 mapped test wells; this is called interpolation. The interpolation algorithm used is the Kriging method. This method is often used in the fields of soil science and geology. Once the process is complete, the result is a coverage of the entire study area of predicted depth to ground water. This layer was classified, based in natural breaks, into 3 classes. The three classes represent High, Medium, and Low sensitivity, based respectively on deep to shallow ground water depths. As opposed to the ESM, the areas designated by this model do not have any direct locational bearing. The High, Medium, and Low areas designated are purely in relation to the suitability of habitation from a ground water perspective, not the perspective of a seventeenth or eighteenth-century settler in Southern Delaware. It is only by combining the two models, one based on an archaeological/environmental view of where to settle and another based on a relativistic environmental hypothesis of where to settle, that a complete early historic sensitivity model is formed (Figure 10).

2.2.2 *RESULTS*

The final Early Historic Sensitivity Model is then derived from intersecting the ESM and the DM model. The areas that are deemed High, Medium, and Low sensitivity from the DM are retained in the final layer only where they are over laid by an area perceived as sensitive based on the ESM (Figure 11), in a sense, adding a sensitivity ranking to the ESM.

As stated earlier, only nine cultural resources are recorded in the study area for this time period. Therefore, testing of this model is nearly impossible without field work. Further, with only three of the nine resources dating prior to 1750, and one of them being of a questionable nature, this sample is heavily weighted to the later end of the time span. Clustering from 1750 to 1770, these resources comprise a non-representative sample of the 1600 to 1770 time period, although included in the sample for testing or evaluating this model.

Figure 8. Example of the Expert System Model attributes being combined to produce areas of Early Historic sensitivity.

2.3 HISTORIC SENSITIVITY

GIS software was used to pinpoint areas of historical archeological sensitivity within the study area. Unlike the modeling developed for prehistoric resources, historic-period sensitivity was based entirely on historic mapping of the area and known locations of recorded properties rather than analysis of environmental variables. Georectified historic-period maps were overlaid on

Figure 10. Results of the Early Historic sensitivity model based on the combination of the Expert System and Deductive Approach.

"Historical GIS" has become a distinct area of study within the field of Geography in recent years. Historical sources, both cartographic and textual, have been used to chart and analyze demographic and land-use changes over time. Perhaps the most extensive example of this is the Great Britain Historical GIS Project at the University of Portsmouth in England (University of Portsmouth 2000). Using historical information dating from the late 1830s into the 1970s, researchers are compiling a GIS for the entire country to map changing administrative boundaries linked to social, economic, and electoral data.

Smaller scale projects are also underway. In the past three years, at least, numerous papers dealing with historical GIS have been presented at The Association of American Geographers annual meetings (Association of American Geographers n.d.). Topics have ranged from practical discussions of historical map sources and their limitations (Rumsey and Williams 2002) to developing predictive models based on land-use patterns and environmental variables (Legg 2003) to spatial analyses of agricultural features and crop types and their relationship to water availability (Bigler 2004).

Figure 11. Early Historic Sensitivity Model for potential archeological sites in the US 113 North/South Study Area.

The National Park Service, through their Cultural Resource Geographic Information Systems Facility, is working on incorporating historic maps into some of their project-specific GIS. By adding these maps to modern background layers and historic site locations collected using GPS, the Park Service hopes to "locate significant historic resources within the modern landscape and target specific areas for protection" (McCarthy 2004; 88).

The digitization of individual structures from historic maps is time-consuming and difficult, but it offers tremendous information potential (Rumsey and Williams 2002a; 10-11). Sheehan-Dean (2002) documents a University of Virginia project that used map information as an analytical tool. Structure locations were digitized from historic maps and linked to demographic data from census records, tax assessments, and “personal manuscripts” to analyze differences between two towns, one northern and one southern, before the Civil War.

Harder to find are studies in which archeologists use resource-specific GIS mapping to predict historic-period site locations. There *are* precedents for this type of analysis, though few on the scale attempted here. Psota and Douglass (2003) applied the method to a 2-mile-long, rural study area in northern California, using both published and manuscript map sources. They identified nine broad areas sensitive for historic-period resources, which were later subjected to intensive foot-survey; seven of the sensitive areas were found to contain historical resources (Psota 2003; 6). Heaton, Smith, and Klein (2003) studied approximately 1000 acres in Ulster County, New York, using mid-19th- and early 20th-century map sources. They identified the expected locations of structures that appeared on historic-period maps and applied a 50-m-diameter buffer to encompass outbuildings and refuse features. Field testing of the model consisted of archeological testing in areas that were *not* considered sensitive (the test areas were based on project plans rather than archeological sensitivity). Although historic-period artifacts were found in all but one of the test areas, they represented low-density sheet scatter (Heaton, Smith, and Klein 2003; 25); no intact features associated with historic-period structures were found, thus providing limited negative confirmation of the predictive model.

Both studies raise the issue of mapping accuracy. Although historical archeologists have long used historic-period maps to help them locate potential sites, the level of accuracy introduced by the GIS software tends to draw attention to the vagaries of historic surveying methods and the inevitable errors introduced by trying to georectify old maps. The best one can hope for is a general guide to areas that are likely to be sensitive for historic-period archeological resources, not a precise map of historic-period roads and features. Individual resource locations should be re-examined once specific projects impacts are determined.

The GIS for historic-period sensitivity was restricted to the two smaller study areas for Milford and Georgetown, which fall at the north and south ends of the larger Delaware Route 113 study area. In addition, dense municipal areas were excluded from the study for the following reasons: 1) these areas are unlikely to be affected by the project; 2) the historic-period maps that were consulted did not include enough detail of densely populated areas to be considered reliable sources; and 3) these areas were omitted from the February 2004 windshield survey, so the inventory of recorded properties has not been field-checked or supplemented. The areas excluded from the study are delineated in a project shapefile (Appendix III).

2.3.1 METHODS

The GIS for historic-period archeological sensitivity was built using a database of cultural resources properties recorded with the Delaware SHPO and a selection of historic maps. The database of previously recorded properties was compiled by JMA from Delaware SHPO records current as of July 2003 and a windshield survey of historic-period standing structures conducted in February 2004. Historic map sources for the Delaware Route 113 sensitivity study were chosen to complement one another, and they are by no means exhaustive. The GIS has been structured so that additional sources can be added to the database as research goals develop.

The earliest map sources consulted were the road papers on file at the Delaware Public Archives, Hall of Records, Dover, Delaware (Figure 12). For this project, JMA collected all road paper plats within the study areas from the earliest on file (in this case, 1792) through 1867 or so (Delaware, State of v.d.). The purpose was to retrieve information on historic resources present before 1868, when Beers *Atlas of the State of Delaware* was published. Nearly 60 road papers were examined, and they are listed, by date, in Appendix II.

Road papers document proposed road construction, and many contain detailed surveys of the intended alignment. For the period covered, the roads were mapped using quadrant bearings and perches or poles (16 1/2 feet), most of which are noted on scale drawings. Almost all of the papers include notations regarding land use and ownership, and many depict structures or other cultural features alongside the proposed roadway. Taken together, the road papers provide a detailed snapshot of the early 19th-century cultural landscape within the study areas. Roads, bridges, mills, houses, stores, river landings, churches, schools, and cemeteries have been mapped, showing the foci of human habitation and the corridors connecting them.

A more static picture of the project area, for the year 1868, was provided by Beers *Atlas*, which depicts both roads and structures (Beers 1868). Most of the structures are identified by owner, and some by function (e.g., mills, cemeteries, schools, and churches). In Delaware, the Beers Atlas is divided by Hundred, and the following maps were consulted:

- Baltimore
- Cedar Creek
- Dagsboro
- Georgetown
- Indian River
- Milford

The latest historic-period map source used for the Delaware Route 113 project GIS was the United States Geological Survey (USGS) topographic quadrangles. Dating from 1928 through 1943, these maps provided a picture of how the area developed in the last quarter of the 19th century and the early years of the 20th century. The USGS quadrangles depict roads and structures, though only a few are identified. Cemeteries, schools, and churches are delineated, however, as are the names of communities. The following maps were used:

- Cedar Creek, 1938
- Cedar Creek, 1940
- Millsboro, Del.; 1938
- Rehoboth Beach, Del.; 1928
- Selbyville, Del., Md.;1943

The modern USGS topographic quadrangles were also consulted to pinpoint disturbed areas and locate previously unmapped cemeteries. The following 7.5-minute quadrangles were used:

- Ellendale, Del.; 1992
- Frankford, Del.; 1991
- Georgetown, Del.; 1992
- Harbeson, Del.; 1992
- Milford, Del.; 1993
- Millsboro, Del.; 1992
- Mispillion River, Del.; 1993
- Selbyville, Del.-Md.; 1992
- Waleysville, Md.-Del.; 1992

Figure 12. Example of sources for the Historic Sensitivity mapping with one specific intersection being depicted through time.

Mapping

The background layer for all historic map data that were digitized for the project GIS consisted of modern aerials, both the 1997 Digital Ortho Quads (DOQQs) and the 2003 false-color aerials. The former were used for mapping the data and the latter were consulted when archeological potential was being assessed (see below).

Two different approaches were taken to digitizing data from the historic map sources (Figure 12). The road papers consisted of photocopies of manuscript sources, and no attempt was made to scan them or georectify the actual maps. Instead, using the metes and bounds specified on the maps, the alignments were drawn in ArcMap with editing tools that allow exact angles and distances to be specified. The distances, which are presented on the road papers as perches or poles, were first translated into meters in an Excel spreadsheet. Two separate road shapefiles were produced from the road papers: 1) a “raw” data file generated from the precise metes and bounds indicated on the maps and 2) the final file reflecting corrections made to the alignments to correlate them with real-world landscape features (see discussion of corrections, below). Structures represented on the road papers were then digitized based on their relationship to distinctive features along the road corridor (e.g., recognizable turns or intersections).

In contrast, the 1868 Beers Atlas hundreds and the early-20th-century USGS quadrangles were digital files that had already been georectified and therefore constitute background layers in the project GIS. Roads and structures were traced, and necessary adjustments made. Not all resources on the later maps were digitized, only those that were not already represented on earlier maps; that is, resources were only recorded when they first appeared in the historic record and were not re-recorded if they appeared again on a later source map. The goal of the data collection was to determine archeological site potential, not the history of individual resources. For this reason, roads were recorded in segments; a continuous corridor was broken into segments whenever different information applied. For example, if a portion of a longer road appeared on a road paper, it was mapped as an earlier segment. Likewise, a new segment was designated whenever the integrity assessment changed along the corridor.

The accuracy of the historic-period maps and their georectification was highly variable, and adjustments in resource locations were made so that the GIS would more accurately reflect the historic landscape. Each historic resource was compared to the modern aerials, previously recorded resources, and the other historic maps to determine if its location appeared to be correct or should be moved. Road alignments as mapped from the road papers could rarely be used in their raw form, although the overall shape was often clearly recognizable as a modern corridor: if, for example, one segment was too short or too long, or the angle was a few degrees off, the road could easily assume an entirely erroneous trajectory. Occasionally structures or features (e.g., bridge crossings) along the alignment could be correlated with previously recorded resources or existing landscape features, adding weight to the decision to adjust the location. Adjustments to road corridors included moving the entire feature or changing some of the vertices to match the modern alignment. Dramatic changes in direction, dog-legs, or apparently aberrant angles were left intact in acknowledgment of the fact that most roads have been subject to alteration over the years. Abandoned segments were rarely visible on the aerials, but they may be detectable on the landscape.

The locations of roads and structures on the later maps were treated likewise, and they were moved or adjusted if enough evidence could be summoned to justify it. This was a highly intuitive process, and there are no objective criteria that can be listed; mapping historic-period resources from primary sources involves a high level of interpretation, and their locations are therefore approximate.

Recorded properties that did not appear on any of the historic maps were added to the database from the datasets compiled by JMA for the Delaware SHPO. Most of the recorded properties are extant, although some of those that were on file with the Delaware SHPO have been demolished since they were originally recorded. Information on each resource was collected and stored in attribute tables associated with the data points and lines (Appendix II).

Roads were assigned "type" designations. On the road papers, these consisted of "mapped," "noted," and "ditch." The mapped roads were the actual road that was being proposed; the noted roads were corridors at either end of the proposed road, or roads that crossed it. Noted roads did not include any bearing or distance measurements and are represented as dotted lines on the sensitivity maps. Occasionally a ditch was noted on the road papers. While these fall into the "noted" category because they never included bearings or distances, it was decided that they warranted a different designation.

The designations "solid" and "dashed" were used for roads on the 1868 Beers map and the 20th-century USGS quadrangles. Solid refers to the major corridors that are represented on the historic maps with solid lines. On both sources, these appear to have been mapped more carefully. Dashed refers to unimproved corridors represented on the historic maps as dotted lines. The original mapping of these roads appears to be less accurate. "Rail" constitutes an additional category of road type on these later sources.

The historic road attribute table includes a field for "Comments." Noted in this field are road names and other pertinent details, such as if the road appeared on a later source with another name. These road names can be important because they often specify the road's historical termini.

Structures were identified by functional type, with "HOUSE" being the default. Other types included schools, churches, cemeteries, bridges, and mills. A name field lists the name as shown on the historic source, if there was one, and a comments field includes notes pertinent to the resource, mostly regarding archeological potential (see below).

Roads were assigned "type" designations. On the road papers, these consisted of "mapped," "noted," and "ditch." The mapped roads were the actual road that was being proposed; the noted roads were corridors at either end of the proposed road, or roads that crossed it. Noted roads did not include any bearing or distance measurements and are represented as dotted lines on the sensitivity maps. Occasionally a ditch was noted on the road papers. While these fall into the "noted" category because they never included bearings or distances, it was decided that they warranted a different designation.

Both roads and structures were assigned relative dates corresponding to their first mapped appearance. For example, roads and structures mapped from the Beers Atlas were assigned the date of "by 1868," since their actual date of construction is unknown. If a property appeared in the recorded properties dataset and had been assigned a more specific construction date, that date was used instead. Properties that did not appear on historic maps but that had been recorded were assigned the dates designated in the SHPO records. Roads represented on the road papers were given absolute dates of construction; existing roads *noted* on a road paper were given relative dates. Roads that are noted as "vacated" were assigned "before" dates.

In addition to mapping locations of roads and structures depicted on the historical maps and in the recorded properties datasets, cemeteries included on the modern USGS quadrangles were manually digitized. All cemeteries were mapped, regardless of age; some of these had already been recorded as cultural resources, but many had not.

Map Source Limitations

The three sources of historical resource locations presented different mapping problems (Figure Sources). In general, the road papers display a high level of precision; that is, angles were measured to the half-degree and distances to the decimal perch. The accuracy, however, can be expected to vary with each surveyor and was subject to the limitations of the instruments available at the time. Although most of the papers were drawn to scale, the locations of structures do not appear to have been measured. For the most part, the position of a structure *along* the road appears to be accurate, but its distance *from* the road is an approximation. Also, it should be kept in mind that the road papers represent plans, not as-built, and in some cases the road alignments may have been altered during construction or abandoned altogether.

The 1868 Beers Atlas appears to be an accurate representation of the mid-19th-century cultural landscape; it is given “fairly high marks” by map historians (Jefferson Moak, personal communication, 2004). The purpose of the maps was to disseminate information about property development and infrastructure improvements for real estate purposes, and attention was paid to making them as accurate and inclusive as possible. The shape of road alignments is largely consistent with modern roadways, and mapped structures correspond to recorded resources. The historic map scans, however, rarely register precisely on the modern aerials, and adjustments to resource locations had to be made. The registration problem is not consistent over an entire map, however, so each resource had to be examined and adjusted individually. Watercourses on the 1868 Beers maps bear little resemblance to modern streams and rivers, and therefore could not be used to help adjust resource locations. Roads proved easier to correct than structures because many of the roads exist on the landscape today. Registration was markedly worse at the edges of the maps, and roads on adjoining hundreds rarely lined up. The locations of structures that occurred adjacent to roads are more likely to be accurate than the locations of those that occurred at a distance from a road: not only is it likely that they were mapped more accurately in the 19th century, but it is easier to find points of reference on the modern aerials. It is unknown how complete the Beers maps are.

Most of the 20th-century topographic quadrangles registered well on the modern aerials, and the locations and shapes of major road corridors appeared to be highly accurate. There were significant registration issues with the 1940 Cedar Creek quadrangle in the Milford Study Area, however, and it was georectified area-by-area as mapping progressed.

Numerous unimproved roads indicated as dotted lines were depicted on the quadrangles, few of which correspond to existing roadways or are visible even as traces on the modern aerials. These may have been ephemeral farm roads that have disappeared over time, or, more likely, were not mapped accurately because they were considered less important than the paved road system. The unimproved roads on the quadrangles were adjusted to correspond to visible modern roads more liberally than other resources, on the assumption that they were not mapped carefully to begin with. Even so, there are numerous segments that seem to have disappeared without a trace. Structures that occur along the major roadways appear to be mapped accurately, as judged by their correspondence with existing structures. The locations of structures that occur along unimproved road segments are only as accurate as the mapping of the road itself, which varies. Not all standing structures are depicted on the maps.

The issue of completeness is a vexing one. Not all resources that are known to have existed—that is, structures that have been recorded, many of which are still standing—are represented on the historical maps. Some of this is undoubtedly due to mapping and georectification inconsistencies, but there are many cases where it appears that the resource simply was not mapped. While the various problems inherent in the datasets prevent the historical GIS of the project area from being an exact representation of reality, it remains a valuable tool that can be put to effective use in planning.

Archeological Site Potential

Each mapped resource was assigned a value corresponding to its assessed archeological potential (Figure 13). Archeological potential was determined based on an examination of the most recent available aerial photographs, in this case the 2003 false-color aerials. The assessment was based largely on the level of ground disturbance assumed from the visual examination of the aerials and did not include any ground-checking to account for activity that may have occurred since 2003. Visual assessments of ground disturbance were checked against a land-use/land cover (LULC) map of the study areas (Earth Data 1997). The archeological potential of resources that occurred within any of the following land-use areas was reconsidered:

- junk/salvage yards (LULC 123)
- industrial (LULC 130)
- reservoirs (LULC 530)
- extraction areas (LULC 750)
- transitional/filled/graded areas (LULC 760)

The assessment of archeological potential did not take into account 1) possible mapping inaccuracies, 2) issues of accessibility, or 3) questions of potential historical significance (e.g., mid-20th-century resources were not assessed any differently than early 19th-century resources).

Five categories of archeological potential were assigned to the mapped historic structures and buildings, as follows:

1. High Potential. The resource is no longer extant and is in an apparently undisturbed location. This designation was reserved for resources that appear to be in the middle of fields or forests, where little or no disturbance is discernible on the aerial photograph. All cemeteries and historic-period archeological sites were categorized as “High Potential” regardless of their age or location.

2. Medium Potential. The resource is no longer extant, but a more recent structure occupies its approximate location. In these cases, it is assumed that there is some potential for intact archeological resources, depending on construction methods and the exact placement of the newer structure, neither of which could be determined by looking at the aerial. In some instances the newer structure is a recorded historic resource, but of a later time period. The resource number and approximate date were included in the “Res_Num” field of the mapped structures database; if the newer structure had not been recorded, “modern” was noted in the “Comments” field.

3. Low Potential. The resource is no longer extant, but the area has been heavily disturbed. Included in this category are areas that have clearly been subjected to heavy excavation, such as holding ponds, quarries, or dense modern developments. The nature of the disturbance was noted in the “Comments” field.

4. Extant. The resource appears to be standing and has been recorded as an architectural property. For resources digitized from the historic maps, this determination was based largely on location: if a mapped historic resource fell close to a previously recorded resource, the previously recorded resource was examined to see if it could possibly have been present at the time the map was made. Occasionally the historic name of a previously recorded resource matched a name on the historic map, but more often it was a matter of confirming an appropriate date range using information from the recent windshield survey of the recorded property records at the Delaware SHPO. If temporal consistency was established, the data point for the mapped structure was registered directly on top of the data point for the recorded resource and the existing resource number was noted in the "Res_Num" field of the mapped structures database. Additional extant properties that did not appear on historic-period maps were derived from the datasets of recorded properties compiled by JMA. Only those properties that were observed during the February 2004 windshield survey were designated as extant.

5. Unknown. The property was previously recorded, but was not re-surveyed in February 2004 and the integrity was not noted in the Delaware SHPO records.

Two categories of archeological potential were assigned to the mapped historic road segments, as follows:

1. Potential. The road is either not visible on the aerial at all, or appears to be no more than a trace. No attempt was made to assess potential disturbance along the segment corridor.

4. Extant. The road is visible on the aerial and appears to be currently in use.

2.3.2 RESULTS

The results of the historic-period sensitivity study for the Delaware Route 113 project are presented in two shapefiles included on the CD at the back of this report (Appendix III). Also included is the shapefile that contains the study area boundaries and the outlines of the dense municipal areas excluded from the study (Appendix III).

A total of 886 historic-period line segments (most of which are roads) were identified within the Milford Study Area and Georgetown South Study Area (Figure 14). Of these, 498 are still evident on the landscape, while 388 have disappeared but may still have archeological potential. More than half of the identified segments (452) appeared on maps before 1900.

The historic point dataset consists of 3,355 properties that include residences, commercial buildings, mills, bridges, schools, and churches, among other property types (Figure 15 and Figure 16). Of these, 1787 were digitized from historic-period maps and an additional 1568 were added from datasets of recorded properties. Most of the properties (2,664) have a high potential for archeological resources or are extant; at least 833 of the properties predate 1900 The historic sensitivity analysis for potential archeological resources within the Milford Study Area resulted in a total of 472 potential sites associated with structures recorded historically but no longer extant on the landscape. Based on the sensitivity criteria presented earlier, 238 of theses potential archeological sites are within high sensitivity, 207 are within medium sensitivity, and 27 have low sensitivity. The historic sensitivity analysis for potential archeological within the Georgetown

South Study Area resulted in a total of 832 potential archeological sites associated with structures recorded historically but no longer extant on the landscape. Based on the sensitivity criteria presented earlier, 443 of these potential archeological sites are within high sensitivity, 319 are within medium sensitivity, and 70 have low sensitivity.

Figure 13. Example of resulting map when existing resources, potential resources, and archeological sensitivity are combined.