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Modeling for Management in a Compliance World

Christopher D. Dore

University of Arizona, cdore@email.arizona.edu

LuAnn Wandsnider

University of Nebraska-Lincoln, lwandsnider1@unl.edu

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Christopher D. Dore and LuAnn Wandsnider

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Abstract

In practice, compliance-driven cultural resource “management” and its requirements for resource location, evaluation, impact assessment, and mitigation manifests a fundamentally different use of geospatial predictive modeling than do research-oriented investigations. This difference primarily results from the lack of an iterative research design. In research-oriented modeling, iterations of model building and model testing gradually build a more robust model and lead to an increased understanding of the variables that condition human spatial behavior in the past. In a compliance environment, spatial models are rarely built and evaluated; rather, once built, they are applied in a single iteration. An assumption is made that the model being used will accurately predict behavior in space. Yet, in

most settings, our knowledge of the factors that condition the spatial organization of activities—and under what conditions these factors are relevant—is just beginning to develop. Coupled with the methodological issues of sample size, changing environmental conditions, functional differences in resource types, the fact that most archaeological deposits represent depositional (as opposed to functional) sets that have accumulated over hundreds of years, spatial variability caused by non-environmental factors, etc., compliance modeling certainly does not represent best practice, even though it is legal under federal cultural resource law.

Rather than modeling the past, a more productive approach to modeling for cultural resource managers is to model the present. Instead of reacting to development and infrastructure projects that have taken the place of our stewardship responsibility, geospatial technologies can be used to design a proactive approach to resource management. With such an approach, present conditions, both natural and cultural, are modeled to predict site and feature visibility and to identify potential threats to surface sites and features. At a regional scale, the use of vegetation, slope, and sediment data can be used to develop erosion models for current and future conditions. Cultural resources can be compared with these models to categorize and prioritize the resources most at risk. At the scale of individual resources, aerial photography and new higher resolution satellite imagery can be used to establish the baseline condition of resources and, with follow-up visits, to establish and compare rates of change from erosion, all-terrain vehicles, and vandalism. At the intrasite scale, new processing techniques can be used with geophysical data to predict the nature of actual cultural features rather than identify data anomalies that then require excavation. These techniques will ultimately lead to absolute, rather than relative, signatures for properties of the archaeological record and provide a truly nondestructive archaeology. We illustrate this geospatial management framework with archaeological examples from western, southwestern, and midwestern North America.

1 Introduction

Although “cultural resource management” (CRM) is the term used to describe applied archaeology! within the United States, in fact, however, there is very little management of archaeological resources, at least in a stewardship context. Landholding federal agencies, while tasked with this responsibility under Section 110 of the National Historic Preservation Act (NHPA), Executive Order 11593, and others, are largely unable to meet this responsibility due to vast landholdings (especially in the western United States), numerous resources, small budgets, and the pragmatic priority of fulfilling compliance obligations such as those required by Section 106 of the NHPA. The Advisory Council on Historic Preservation (2001) recently stated, “In spite of the important stewardship responsibility entrusted to Federal agencies for much of our Nation’s heritage, other agency mission priorities often force historic

preservation activities, programs, funding, and staffing to take a back seat.”

Compliance with Section 106 requires that federal agencies take into account the effects of undertakings on historic properties and that the Advisory Council on Historic Preservation (Advisory Council) be given the opportunity to comment. In practice, four steps are usually taken to fulfill compliance responsibilities with Section 106 and other environmental laws, and thereby “manage” cultural resources: identification of resources, evaluation of resources, assessment of the effects of a project on significant resources, and an identification of ways to lessen effects that are deemed adverse.

Predictive modeling, done both within and outside of geographic information systems (GIS), has long been a part of federal cultural resources compliance (e.g., Ambler 1984). When modeling is implemented in the compliance process, it is almost exclusively used in the resource-identification phase. Driven by the high cost of systematic field surface surveys, federal agencies and nonagency project proponents have searched for ways to reduce the costs of resource identification. Sample surveys have been the cost-saving strategy of choice, and predictive modeling, sometimes less formally called sensitivity analysis, is the method most often utilized to spatially define sampling strata.

From a legal perspective, there is no mandate to comprehensively survey a project area, called the area of potential effects (APE). Likewise, when undertaking a compliance investigation, there exists no requirement necessitating that all resources be found within the APE. The legal burden is that a reasonable and good-faith effort be made to identify resources within the project area (36 CFR 800.4(b)(1)). Using predictive modeling to identify areas most likely to contain resources is not only allowable (U.S. Secretary of Interior 1983), it has been informally advocated by the Advisory Council (McCulloch 1999). As we will outline below, while legal for compliance purposes, we believe that the use of predictive modeling within a compliance framework is not best practice and actually perpetuates stagnation in our understanding of past human land use.

Most predictive modeling to identify resources is not best practice for a variety of reasons discussed below. Insofar as this is true, that aspect of “cultural resource management” encompassed by “identification” is similarly challenged. But, with the emergent perspective of landscape management coupled with widely available geospatial technologies (emphasized here), management in general and, especially, two other common compliance activities - assessment of project effects and ways to lessen adverse effects - become approachable. In what follows, we identify some of the problems with modern modeling applications in compliance-driven cultural resource management, concluding with examples of the application of geospatial modeling to stewardship-oriented management of cultural resources at a variety of scales. Through these efforts, we aim to put the “M” back in CRM.

2 Predictive Modeling and Compliance

Critiques and discussions of the methods involved in predictive modeling and sampling have permeated our professional literature over the last 30 years. Many of the issues we identify here have been outlined by others, including Kohler and Parker (1986), Kvamme (1989, 1990), contributors to Judge and Sebastian (1988), Church et al. (2000), and Ebert (2000). While, collectively, we are well-informed about the theoretical and methodological issues in modeling, this knowledge rarely seems to be considered in the design and application of models in the compliance community. With geographic information system software on the desktop of most agency cultural resource managers and cultural resource consultants, and with pressure to lessen the cost of compliance, the lure of technology has made predictive modeling vogue in the compliance world. Unfortunately, many of these modeling efforts have been flawed by methodological and application mistakes. Given these oversights, we feel that it is beneficial to briefly restate these issues with an emphasis on compliance applications, focusing especially on model building, model testing, and the theoretical issues that underlie each of these tasks.

2.1 Model Building

Archaeologists (Altschul 1988; Ebert and Kohler 1988) often distinguish between inductively and deductively derived models. No matter the mode of model building, decisions about data inclusion and data quality affect model performance. The appropriateness of the environmental base data used to build a model is rarely scrutinized sufficiently. Research projects may factor in data adequacy as a prerequisite to selection of a study area or incorporate building environmental data sets into the research program, but compliance investigations rarely have this luxury. The project area for a compliance project has been selected *a priori* by the nature of the undertaking, and investigators have little choice in the availability of environmental base data. Custom-designed data sets are virtually never created due to limitations in project schedules and budgets. Base data for model building in a compliance investigation almost always means using “off the shelf” data, usually from the United States Geological Survey (USGS), one of the private firms in the new value-added spatial data industry, or clients. Insufficient time is spent evaluating the metadata and asking if these data are appropriate at all for the scale of human landscape utilization of interest. Quite apart from issues of data scale, resolution, and algorithms used to create data sets (e.g., Hageman and Bennett 2000; Kvamme 1990), the actual accuracy; error, and precision of these data as expressed in the National Map Accuracy Standards is in fact too low to support high-resolution modeling efforts attempted in compliance exercises (Marozas and Zack 1990).

Another problem arises from the oversimplification of the natural environment as related to human land use (Church et al. 2000; Wescott and Kuiper 2000). For example, the distance to nearest water is frequently used as source data for models, but rarely do model builders consider the type of water. Is the modeled water snow, a stream, lake, spring, or ocean? If a body of water, is it brackish or fresh? If a stream, is it annual or perennial? Is it habitat for anadromous fish or other resources? These types of distinctions have very different ramifications for how people use the natural landscape.

Similar problems exist with the archaeological data used to establish the correlations. These data sets usually come from the records of the landholding federal agency. The geospatial controls for the spatial component of these data come from a wide range of sources, and accuracy metadata often do not even exist. In determining the accuracy of the Nebraska statewide archaeological database, for instance, we found that the archaeological resource database data error ranged dramatically over an order of magnitude in the hundreds of meters (Wandsnider and Dore 1995). To ensure at a 90% confidence interval that a site was actually located where records claimed it was, sites recorded with universal transverse Mercator (UTM) coordinates had to be buffered by 353 m, and sites recorded by legal description needed a 1000-m buffer for the same accuracy confidence - and this was after discarding sites with larger errors clearly originating from coding and data entry.

Additional problems, besides those of spatial accuracy, also exist with the archaeological component of modeling data. Many times, the number of available sites used to build an inductive model is insufficient to draw statistically meaningful correlations between resources and landscape features. This is particularly problematic in compliance investigations where project areas can be quite small and good spatial data sets in adjacent areas are lacking. Likewise, the functional class of archaeological sites is too often ignored. That is, sites are treated as unifunctional; the investigator fails to consider that habitation sites, processing sites, quarry sites, etc. are located on the landscape using different, and sometimes contradictory, criteria (but see Hasenstab and Resnick 1990; Savage 1990; Wescott and Kuiper 2000). Further, temporal distinctions are often slighted, especially beyond the simple historic/prehistoric division (but see Altschul 1990). These oversights exist even though, after doing archaeology for over 100 years, we have learned that human land use did change with time in response to social, economic, and environmental dynamics. Unfortunately, when a savvy model builder does in fact discriminate along temporal and functional dimensions, the sample size within each class can be reduced to meaningless levels, making a bad situation worse.

Finally, most archaeological sites that are known, and that exist in spatial databases for use by model builders, are sites discovered through surface survey. While this is less problematic in some portions of the desert west where 10,000 years of human land use is visible on the surface, in most places only a fraction of the resources have surface signatures. Thus, in most cases, we can

only state where sites can be found, not where sites are not found, and models built upon these data best predict the *visibility* of a resource on the ground surface as opposed to the actual presence of a resource, whether surface or sub-surface. (See discussion in Warren and Asch [2000: 27-28] and Cashmere and Wandsnider [1995] for explicit attempts to model surface visibility.)

Combining environmental and archaeological data sets presents problems of its own. Do the two data sets even belong together? How representative is the environmental data of the landscape that existed when locations and landscapes were utilized (Church et al. 2000)? As previously mentioned, most data from compliance projects is off-the-shelf data, and almost all of these data are from the post-Landsat era (post-1972). These data may or may not be appropriate for modeling depending upon the degree of environmental change that has taken place. From a compliance perspective, attempting to draw correlations between the modern environment and the locations of archaeological sites is desirable. As archaeologists and scientists, however, what we really want to understand is how people interacted with past environments. Further, the correlations that may be established between the present environment and archaeological resources may be "false" correlations that may really be showing areas where past and present landscapes correspond (Duncan and Beckman 2000: 55). A second concern when combining environmental and archaeological data sets arises from stacking, or the vertical layering, of data sets. As Marozas and Zack (1990) have pointed out, the overall horizontal error is additive: the error of each layer is added together to produce composite error. Given the accuracy of individual data layers and their degree of heterogeneity, the error can quickly affect any possible associations produced by the model. This problem can be quite substantial if, for example, the accuracy figures we calculated for the Nebraska data set are representative of other archaeological data sets. This is unfortunately a likely scenario.

2.2 Model Testing

The U.S. Secretary of the Interior's Standards for Identification (1983) state that the accuracy of the model must be verified and that predictions should be confirmed through field testing. If necessary, the model must be redesigned and retested. Such actions, however, are virtually never taken within compliance investigations. The common scenario is that a model is built based upon resources in surveyed portions of the APE or upon surveyed areas in the general region. This model is then applied to unsurveyed portions of the APE to stratify the APE into areas likely to contain resources, as well as areas unlikely to contain resources. Field surveys are then conducted in these areas to find resources. In the worst cases, field surveys are only conducted in high-probability areas. In better-quality compliance investigations, sample surveys are conducted in all stratified areas to actually test the predictive power of the model. Even in compliance investigations that conduct field surveys in all stratified

areas, a common methodological error is that areas of high site probability are surveyed more intensively than areas of lower site probability, and resource totals are not adjusted to reflect the search intensity. The result is that field surveys are self-fulfilling and almost always confirm the model; more sites are found in higher probability areas than are found in lower probability areas (but see Dalla Bona 2000).

One of the reasons that this methodological error is ignored is the disjuncture between the paradigm and units employed in a compliance investigation versus those in predictive modeling. In a compliance investigation, the tangible data unit, as defined by law, is a building, structure, object, or site.² In contrast, the meaningful unit in a predictive model is a region or land parcel: an area within which there exists a probability for finding a building, structure, object, or site (Kvamme 1988, 1989). The priority in a field survey of a modeled probability area for a compliance investigation is not to evaluate the probability; it is to find sites. When sites are found, further work is spent evaluating the resource for its significance and assessing the effects of the project on the resource rather than closing the iterative loop by reassessing the model.

Under this scenario for the application of a predictive model, there is a single iteration. A model is developed and applied in an attempt to limit the amount of field survey that must be done to identify archaeological resources. This kind of modeling is problematic for two reasons.

First, the model is not tested; it is applied. In doing this, an assumption is made that an adequate understanding of the factors that condition human land use exists for the APE. Although an argument can be made that the role of the compliance archaeologist is not to build theory but, rather, to apply theory constructed by research-oriented academic colleagues, it is clear that we are only beginning to understand the variables at play in conditioning human land use. Because a compliance investigation most often will result in the damage or destruction of archaeological resources from either archaeological excavation or the construction of the project, is it wise to use predictive modeling in this way? We believe not.

Second, one of the criteria for evaluating a resource for its eligibility to be listed in the National Register of Historic Places, Criterion D, is the resource's ability to have yielded, or its likely ability to yield, information important in prehistory or history. The degree to which a resource meets this criterion is inversely related to the resource's predictability in a predictive model. For example, if a resource is found in a location specified by a model, the factors conditioning the resource's placement on the landscape are understood. Therefore, it has less potential to provide data about the past, at least from a land-use context. Alternatively, a resource that is found where it is not predicted has great potential to provide information important in prehistory or history because of the fact that it was found where it was predicted not to be (Altschul 1990). This is one of the reasons why the methodological error of surveying less intensively, or even not at all, in low-probability areas is of concern.

2.3 Theoretical Issues

In addition to the problems we have pointed out in the areas of model building and model testing, there are some additional theoretical issues of predictive modeling that are worth mentioning briefly. First, most models assume that the selection and utilization of a place on a landscape is based upon environmental criteria. While environmental criteria are important for the location and performance of many activities, it is erroneous to build site-location models on these criteria alone, or at least for all activities. While cognitive and other perceptual criteria can and have been incorporated into models, working with nonenvironmental variables is not widely done in North America, although this has been explored extensively in Europe (contributors to Lock and Stančič 1995; Gaffney et al. 1996).

Second, the emphasis in archaeological predictive modeling is on sites normally assumed to be residential settlements and special-use locations (quarries, rock art, etc.). Two problems follow from this practice. Low-density archaeological remains are rarely considered. While it is not useful to revisit the site-nonsite debate here, suffice it to note that the nonsite approach has merit as a framework for understanding human land use even though this framework is not usually used in predictive models. The primary reason that nonsite data are not used is because of the paucity of available nonsite spatial data sets. Even if such data sets existed, within a compliance context, isolated or low-density evidence of human land use is routinely held to lack significance by the very nature of its being isolated or low density and is therefore slated for dismissal. Yet, the low-density archaeological record comprises substantially high numbers of discarded tools, usually taken to be great sources of information on past place use (Wandsnider 1988).

More critically, however, "sites as settlements" denies the temporal and taphonomic (Dunnell 1992; Kelly 1988) nature of site archaeological deposits. That is, when we find Nebraska-phase ceramics at a particular location, what settlement temporality can we infer for that location? A season? Many seasons? Extended or intermittent occupation over many years? Many decades? A constellation of other information - the presence/ absence of structures, middens, and so forth - are commonly employed to "temporalize" settlement assessments. But this temporal information, beyond coarse chronology (Le., "Central Plains Tradition settlement") is not commonly incorporated in settlement-modeling attempts. Yet, long-term Central Plains occupation and reoccupation is a very different kind of place use than brief, nonrecurring occupation. It may be that we must wait for the development of accessible temporal GIS (TGIS; Lan- gran 1992) to fully deal with the temporal and taphonomic variation that our archaeological site deposits actually contain.

Third, correlation is not explanation. Correlating variables in a predictive model may establish relationships among data, but it does not, by itself, explain the dynamics of human land use (Church et al. 2000). What we really

want to understand are the “whys” that led to the performance of different sets of activities at different places at different times. How are places on a landscape linked together through human organizational systems? Additional theoretical constructs and bridging arguments must be used to supplement the correlation of landscape features to provide explanation.

Fourth, in a compliance context, the current application and use of predictive modeling actually leads to a stagnation of our understanding about the past. This is due to the lack of model building, model testing, and model refinement iterations. When models are only created and applied, nothing new about the past is learned. The current state of knowledge about land use is quantified into a model, and then fieldwork, because of some of the application problems we have noted, usually confirms the model. Sites in low-probability areas, the ones that have the highest potential to be significant to our understanding about the past, but that are usually not found, are destroyed by the project that is undertaken. Thus, we rarely learn anything new and essentially continue to build the same model from project to project (Ebert and Kohler 1988; Ebert 2000).

2.4 Summary

In the preceding, we have criticized the use of predictive modeling in compliance investigations by pointing out many of the problems in model building, application, and theory. Nevertheless, we do not advocate discarding predictive modeling in archaeology. To the contrary, predictive models, both within and outside of a GIS environment, provide a very robust tool for understanding past human-land interactions. Within a research framework, when iterations of model building, testing, and refinement can be undertaken, this tool has been shown to advance our understanding of the past. In a compliance framework, however, where predictive modeling is characterized by a lack of iterations, we feel that predictive modeling serves neither the compliance process nor the advancement of knowledge about the past.

3 Managing with Geospatial Technologies

We believe that with a different orientation, predictive modeling can have a productive role in cultural resource management. As we noted at the beginning of this chapter, the management of archaeological resources has been forced to a low priority by many landholding federal agencies due to vast landholdings, numerous resources, small budgets, and the pragmatic priority of fulfilling compliance obligations such as those required by Section 106 of the NHPA. Although predictive modeling is largely unsuitable for the identification component of compliance, we believe that such models can be used to better purpose to put the “M” back in CRM.

To borrow from Judge and Sebastian (1988), who titled their publication *Quantifying the Present and Predicting the Past*, rather than using contemporary data to model the past, we propose a framework that consists of modeling the present and predicting the future. Using this framework avoids most of the methodological problems mentioned earlier and can easily and economically be implemented by federal cultural resource managers even with large land areas, small budgets, and little time. To illustrate this framework, we will present examples at the regional, site, and feature scales. All of these examples have in common the use of contemporary data about the archaeological record and natural environment to characterize the present and predict future conditions.

3.1 Regional Scale

Our first example comes from northwest Nebraska, on a portion of the Nebraska National Forest, and illustrates how the threat of natural erosion on archaeological resources can be assessed, predicted, and managed. In this example we have identified two of the major variables contributing to sediment erosion: steep slope and lack of vegetation cover. The principal variable, precipitation, can be assumed to be even over this region that covers 142 km². Another major variable, soil type, was not factored in even though these soil data were available. Lacking this data layer does not negate the results of our analysis, but using it would certainly have enhanced and refined the results. We did use off-the-shelf data for this analysis: a 7.5-min digital elevation model (DEM) from the USGS and a multispectral Landsat thematic mapper (TM) image (Figure 1).

To calculate the quantity of vegetation, we used the transformed vegetation index (TVI) on TM bands 3 (0.63-0.69 μ m, red) and 4 (0.76-0.90 μ m, near infrared). The TVI is one of several vegetation indices that can provide a rough, relative indication of the amount of vegetation. In this image (Figure 2), the quantity of vegetation is shown grading from none (white) to dense (black). Note that the northern portion of this area consists of agricultural fields cross-cut by riparian corridors, while the southern portions are predominantly covered in pine forest. The DEM was used to compute the degree of slope (Figure 3). White indicates low slope; black indicates high slope. Then the inverse of the vegetation values was computed so that high values represent low vegetation. The slope and TVI values were then rescaled into the same 8-bit data space (256 distinctions). These two data sets were then added together to produce a numerical index representing the relative threat of erosion. As seen in Figure 4, the threat values grade from low (white) to high (black). Known archaeological sites were then added to the analysis and can now be ranked according to their potential for erosion.

A federal cultural resource manager, with little time to monitor sites and a small budget to spend on preservation, can use these results to predict which sites are at the greatest risk and where, perhaps, cattle grazing might be

Figure 1. Transformed vegetation index for the 7.5-min study area calculated from Landsat 1M data.

reduced. Similar models can be constructed for looting, recreational damage, military training, etc. Scarce resources can then be spent most effectively on the sites that really need the attention. This erosion model that we have presented is, admittedly, simplistic and could certainly be refined by better data assessment, more careful model building, ground truthing, and iterative refinements. Our point, however, is that even these simplistic models—this one completed in less than two hours—can offer the cultural resource manager effective tools for proactively managing archaeological resources.

3.2 Site Scale

Similar techniques can be applied at the site scale to help the cultural resource manager monitor the condition of sites. In the western United States, erosion, vandalism, and recreational activities such as the use of all-terrain vehicles (ATVs) can irreparably damage archaeological sites. At Vandenberg Air Force Base in California, a systematic aerial monitoring program is being used to maximize limited CRM resources. Cultural resource managers responsible for large federal land parcels, although short on funds, often have access to aircraft. Even “casual” aerial photography done out of the side of a plane with a 35-mm or video camera can provide extremely valuable management results.

Figure 2. Slope model calculated from a USGS 30-m digital elevation model.

This example shows two images. The first was taken in 1997 (Figure 5), and the second was taken in 1998 (Figure 6). Note that the oblique angle, scale, and camera position are different in each image. Using image-analysis techniques, the two images can be placed in the same geometry. In this case, the 1997 image was transformed into the geometry of the 1998 image. This analysis was done relatively, but with ground-control points and absolute geographic coordinates obtained from the global positioning system, both images can be placed into geographic space (Figure 7).

Following the transformation, the limit of the bank erosion was marked for each year. With the limits of erosion identified, the lines are simply subtracted from each other, leaving polygons that represent the amount of the site lost to erosion (Figure 8). Because the time that elapsed between the two photographs is known, the rate of erosion can be determined. As in the previous example, this rate can then be compared with other sites in the area to determine the resources that are most at risk (Figure 9). With knowledge of rates of change, cultural resource managers are then in a position to predict future site damage and can direct resources appropriately.

Figure 3. Model of erosion potential.

3.3 Feature Scale

Our last example is an intrasite example and is at the scale of the individual feature. This prototype study was completed for the City of Albuquerque and illustrates how a predictive model can work in the present. The city has purchased a prehistoric archaeological site to protect it from development. While the initial goal was to create an active archaeological park with ongoing excavations, Native American objections caused the city to reconsider their plans. Subsurface remote sensing was then proposed as a nondestructive option to map the architectural remains of the pueblo. However, because excavation could not be used to verify and identify geophysical anomalies, an alternative geophysical methodology needed to be developed. An additional problem that needed to be overcome on this project was that the architectural features of interest were unburned adobe. Adobe that is unburned does not usually have properties that make it readily distinguishable from the surrounding sediment matrix, at least in terms of most geophysical properties.

The key to developing our approach was the fact that the city's archaeologist had noticed that, under the right conditions, several wall segments could

Figure 4. Archaeological site-erosion threat assessment and ranking.

occasionally be seen faintly exposed in the ground surface. Over a period of several years, a number of wall segments were mapped to the extent that both walls and room fill could be spatially defined over a small area. With known features identifiable, we designed an approach based upon multispectral satellite remote sensing using supervised classification. A similar approach using unsupervised classification had been used by Ladefoged et al. (1995) in New Zealand. To cope with the unburned-adobe problem, we decided to use three geophysical techniques to raise the discriminatory potential above what any single method can achieve. We used magnetics (gradiometer), resistance, and time-sliced radar data as the “spectral bands” (Figure 10). Given the thickness of the known wall segments, about 20 cm, particular attention was given to both the spatial resolution of data and the spatial control of data. It was essential that any error in correspondence between all data layers be less than half the wall thickness, about 10 cm.

The supervised classification method is essentially a model-building and prediction technique. In the computer, classes of phenomena are identified and marked on top of a stack of data layers. In this case, walls and room fill were the two classes of interest (Figure 11). There are a variety of classification algorithms that can be used to differentiate features. For this study, we used the Mahalanobis classification algorithm, which is based upon neural-network classification principals. Regardless of the particular algorithm, however,

Figure 5. Oblique aerial photography used for monitoring and the 1998 aerial image. (Courtesy of Applied EarthWorks with support of Vandenberg Air Force Base. With permission.)

Figure 6. The 1997 aerial image placed in the geometry of the 1998 aerial image. (Courtesy of Applied EarthWorks with support of Vandenberg Air Force Base. With permission.)

Figure 7. After georeferencing, the edge of the bank was defined in each image. (Courtesy of Applied EarthWorks with support of Vandenberg Air Force Base. With permission.)

Figure 8. The lines defining the edge of the bank are subtracted from each other, leaving polygons that define the bank erosion that took place between the 1997 and 1998 photographs.

Figure 9. Aerial photograph showing the approximate site area and the areas of geophysical data collection.

the strategy of each is identical: to examine the variability in the data for the known features, referred to as the training set, and develop mathematical criteria for distinguishing each feature from the others. These criteria form the predictive model. In a second phase of analysis, the model is applied to unknown areas of the data set and predicts, or classifies, data into the typology that was defined. In our example, this would be either adobe wall or room fill. In an ideal situation, of course, there would be iterations of prediction, testing through excavation, and model refinement, but in this case there is no immediate means of obtaining additional verification. The final step is to evaluate the classification results against the original training data (Figure 12). In this study, a 69.6% success rate was obtained, quite good given the nature of unburned adobe, a small sample size, and some problems with the radar data.

This technique illustrates one way in which predictive models can be used at the intrasite scale to manage resources in a nondestructive way. Additionally, it takes the important step of realizing the nondestructive potential of geophysics by beginning to develop absolute signatures for particular materials and feature types. Archaeological geophysics, at least as it is most commonly practiced, involves identifying an unknown anomaly that is then excavated to determine what it is. The geophysics technique may be nondestructive, but the application of the technique is no less destructive than traditional excavation without using remote sensing. We would hope that, in the future, a library of absolute signatures would exist for subsurface archaeological phenomena

Figure 10. Different types of geophysical data are treated as if they were different bands of multispectral data. Using the known sample of walls and room fill as the training set, these geophysical data are then classified using a supervised classification technique.

similar to those available for many plants, minerals, and sediment types on the ground surface (e.g., ASTER Spectral Library, Johns Hopkins University Spectral Library, NASA Jet Propulsion Laboratory Spectral Library, USGS Spectral Library [Clark et al. 1993]).

4 Summary

In this chapter, we have attempted two things. First, we have argued that, for many reasons, the use of predictive modeling in cultural resource compliance, at least as it is most frequently applied, is not best practice. As with any other method, we encourage our colleagues to critically evaluate the appropriateness of predictive modeling for each particular application and not to use the method when it is not warranted. We understand the desire to reduce field time and labor costs in the resource-identification phase, but we hope that our

Figure 11. Graph showing the lack of difference between the mean data value for walls and room fill across three geophysical techniques. Thus, the potential for anyone individual technique to discriminate between these two material classes is low.

integrity as scientists and as stewards of the archaeological record supersedes the pragmatic realities of the business of compliance archaeology.

Second, we have tried to provide, through the examples presented here, a different perspective on predictive modeling in archaeology. In this framework, the present is not characterized to retrodict the past, but to predict the future and contingent state of extant resources. We believe that this framework can productively be used by cultural resource managers, even within their current constraints and compliance responsibilities, to regain their stewardship responsibilities by intelligently assessing, prioritizing, and responding to the needs of the resources they manage.

Notes

1. As well as a number of other applied disciplines, including architectural history, ethnology, history, etc.
2. While landscapes and districts do exist in the compliance world, these are actual entities as opposed to areas of probability.

Figure 12. Results of supervised classification using the Mahalanobis classification algorithm. Evaluating the classification model against the original data places the accuracy of the model at 69.6%. Rectilinear room blocks can be seen in the left portion of the image; the right portion is an area of architectural collapse.

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