Causality and Cross-Purposes in Archaeological Predictive Modeling

Thomas G. Whitley

Brockington and Associates, Inc.,

email: tomwhitley@brockington.org

Abstract

In recent years numerous archaeological approaches to predictive modeling have been presented in the literature. Most of these have taken the "inductive" perspective of applying known site locations to an analysis that estimates probable site location based on a mathematical equation and presents predictive surfaces in a GIS. Conversely, "deductive" models have also been used in which "expert systems" or site selection variables have been quantified as probability surfaces. There has been little discussion, though, of the theoretical differences between CRM and research-oriented predictive modeling and how it has influenced the state of the "science" today.

Generating more refined correlative predictive models either through the use of higher quality site location data or through more complex statistical techniques, runs counter to the implicit goals of CRM-based predictive modeling. A simple cognitive GIS approach which assumes a causal explanatory relationship creates comparable or better results (especially in homogenous areas) with no negative effects on these limited goals. Ultimately, the dichotomy between correlative and cognitive approaches is not in theoretical orientation, rather it is embodied in our understanding (or failure to understand) that correlative predictive modeling is really a tool useful only for land management in some very restricted circumstances and never for interpretive archaeology.

Introduction

Archaeological predictive models are currently being employed in numerous places and with varying degrees of success. Although they originated in the United States in the late 1970s, becoming widespread in the early 1990s (Kvamme 1995:3), they are increasingly attracting attention in European settings (e.g. Kamermans 2000, Verhagen and Berger 2001, Stančič et al. 2001, Stančič and Kvamme 1999, van Leusen 2002:Chapter 5). In this discussion I will focus on the conflict between some of the basic underlying assumptions of certain kinds of predictive models and the purposes for which they were

originally intended. Ultimately this takes the form of an absence of causality and explanatory power even in models which are becoming increasingly complex and more difficult to employ. In essence, the methods of predictive modeling often fall far short of the theoretical assumptions (cf. Ebert 2000, and Church et al. 2000).

This discussion is not intended to regurgitate the history and development of predictive modeling in archaeology (e.g. Kvamme 1995, 2001, van Leusen 2002, Warren 1990). Instead I would like to narrow the scope to address some key theoretical elements of all predictive models, whether they arose in the United States, Europe, or elsewhere. Foremost among these is the purpose (or more correctly the purposes) of predictive modeling.

Purposes and Applications of Predictive Models

What are the purposes of predictive models? Why do we use them? Who pays for their development and application? The primary use of predictive models to date is almost invariably for large scale Cultural Resource Management (CRM) applications, and they typically occur in North America. Some notable examples include the Ontario Ministry of Natural Resources (OMNR) Model (Dalla Bona 1994), the Minnesota Model (Hudak et al. 2002), and the North Carolina GIS Archaeological Predictive Model Project (NCDOT n.d.)

The corporations, state and federal agencies who paid for these models do not particularly care about the implications of predictive models on our interpretations of past human cognition and behavior. They merely want to reduce their costs to a more manageable level by controlling expensive archaeological survey. For their part this is seen as good land management practice, and there are two ways in which such cost reduction strategies are usually employed.

First, a predictive model can be used to argue for a reduced level of field effort in areas deemed to be "low potential" and a proportionally higher or, at least fixed, level of effort in other zones. For example, if we expect that some areas of a large land tract are not going to be "productive" based on a predictive model, then perhaps those areas can be field investigated with a coarse sampling strategy or even eliminated from survey altogether.

The drawback of this approach is that any site which would have been found in low potential zones should, theoretically, be more significant merely by the fact that it was not expected. Therefore, the counter-intuitive argument could be made that low potential zones are the areas which should be

more intensively scrutinized, and well understood high potential zones should have a reduced level of field survey. This is an example of the inherent conflict between *significance* and *abundance* of sites. The most significant sites are almost always those of which there are few examples.

In contrast, the second approach is more acceptable for archaeologists and preservationists, but tends to be applicable to only certain kinds of undertakings (such as new highway corridors, etc.). That approach is one of *alternatives analysis*. In this application, a predictive model is used to determine which areas are more likely to produce archaeological sites, and which are less likely to do so, but the field effort is not changed between high and low potential zones. Instead, the same level of effort is employed throughout, but where there are several different options the planners are forewarned about the specific costs which are likely to be entailed with each alternative. Therefore, they can choose the one which will probably be less costly in terms of archaeological survey. Plus, later testing and mitigation costs can be anticipated.

Now, the second primary purpose for which predictive models have been developed is that of understanding past land use or what can be called *site selection processes* (cf. Whitley 2000). It was recognized early on that predictive models provided a quantitative aspect to what was well understood as the qualitative realm of settlement pattern analysis (e.g. Allen et al. 1990). Clearly, predictive modeling is seen as a means by which we might address some of the complex issues of human/landscape interaction, typically in a GIS framework. This is precisely why it has attracted recent attention in academic settings and particularly among the landscape approaches common to European Archaeology (Harris and Lock 1995:353-355, Kamermans 2000, van Leusen 2002:Chapter 5, van Leusen et al. 2002:3-6).

The implication is that a successful predictive model has an inherent explanatory capacity and an ability to allow us to see causal relationships between sites and site selection factors. For a variety of complex reasons, however, understanding past land use from an explanatory and causal perspective is incompatible with the typical correlative applications of predictive modeling currently being employed in CRM. To explore this point further I will first move on to some other key aspects and assumptions of all predictive models.

Assumptions of all Predictive Models

Regardless of the practical application of any particular model, there are several assumptions that go hand in hand with quantitative predictive modeling. First among these is the probabilistic assumption

that the potential for any land unit to contain (or be part of) an archaeological site lies between 0 and 1 (or no chance to 100% likely). Any area which was chosen as a site, or in which a site was inadvertently created, must be scored as a 1 (a site) while any other area must be considered a probability value reflecting our *interpretation* of how likely it is that the area was chosen as a site, or that a site was inadvertently created. This means that all unsurveyed land units range in probability value between 0 and 1 (what we *think* their site value is), while all completely surveyed land units must rank as either 0 *or* 1 (what we *know* their site value is; a site or a non-site).

Using Bayesian probability terminology we can address the assumptions of what makes up those site probability estimates. Though Bayesian statistics is not invoked in all predictive models, the underlying structure of Bayesian probability *is* assumed for all of them. The first fully articulated assumption of all archaeological predictive modeling is a form of the Bayesian rule of "total probability" (cf. Pearl 2000:3). This assumption can be stated as:

> *The probability of any land unit being a site (or a portion of a site) is the sum of the probabilities of all exhaustive and mutually exclusive variables that cause a land unit to be chosen as a site or to unintentionally be made one.*

Put simply, this means that the presence of a site in any area is a factor of all possible influencing variables (intentional or unintentional). This invokes a direct causal relationship between archaeological sites and a host of possible variables; the underlying principle of all predictive models. This is further elaborated by the "conditional rule of Bayesian probability" (cf. Pearl 2000:3-4). This can be stated in archaeological terms as:

> *The probability of any land unit being a site is the sum of the probabilities of each causal variable multiplied by the conditional probability of that variable.*

Put simply again, this means that not every factor is as influential as every other factor; that they each respond to other conditions, or in effect provide an individual weight to the final probability of any land unit being part of an archaeological site. The diversity in influence of different variables allows predictive modelers to statistically assess, or make expert decisions about, what they find to be the most influential factors and build their models accordingly. This concept was described as the *Weighted Additive* type of predictive model by Kohler and Parker (1986:422-424).

When a model is complete, how do we measure its success? What do we mean when we say a predictive model is successful, and what are the requirements of all successful predictive models? How do we know that they provide some useful understanding of the relationships between human behavior and the landscape?

There are two primary and necessary ways to measure the success of any predictive model. Every successful model must have both high *accuracy* and good *precision* (described as *specificity* in van Leusen et al. 2002:9). With accuracy we mean how well the high potential zones capture known archaeological sites. With precision we mean how well the model reduces the area within which sites are expected (the high potential zones) from the entire tract to as small as possible.

A model which is highly accurate but not precise is of little use. For example, if given a tract of land measuring 1000 hectares with a known population of 100 sites, we could produce a model which accurately places all 100 sites within a designated "high potential" zone - giving an accuracy of 100 percent. However, if all 1000 hectares (or at least a high percentage of the tract) falls within the high potential zone then the model is not precise and provides no way of limiting survey or understanding land use patterns; the two purposes of predictive modeling.

A model which is very precise, but inaccurate, is likewise of little use. Given that same tract of land, we could produce a model which reduces the high potential area to a mere 100 hectares out of the 1000, but if it fails to capture any of the known archaeological sites, then we cannot assume it has any decent level of accuracy, and it provides little chance to actually reduce survey costs or give insight into land use patterns. To be successful a predictive model must be both accurate and precise.

A measure of these two distinct values combined is typically expressed as the *gain statistic* (Kvamme 1988:329), which is a function of total land area with high or high/moderate potential zones and total percentage of the modeled site type which falls within those zones. A gain statistic value ranges from 0 to 1, with 0 meaning the model is no better than random chance and 1 meaning that it is 100 % accurate and 100 % precise.

A good predictive model should achieve a gain statistic at least above 0.5, but it would be generally unlikely for a model to achieve anywhere near 0.9; since that would require quite dense settlement of nearly every suitable location in the project tract. Ebert (2000:133) argues that gain never seems to exceed 0.7 in practice, and Wansleeben and Verhart (1992:103-107) provided a method for normalizing the gain statistic with respect to the proportion of sites included in the model.

Unfortunately, the gain statistic is not infallible, nor the final word on model success. It is quite easy to produce false high gain statistic values if the site dataset is too small, biased, or unrepresentative of the aspects of settlement which were modeled. Likewise, strongly negative correlations between a few significant sites and high predictive values can be overlooked as long as the project area contains a great deal of low potential area. This suggests that much closer attention needs to be paid to how we define the sites which are of the greatest interest to us as archaeologists. The gain statistic also assumes that equal weight is placed on both accuracy and precision in determining model efficiency, but there may be situations in which one is more important than the other for modeling purposes, and the interaction between the entire range of predictive values and their expressions in the landscape could be enlightening. Van Leusen et al. (2002:9-11) provides a more detailed discussion of measuring model quality.

Theoretical Implications

So, what are the theoretical implications of the foregoing assumptions? The most obvious is that *the site* must be a valid and useful concept to explain human activity. Also, that sites are definitive and absolute in their ability to be identified, and that the characteristics used to identify sites are strictly correlative with human behavior, and not other phenomena. That correlation is assumed to mean that the most common or abundant behavior(s) are the most significant with respect to the purposes of predictive modeling, and that the success of predictive models is a factor of their ability to identify the most common site-selection behaviors.

Are these implications necessarily true, though, and what is not implied by these assumptions, but may be true? First of all, sites may not be easily distinguished by empirical evidence, and they may not be considered strictly representative of human activity (cf. Dunnell 1992). Different activities result in different kinds of sites, and different kinds of sites may have many different kinds of manifestations. Some may have easily recognizable archaeological characteristics while others may have none. Strictly speaking, significance of archaeological sites cannot be equated with abundance, and models geared toward identifying the most common elements of site selection may, in fact, overlook very significant sites in supposedly low potential zones.

The observable variables are also not always exhaustive nor mutually exclusive. Although they may have some causal influence on site placement (either intentional or inadvertent) they also have causal relationships and *auto-correlations* within and amongst each other. This is repeatedly discussed

in many examinations of archaeological predictive modeling (e.g Warren 1990, Ebert 2000, Church et al. 2000, van Leusen et al. 2002, Whitley 2000:Chapter 3).

Different causal variables for site placement may also be cognized or entirely subconscious, or somewhere in between. This is especially important to understand if one is building a model which focuses on identifying site selection *intentionality*. Similarly, weights of variables may be constant or shifting, they may change in relation to other variables, or they may be entirely random, even with respect to the same individuals making site placement decisions. This implies a dynamical aspect to site placement and an inherent rejection of determinism.

Determinism and Causal Explanation

What are the implications of determinism? Why should it matter if we hold deterministic ideas with respect to predictive models? This may be the root issue behind the so-called *inductive/deductive* dichotomy, and if we look at models from the perspective of their theoretical relationship to causal explanation, we may be able to understand the nature of the conflict.

Interestingly, archaeologists employ the terms *inductive* and *deductive* in ways that are quite limited with respect to their meaning in the realm of scientific explanation. In philosophy of science, the terms *inductive* and *deductive* refer to the difference between logical arguments based on universal laws and statistical tendencies. Deductive explanations are based on mathematically consistent and provable laws, while inductive ones are based on observing statistical trends (cf. Hempel 1965, Salmon 1971, 1998).

In archaeological predictive modeling, however, *inductive* and *deductive* do not refer to methods of explanation, rather to practical means by which probability values are calculated (e.g. Kohler and Parker 1986:422, Church 2000, Ebert 2000, Kamermans 2000, Stančič and Kvamme 1999). In the end, all predictive models are trend-based, or inductively explanatory; even so-called *deductive* ones. Instead, the distinction should be made between models as being either *correlative* or *cognitive* in nature, and the failure to recognize this is perhaps due to an unfamiliarity with the debates in the philosophy of science (cf. Salmon 1998).

Correlative models are those which use existing site data and currently measurable environmental variables to build statistical relationships which can then be generalized from previously surveyed areas to those which have not been surveyed (such as through regression analysis). These

take the form of probability surfaces based on a formula that attempts to encompass every site in the dataset (Kohler and Parker 1986:422). As such, correlative models are strictly empirical by nature and make the assumptions of determinism.

Deterministic explanation comes in several forms (cf. Hempel 1965, Salmon 1971, 1998) but in general the Bayesian rule of conditional probability, in a deterministic framework, would embrace the idea that the inaccuracies of any predictive model are the result of not having enough information. All probabilities could be identified, in principle, if we only had the ability to do so. This is distinct from environmental determinism, though, since a correlative model does not, of necessity, require *only* environmental factors, but could, theoretically, include cultural ones if they were to be currently measurable. Granted this is a simplification of correlative modeling, and some models are much more keenly aware of their theoretical and practical biases. But, in general, correlative modelers assume that additional data will always increase the accuracy or precision of their models.

Cognitive models are those which are not limited by existing archaeological data. Hypotheses of site placement are built on understanding more complex issues involved in the cognitive selection of suitable areas. Then, presumed important variables are measured and classified in a way hypothetically similar to how prehistoric populations may have done so, and probability surfaces are projected across the entire landscape. A single cognitive model may, in fact, produce many different permutations which can be tested. Once complete, the known dataset of archaeological sites is *then* compared to the projected probability zones and accuracy and precision estimates are made. Cognitive models are not necessarily deterministic, though they can be. But they do have the potential to embrace indeterminism, since they are not built from correlative evaluations.

A good way to understand the difference between deterministic and indeterministic explanation can be illustrated by this example (adapted from Mackie 1974:40-41 and Salmon 1998:145-147). Imagine three candy machines. The first is purely deterministic; if you put in a Euro, a candy bar is always ejected. No other coin or object will cause the candy bar to be released, and no candy bar will ever be inadvertently released without the insertion of a Euro. We know that the function of inserting a Euro is both *necessary* and *sufficient* to cause a candy bar to be ejected. We can therefore deductively explain the presence of a candy bar with the deterministic rule that a Euro must have been inserted.

A second machine, though, is somewhat different. With it the insertion of a Euro will always produce a candy bar, but sometimes insertion of other items will have the same effect. Thus, a Euro is a *sufficient* cause of the presence of a candy bar, but it is not the only possible (or *necessary*) cause. The

presence of a candy bar, therefore cannot be deductively explained by a rule stating a Euro must have been inserted, rather it becomes an issue of inductive probability. There is a certain likelihood that a Euro may have caused the appearance of the candy bar (which can be calculated by assessing the state of the system over a period of time or a set number of observations). The machine is still deterministic, though, because we assume that if complete information were available, we could always explain the presence of a candy bar. That complete information would include knowing every other coin or object that might cause the release of a candy bar.

A third machine differs in that inserting a Euro or other items triggers an instantaneous analysis of the spin of a quantum particle trapped in the machine. If the spin is in one direction it will result in the release of a candy bar, but in the other direction it will not. Similarly, sometimes with no insertion of any coins, the particle's spin will be measured and a candy bar will be ejected. Here, the insertion of a Euro is neither *sufficient* nor *necessary* to explain the presence of a candy bar. We do not have any explicable deterministic way of addressing the presence of a candy bar from this machine. We could assume that more information is needed, but clearly even when we have a suspected causal factor, it does not always result in the release of a candy bar (hence prediction is impossible). In order to fully understand the nature of the machine we need to address all of its constituent parts and the mechanistic effects of all possible causal factors, even if some of those may be reliant on fundamentally indeterministic variables (such as quantum mechanics or human free will).

When dealing with archaeological sites, we are faced with a similar circumstance. Correlative models assume that all variables are either present and have been measured, or that they could be if we only had the information. Ironically, this is termed *deductive chauvinism*, (Salmon 1998:142-163) and it implies that given all variables and all parameters, all probabilities could be determined and prediction would be 100 % accurate and 100 % precise. Correlative modelers, though, do not deny the influence of human behavior and cognition in making site placement decisions. Yet, the acceptance of this perspective assumes that all human cognition is a deterministic system and implies an absence of free will (Salmon 1998:28).

Thus, correlative models are only capable of identifying *necessary* factors to produce archaeological sites, and only those which are both frequently necessary and commonly observable (even today). Correlative models are not capable of providing insight into the *sufficiency* of site placement factors to explain the presence of a site, nor the mechanisms of how site selection processes are determined. This is in direct opposition to the second purpose of predictive modeling.

Cognitive models assume, at least, the limitations of the second machine, but allow the possibility of the third (where some aspects of site placement decisions may be, in principle, inexplicable). This assumes that some aspects of human systems are dynamical. Dynamical systems do not imply the absence of predictability for all aspects of the system, merely that they range on a scale between entirely predictable to entirely unpredictable. A correlative analysis, though, is by its very nature limited to only those aspects which are highly predictable, and cognitive explanation must focus on causal-mechanistic issues instead (cf. Salmon 1971, 1998). This requires the adoption of explanatory frameworks which deal with indeterministic phenomena (such as Salmon's causal-relevance model of explanation - Salmon 1998:345).

Correlative Models - Problems

So, this brings us to the point at which we might ask; why do so many applications of predictive modeling tend to be strictly correlative? The first reason is probably one of convenience. It is relatively easy to take an existing dataset of archaeological sites and environmental values, perform some standard statistical analyses (such as multiple nonlinear regression), and produce a handy formula. The formula can then be turned around and applied in a GIS and a fairly accurate and precise model *sometimes* results. Usually, though, the results are not sufficient and additional data has to be generated (or the dataset has to be cleaned up at great expense). The correlations, though, can be used without ever thinking about causality.

Second, correlative models are often presumed to have some level of objectivity. There is something almost mystical about statistics for the typical audience (and archaeologists are no exception) that goes beyond mere logical justification. It is almost as if the mathematics provides an impartial verification to the model for no apparent reason. Since the math is typically beyond the immediate grasp of social scientists, it is assumed that the methods need no questioning.

With respect to predictive models, I think it is often assumed that more complex statistics means greater objectivity. Such methods have their uses, but the old maxim of "bad data in, bad data out" applies regardless of the methods of mathematical manipulation in between. This was illustrated quite succinctly by Cowgill's warnings against placing too much emphasis on mathematical models at the expense of theoretical profundity (Cowgill 1986:387).

This brings up another point about peer acceptance. Although I do not believe that predictive modelers intentionally try to deceive the target audience, they do tend to, perhaps inadvertently, confuse

their audience with complex ways of saying simple things. This applies specifically to glossing over data inadequacies by expounding on the details of complex mathematics where it may not be needed. Mathematically unsophisticated audiences (as most archaeologists are, and will readily admit) will tend to accept the generalizations, or results of the model without question, because they cannot decipher the math and spot the inadequacies in the data or the theoretical shortcomings. This suggests that more effort needs to be placed in training archaeologists to understand the complexities of predictive modeling and statistics in general.

Another issue of concern is the lack of experience, on the part of archaeologists (especially North American ones) with the debate regarding these very ideas in other disciplines. The nature of human decision-making has been a topic in many areas of research including; psychology (e.g. Shanks et al. 1996), computer science (e.g. Oliver and Smith 1990), and philosophy (e.g. Hume 1739, Hitchcock 1996). Likewise the basis of spatial patterning, including the specific interest in site selection processes, has long been the domain of human geography (e.g. Downs and Stea 1977, Tobler 1993), economics (e.g. Weber 1929), sociology (e.g. Christaller 1935), and even linguistics (e.g. Levinson 1992). The precise nature of explanation, causality, and probability, has been addressed by numerous researchers in the philosophy of science (e.g. Popper 1959, Nagel 1961, Hempel 1965, Salmon 1998), mathematics (e.g. Pearl 2000), statistics (e.g. Cox 1992), and computer science (e.g. Besnard and Hanks 1995), specifically, but peripherally in many other disciplines. Archaeologists, typically, are unaware of, or ignore, these debates and tend to wade through theoretical battlegrounds fought over many times before.

So, then what is lacking from most correlative predictive modeling attempts? The most glaringly absent constituent is an explication of causality. In other words; what *causes* the correlations observed in the archaeological record? Correlation is assumed to be the ultimate important observation and causality is unnecessary. Another missing item is a discussion of the cognitive basis of spatial decision-making. Though it is often implied that specific variables were chosen for their suitability, the mechanism of making that choice is never explained. The incorporation of sociocultural variables is typically also excluded from correlative models, not on theoretical grounds, but out of a practical failure to identify them in spatially measurable terms.

From the other perspective, what is lacking in the dataset to allow completion of successful correlative models? The primary missing element would be sufficient existing data. All correlative models require statistically significant samples to produce results. Obviously, the larger the sample the more accurate the results will be (at least that is the expectation). Sufficiently large samples of archaeological sites typically range in the thousands. Anything less produces poor or inconclusive results. Similarly,

sufficient numbers of currently measurable variables are required. Since these are almost invariably environmental in nature, there are strict limitations on what the correlations can produce, and correlative models are glaringly environmentally deterministic in practice.

How do correlative predictive modelers attempt to compensate for these problems? I've already discussed the effort put out to dedicate more resources to "cleaning up" the database and the drive for more complex statistics to provide "better" results. But the most common methods of improving model results is to expand the area of coverage to include more data and/or to combine temporal periods into a larger set of useable sites. This becomes dangerous territory, in which our assumptions about the appropriateness of the data is often very questionable.

Lowest Common Denominator Variables

But, ultimately, why is it that correlative models seem to work, at least on occasion? The main reason a correlative model does achieve success is based on what might be called the *lowest common denominators* for site selection. These are several variables that correlate highly with archaeological sites simply because they are limiting factors on all human behavior; primarily slope and distance to water. Invariably, every successful correlative predictive model uses slope and distance to water, in some form, as key factors in developing correlative formulas, and they almost all occur in semi-arid or highly dissected areas.

In fact, many models extend the functionality of correlative statistical analyses by splitting simple variables, such as cost distance to water, into a series of more complex variables, such as exponential cost distance to water, distance to certain types of streams and wetlands, lake edges, prehistoric water features, springs and seeps.

Likewise, slope can be reclassified as many different kinds of variables or ones related to topographic situations, such as hilltops, hillsides, terraces, etc. Splitting variables in this manner tends to build an additional layer of presumed causality through the application of our own classification systems, which we already accept as meaningful. Causality, though, has not been addressed in such correlative models. It is assumed that because of the correlation between known archaeological sites and particular variables, that they were actively used as suitability indicators for sites.

In reality, though, I argue that most environmentally correlative variables (especially slope and distance to water) act primarily as auto-correlations and were probably rarely cognized as variables of

choice. In that sense, they may be considered necessary factors for site selection, but their importance is auto-correlative with all human activity not causally conditioned by it. Thus, they cannot be seen as sufficient cause for site placement.

Other factors, such as cultural boundaries, seasonal resource acquisition, temporal-spatial limitations, trade, and warfare, may have played a much greater cognitive role in determining site locations, but cannot be framed with a correlative analysis because our classification of many different kinds of human behaviors into a single category of "site" is inadequate and important sociocultural variables are not easily quantified.

Cross-Purposes in Correlative Models

So the upshot of this long-winded discussion is; how do correlative models fail to meet the goals of predictive modeling? Several things would be required for successful application of a correlative model. First, the project would need to be located in a region that is sufficiently arid and dissected enough that slope and distance to water are meaningful limiting factors, or suitable alternative limiting factors can be identified. Second, it would require a large dataset of accurate and well described archaeological sites from all temporal periods of similar function, and which do not cross multiple cultural boundaries. Third, it would require an additional dataset which could be used to test the accuracy and precision of the model, or alternately a large enough initial dataset of sites that a "jackknife" sample can be held back and used for testing. Fourth, it would require a well developed environmental dataset from which measurable variables can be extracted.

The problem is that there are few locations within which all of these criteria are met. Almost invariably the project areas do not have such ideal conditions or large and accurate datasets, and those conditions can only be met by vast amounts of data gathering at a very high cost. It therefore becomes too costly or even impossible to do a correlative predictive model in many cases, and ultimately the resulting model does not provide better insight into site placement processes than intuition.

As the cost of doing the predictive model increases, the reasons it was initiated become increasingly irrelevant from a land management perspective. Since slope and distance to water are the primary important limiting factors in most correlative models, they contribute the greatest percentage to a model's success. Any variables beyond the primary ones add proportionally less to the gain statistic and therefore are of smaller and smaller consequence. Conversely, though, the means of extracting the influence of those additional variables adds increasingly to the cost of the model.

This sets up a losing battle where correlative predictive models have very limited applicability in terms of region as well as purpose, yet are often prohibitively expensive. Simple limiting factor models (as historically implemented with intuitive ideas about slope and distance to water) applied in a GIS, can produce gain statistics well within the range of expectations at a fraction of the cost (e.g. Whitley 2002a). Similarly, cognitive models can be created and applied in homogenous areas with small useable datasets and better results, also at much less cost (e.g. Whitley 1999, 2001).

Ultimately, this sets up the question of; how should we create and apply quantitative archaeological predictive models? What purposes are appropriate, and who should pursue them? I argue that we need to recognize that correlative predictive models (regardless of their methods and area of application) have severe theoretical and explanatory limitations. They can be used in some situations to give insight into land management activities; specifically alternatives analysis. But they should not be mistaken as tools of interpretative archaeology. Likewise, it would be inappropriate to consider correlative models as a means to protect significant archaeological sites or high potential areas, as they would be limited to only abundant kinds of sites and a few, probably auto-correlative, environmental factors.

We should also consider that cognitive models are distinctly different and provide a far superior means of addressing site selection processes in a causal and explanatory manner, but should not be referred to as predictive in nature, since we can assume that human cognition is dynamical and indeterministic. Since they can incorporate both suitability and likelihood of land use, based on combining cost-benefit classification and perception surfaces (Whitley 2003:10), cognitive models are truly *probabilistic* rather than *possibilistic* (cf. van Leusen et al. 2002:6-7).

The use of complex statistical analyses may be appropriate for many analytical models, but is in no way limited to strictly correlative types of investigations. Bayesian causal networks, for instance, can be elaborated and both prior and posterior probabilities filled-in for variables that go well beyond the typical environmental parameters and their permutations. This is especially important for recognizing causality and intentionality. Using spatial proxies to simulate cognitive site selection variables (cf. Whitley 2002b) is a means by which this can begin to be addressed. Without causality, predictive modeling may be a useful land management tool in some severely limited settings and with nearly unlimited funding, but it provides no explanatory power and forces a deterministic and facile understanding of human cognition.

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