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Modeling Human Locational Behavior

in Montane Southeast Idaho

by

Maegan J. Tracy

A thesis

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To the Graduate Faculty:

The members of the committee appointed to examine the thesis of MAEGAN J TRACY find it satisfactory and recommend that it be accepted.

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Abstract

In this research, three models were developed to predict the potential spatial distribution of archaeological sites for the prehistoric period in the mountainous Minidoka Ranger District of the Sawtooth National Forest in southern Idaho and northern Utah. A Geographic Information System (GIS) was used to assemble and process archaeological data and parameters of the geographic and ecological environment, and statistical analyses were used to build the models. Predictor variables were statistically evaluated to discover correlates with human locational behavior and compared against a control dataset. Three methods, logistic regression, regression tree, and random forest were used to create the final models and assessed for efficacy using k-fold cross-validation and gain statistics. Although the relationships observed could result from biases in archaeological data and predictors, the models suggest a strong correlation between environment and the location of prehistoric sites.

I. Introduction

Modeling human behavior is fundamental to archaeological interpretation. The development of modeling in archaeology can be traced to the theoretical framework established by processual archaeologists in the 1960's and 1970's, who were the first to apply the scientific method in answering new questions about past humans and human societies (Verhagen and Whitley, 2011). The past cannot be known in its complex entirety, but it can be understood, extrapolated, and explained through building simplified representations of reality (Lock, 2003). Landscape archaeology looks at the ways that humans consciously or unconsciously shape the land, organize space, and manifest symbolic content and power both *in* and *through* landscape(Lock, 2003). This interest in spatiality has become one of the primary concerns of modern archaeology, and vast improvements over the past decades in methodological tools have contributed to the development of sub-disciplines such as landscape archaeology, spatial statistics (García et al., 2012), and the kind of Geographical Information Science (GIS) –based modeling that is presented in this thesis (Killick, 2015). Research that examines variation among both past and present-day hunter-gatherers is important to anthropology and archaeology as a whole, in order to explore diversity among human cultures and behaviors and attempt to investigate possible sources of that variability (Ames, 2009).

In archaeological practice, a related question has become increasingly important in Cultural Resource Management (CRM): how to best identify areas that have a high potential to yield archaeological sites. A better understanding of human locational behavior can help to inform and improve strategies for managing cultural resources. The Sublett Division of the Sawtooth National Forest in southern Idaho is an area that remains largely understudied in CRM and in archaeological research more generally, and about whose prehistory relatively little is known.

The Sublett represents an ideal area in which to develop predictive and spatial models that have the potential to advance the theory of archaeology as well as its local practice.

This research will address these questions by generating models that examine human exploitation of the area's landscape by compiling a GIS system of known prehistoric sites and analyzing their distribution to determine the influence of relevant environmental and geographic parameters. These models may be further used to determine archaeological resource potential, specifically focused on hunter-gatherers. Output consists of map visualizations representing quantified archaeological potential calculated from a statistical analysis of input parameters. This predictive model of archaeological resource potential will be suitable for use by both government agencies and by local tribal organizations - the Shoshone and Bannock peoples in particular - in the future managing of cultural resources (Carleton et al., 2012).

Statement of Purpose

The central goals of this project are to contribute to the understanding of hunter-gather ecology and create a useful management tool that can be utilized in decision-making by land management agencies tasked with CRM. A second practical goal is to assess the potential research value of creating predictive models for site location, specifically in a semi-arid alpine environment. The advantages of utilizing predictive modeling in CRM are in improving cost-effectiveness and expediting planning by entities involved in land management. Federal and state agencies mandate the identification and preservation of cultural resources, but a complete inventory of past human activity on the land remains, for financial and practical reasons, out of reach. Work of this kind has the potential to be used early in project planning to minimize disturbance of cultural resources (Kohler and Parker, 1986).

Previous Research

The Sawtooth National Forest manages the Minidoka Ranger District and its five subdivisions, the Albion, Black Pine, Cassia, Sublett, and Raft River. Situated at the edge of the Great Basin catchment and physiographic province, the forest is within an area of known prehistoric interaction between the peoples of the Great Basin and Columbia Plateau cultural areas. As part of its cultural resource management mandates, the Forest Service has completed a number of pedestrian surveys in the area to determine the presence and explore the nature of cultural resources. These surveys were typically opportunistic in nature; they discovered a number of diagnostic artifacts on the surface, but little subsurface testing was done. Limited small-scale systematic survey and testing was carried out as a part of the Idaho State University Field School in the Sublett Division during the summer of 2013. The only sites to be tested at that time were the Sublett Troughs and Summit Spring sites, where artifacts were uncovered up to a depth of two meters (Tracy et al., 2015). Prior to this study it was believed that there was little potential for deposition and thus little possibility for the existence of intact archaeological sites.

Data acquired during the 2013 Field School suggests that instead, there is substantial potential for intact subsurface elements and demonstrated that the area is in critical need of further research. Large scale reconnaissance survey requires a considerable and costly investment of time and resources, and predictive modeling can help focus efforts strategically to increase the likelihood of site discovery. Such research also has the potential to uncover previously unknown sites and enhance our understanding of human interaction with the environment, specifically by prehistoric hunter-gatherers. Previous surveys in the Sublett leave much to be accomplished in investigating these questions, especially through research on land-use patterning.

Assumptions and Limitations

Criticisms of the use of predictive modeling in archaeology vary, but tend to focus on two main issues: a perceived lack of either theoretical rigor in inductive approaches or scientific rigor in deductive approaches. These criticisms in some ways reflect ongoing debates among archaeologists about the evolution of archaeological theory, practice, and the nature of archaeology as a science. This research does not presuppose the ability to explain whole cultures across enormous time depths solely through the application of statistical analysis; the purpose instead is to use the analysis to develop a data-driven understanding of the broad patterns of human activity on a regional level. Ethnographic research on existing hunter-gatherers and contextual data of various kinds will be used to enrich this understanding. Inductive modeling performs well at describing variation, but developing ways to determine the underlying causes of that variation is a much more complex task. As a result, it is still an open question of how to best integrate the study of underlying processes in Human Behavioral Ecology (HBE) research, especially in the context of transmitted culture. Attempts to include discussions of causality can sometimes muddle an otherwise empirically productive model (Nettle et al., 2013). In part the tendency of archaeologists to engage in spatial analysis that utilizes environmental parameters rather than social ones is a result of the ability to easily quantify and digitize the environment, two qualities that social variables often lack (Gaffney and van Leusen, 1995).

Concentrating on environmental parameters as inputs in site selection modeling relies on a number of assumptions. First and foremost is one that arose from Julian Steward's data-driven ethnological work in the Great Basin that established an intellectual tradition which strongly influenced much of the archaeological work done in the region. Responsible for basic anthropological concepts such as "hunter-gatherer" and cultural adaptation, Steward's early influence cannot be overstated in research of this kind (Clemmer et al., 1986). This assumption is that human behavior evolves in relation to ecological conditions (Nettle et al., 2013). A complementary intellectual tradition in anthropological research in this area is that of Human Behavioral Ecology (HBE). This deductive theoretical approach utilizes rational choice theory as its basic framework and continues to influence archaeological work to this day in the Great Basin (e.g. Morgan and Bettinger, 2012). Human ecology assumes that humans tend to minimize the time and effort required to access resources, and that economic transactions with the environment drive decision making. Through these assumptions, the distribution of environmental features can be used to predict the location of human settlements (Kohler and Parker, 1986, p.400). There are likely to have been significant effects on locational decision making related to changes in climate and landscape over time that cannot be adequately known, especially within large spatial extents and time scales that span many thousands of years of human occupation. A significant limitation of the research presented here is that it relies primarily on observing site patterns as they relate to the environment in its current form, and does not include paleoclimatic data.

Predictive models have been applied to archaeological research questions since the late 1960's, and although approaches and methodologies in constructing models vary, archaeological spatial analysis follows the same basic principle. Modeling employs at its core a proven methodology, used in many sciences, of pattern recognition and classification of features. The theoretical approach used in this study is that human ecology is a natural as well as social science, and it can be conducted using the same conceptual basis and analytical and methodological approaches that apply to non-human systems (Burnside et al., 2012). Techniques adopted from other natural sciences such as species distribution modeling could be profitably used in addressing anthropological research questions (Franklin et al., 2015).

Human-environment interactions tend to exhibit enormous variation over spatial and temporal scales, but it is possible to document patterns in those interactions and to evaluate hypotheses about the underlying processes of adaptation determining them. A macroecological approach will be used here, as proposed by Burnside et al. (2012), who used comparative statistics to identify patterns of variation and test for causal relationships in human-environment systems. The small-scale ways in which humans adapt to and transform the landscapes and environments around them can in this way be linked with large-scale, emergent patterns and their underlying processes.

Significance

The guiding principles of archaeological modeling are that human locational behavior is related to environmental conditions, and that within a particular time period or geographic area, patterns of site selection can be identified. Elucidating such patterns can result in identifying previously unknown locations of similar human activities. A predictive model attempts to establish a statistical relationship between a set of environmental parameters and known site locations in order to create a model that can be applied to predict sites in previously unsurveyed areas. These models typically use a combination of geospatial and cultural features of the study area and subject (Balla et al., 2014a).

As computing power increased beginning in the 1980's, predictive modeling techniques became a major area of interest in North American archaeology. One of the primary concerns of this type of research is rooted in an awareness of the CRM obligations of various state and federal agencies that must manage large land areas based on limited survey (Lock, 2003). The potential advantages of utilizing predictive modeling in CRM lie in improving cost-effectiveness and planning. Federal and state laws mandate the identification and preservation cultural resources, but a complete inventory of human activity on the land remains impractical. Use of predictive models early in project planning makes it possible to avoid the destruction or disturbance cultural resources entirely (Kohler and Parker, 1986).

Exploring different kinds of land use is especially important in the Great Basin as human population densities and distributions shifted due to pressures of Holocene climate change. The impact of Middle Holocene warming may have depressed population density, especially in lowland areas, driving people to inhabit more mountainous areas (Antevs, 1948). It is now known that the Middle Holocene was not homogeneously hot and dry and was instead marked by significant episodes of increased and decreased effective precipitation (Louderback et al., 2011). This fluctuation may have favored selective pressure for behavioral plasticity.

II. Review of Literature

The modeling techniques used in this study are primarily based on an inductive and inferential approach. Interactions of site location and environmental parameters are analyzed using statistical procedures to produce a set of independent variables that are demonstrably correlated with the distribution of observed sites (Kohler and Parker, 1986). Various physical features in the landscape may be used as stand-ins or proxies for more abstract cultural parameters, since human systems are known to respond to environmental pressures in nuanced ways. The prehistoric Northern Great Basin shows notable consistency in human ecological patterns throughout its time depth of habitation in the region. Because geographic patterns of diversity of human indigenous groups parallel similar patterns of diversity in plant, animal and microbial species (Burnside et al., 2012), a regional boundary can be used to constrain the study area.

Subsistence strategies among hunter-gatherers in North American prehistory have been broadly grouped into three periods: the Prearchaic, Archaic, and Prehistoric. Early periods of human occupation in North America are largely known from associated projectile point typologies, and as late as the 1970's and 1980's the cultural chronology of the prehistoric North American Desert West "consisted of little more than changing projectile point forms" (Thomas and Bettinger, 1976, p.280). The known 6,600 year known duration of the Western Stemmed Point Tradition throughout a period of substantial environmental and climatic variability provides support for hypotheses of low population and high residential mobility.

Consistency in the general pattern of archaeological remains in the Northern Great Basin suggests that Prearchaic foraging strategies were resilient and well-adapted to high variability in climate and available resources. As basin wetlands disappeared in the latter part of the Early

Holocene, travel time between wetland patches would have increased, making alpine and subalpine ecotones more desirable for habitation. Introduction of intensive seed grinding appeared in the Middle Holocene and may represent the emergence of a more rigid division of labor by gender during the transition from Prearchaic to Archaic subsistence patterns (Elston and Zeanah, 2002). Some authors, e.g. Zeanah (2004) have proposed that shifts in diet breadth are unlikely to generate gender-related changes in foraging strategy and that residential bases are instead sited in order to minimize conflicts between men's and women's interests in provisioning. A general pattern of low population and high mobility throughout human prehistory in the Northern Great Basin is also supported by fundamental concepts of ecology such as the home range, and by the low linguistic diversity evident in the contact-period Great Basin (Burnside et al., 2012).

These characterizations are not meant to imply that the peoples who inhabited the Great Basin prior to the arrival of Europeans were nothing more than simple hunter-gatherers eking out a marginal living, a point debated at length by generations of scholars since Steward (see Clemmer et al., 1986). Recent anthropological research into foraging goals of Great Basin peoples has recognized greater variability in regional diet breadth and mobility patterns (Morgan and Bettinger, 2012). Research in the past few decades in the Columbia Plateau cultural area has also expanded knowledge of hunter-gatherer cultural diversity and evolutionary processes (Prentiss et al., 2006).

Study Area

The geographical boundary for this study is the Minidoka Ranger District of the Sawtooth National Forest, areas of mountain ranges in Southeast Idaho and Northern Utah which include many previously unsurveyed areas. The Sublett Mountains, of particular interest for future research for both the Forest Service and ISU Field School activities, stretch approximately 55 miles (89 km) longitudinally across Southeastern Idaho and cover an area of approximately 886 mi^2 (2295 km^2).

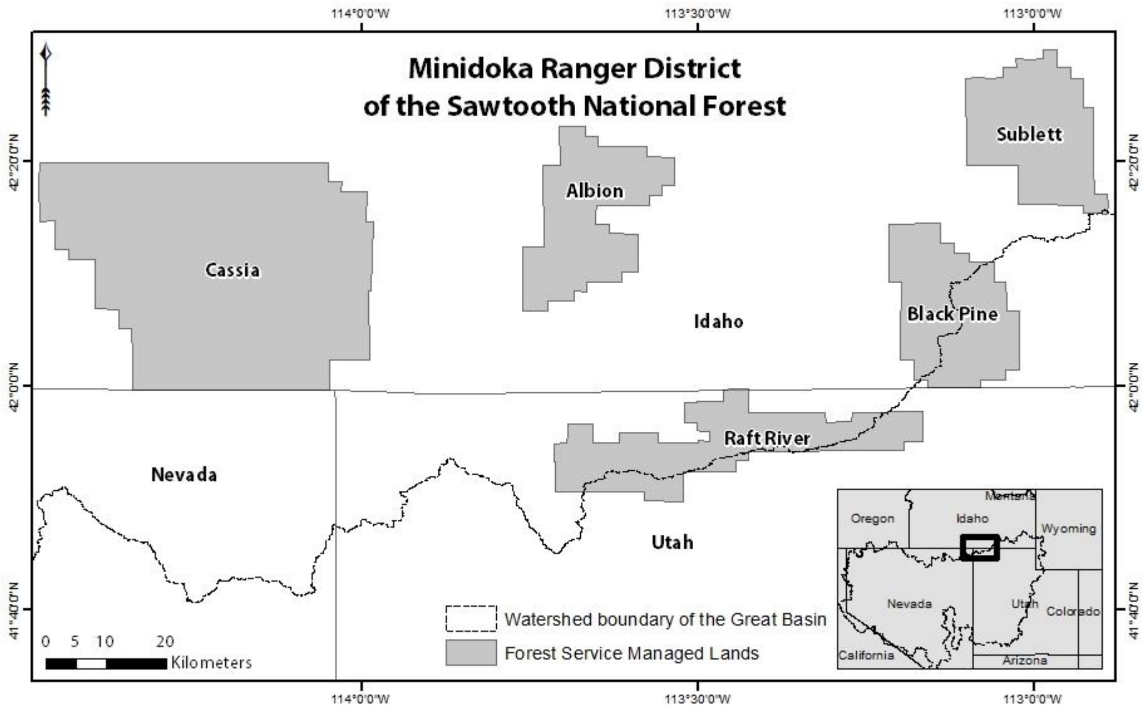


FIGURE 1: STUDY AREA

The geographic setting of the Minidoka is located on the edge of the northeastern Great Basin and is a part of the Basin and Range Province, bordered by the Snake River Plain on the north and the Bonneville Basin in the south. The topography is rugged, with lots of elevation change among relatively low peaks, the highest of which is 10321 ft (3143 m). The Sublett division is characterized by comparatively lower peaks, the highest at 7492 ft (2284 m). The modern plant community varies between sagebrush steppe, wetland meadows with herbaceous shrubs, montane shrub, and some areas heavily treed with aspen and douglas fir. The Minidoka is situated culturally in a boundary area between three broadly-defined cultural areas in North America; the Great Basin, Columbia Plateau, and High Plains. The peripheral nature of this area suggests that it may have been inhabited over time by peoples associated with one or more of these cultural areas, although it appears to have regularly been included in a broader pattern of north-south movement within the eastern Great Basin, paralleling the orientation of mountain ranges and valley basins (Jones et al., 2003).

Vegetation of the Great Basin is predominantly a desert community and mountain biomes are home to primarily xerophytic plants. Most rivers and streams are ephemeral and run seasonally, disappearing into the playa bottoms in lower elevations with no outlet to the sea. Common plants are shadscale (Atriplex confertifolia), saltgrass (Districhlis stricta), greasewood (Sarcobatus sp.), rabbitbrush (Chrysothamnus sp.), sagebrush (Artemesia sp.), Mormon tea (Ephedra nevadensis), and grasses. Singleleaf piñon (Pinus monophylla), piñon pine (Pinus edulis) and western juniper (Juniperus osteosperma) co-occur in the northern portion of the province in mountain ranges and along the Snake River (Kelly, 1997).

As of the Younger Dryas, a vast majority of Pleistocene large mammals were regionally extinct, and modern large mammals already characterized the typical faunal inhabitants of the region (Goebel et al., 2011). These fauna appear consistently in archaeological evidence of prehistoric human subsistence. The modern large mammal community consists primarily of artiodactyls such as Pronghorn antelope (Antilocapra americana), desert bighorn sheep (Ovis canadensis), mule deer (Odocoileus hemionus), elk (Cervus canadensis), and moose (Alces alces). Bison (Bison bison) were endemic to the region in prehistoric times although their modern range is artificially limited. Jackrabbits (Lepus californicus) and other small mammals such as Townsend's ground squirrel (Spermophilus townsendii) are plentiful subsistence resources. A wide variety of tubers, roots, shoots, corms, berries, leaves, fish, insects, and fowl are also known to have been consumed in prehistory (Kelly, 1997; Smith, 1988; Thomas and Bettinger, 1976).

Significant occupation in this area began in the Late Pleistocene/ Early Holocene, coinciding with the late-regressive phase of Lake Bonneville and other pluvial lakes (Oviatt et al., 2003). The paleoecological record of the Bonneville basin shows evidence of episodic changes, suggesting that modern plant and animal communities are subject to a recurring pattern of environmental change as well as longer trajectories of species change (Madsen et al., 2001). This evidence supports the use of a modeling approach that relies on environmental parameters, since smaller-scale and local changes would be masked by the longer-term developments included within this broader pattern. Some sites in the Sublett range are known to reflect the hunting and gathering activities of the Shoshone-Bannock peoples who still inhabit the area (Mart, n.d.). The range was also used as a travel corridor in recent prehistoric and historic times between the Goose Creek area and the Snake River and Fort Hall winter camps (Mart, n.d.).

Archaeology of the Great Basin

Prehistoric cultures of this study area have typically been defined almost entirely in terms of the lithic technologies associated with recorded sites due to the lack of preservation of diagnostic artifacts other than projectile points. While these assemblages provide much useful information (Beck and Jones, 1997), other research has been conducted to include a more holistic understanding of prehistoric lifeways including settlement and mobility, local adaptations, and subsistence practices beyond big game hunting (Elston and Zeanah, 2002; Smith, 1988; Stirn, 2014; Thomas and Bettinger, 1976).

Diet-breadth indices derived from faunal, floral, and tool assemblages recovered from sites in the Bonneville and Little Boulder basins in the Great Basin suggest that patterns in the archaeological record in this area reflected climatically driven variability in foraging efficiency and diet breadth (Kent, 1999). Paleoindians employed strategies featuring a highly mobile settlement pattern consisting of short-term redundant occupations of sites and long-distance residential moves of up to 400 km. Subsistence pursuits focused largely on artiodactyls, leoprids, birds, insects, fish, supplemented by some plant foods. More intensive utilization of plant resources occurred after the Younger Dryas (Goebel et al., 2011).

Many archaeological investigations in the area have demonstrated that both the cultural remains and mobility patterns of Prearchaic peoples differed from those of later Holocene peoples, due to the changing landscape and biota in the Pleistocene-Holocene transitional phase. The lower-elevation subalpine steppe environment of the Sublett during the Early Holocene would have sustained a rich community of fish, waterfowl, and mammals that occurred at lower elevations than at present (Elston and Zeanah, 2002) in turn supporting a flourishing population of Great Basin hunter-gatherers. The Middle Holocene marked an increase in diet breadth, although fluctuations in resource abundance would have demanded that both Prearchaic and Archaic period foragers make frequent adjustments in resource procurement strategies from seed harvesting to big-game hunting on a regular basis. This interpretation is supported by the persistence of some Prearchaic projectile point types into the Middle Holocene epoch (Simms, 1988).

A behavioral ecological model put forth by Elston and Zeanah (2002, p.121) suggests that the archaeological record of Prearchaic sites in the Great basin is biased in favor of sites “positioned primarily to access women’s resources, but bearing a technology reflecting men’s subsistence and mobility strategies.” The authors propose that a more varied representation of different gendered resource-gathering could be discovered in valley piedmonts and mountain passes, instead of the valley-bottom wetland settings where a majority of Prearchaic sites have been found to date. The Sublett is well suited to this type of investigation due to its topography and location.

As outlined above, more recent archaeological research in the Great Basin has embraced principles of human ecology and applications of evolutionary theory in analysis of site distribution and interpretation of material remains. For example, Byers and Broughton (2004) tested prey body size and ranking as measures of foraging efficiency and diet breadth to examine how Northern Great Basin prehistoric peoples may have responded to climate-driven changes in artiodactyl densities. Other recent research has made a substantial contribution by employing niche-construction theory to investigate how socio-ecological conditions may have structured past behaviors of Western Great Basin hunter-gatherers (Broughton et al., 2010).

Ethnohistorical Approaches to Understanding the Prehistoric Great Basin

The development of archaeological research in the Great Basin has its roots in the processual and culture-historical theoretical framework established by theorists such as V. Gordon Childe, who emphasized the adaptive capacity of material culture. Julian Steward's cultural ecology proposed that historical trajectories of cultural development resulted in technologies available to exploit the resources of varied environments, and social organizations that could be modified in response to seasonally changing conditions. It was argued that the Great Basin Shoshonean (Numic) "culture core" was a result of the patchy and unpredictable productivity of local biota, and consisted of mostly simple hunting technology but sophisticated plant processing technologies. The culture core, which Steward defined as the cultural elements most closely related to subsistence, was comprised of small, mobile family bands that practiced a pattern of aggregation and dispersal based on the varying seasonal availability of key resources. These groups merged into larger communities subsisting on stored piñon nut in the winter and dispersed during the remainder of the year into small patrilineal bands to hunt and gather a broad spectrum of spatially less-concentrated seasonal resources (Steward, 1938).

In “Basin-Plateau Aboriginal Sociopolitical Groups,” Steward defined the lifeways of the Shoshone, people who still inhabit the region today, as being organized based on a seasonal round of transhumance. The seasonal round was structured on ecological relationships that limited population size, shaped mobility patterns, and helped determine the distribution of local groups (Steward, 1938, p.230). People were dependent upon a subsistence pattern in which they exploited contiguous but dissimilar microenvironments throughout the year. This pattern relied on movement between ripening plant food resources such as piñon nuts and other hard-shelled seeds from herbaceous plants, supplemented by hunting and fishing. Subsistence-settlement networks were organized around seasonal variation in availability of these foods. This demographic pattern centered about a semi-permanent winter village encampment, often located on the ecotone between the sagebrush flats and the alpine piñon-juniper biome. Villages were argued by Steward to be sited according to "accessibility to stored seeds, especially pine nuts, water, sufficient wood for house building and fuel, and absence of extremely low winter temperatures" (Steward, 1938, p.232). This explanation of subsistence and settlement pattern is centered on a patrilineal organizational structure, due to the key importance of hunting relatively small, non-migratory game (especially deer), and the consequent importance of intimate familiarity – presumably by men – with the territory.

In a 1973 study using rudimentary computer-based predictive analysis, David Hurst Thomas used a classification of artifact assemblages derived from Steward’s ethnographic work (i.e. those used for butchering, hunting, plant procurement, and habitation) in the Reese River Valley in central Nevada. It was found that over 75% of all predicted artifact assemblage frequencies in the valley were verified by the random sampling of archaeological remains. This early model of locational decisions was applied to a prehistoric Shoshonean context and defined several environmental variables believed to be important to decision-making regarding site selection, including considerations of slope, distance to water sources, landform (specifically ridges and saddles), and proximity to piñon pine ecotones. This subsistence-settlement pattern correlated well with the ethnographic description of the Shoshonean seasonal round (Thomas, 1973). Further research in the Sublett would benefit from an attempt to characterize artifact assemblages at known sites, in order to better understand the seasonality of site distribution in the area and make inferences about the patterns of subsistence and settlement at work in the area.

A notable gap in this understanding of prehistoric peoples is the lack of inclusion of the complex influences of culture in driving human decision-making that can override more basic concerns of subsistence and environmental context. One example are the native cultures of the American Southwest and the Great Basin who established habitation sites on cliff walls with no direct access to either food or water. This was a response to the political rather than natural environment, i.e. to endemic warfare. As research into human lifeways in the Great Basin evolved in the 1980's, many archaeologists used Binford's forager-collector continuum (1980) to understand how environment affected foraging strategies and responses. Binford's model proposed that sociocultural complexity in the region was based mainly on richness of environment, dividing peoples broadly into foragers, small groups who moved frequently between resource areas, and collectors, larger and more sedentary groups who stored seasonally available resources. Criticisms of this approach focused on the reductive explanations that functionally linked environment and technology with behavior. Responses to these critiques involved in many cases the adoption of optimal foraging theory, which made use of cost-benefit models from borrowed from ecology and economics (Morgan and Bettinger, 2012).

A more contemporary study of the foraging behavior of Great Basin peoples found that their practices demonstrated resilience and persistence, common themes in the culture history of the

Great Basin. Because many of the material remains left behind from plant foraging practices are not preserved in the archaeological record, many sites in the Great Basin may have been improperly classified as hunting sites. Couture et al. (1986) suggest that the pattern of prehistoric foraging activity included in some areas the utilization of plant resources as a primary focus of activity.

Beginning in the 1990's, Great Basin archaeology moved away from culture-historical analysis but continued to employ an evolutionary ecological approach. It soon became apparent that analysis of macroregional patterns can contribute to a better understanding of spatiotemporal patterns in behavior (Morgan and Bettinger, 2012). Processes of population growth, emigration, and cultural competition were shown to be interrelated with changing physical and social environments (Kelly, 1997). Current knowledge of adaptations in the Great Basin is informed by a fundamental ecological dialectic, according to which behavior is seen to be driven primarily by environment, with cultural transmission "guiding the adoption, persistence, and demise of various behaviors" (Morgan and Bettinger, 2012, p.196). Climatic variation may have altered resource abundance and diet breadth, and human population increases may have then led to expansion into new areas or to the intensification of different resources. Traditional modes of cultural transmission likely defined which behaviors and technologies persisted in light of both their efficiency and their relationship to existing or evolving social norms (Morgan and Bettinger, 2012).

Modeling in Archaeology

Within the archaeological community the primary criticism of predictive modelling has been that it relies on a functionalist interpretation and is guilty of a form of environmental determinism (Gaffney and van Leusen, 1995). When GIS began to be used in addressing archaeological questions, its harshest critics referred to modeling with environmental parameters as an “unacceptably reductionist version of complex social decision making” (Lock and Stancic, 1995, p.170) or asserted that GIS was inherently environmentally and functionally deterministic. Other authors, such as Gaffney (1995), argued in favor of essentially sanctioning “environmental determinist” approaches in deductive modeling when used in CRM contexts. This was seen as desirable due to the practical limits on time and money available, since researching environmental correlates of site locations can assist greatly in effective and economical protection of cultural heritage (Gaffney and van Leusen, 1995). Others foresaw an oncoming polarization between the goals of archaeology and those of natural science that they believed could not be reconciled, a radical split that fortunately did not ultimately transpire (Torrence et al., 2015).

Many of these criticisms have since subsided as spatial analysis has become integral to a large number of sciences. The trend over the past 40 years has been one of increasing focus on the use of science in addressing archaeological questions (Torrence et al., 2015). Boivin (2005) pointed to emerging new perspectives on the interplay between materiality and culture that speak to a “post-textual archaeology” and movement away from the post-processual discourse that dominated the 1980’s and 1990’s. Killick (2015) notes that although it is still maturing, in the last fifteen years archaeology has been thoroughly transformed by new and improved scientific methods. Earlier prejudices against science from within the broader discipline of archaeology are largely overcome, due to the positive results that scientific analyses have now undeniably generated in discussions of the prehistoric past.

Archaeological science requires advances in theory as well as method – not to mention practice – to help extract information from a fragmentary material record and structure its interpretation. In biological disciplines, it would not be radical to suggest that a living organism can be understood by applying the general theory of evolution by natural selection to its analysis. In the context of studying humans, this has become known as Human Behavioral Ecology (HBE) (Bird and O'Connell, 2006; Broughton et al., 2010). HBE assumes that behavior is shaped by natural selection, just like that of any other animal; and that this assumption can be tested in archaeological contexts through careful analysis of material remains. HBE can advance archaeological science in the future by directing research towards systematic analysis of variability in human behavior and its material consequences, with the ultimate goal of explaining variability across the entire range of human experience. Theoretical frameworks that make explicit use of scientific methods in hypothesis-driven research have been used successfully to model and understand human behavior. In particular, HBE can be used to structure research on subsistence, on settlement, and on the evolution of settlement patterns through time (Codding and Bird, 2015).

The assumption that organisms will behave in a way that maximizes their evolutionary fitness can be used to generate hypotheses about what behaviors might be observed under particular ecological conditions. Selective evolutionary pressures do not generate behavioral strategies that are under direct genetic control, but instead favor the emergence of phenotypic and behavioral plasticity because they allow individuals to acquire locally adaptive behavioral strategies over a range of environments (Pigliucci, 2005). Longer timescales can include many short-term shifts in cultural behavior that potentially result in less strong patterning of relationships. This could be seen as "noise" in the resulting data, or unpatterned locational behavior, when it may represent the influence of some currently unknown social or environmental factor. It is hypothesized then that the consistency in locational behavior observed over long timescales in the montane environment of the Minidoka results from selective pressures that favored plasticity in cultural adaptation. Although this hypothesis cannot be directly tested through experimentation, modeling research of this type can be evaluated to determine whether or not it supports the hypothesis of behavioral plasticity.

According to Codding and Bird (2015), human behavior can be explained at least partly through its material consequences by building on principles of natural selection to provide a general theory of behavior, and clearly linking behavior to expected material outcomes. Effective modeling of relationships between species and environment is an important goal of any ecological research, and recently the focus of such modeling has shifted towards prediction, with less emphasis on description and explanation (De'ath, 2002). Predictive accuracy is now routinely used as a criterion for selection of a statistical model (Breiman, 1999) and can replace the formerly widely used practice of repeated hypothesis testing, which may lead to the inclusion of spurious explanatory variables (De'ath, 2002).

Clearly prediction cannot necessarily be equated with explanation. It is important to understand the underlying variables and principles that drive a given distribution of sites, and more reliable empirical correlative models may result in interpretable results that can inform an understanding of locational behavior. Thus the twofold goals of this project may be realized; by demonstrating the ability to correctly classify site presence or absence, and using the information gained from site modeling to improve our knowledge and understanding of human locational behavior. Theoretical interests and more practical CRM interests can be seen as more congruent by considering each CRM project, including this one, as contributing to an evolving regional research design, thereby providing a valuable service while incorporating CRM into wider research concerns (Kohler and Parker, 1986).

A discussion of how to best integrate human behavior into spatial analysis from an anthropological perspective is ongoing (see García et al., 2012). In applying GIS in research and fieldwork, archaeologists seek to understand human beings and gain better knowledge of the spaces they inhabit. Through modeling it is possible to explore how changes in specific socioenvironmental conditions could be related to observed variation in human behavior. Results of spatial analyses can then be integrated into a broader anthropological and historical framework (García et al., 2012).

III. Methods

Technological developments in both hardware and software have transformed the ways in which spatial analysis is carried out, although it remains computationally intensive. Opportunity cost that was at one time prohibitive (Anselin and Getis, 1992) is now much lower with the introduction of a variety of open-source, freely available software options. Hardware remains a limiting factor, although the rapid innovation and exponential growth in computational capability makes regional-level analysis much more accessible today than even five years ago. Species distribution modeling, a method widely used to develop empirical models of species-environment relationships in biological fields, has been supported by the development and dissemination of GIS methods (Franklin et al., 2015).

The modeling techniques used in this study are primarily based on an inductive/inferential strategy. Correlates of site location and parameters are identified using statistical inferential procedures to produce a set of independent variables that are demonstrably correlated with observed sites (Kohler and Parker, 1986). The rasters used to define site characteristics were developed using GIS-based, map algebra methods. A data-driven model was constructed and validated using three approaches. The methods employed here, logistic regression, regression tree, and random forest, were successful in correctly classifying archaeological site location in the Minidoka. Predictive models based largely on environmental parameters tend to perform better for hunter-gatherer populations than for more politically complex populations, which may be exhibiting locational behavior based more on social than environmental capital (Ebert, 2004). However it is clear from macroecological analysis that even politically complex cultural groups are subject to influences from the natural world that exert strong pressures on behavior (Burnside et al., 2012).

Regression trees are a machine-learning method that construct predictive models by recursively partitioning the data and fitting a model within each partition. This process can be visualized graphically as a decision tree and output to a binary predictive mappable surface. Random forest is an ensemble machine-learning algorithm that generates many classifiers and aggregates their results. This method is built on classification and regression trees and further utilizes “bagging,” in which successive trees are built that are independent of earlier trees using a bootstrap sample of the data, and adding another layer of randomness through changing how the classification or regression trees are constructed (Breiman, 1999).

Logistic regression characterizes interactions between the categorical dependent variable (site presence or absence) and the collected independent variables by estimating coefficients. Independent variables were chosen in this case through review of regional archaeological literature and landscape analysis. Random forest has comparatively stronger predictive power than regression, but lacks explanatory power since it relies on “black box” functions that cannot be successfully extracted to generate a model beyond relative weighting of parameters. Logistic regression has less predictive power but greater explanatory power than does random forest. Logistic regression models have been demonstrated to be effective in building models for archaeological investigation (Brandt et al., 1992; Kvamme, 1989; Wheatley and Gillings, 2003). Random forest models have only recently been applied to archaeological modeling (Märker and Heydari-guran, 2009; Menze and Ur, 2014).

Model-Building Process

The workflow is based on the following procedures: through spatial analysis, correlations between site location and environmental parameters are established, resulting in selection of a set of criteria with the greatest influence on site selection. The most frequently used parameters in archaeological modeling are land use, elevation and proximity to water bodies. Less frequent are insolation, viewshed, and Euclidean distance or cost distance between features of interest (Danese et al., 2014). Variables used in this study are measurable spatial variables which “stand-in” for those that are unmeasurable: the whole of human behavior involved in locational decision making (see Table 4 for a complete list of independent variables used in model construction).

Workflow

A. Data selection & archaeological research
B. Selection and theoretical approach of parameters
C. Quantification of parameters
D. Sources of error
E. Discussion of model types/model building
F. Model selection
G. Validation/model assessment

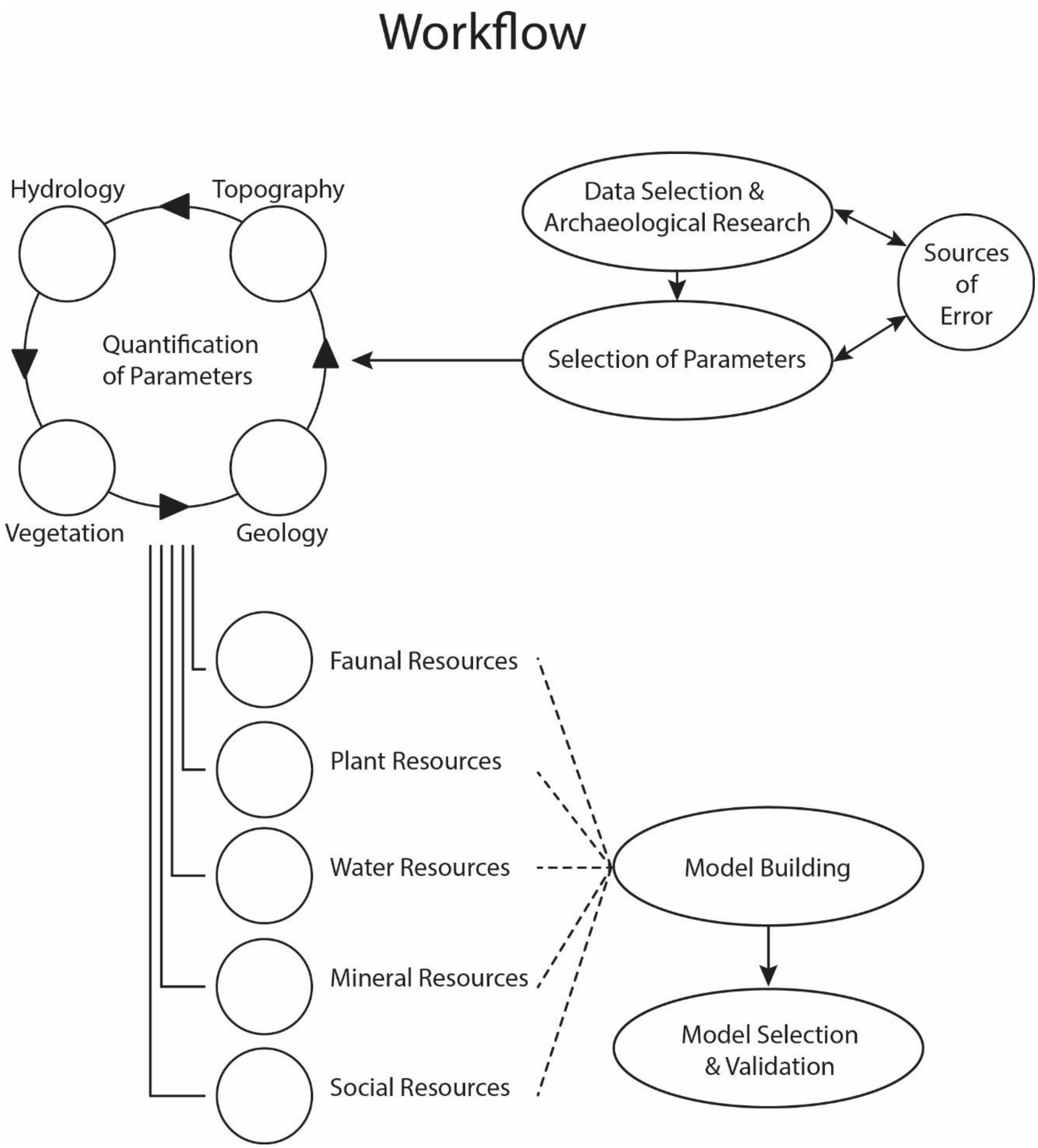


FIGURE 2: PREDICTIVE MODELING WORKFLOW

A. Data Selection & Archaeological Research

All data were compiled in a GIS environment using ArcMap 10.3 and converted to a common projection for interpretation and display, Universal Transverse Mercator (UTM) zone 11N NAD 1983. This allows spatial statistics to be compiled in common scales of meters. The final dataset is comprised of 112 prehistoric and multicomponent sites, reduced from a set of 893. Historic sites and those without sufficient identifying information were excluded from the analysis. Sites with areal extents were converted into centroid points for direct comparison with those recorded as single points. The majority are small, possibly ephemeral sites, but it is also possible that these represent sites which were not surveyed or tested thoroughly enough to yield a representative artifact assemblage. As a result most have not been dated with absolute methods, and also cannot be assigned to a cultural period reliably only through diagnostic artifacts (De Reu et al., 2011). Because surface site assemblages may contain too few diagnostic types that are representative of a number of different occupation events and a complete chronological inventory of the data is absent, dates of occupation were not included in the analysis.

Although a number of functional site-types ultimately are defined within the dataset provided by the USFS, some with identifiable chronological associations, site location modeling in the Minidoka is focused only on site presence. This binary outcome was chosen as the dependent variable since the dataset is not rich enough to have functional types or chronologies associated with every known site. Combining a variety of site types results in a potentially less robust model, since previous work has shown that sites corresponding to different functionalities or cultural groups may be located according to different criteria (Lock and Stancic, 1995).

The primary goal of this model is to identify open-air sites as opposed to rockshelter or cave sites. Open-air site location preference is assumed to be a function of human choice in terms of maximizing desirable environmental factors, while rockshelters occur at locations determined by a small range of geologic conditions not easily identified by the type of data used to build independent variables in this study (Kvamme, 1992). Since the dataset of known sites in the Minidoka consists almost entirely of open-air sites, the model is restricted to identifying additional sites that fit the general pattern of environmental relationships.

Landscape archaeology often deals with aggregated data and phenomena that interact with the environment at different spatial scales. It is important to understand how the results of analyses are sensitive to the definition of units for which data are collected in order to build models that minimize bias and avoid spurious relationships. Categorical classes for data should be defined as objectively as possible, and continuous variables are best used whenever possible to avoid arbitrary categorizing that can result in “archaeological gerrymandering” (Harrower, 2013). It is common in spatial analysis to work with many sources of data of varying quality or spatial accuracy. Inexactness is inherent to the practice of geography since any data must serve as a higher level of generalization than the real-world phenomena it represents (Magnin, 2015).

Background data are necessary for describing the distribution of sites in particular environments against the general pattern of the environment. This data is not a targeted effort to guess at particular site absence locations, but rather to characterize the environmental domain of the study region. A comparison set of “nonsite” point locations were generated within the boundaries of the Forest Service managed lands using random point generation with a minimum separation distance of 100 m. Those within 1000 m of known sites were excluded from the dataset, resulting in a set of 125 nonsites for use in producing a statistical comparison of site characteristics against background values. Actual surveyed areas known to be nonsites were not used as a dataset for this purpose due to the strongly biased nature of the surveys; since most were conducted for the purposes of road improvements, fencing projects, or cattle watering infrastructure, they did not represent an unbiased sample of the topography and ecology of the background environment. Surveyed nonsites also comprised an areal sample too small to be effective in statistical analysis.

Nature of the Sample

Datasets used in this analysis were assembled without a specific sampling design. This results in bias due to the following intrinsic and extrinsic factors: in some cases only specific topographic areas were investigated, buried material was not detected at the surface, or only positives are reported, and in most only surface finds are reported with no subsurface testing (Märker and Heydari-guran, 2009). Another source of bias centers on the taxonomy of archaeological sites and criteria used to define sites. Less dense evidence of past human activity, defined as “the presence of fewer than 10 artifacts in a 10 m x 10 m area or are found to be re-deposited material that lacks significant locational context, and there are no other associated artifacts or features within a 30 meter radius of the location” (The State of Idaho State Historic Preservation Office and The Bureau of Land Management, 2014) is considered an Isolated Find (IF). Although this statistical criterion exists, context, potential for buried deposits, and professional judgment play a significant role in classification of sites and isolates.

This approach has several limitations, the most important of which is that the data used to derive environmental parameters is incomplete and sometimes inaccurate (Verhagen and Whitley, 2011). An analysis including a Normalized Difference Vegetation Index (NDVI) demonstrated a strong negative correlation with recorded sites and green vegetation density; this demonstrates that the recording and survey techniques used to build this dataset are subject to a strong discovery bias. Although there is a statistically significant relationship between NDVI values and site presence, this parameter was excluded from the model since it would preclude discovery of sites at vegetated locations.

It is a clear limit of the dataset that site presence is negatively correlated with NDVI since the goal of generating a predictive model is to predict site locations instead of merely site visibility.

It would be reasonable to expect the opposite: that site location would be positively correlated with NDVI since in the Northern Great Basin healthy green vegetation tends to occur in association with well-developed soils, lesser degrees of slope, reliable water supply, and depositional surfaces. All of these factors should also positively correlate with both site presence and site preservation. It could therefore be hypothesized that an inductive-deductive model might perform better than a strictly inductive model when tested against new data. The data available are imperfect, but that imperfection need not limit the inferences one can make.

Spatial Autocorrelation

Multiple logistic regression assumes that the observations are independent. However it frequently occurs in spatial analysis that an observed phenomenon is not independent: the tendency of a set of data to be clustered together in space or dispersed is known as spatial autocorrelation (Bivand, 2010). If the relative outcome of site presence in the Minidoka is related to intra-site distance, sites are spatially autocorrelated. In other words, are sites in the Minidoka located without any influence of near-site proximity, or are do they cluster or disperse as a result of some human locational preference that drives siting? If sites in the dataset are contemporary, then one can expect that they would be positively spatially autocorrelated, potentially representing groups or bands of associated people who prefer to live near each other. It is also reasonable to assume that sites associated with unrelated groups or bands may be negatively autocorrelated, since human social and cultural units tend to occupy non-overlapping home range territories (Burnside et al. 2012).

Temporal autocorrelation cannot be detected in this dataset since it does not contain information about site occupation dates. Sites may also be occupied continuously or discontinuously/intermittently for many thousands of years. Predictive modeling methods typically assume spatial stationarity and isotropy, meaning that both spatial autocorrelation and the effects of environmental correlates are constant across the study region and that there is no variance due to directionality. Few methods directly address non-stationarity (F. Dormann et al., 2007). One method able to accommodate, although not remove, spatial variation in autocorrelation is Geographically Weighted Regression (GWR) (Brunsdon et al., 1998). Another method is to subsample the data and re-run each model, although smaller sample sizes may result in undesirable outcomes due to over-representation of certain site types.

Because observations are limited to those that fall within the boundaries of the Forest Service land, a semivariogram was generated for each division: the Albion, Black Pine, Raft River, and the Sublett. Results indicate that sites at less than a mean range of 2782 m are positively spatially autocorrelated. The fact that all divisions display a similar nugget, range, and sill indicates that the underlying cause is consistent between all divisions and upholds the assumption of second order stationarity in model development. Analysis of the complete dataset results in a range of 2748 m. The data does not display geometric or zonal anisotropy.

Geographic Subset	Semivariogram Range
Albion	2612.4
Black Pine	3336.8
Raft River	2615.3
Sublett	2563.8
Mean	2782.1
All subsets included	2748.4

TABLE 1: SEMIVARIOGRAM RANGE OF DATA

Unfortunately the limited nature of the cultural data available precludes answers to these questions. The degree of spatial autocorrelation can be estimated, but it is beyond the scope of this project to hypothesize the causes behind it. Areas of future research could also include analyses of the interaction between spatial distributions. Because other natural features of the landscape may be autocorrelated as well, concordance of these patterns of spatial variation in habitat components can be used to determine whether distribution of humans might in part reflect patterns of spatial autocorrelation of environmental variables (Fleishman and Mac Nally, 2006).

B. Selection of Parameters

One of the fundamental goals of archaeological research is understanding how prehistoric human populations utilized natural resources. Because hunter-gatherer economies are closely tied to the distributions of animal and plant resources, it can be assumed that understanding the variation in these distributions will lead to a better understanding of hunter-gatherer lifeways. The paleoenvironment can be reconstructed through direct zooarchaeological and paleobotanical evidence recovered and associated with modern environmental patterns that are correlated with those species (Franklin et al., 2015). For example, if a site in the study area has a record of past humans eating a particular diet, is it possible to extract a collection of environmental parameters that are correlated with the distributions of those resources, and further to assume that similar site selection criteria driving decision-making can be applied to undiscovered sites as well.

Another benefit of inductive research is that a predictive framework for locational behavior must be consistent rather than allowing the application of theory post hoc. Application of theory to explain observed distribution of sites or materials may result in inconsistencies that belie the complexity of human locational behavior. Therefore, the risk of proceeding with a deductive model is that the totality of human-landscape interaction is extremely complex, and a locational model based on assumptions of past human behavior and environmental structure may be incomplete or poorly informed (Kohler and Parker, 1986).

Deductive models typically derive predictive variables from ethnohistoric sources and those identified in previous correlative research. Hassan et al. (n.d.) suggest a complete model for determining human activity locations must include variables measuring the following, in descending order of importance: hazard avoidance, proximity to vital resources, transportation costs and accessibility, security, social factors, and aesthetics. However, a model built utilizing all of these parameters would exclude expedient hunting camps, quarrying sites, and other locations of human activity that are task-specific and do not follow this "complete" model of settlement pattern.

Whitley (2002) suggests that North American approaches to modeling, heavily influenced by processualism, could benefit from a more enriching discussion of human agency and social theory, without deviating into a "speculative form of epistemological argumentation" (Whitley, 2002, p.2). It is the nature of research into the behavior of past humans that discussions regarding causality may only be speculative. One way to begin a discussion of behavior is to use the spatial variables derived from this study as proxies for cognitive decision-making and social agency. This relies on a series of assumptions. The first is that past humans thought and behaved in much the same way as present-day humans and that their activities left observable traces in the archaeological record, and that these observations can be adequately interpreted and explained. Nearly all archaeologists would agree upon these assumptions, but there is a wide range of techniques available through which to interpret them (Verhagen and Whitley, 2011). This research does not address the "why" behind spatial behavior, instead leaving such explorations to future studies.

Hunter-gatherer populations are known to modify their environments in a variety of ways, including the construction of fishing weirs, antelope drives and irrigation ditches (Steward, 1938). Habitat modification through the use of anthropogenic fire, which has a long evolutionary history, is frequently employed to lower search costs and effect long-term increases in patch quality. Anthropogenic landscape change may have had profound effects on ecosystem function, which in turn shaped mobility, settlement, and social organization (Codding and Bird, 2015). Ethnographic research also provides evidence of the common practice of burning of brush to facilitate growth of wild seed plants by the Shoshone on the plains surrounding the Bear River and Snake River (Smith, 1988; Steward, 1938). A dominant theme in research into human prehistory in the Great Basin has been that basic subsistence concerns drove cultural development, and thus help to explain things like technology, social structure, settlement pattern, and even ideology (Zeanah, 2004).

In archaeological studies, both spatial and temporal distribution play an important role in enabling researchers to detect patterns. Paleo-environmental conditions specific to the time frame under study are not known with precision, so it is necessary to account for the ways in which former conditions may have changed and cycled through comparable conditions in the past. The present-day landscape frequently contains conserved features from the Pleistocene-Holocene transition onward, especially if morphodynamics are low. Since the last period of dramatic landscape change in this area was during the last glacial maximum in the Pleistocene, many of the landforms have remained relatively stable. Therefore, analysis of present-day topography may reveal information relevant for past conditions and that will be useful in model generation (Märker and Heydari-guran, 2009). Specific parameters relating to long-term landscape change or paleoclimatic variability are not reflected in the model. Instead, it shows the interaction of variables as they exist in the present. Modeling research that includes prehistoric climate (e.g. Franklin et al., 2015) provides an opportunity for greatly enhanced understanding of the relationship between humans and the natural world, but is beyond the scope of this project.

One significant resource that prehistoric peoples encountered in the area is a wide variety of lithic resources, most notably obsidian sources related to rift valley volcanism in the Snake River

Plain that began around 15 Ma (Hackett and Morgan, 1988). Lithic resource availability is one marker that, due to its durability in the archaeological record, is frequently employed to track mobility and trace processes of exchange of raw materials and manufactured goods (Conolly and Lake, 2006). The many obsidian sources in the area – Malad, Browns Bench, Bear Gulch, Wolverine Creek, Big Southern Butte, Obsidian Cliff, and others – were all actively quarried and visited frequently by prehistoric peoples. The mountains surrounding these sources provided not only transportation corridors but habitation sites, as highly mobile prehistoric peoples traveled between habitats and their associated resources such as wetlands, different game and fowl habitats, and plant communities (Jones et al., 2003). Nodular chert formations found in Permian and Pennsylvanian sedimentary rocks in the Minidoka are also known to have provided a source of raw lithic material. The conveyance of obsidian throughout the Great Bain through travel or trade has been well documented as an element of broader mobility patterns and cultural contact (Jones et al., 2003). It is also important to note that lithic sourcing choices are not a simple result of availability and instead can represent socially important functions. Raw material circulation has been studied in many regions as a way to understand provisioning strategies of mobile hunter-gatherers (Magnin, 2015).

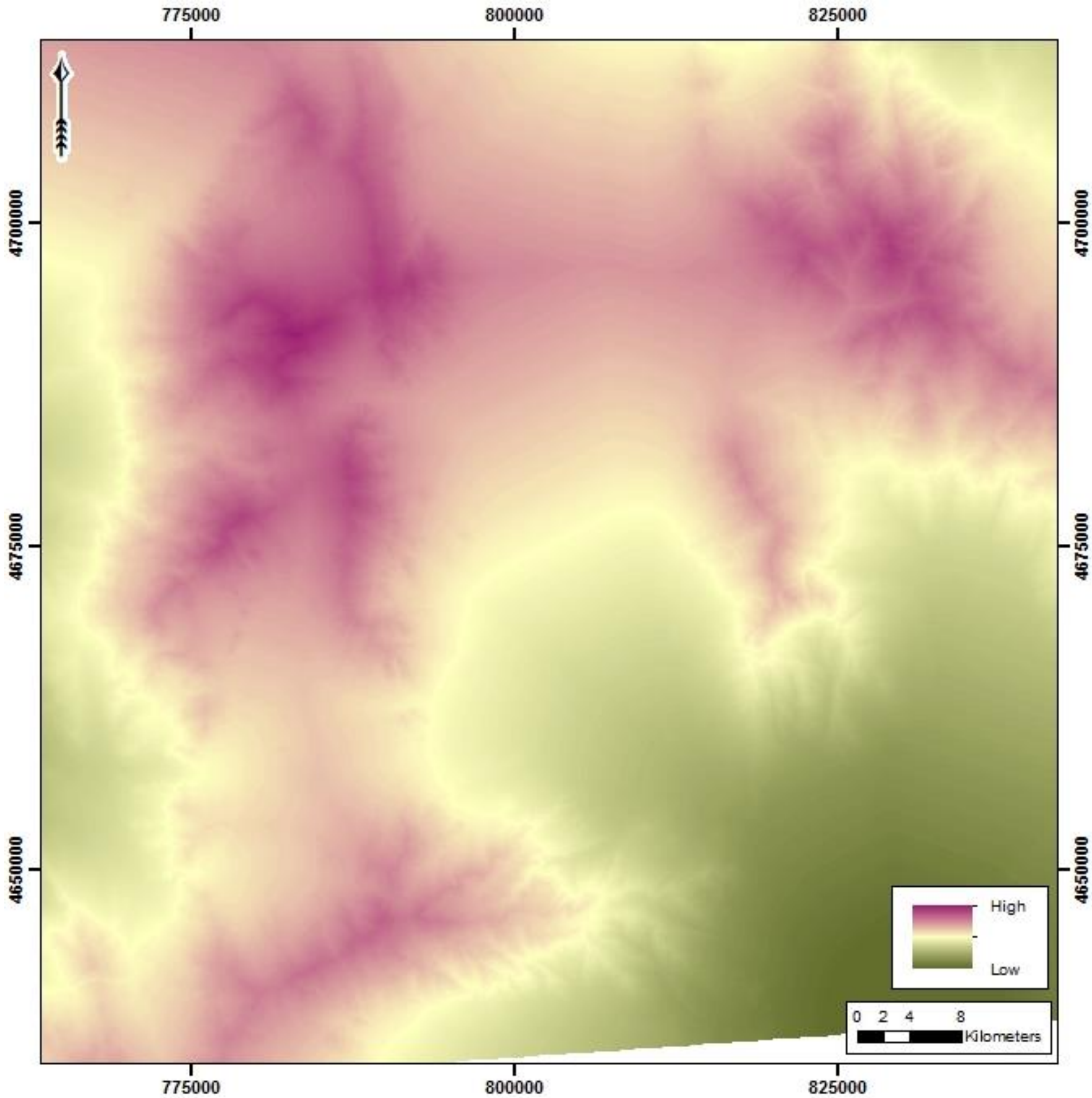


FIGURE 3: COST DISTANCE TO OBSIDIAN SOURCES USING SLOPE AS AN INPUT BARRIER

The Cassia division of the dataset is dominated by a lithic landscape formed by the Browns Bench obsidian source, and sites are typically characterized by primary reduction activities and ephemeral campsites. The primary controlling independent variable in archaeological site patterning is in this case is apparently the obsidian source, which is not localized but instead is dispersed over the landscape continuing north across the Snake River Plain. This pattern is due to the intercalated rhyolite, volcanic glass, and felsic and ash layers that are present (Bowers and Savage, 1962). This observed pattern of human site preferencing differs from the occupation type in the remaining divisions of the Minidoka Ranger District and thus is excluded from the analysis even though it represents a large sample size.

Possible vegetation resources that may have impacted site selection include Pinus edulis and monophylla (piñon pine), Typha (cattail), Prunus virginiana (chokecherry), and Camassia quamash (camas) as well as a long list of other plant resources that are present in the area and are known to have been exploited by Great Basin peoples, based either on archaeological or ethnographic resources (Couture et al., 1986). It is hypothesized that the region's abundant natural springs positively impacted site patterning, especially in late summer and fall when ephemeral streams are dry. The presence of springs may also have been positively correlated with desirable food resources and fertile hunting grounds.

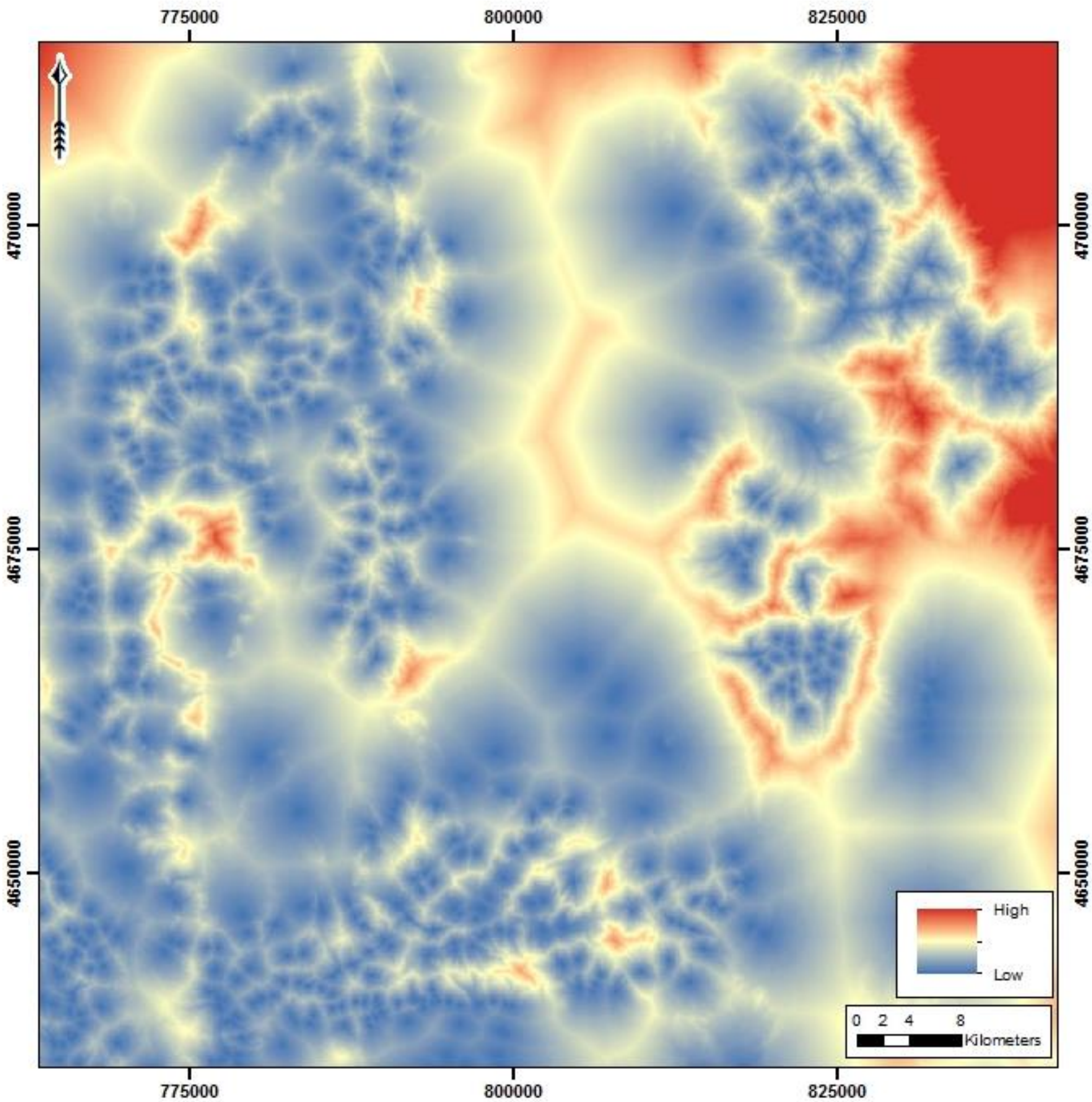


FIGURE 4: COST DISTANCE TO SPRINGS USING SLOPE AS AN INPUT BARRIER

Many of the variables discussed here are likely to be in fact social instead of environmental variables, however the link between what is measurable and its possible social value is not always clear. Inter-site distance, viewshed, and intervisibility have been proposed as some of the social values that can be measured by proxy using spatial analysis. Viewshed measures the range of visibility from a site which would offer visual control over a territory, which can be an important factor in a site's defensibility. Site intervisibility can be important for communication between inhabitants of contemporaneous sites, and inter-site distance influences the ability of site locations to engage in economic support and trade activities (Stančič and Kvamme, 1999). Another social factor is control of non-renewable resources; just as in the modern era control of finite resources such as petroleum is politically and socially important, in the prehistoric, control of obsidian sources may have been an important social variable that can be measured by distance to sources. Viewsheds represent not only all locations visible from a point but also all locations from which a point of interest is visible. Thus viewshed can be significant to the construction of symbolic features in the landscape, defensibility, and to territoriality in general (Kvamme, 1999; Wheatley and Gillings, 2003). Least-cost paths between important resources can be calculated in a GIS and used as a proxy for community knowledge of traveled routes, and together these variables can help to explain agent-based cognitive processes (Whitley, 2004).

It is common for archaeological modeling to use aspect as a parameter (Brandt et al., 1992) under the assumption that south-facing slopes are a more hospitable place to live, especially in the winter months. Characterizations of human habitation in the Northern Great Basin have included south-facing slopes at least as early as Steward (1938). The montane sites under investigation here could potentially exhibit a preference for either north-facing or south facing slopes, depending on the time of year that habitation occurred. North facing slopes in the summer months may be significantly more desirable due to their soil-moisture preservation properties, improving potential for vegetation resources and game habitat. This parameter also affects insolation, or the amount of daylight hours and solar radiation, which is linked to mobility strategies of foraging communities since it affects the microclimate of a potential habitation site dramatically (García-Moreno, 2015).

Correlations between known sites and their environmental parameters can help describe the typical microenvironment of sites in this area. Relevant data that was sourced for this project includes NOAA Landsat data; Idaho Hydrography; National Elevation Datasets (NED) and 1/3 arc Digital Elevation Models (DEM); Landcover data; mineral resources data; and National Agriculture Imagery Program (NAIP) 0.5 meter orthoimagery. Data was procured via the United States Geological Survey (USGS) and the Interactive Numeric & Spatial Information Data Engine (INSIDE) Idaho.

DEMs & topographic analysis

As is typical in geomorphologic studies, DEMs formed the information base for extracting basic components and terrain classes. Topographic forms of the earth's surface including slope vary with the scale at which they are measured, and hence, the characteristics of landforms derived using slope are also scale-dependent (Mokarram et al., 2015). Because of this inherent scale-dependence, feature detection often needs to be performed at different scales of measurement in order to determine which is best suited to the study design. The scale at which humans interact with the environment also varies, but can be grouped into two main categories; the "viewshed", which ranges approximately from 500 to 3000 m; and the "local", which ranges approximately from 250 to 1000 m. These two measurements, the distance at which people can see their surroundings and the area that they might live in, are the scales used in topographic analysis for this study. A neighborhood of 250m was chosen as a local "living surface" scale and a neighborhood of 1500m was chosen as a "viewshed" scale. Other neighborhood sizes were tested and discarded due to a lack of relationship between classes and human activity, or because they resulted in over-generalization of the landscape, for example at 2000m (see Figure 5).

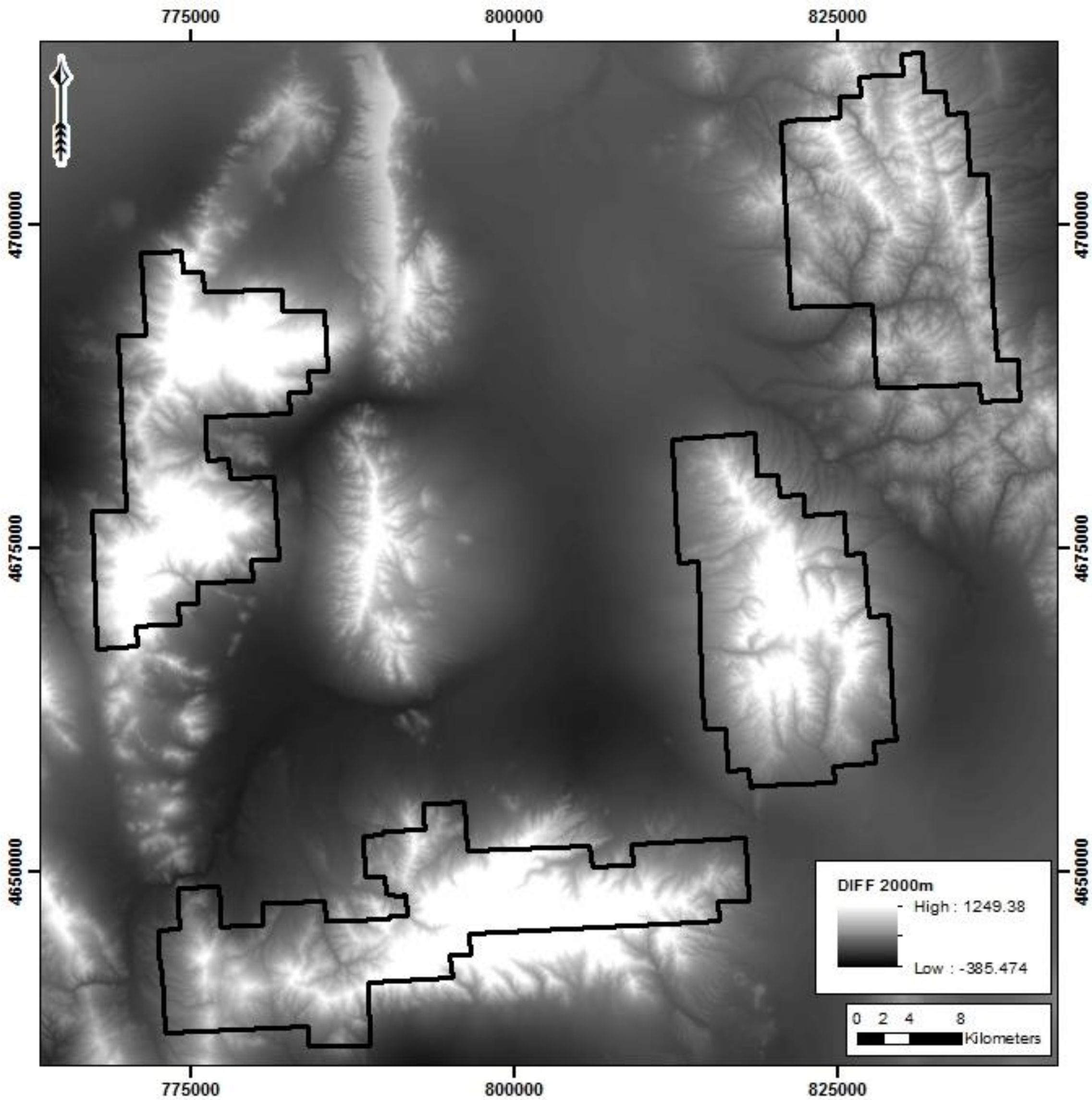


FIGURE 5: OVERGENERALIZATION OF LANDSCAPE AT 2000M NEIGHBORHOOD SIZE

Topographic characterization

Local topography is an important parameter in determining site preference for a certain location in the landscape, and can help refine the model when added to other specific topographic parameters such as slope, aspect, and curvature. Based on De Reu et al. (2011) methods utilizing focal statistics were used to assess the relative topographic position of sites in the Minidoka using a predetermined neighborhood for each function (see Table 2). Difference from mean elevation (DIFF) measures the relative topographic position of the site as the difference between site elevation and mean elevation. Deviation from mean elevation (DEV) calculates the relative topographic position as the difference of site elevation from mean elevation divided by the standard deviation of elevation (See Figure 6). Neighborhood size affects analysis in a number of ways; a larger neighborhood assesses site selection against broader landscape units while a small neighborhood will highlight small environmental features. Different neighborhood sizes can emphasize or generalize landscape features, so it is necessary to produce a variety of classifications at varying scales to determine which is best suited to the research topic. This study considered circular neighborhood sizes of 250m, 500m, 1000m, 1500m, and 2000m for landscape analysis. The intermediate classes were discarded due either to strong multicollinearity with other neighborhood sizes or lack of relationship with site presence. The 2000m neighborhood was discarded due to both overgeneralization of the landscape and lack of correlation with site presence. A final selection of 250m and 1500m was used in model-building.

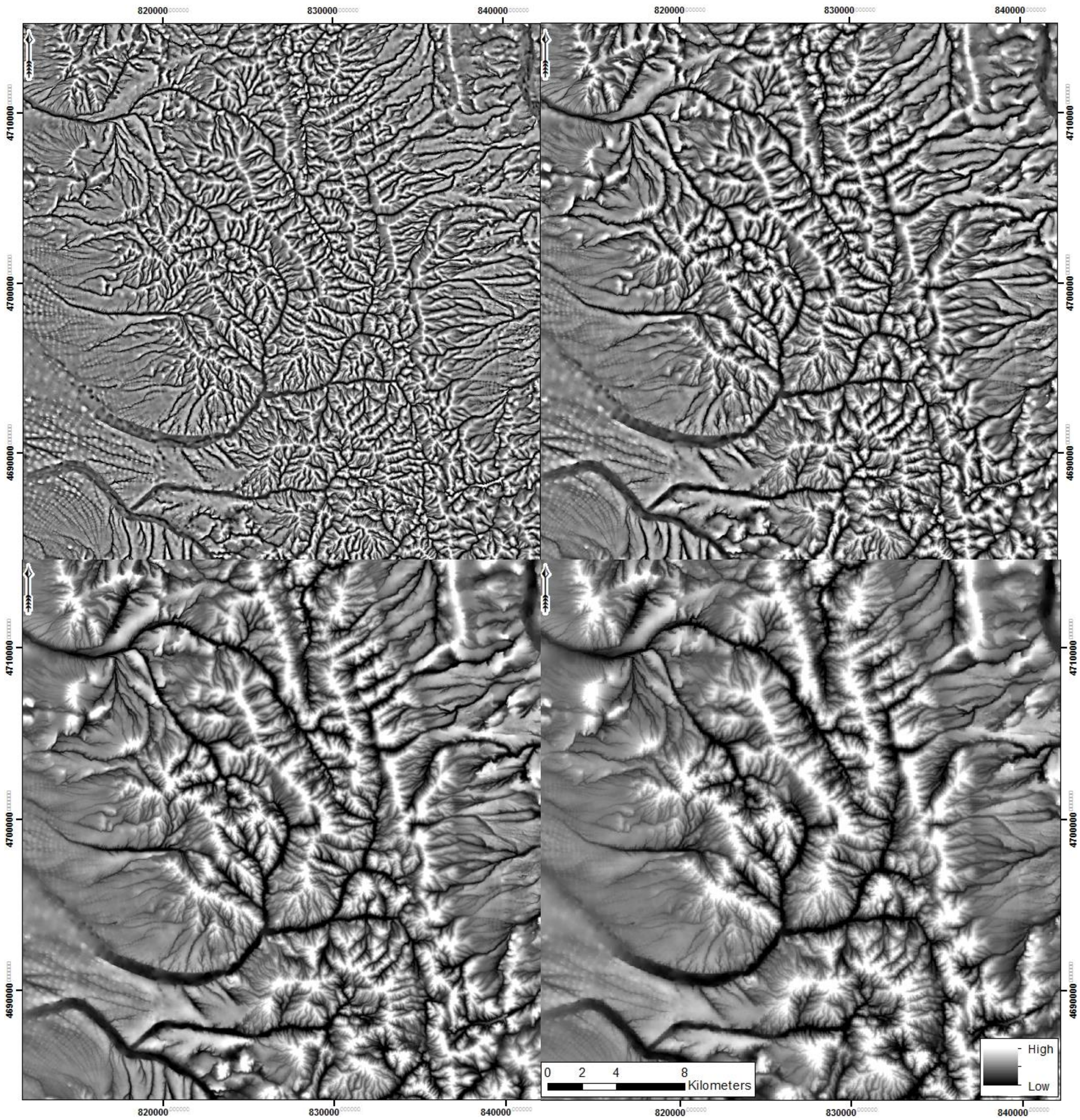


FIGURE 6: TOPOGRAPHIC CHARACTERIZATION OF THE SUBLETT RANGE LANDSCAPE USING DEV, FROM TOP LEFT: 250M, 500M, 1000M, 1500M

The neighborhood radii chosen for focal statistics and landform classification are also within the daily foraging ranges of a Late Prehistoric Great Basin hunter-gatherer group as calculated by Morgan (2008) who found peaks in mean foraging radius between 500 and 5000m. These foraging distances supported winter group aggregations and facilitated mobility through caching behavior, representing the average distance people would have routinely traveled from a central settlement location.

Method	Algorithm	Description
Mean elevation *(MEAN, $\overline{z}$)*	$\frac{1}{n_R}\sum_{i\in R} z_i$	Average DEM value around a central point (z_0), within neighborhood (R).
Elevation range (*RANGE*)	$\max_{i\in R} z_i - \min_{i\in R} z_i$	Difference between highest and lowest DEM value around a central point (z_0), within neighborhood (R).
Standard deviation of elevation (*SD*)	$\sqrt{\frac{1}{n_R - 1}\sum_{i=1}(z_i - \overline{z})^2}$	Standard deviation (variability) of DEM values, around a central point (z_0), within neighborhood (R).
Percentile as percentage of elevation range (*PCTG*)	$100\frac{z_0 - \min_{i\in R} z_i}{RANGE}$	Ranking of central point (z_0) as percentage of elevation range (RANGE), within neighborhood (R).
Difference from mean elevation (*DIFF*)	$z_0 - \overline{z}$	Difference between central point and mean elevation around central point (z_0), within neighborhood (R).
Deviation from mean elevation (*DEV*)	$\frac{z_0 - \overline{z}}{SD}$	Relative topographic position of central point (z_0) as difference from mean divided by standard deviation, within neighborhood (R).

TABLE 2: METHODS FOR RELATIVE TOPOGRAPHIC POSITION ANALYSIS (ADAPTED FROM GALLANT AND WILSON, 2000)

Elevation percentile (PCTG) calculates the ranking of the central point as a percentage of the elevation range (RANGE), within a predetermined neighborhood. This value can be used to assess whether sites are situated on a prominence, since values less than 50 correspond with lower locations such as valleys, sinks, or downslope areas, while values of greater than 50 correspond with higher places in the landscape such as ridges, hilltops, or upslope areas (De Reu et al., 2011). Quantifying the landscape in this way is significant to model formation since it provides a stand-in for a variety of possible culturally significant choices; for example in some cultures landform prominence is associated with social status, and sites may be chosen based on the viewshed or protection that they offer.

DIFF measures relative topographic position as the difference between site elevation and the mean elevation within a neighborhood (Table 3) (Wilson and Gallant, 2000). The resulting value is positive when the site is situated higher than its neighborhood mean, or negative when site location is lower than its neighborhood mean. The resulting range of DIFF values varies with the size of neighborhood chosen and topographic variability. A more rugged landscape, such as the montane Minidoka, will necessarily result in a wide range of output values.

DEV measures relative topographic position as DIFF divided by standard deviation of elevation (SD) within the neighborhood. DEV values typically range between 1 and -1 and are measured as a fraction of local relief normalized to the local surface roughness (Wilson and Gallant, 2000). Positive DEV values result from a site situated higher than its average neighborhood and negative values result when a site is situated lower than its average neighborhood.

A methodology to classify the landscape into morphological classes representing landscape entities was adapted from Weiss (2001) and is similar to Topographic Position Index (De Reu et al., 2013; Weiss, 2001). The method uses the standard deviation (SD) of the DIFF values of the background landscape (DEV). Values higher than 1 SD indicate ridges, while values lower than -1 SD represent valley bottoms. Upper slope area values are between 0.5 and 1 SD. Middle slope values are between -0.5 and 0.5 SD, with a slope greater than 6 degrees. Flat area values are between 0.5 and -0.5 SD, with a slope of less than 6 degrees. Lower slope area values are between -0.5 and -1 SD (Table 2).

Morphologic class	Value	Map Symbology
Ridge	$z_0 > 1\ SD$	
Upper slope	$SD \geq z_0 > 0.5SD$	
Middle slope	$0.5SD \geq z_0 \geq -0.5SD$, slope > 6°	
Flat area	$0.5SD \geq z_0 \geq -0.5SD$, slope ≤ 6°	
Lower slope	$-0.5SD > z_0 \geq -SD$	
Valley	$z_0 < -1\ SD$	

TABLE 3: CLASSIFICATION OF THE LANDSCAPE INTO MORPHOLOGICAL CLASSES (ADAPTED FROM WEISS 2011)

Landform classification is an important component in model-building since many biophysical processes in a given landscape are highly correlated with topographic position. This includes effects from geomorphological processes, such as soil erosion and deposition or hydrologic balance, as well as climatological processes such as wind exposure and ambient temperature. These attributes are predict habitat suitability, community composition, and species distribution and abundance for plant and animal communities (Weiss, 2001). Human ecology is affected in turn by these environmental elements.

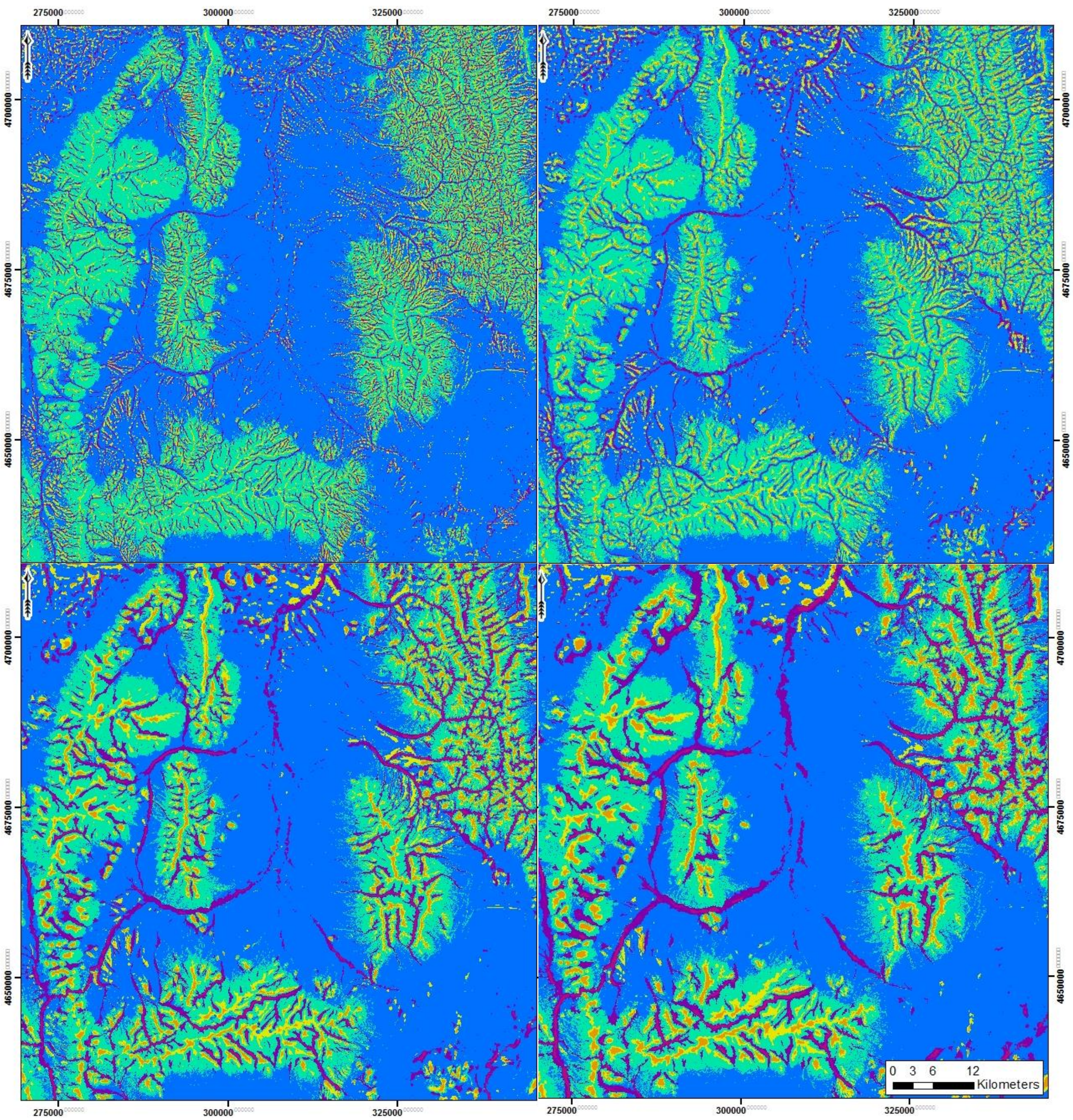


FIGURE 7: NEIGHBORHOOD EFFECTS ON LANDFORM CLASSIFICATION, FROM TOP LEFT: 250M; 500M; 1000M; 1500M

C. Quantification of Parameters & Data Aggregation

The inclusion of least-cost strategies arises from fundamental assumptions about past decision making in an environment known in detail. Cost distance rasters were created using ArcGIS 10.3 and inputs of a DEM-derived slope raster combined with resources derived from publicly available datasets (e.g. USGS, NHD) and original research (Dr. Rick Holmer of ISU). These include locations of permanent water resources such as springs or streams, obsidian quarries, and plant resources such as piñon stands or deciduous shrubs. A cost distance surface may provide a more accurate representation of the ability to acquire resources than a simple Euclidean distance which does not take into account topographic barriers. Cost distance rasters were also exported to UTM projection and a common pixel size of approximately 9.3 m using geoprocessing tools. Viewshed was calculated using both nonsites and sites as observer points with the mosaicked DEM as a topographic surface. A mean of viewshed values was extracted using the neighborhood sizes described above to determine whether visible area has an effect on locational preference. This process can help to identify whether sites are situated preferentially for intersite visibility.

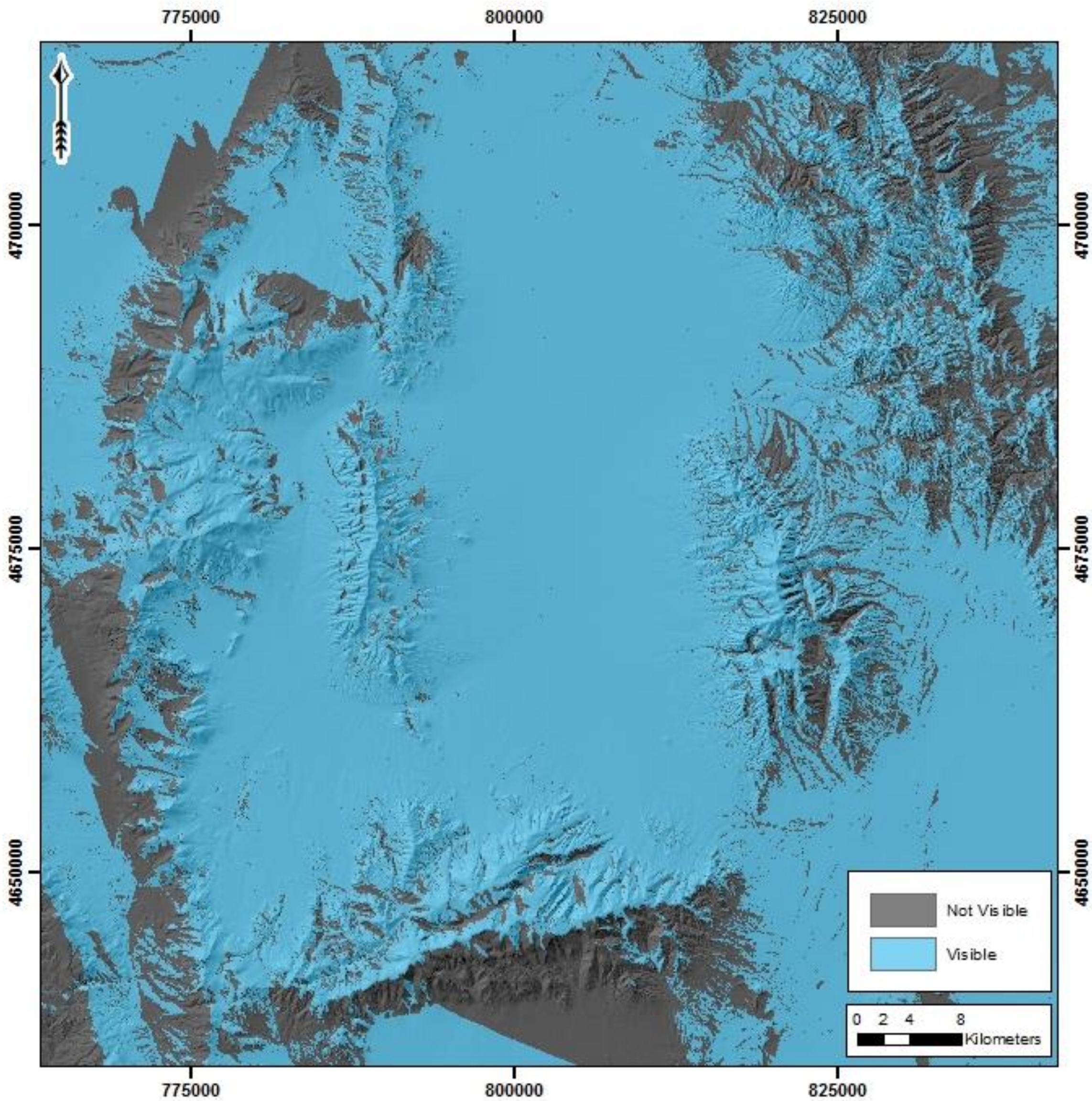


Figure 8: Viewshed calculated using both nonsites and sites as observer points

Geologic layers were used as a parameter in the model not because humans are likely to exhibit some kind of locational preference for a particular rock or mineral substrate (except in the obvious cases of cliff dwellings and rockshelters), but because the geology of an area can play a role in the vegetation community, topography, and differential outcomes of site preservation or destruction. Although preliminary results of analysis suggest that it was a strong predictor of site location, geologic unit was removed as a possible independent variable since it corresponds to uplifted exposures of units that are common to the area, and thus demonstrates a strong recursive locational correlation with alpine site location. This correlation however is not a meaningful indicator of human decision making or of preservation outcomes.

Because the result of spatial analyst tools measure aspect in degrees, statistical analysis of compass measurements is problematic; a value of 359° and 1° are both "north," but a logistic regression would treat these as very different values occurring at the opposite ends of the scale and muddying results (Jenness, 2005). To compensate for this, aspect was recalculated to a measure of "northness," or deviation from north, using a raster math conditional statement:

IF aspectValue > 180, northnessValue = 360 – aspectValue, else northnessValue = aspectValue

This results in a raster that may be included in statistical evaluations that depend on continuous variables by producing a measurement of landscape aspect on a scale of 0 to 180 in which the lowest values are the most northerly and the highest are the most southerly. This choice of transformation relies on the assumption that there is no preferential selection of east or west facing slopes.

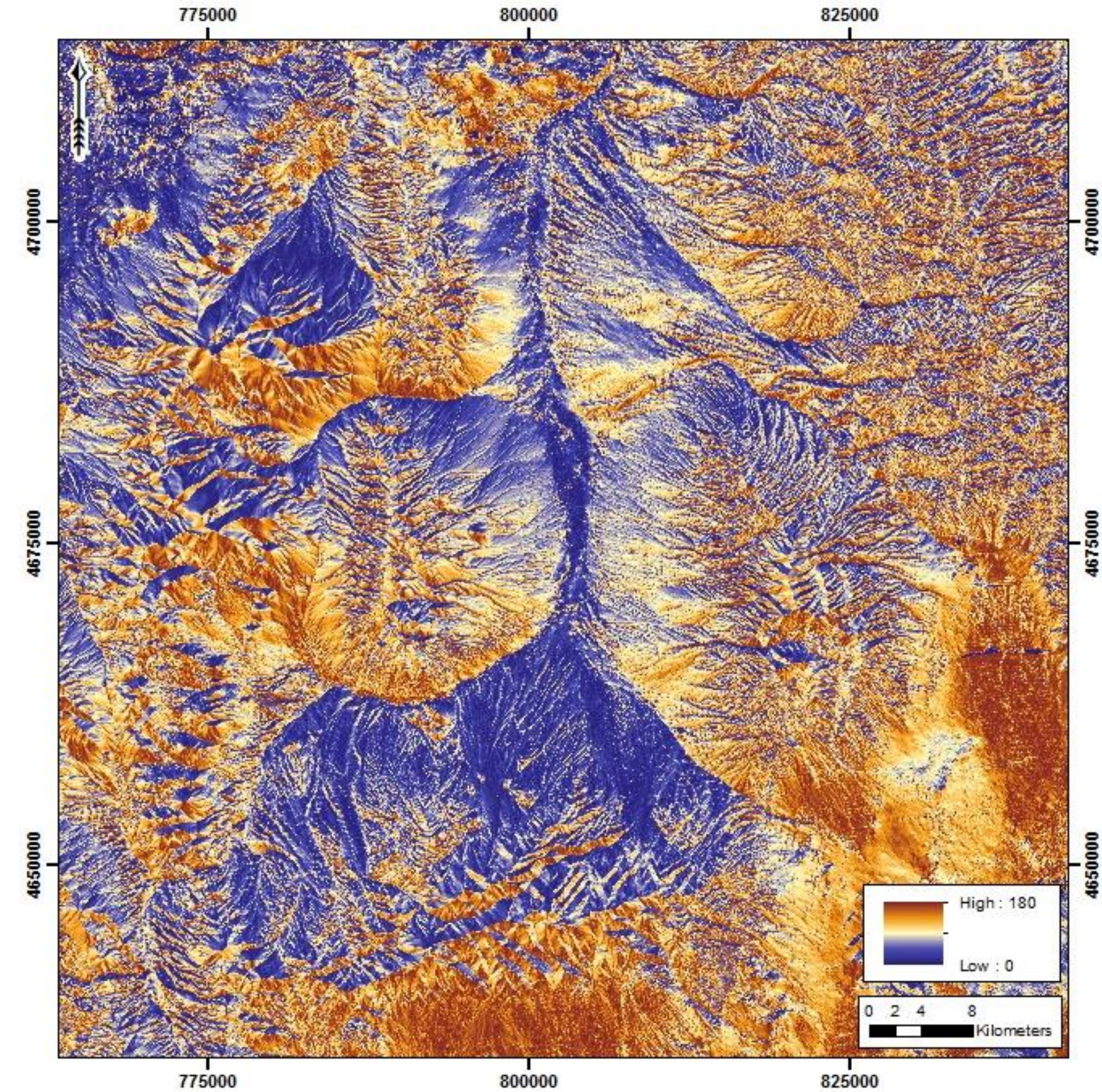


FIGURE 9: ASPECT OF LANDFORMS CONVERTED TO "NORTHNESS"

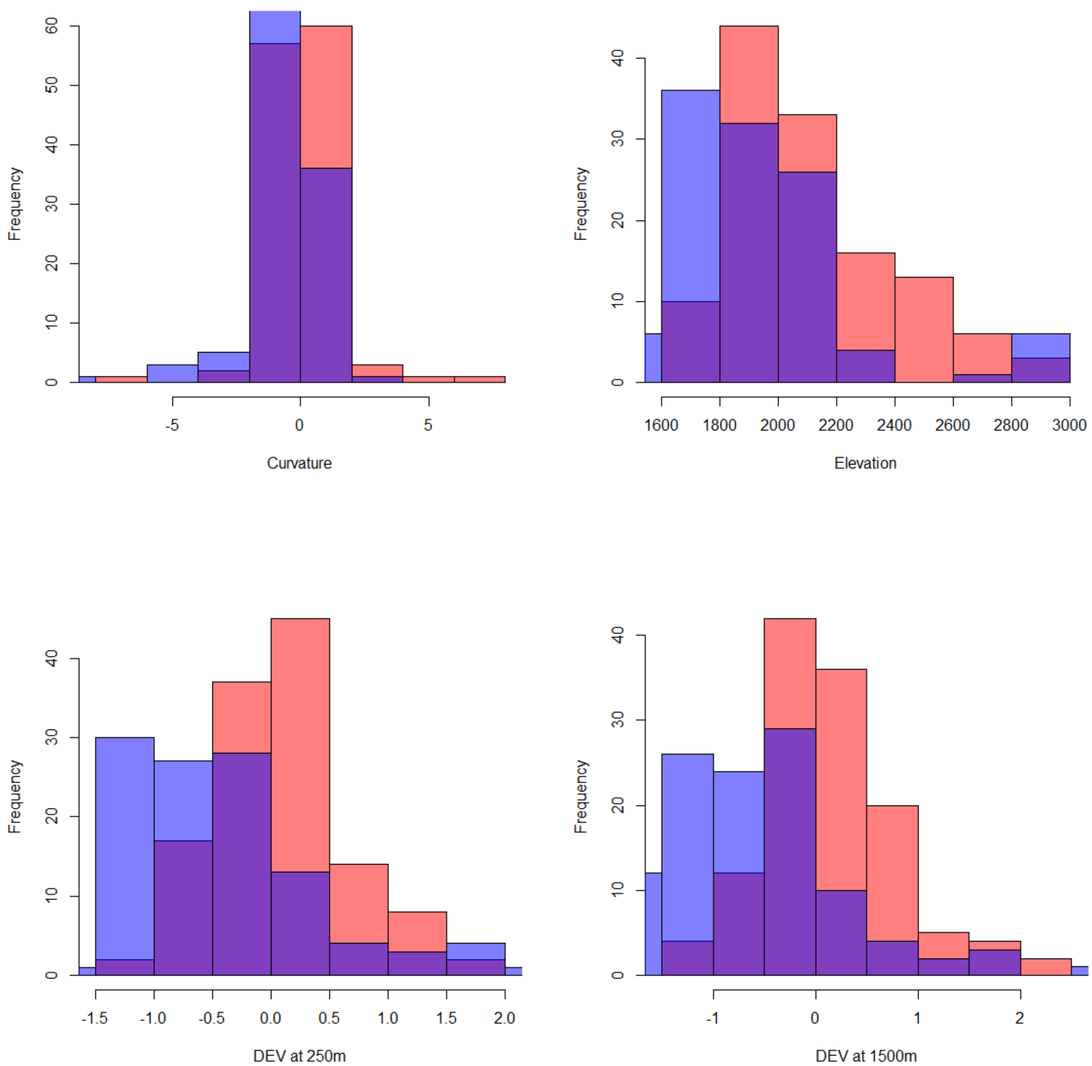
Once parameters are rasterized, values are extracted to the dataset based on a centroid of the site point. This results in a table that may be further analyzed for relationships between independent and dependent variables. Rasterized parameters are listed in the table below. Those marked with stars were excluded prior to modeling due to spurious correlations or multicollinearity, which is a problem because it can increase the variance of the coefficient estimates and make the estimates overly sensitive to minor changes in the model.

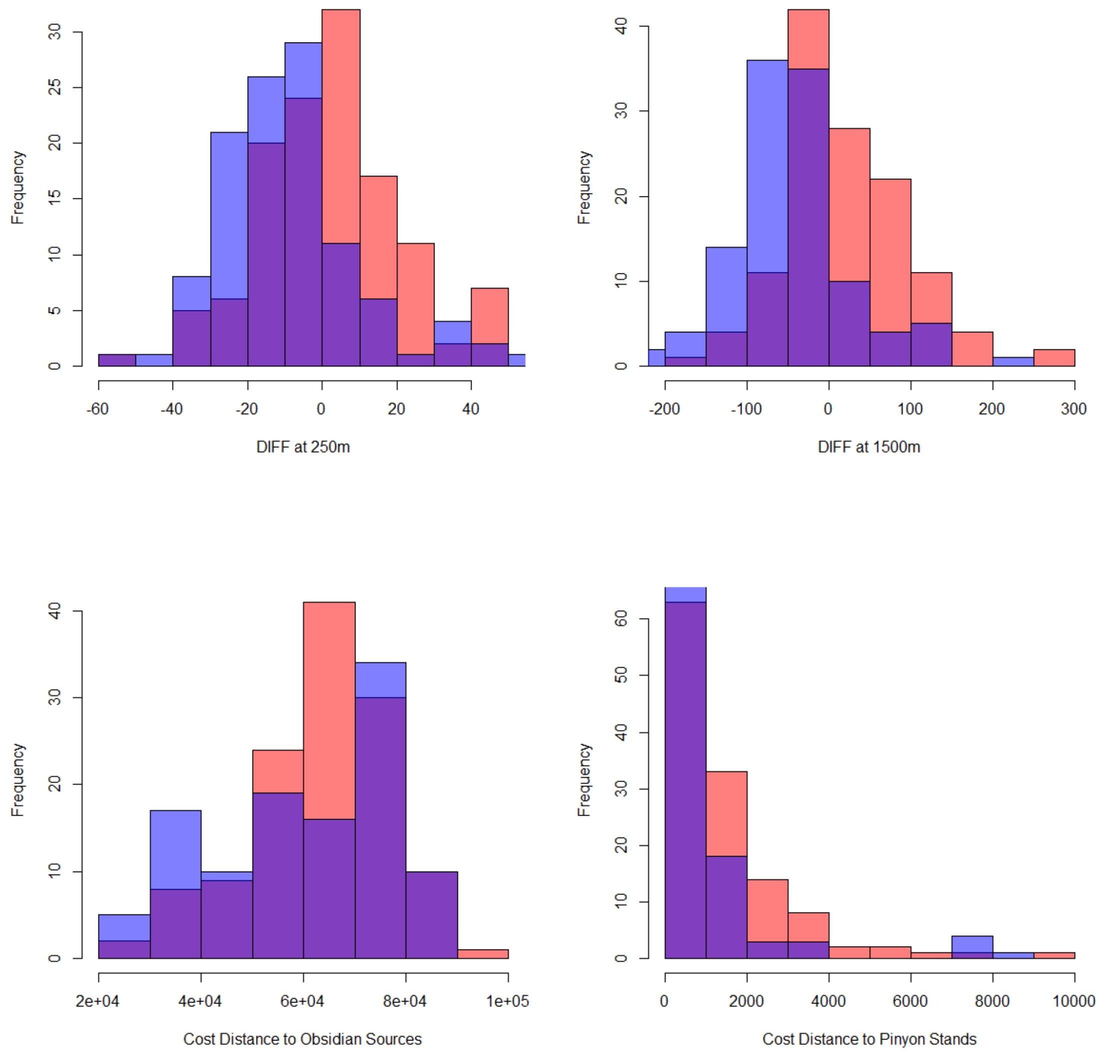
Multicollinearity was tested in R using Variance Inflation Factor (VIF) which indicate the extent to which multicollinearity is present in the logistic regression analysis. A VIF of 5 or greater indicates a highly correlated predictor variable. This was examined using the following expression:

sqrt(vif(model)) > 2

Criterion
Aspect (Converted to "Northness")
Curvature
DEV 250m
DEV 500m*
DEV 1000m*
DEV 1500m
DEV 2000m*
DIFF 250m
DIFF 500m*
DIFF 1000m*
DIFF 1500m
DIFF 2000m*
Elevation
Geologic unit*
Insolation*
Landform 250m
Landform 500m*
Landform 1000m*
Landform 1500m
Landform 2000m*
Landsat-derived NDVI*
Obsidian source cost distance
PCTG 250m
PCTG 500m*
PCTG 1000m*
PCTG 1500m
PCTG 2000m*
Permanent streams cost distance
Piñon stand cost distance
Slope
Springs cost distance
Viewshed 250m
Viewshed 500m*
Viewshed 1000m*
Viewshed 1500m
Viewshed 2000m*

TABLE 4: COMPLETE LIST OF PREDICTOR VARIABLES ASSESSED




Frequency
0
5
10
15
20
25
30
-60
-40
-20
0
20
40
DIFF at 250m
Frequency
0
10
20
30
40
-200
-100
0
100
200
300
DIFF at 1500m
Frequency
0
10
20
30
40
2e+04
4e+04
6e+04
8e+04
1e+05
Cost Distance to Obsidian Sources
Frequency
0
10
20
30
40
50
60
0
2000
4000
6000
8000
10000
Cost Distance to Pinyon Stands

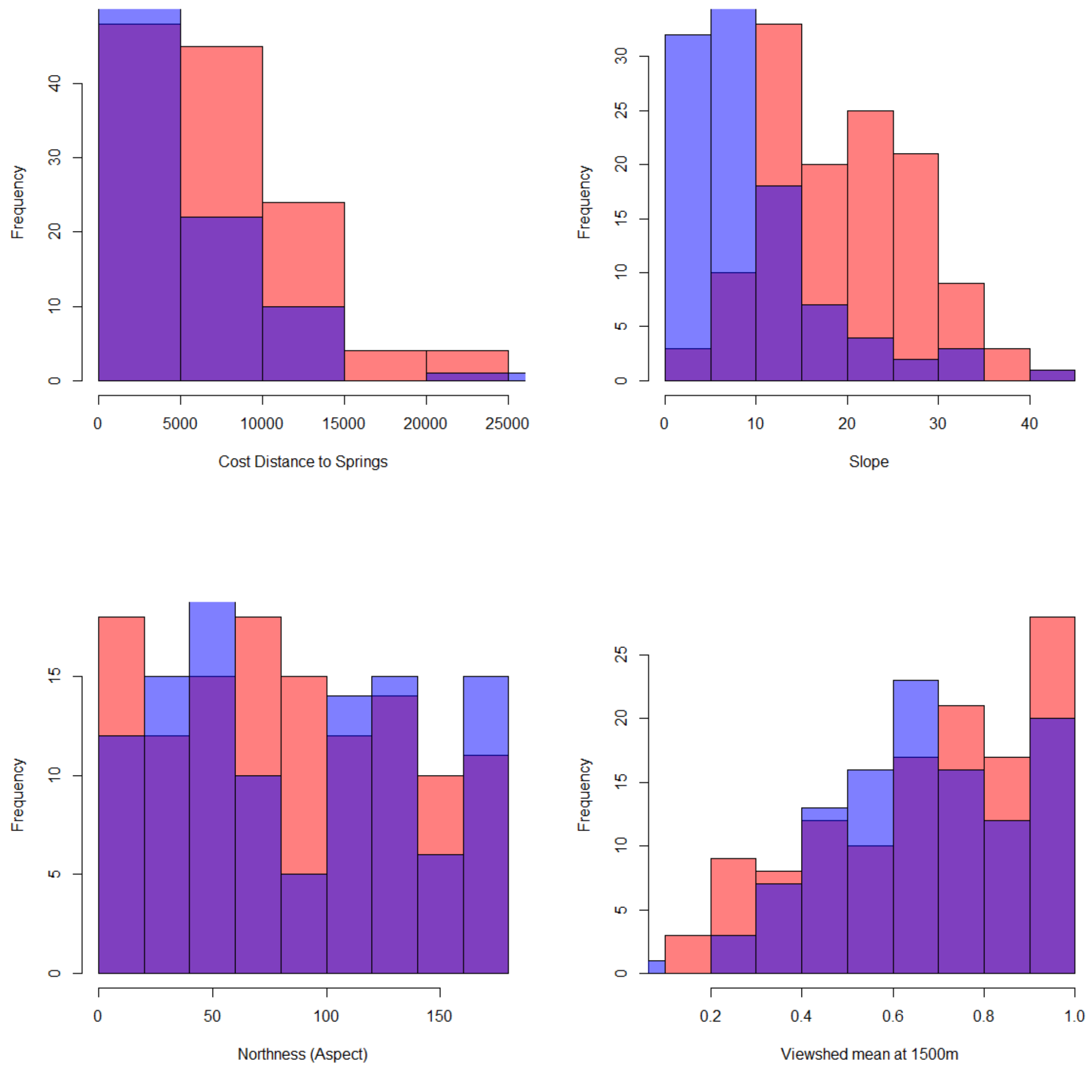


FIGURE 10: HISTOGRAMS CHARACTERIZING SITE PARAMETERS

The final parameters used in model-building are shown above using red to indicate nonsite (background) values and blue to indicate site presence values, with overlap in distribution shown in purple. These figures describe the ways in which human habitation sites differ from the landscape as a whole.

D. Sources of Error

A variety of sources of error are introduced by the archaeological dataset used in evaluation. The first is that data collected in the earliest periods of management by federal agencies under the mandates of cultural resource law was typically done through opportunistic sampling protocols that produce dramatically biased samples. As practices later evolved, different sampling strategies were employed to reduce this bias; however it is still evident in the dataset, as most surveys were conducted along roadsides in preparation for grading or development. A second source of error is that the technology used to record sites or isolated finds has changed dramatically over time, having originated in hand-drawn maps created with a compass and topographic map. The accuracy of hand drawn maps depends greatly on the practitioner, and can potentially introduce large errors, for example when sites are mapped in a neighboring drainage that is topographically similar by accident. This evolved into the now-standard use of GPS systems to record site location and map features, a tool that introduced up to 500+ m positional errors in its early iterations. Modern GPS with differential correction can be used to record archaeological features with sub-meter accuracy, although they are still subject to error sources from atmospheric effects, multipath signals, and signal interference (Bolstad, 2005).

A second main source of error is introduced by the many GIS processes used in generating the environmental parameters used in the model. A variety of these are derived products generated from a mosaicked DEM with a spatial scale of approximately 10 m. Errors that exist in first-order data products may be amplified when derivatives such as slope or aspect are calculated, confounding relationships between computed terrain attributes and terrain-controlled site conditions (Bolstad, 2005). It is critical that processing of DEMs, including mosaicking and projecting to different coordinate systems, utilize bilinear or cubic resampling instead of nearest neighbor to avoid the generation of spurious artifacts in the derivatives. Since all of the parameters used in this study were rasterized and matched to the cell size of the DEM, they may be considered derivative products. A thorough examination of the sources of error in DEMs as well as the variety of methods possible to correct error is available in *Digital Terrain Analysis* (Wilson and Gallant, 2000).

For these reasons, a precise measurement of error is extremely difficult to quantify since it varies over time within the archaeological dataset as well as within the variety of sources used to generate derived data and first-order data. A baseline for accuracy is that it will be at minimum ±10 m, but is likely to be larger in reality.

E. Model Types

Model 1: Multiple Logistic Regression

Logistic Regression, also called a logit model, is used to model dichotomous (binary) outcome variables. In the logit model the log odds of the outcome is modeled as a linear combination of the predictor variables. This technique was used to analyze which independent variables are most useful in predicting site presence or absence. Since the data available for analysis was primarily collected through pedestrian survey, a continuous response variable such as intensity of occupation or duration of occupation is not available and the few data-rich sites that do exist would result in a dataset too small to build an effective model. Logistic regression models have been used successfully in building models of archaeological potential using environmental parameters (e.g., Clark, 2012; Duncan and Beckman, 2005; Espa et al., 2006; Kvamme, 1983, 1992; Warren and Asch, 2005; Wheatley and Gillings, 2003).

The statistical null hypothesis is that the probability of the dependent variable (site presence) is not associated with the value of the independent variable. In this case the line describing the relationship between an environmental parameter and the probability of the site presence has a slope of zero. R statistical software and Weka 3, both open source software, were used for logistic regression.

Model 2: Regression Tree

In the last few decades, geoinformatics, statistical and machine-learning methodologies have made significant progress (Märker and Heydari-guran, 2009), especially in use with archaeological datasets. Regression trees are a statistical learning method that can help to meet the fundamental objectives of both accurate prediction and explanation. These methods have been applied in a wide range of geomorphologic and ecological studies, but are not as frequently used in archaeology in spite of their predictive utility (Breiman, 1999; De'ath and Fabricius, 2013; Märker and Heydari-guran, 2009). Regression trees and random forest analyses have also been used to explore the development of cooperation in hunter-gatherer societies (Santos et al., 2015). Interactions between predictors and response variables are quantified and visualized. R statistical software and Weka 3 were also used for regression tree generation.

Model 3: Random Forest

Random Forest algorithms are used frequently in data-mining where large datasets of binary outcomes are important, such as in medicine, but have also recently been applied to archaeological prospection (Märker and Heydari-guran, 2009; Menze and Ur, 2007; Santos et al., 2015; Verhagen and Whitley, 2011). This nonlinear ensemble classifier performs an internal feature selection, choosing features with a high relevance to the classification task while safely ignoring irrelevant predictors. Thus error converges as the number of trees increases. Individual trees in random forests cannot be distinguished in terms of simple interpretations of its mechanisms. Use of internal out-of-bag estimates and model re-runs using only selected variables can help to improve understanding of variable interactions that are providing predictive accuracy (Breiman, 1999). As with models 1 and 2, R statistical software and Weka 3 were used for random forest generation.

F. Model Selection & Validation

Model selection involves an iterative process of creating many models and estimating their performance of in order to choose the best one. The method used to test model performance was to split the data into 5-fold cross-validation sets. Cross-validation assesses performance by testing how the results of a statistical analysis on a training dataset will generalize to an independent (testing) data set. Both the training and testing sets are extracted from the entire dataset of preclassified dependent and independent variables. Using supervised data mining algorithms, the training set is used to build the model. The test set is then used to evaluate how well the model performs with data outside the training set by withholding the test set from the model-building stage and using it as a comparison against model results. The model is then reiterated and adjusted to minimize error on the test set.

G. Model Assessment

Having chosen a final model, its prediction error (generalization error) must be estimated on new data. In the 2014 field seasons, limited new data was collected using reconnaissance survey and subsurface testing methods. Due to budget constraints, the sample acquired is not large enough to provide an accurate assessment of the predictive power of the models, but it does give some indication of preliminary outputs.

Errors of Omission/Commission

Data for nonsite locations is required to evaluate the efficacy of a predictive model and compare the results of discovery against chance. Given that the study area consists of a rasterized grid of 15196341 pixels, and that 4705 pixels contain known sites, the probability that a randomly chosen pixel will contain a known site is 0.000309614 or 0.03%. Errors of commission (false positives) identify areas as sites when in reality none exists, and errors of omission (false negatives) fail to identify an area as a site when one does exist. The sensitive legal and cultural issues surrounding CRM in the United States necessitate a model that minimizes errors of omission.

IV. Results

The methods discussed here can be used to determine areas where previously unknown cultural resources might be located. It is strongly cautioned however that these results do not make causal connections between the environmental parameters under study and the locations of human activities. Site presence is an effect correlated with other independent effects, rather than caused by them. This study may, however, provide a starting point from which to form new hypotheses regarding causal relationships associated with the environmental parameters that determine site location.

Results from Model 1: Logistic Regression

Results of this model type are presented in the table below. Significance codes are as follows: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. The dispersion parameter for binomial family is taken to be 1, and 5 Fisher scoring iterations are used. Akaike's Information Criterion (AIC) is used as an index for selecting between competing models, under the assumption that it represents the most parsimonious available model given the data supplied. This index takes into account both statistical goodness of fit and the number of parameters that must be estimated to achieve a particular degree of fit, and imposes a penalty for increasing the number of parameters. Standalone AIC values are not interpretable due to arbitrary constants and effects of sample size, however a comparative reduction in AIC indicates a more robust model, i.e., one with the fewest parameters that still provides an adequate fit (Burnham, 2004).

model <- glm(site presence ~ curvature + elevation + dev_1500m + dev_250m + obsidian_c + pinyon_c + slope + northness + spring_c + view_1500m, data=data)

The first trial model resulted in a null deviance of 235.00 on 235 degrees of freedom and residual deviance of 135.91 on 225 degrees of freedom with an AIC score of 563.5. This model run suggests that the most important predictors for site location are the cost distance to springs and obsidian sources, slope, and aspect. However, the inclusion of all possible parameters masks effects of other predictors that may be contributing to the response variable. A stronger model is created by a stepwise reduction of parameters judged by resulting AIC. Stepwise reduction is performed using an algorithm that automatically chooses from among a set of available predictors to create the regression model. The following expression is used to perform the stepwise regression:

step.model <- step(model, direction="both")

Coefficients	Estimate	Std.	Error	z value	Pr(>|z|)
dev_1500m	-2.39E-01	5.65E-02	-4.229	3.39E-05	***
obsidian_c	-1.02E-01	5.33E-02	-1.91	0.05741	.
slope	-4.53E-01	5.42E-02	-8.361	5.99E-15	***
spring_c	-1.79E-01	5.98E-02	-2.986	0.00313	**
view_1500m	-1.19E-01	5.28E-02	-2.261	0.02467	*

TABLE 5: LOGISTIC REGRESSION RESULTS FROM AIC STEPWISE REGRESSION MODEL.

The pared-down model using stepwise reduction represents the predictor variables with the most influence on site selection, in this case, slope, DEV at a neighborhood of 1500m, cost distance to obsidian sources and springs, and the mean viewshed at a neighborhood of 1500m. Null deviance remains the same at 235.00 on 235 degrees of freedom, and residual deviance increased to 136.6 on 230 degrees of freedom. AIC was reduced from 563.5 to 554.69 in the pared-down model, suggesting it is the most parsimonious model available. All parameters used have a significant effect on site presence, with slope, DEV at 1500 m, and cost distance to springs having the strongest influence. It is of interest that aspect, although commonly used by other researchers as a parameter in modeling in this area, had no relationship with site presence in the Minidoka.

In order to determine which of the variables might be contributing the most to site selection behavior, the model was run using scaled variables. For example in R statistics software, the following command was used to scale the input data to common units for direct comparison:

data <- data.frame(scale(data, center = TRUE, scale = TRUE))

An assessment of relative importance of variables included in the final logistic regression model shows that slope, DEV (specifically at a 1500m neighborhood), and cost distance to springs are the three parameters that account for most of the variation seen in site distribution (see Figure 11). This demonstrates that the other factors included in the model account for only a small proportion of the variance, and suggests that the primary concerns in site selection are considerations of landform suitability and access to fresh water from natural springs. To calculate relative importance for each predictor, the following statement was used to bootstrap measures with 1000 samples:

boot <- boot.relimp(step.model, b = 1000, type = c("lmg", "last", "first", "pratt"), rank = TRUE,
diff = TRUE, rela = TRUE)
booteval.relimp(boot)

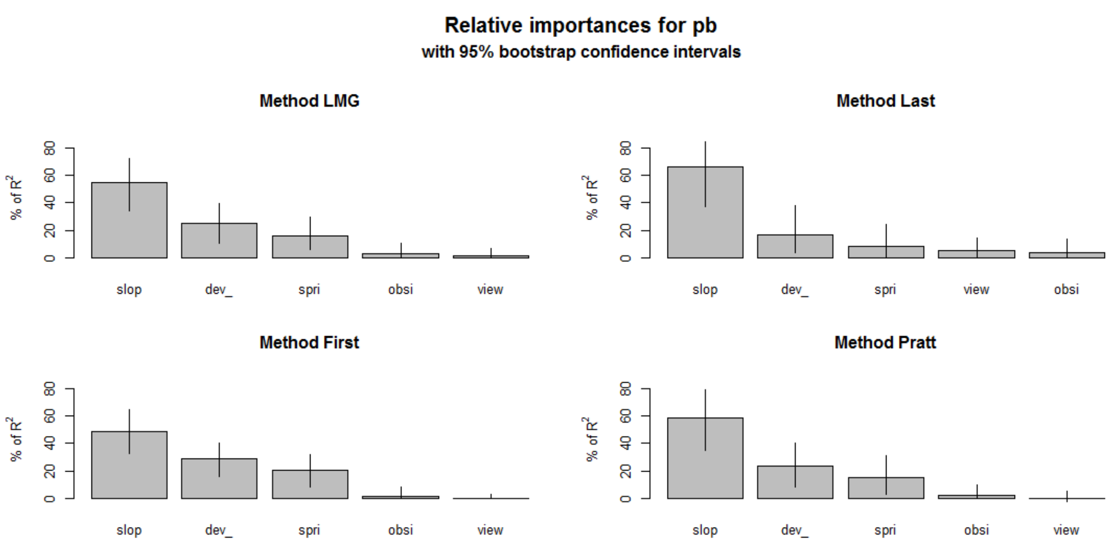


FIGURE 11: RELATIVE IMPORTANCE OF VARIABLES FOR DETERMINING SITE PRESENCE OR ABSENCE

Model selection and validation for Model 1 used the Receiver Operating Characteristic (ROC) curve to assess the performance of the model by cross-validation. ROC is a graphical representation that can quantify a binary-outcome model's performance by evaluating its performance against a test set. Created by plotting the true positive rate against the false positive rate, this measure can assess accuracy by measuring the Area Under the ROC Curve (AUC) (Metz, 1978). An area of 1 represents a perfect model in which it is able to correctly classify the dependent variable in every instance of the test data, while an area of 0.5 or less represents a worthless test (in which the model performs below chance). In general, an AUC of greater than 0.90 is considered to be excellent, 0.80 to 0.90 to be good, 0.70 to 0.80 to be fair, and 0.60 to 0.70 to be poor (Zou et al., 2007).

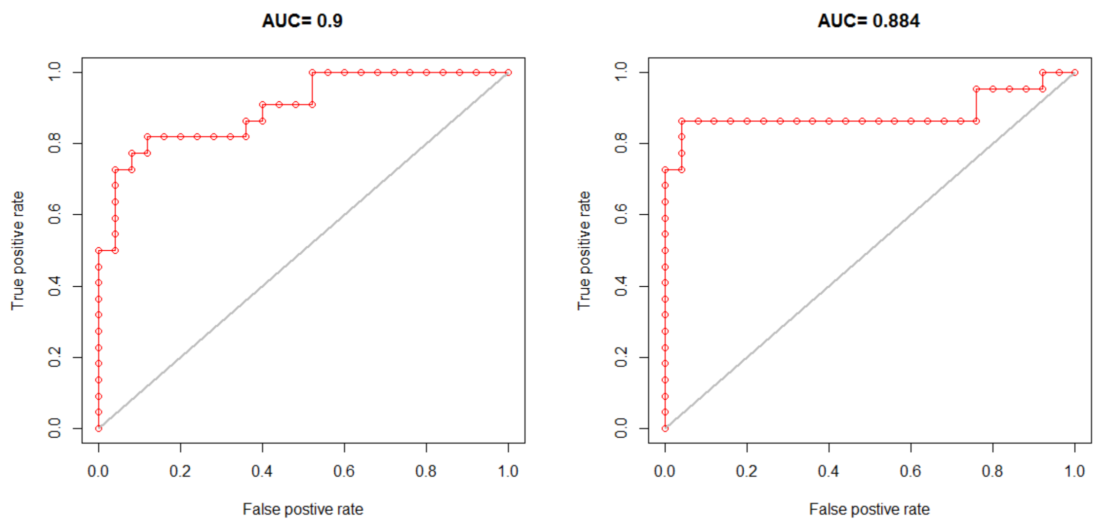


FIGURE 12: PLOT OF AUC RESULTS FOR LOGISTIC REGRESSION, AT LEFT: COMPLETE LOGISTIC REGRESSION MODEL 0.90, AT RIGHT: AIC STEP-WISE REDUCTION MODEL 0.88

The AUC results obtained show that both models are performing very well at correctly classifying site presence when tested against the 'test' data. The small reduction in AUC from 0.90 when testing the full logistic regression model to 0.88 when testing the stepped model is not significant enough to include all possible parameters, since it would run the risk of over-fitting the model. This result shows that the more parsimonious model still performs as well as the full model when tested against a subset of the data.

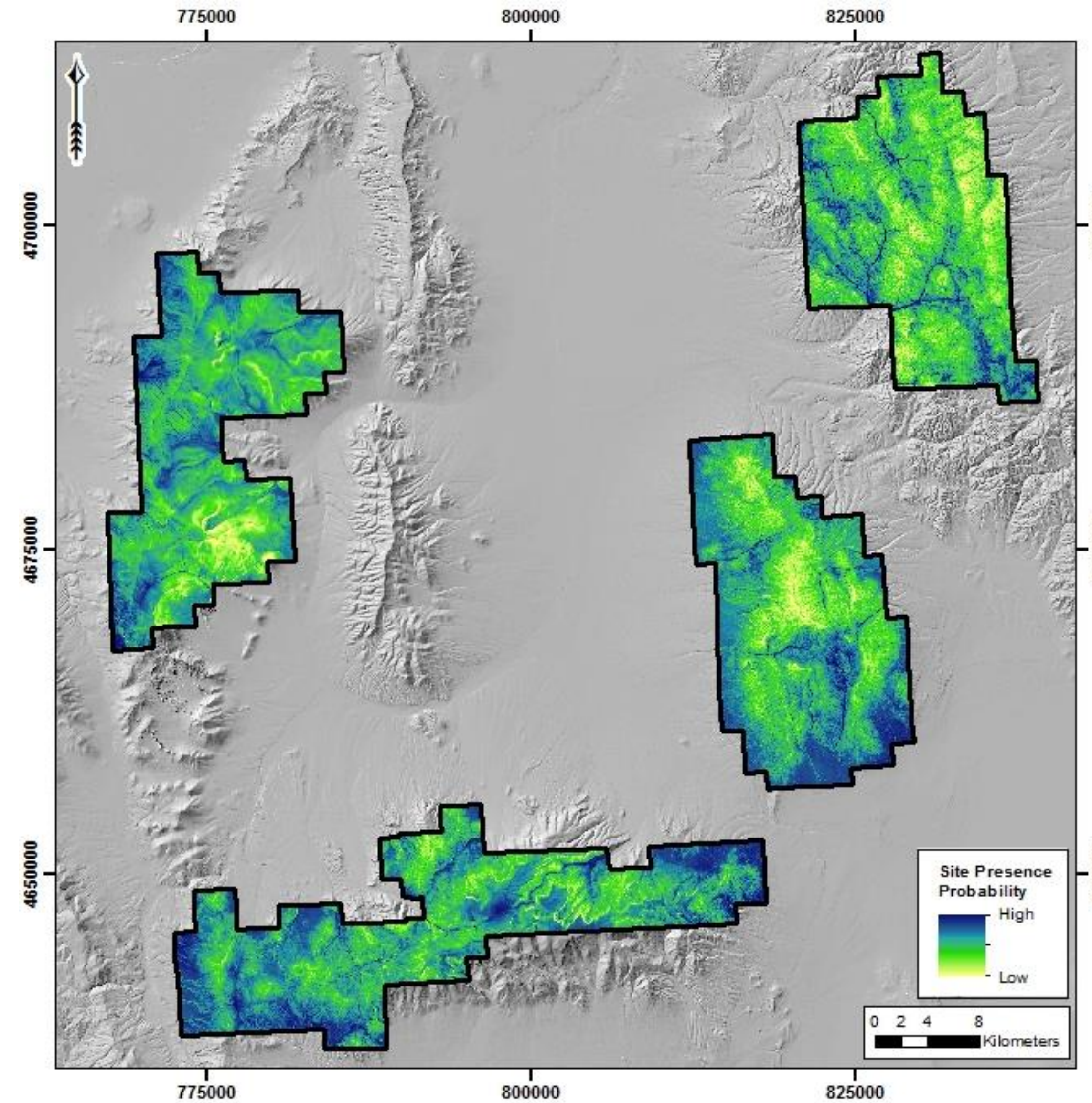


FIGURE 13: PREDICTIVE MAP OF MINIDOKA DISTRICT GENERATED USING LOGISTIC REGRESSION; DARKER BLUE INDICATES AREAS OF HIGHER PROBABILITY

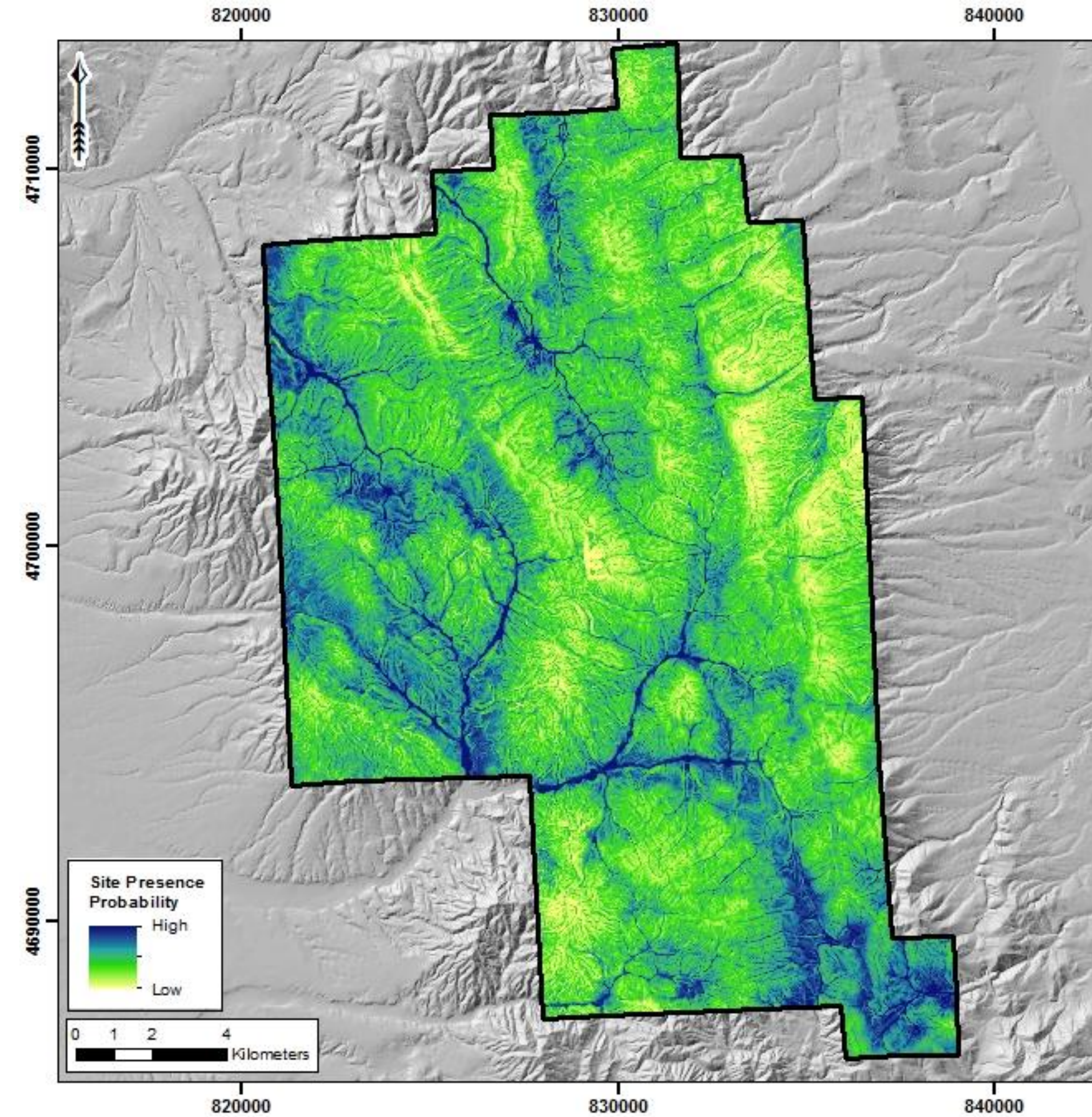


FIGURE 14: PREDICTIVE MAP OF SUBLETT DIVISION GENERATED USING LOGISTIC REGRESSION

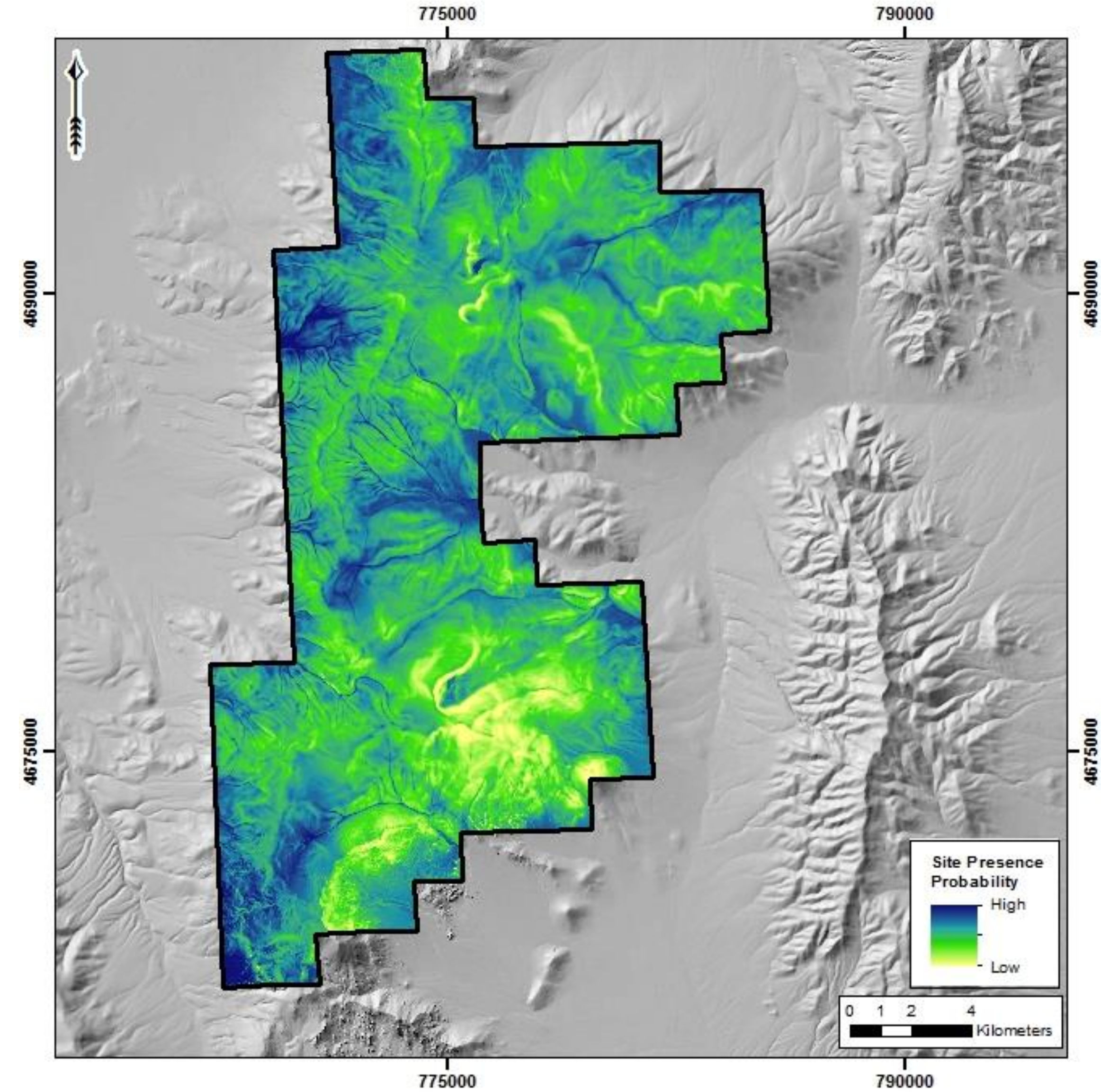


FIGURE 15: PREDICTIVE MAP OF ALBION DIVISION GENERATED USING LOGISTIC REGRESSION

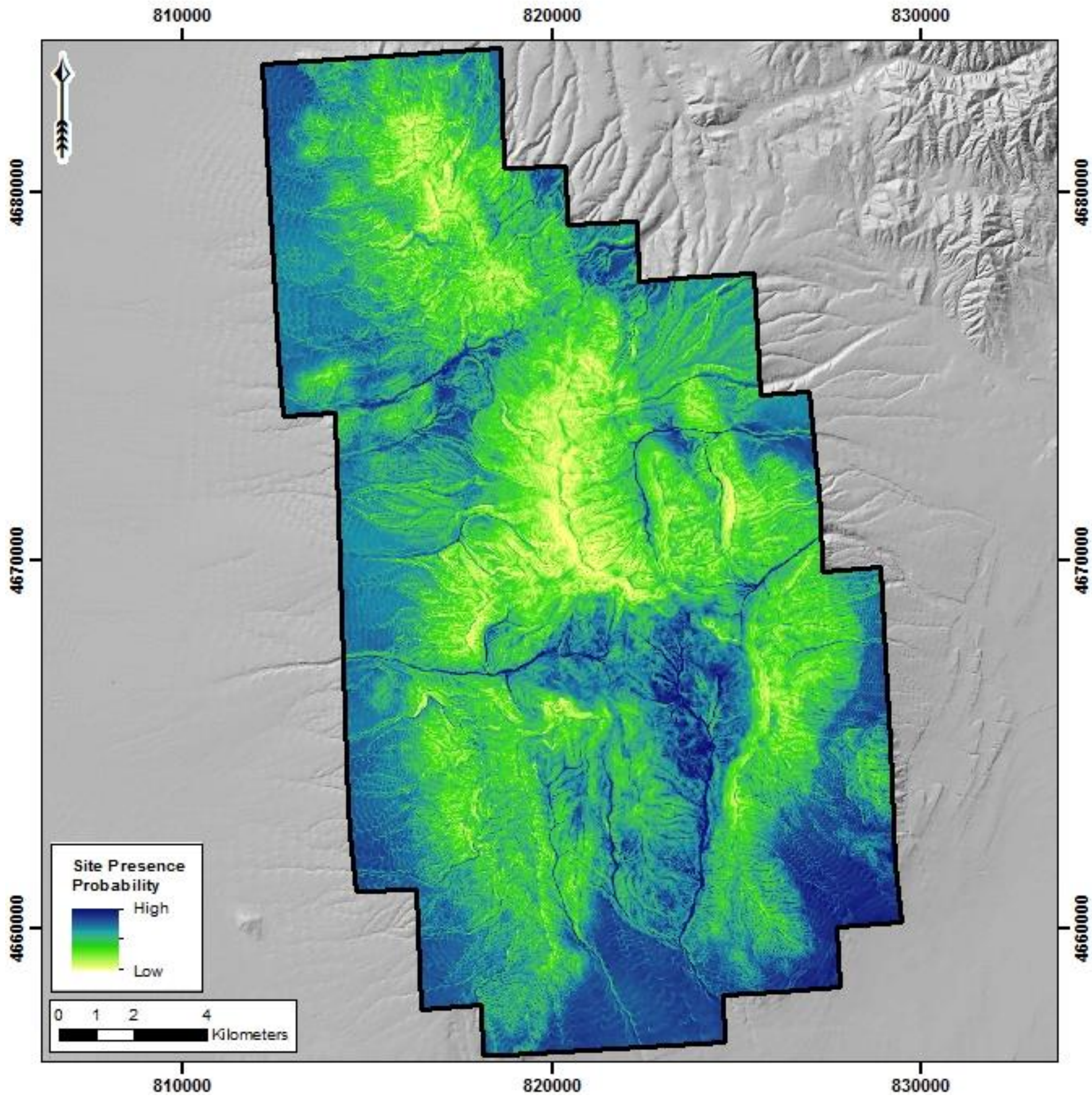


FIGURE 16: PREDICTIVE MAP OF BLACK PINE DIVISION GENERATED USING LOGISTIC REGRESSION

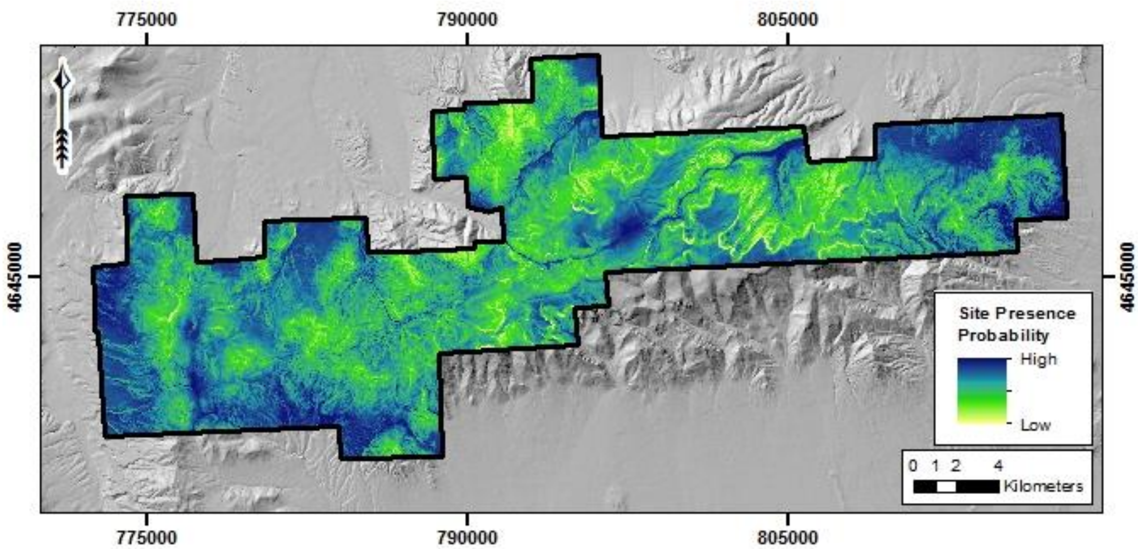


FIGURE 17: PREDICTIVE MAP OF RAFT RIVER DIVISION GENERATED USING LOGISTIC REGRESSION

The predictive raster outputs above were generated using the AIC stepwise logistic regression model. Dark blue corresponds to areas of higher probability, and yellow corresponds to areas of lower probability. This rasterized grid was masked to the boundaries of the study site since it represents only the pattern of locational behavior observed in montane sites and would not accurately predict site presence in open areas. The Cassia division was omitted from the rasterized model output as well.

One method to account for the effects of spatial autocorrelation that was encountered in this dataset is subsampling the data and rerunning the model. There are a number is issues that arise from a subsample in this case, most notably that the sample size of positive responses is reduced to a much smaller size (n=33). Logistic regression performs best when the proportion of positive and negative responses is approximately 50%, which requires that the nonsites dataset be subsampled as well. The result is a combined dataset smaller than the minimum sample size (n=100) necessary to achieve a minimally acceptable level of statistical power (Long, 1997). The subsampled dataset resulted in a model that reduces the probability that it is correctly able to reject the null hypothesis due to its reduced statistical power, increasing the chances of a false negative. Logistic regression model rerun produced a model that corresponded well to the model using the full dataset, with slope, DEV at 1500m, and cost distance to springs as the statistically significant parameters. Obsidian cost distance is not statistically significant to site location with the subsampled data. It should be cautioned however that subsampled modeling in this instance will necessarily reduce model confidence due to the smaller sample size.

Results from Model 2: Regression Tree

Weka software was used to generate the regression tree using the RepTree algorithm. This algorithm uses regression tree logic to create multiple trees in different iterations and selects the best one by pruning. The mean square error of predictions is used to prune the tree. Run information for the regression tree model is displayed below:

=== Run information ===

```
Instances: 236
Attributes:
        Presence
        curvature
        dev_1500m
        dev_250m
        diff_1500m
        diff_250m
        northness
        obsidian_c
        pinyon_c
        slope
        spring_c
        stream_c
        view_1500m
        view_250m
Test mode: 5-fold cross-validation

=== Classifier model (full training set) ===
REPTree
============
slope < 8.92 : site (39/3) [41/6]
slope >= 8.92
|   spring_c < 2476.25
|   |   view_1500m < 0.83 : site (11/0) [19/7]
|   |   view_1500m >= 0.83 : nonsite (4/1) [1/0]
|   spring_c >= 2476.25
|   |   dev_250m < 1.52
|   |   |   diff_1500m < -58.09
|   |   |   |   pinyon_c < 1294.68 : site (3/0) [4/1]
|   |   |   |   pinyon_c >= 1294.68 : nonsite (5/0) [5/1]
|   |   |   diff_1500m >= -58.09 : nonsite (53/2) [47/4]
|   |   dev_250m >= 1.52 : site (3/0) [1/1]
```

Size of the tree: 13

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	190	80.5085 %
Incorrectly Classified Instances	46	19.4915 %
Kappa statistic	0.6088	
Mean absolute error	0.2733	
Root mean squared error	0.3889	
Relative absolute error	54.8426 %	
Root relative squared error	77.9171 %	
Total Number of Instances	236	

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.793	0.184	0.793	0.793	0.793	0.85	Site
	0.816	0.207	0.816	0.816	0.816	0.85	Nonsite
Weighted Avg.	0.805	0.196	0.805	0.805	0.805	0.85	

TABLE 6: DETAILED ACCURACY BY CLASS FOR REGRESSION TREE

Site	Nonsite	Classified as
88	23	Site
23	102	Nonsite

TABLE 7: CONFUSION MATRIX FOR REGRESSION TREE

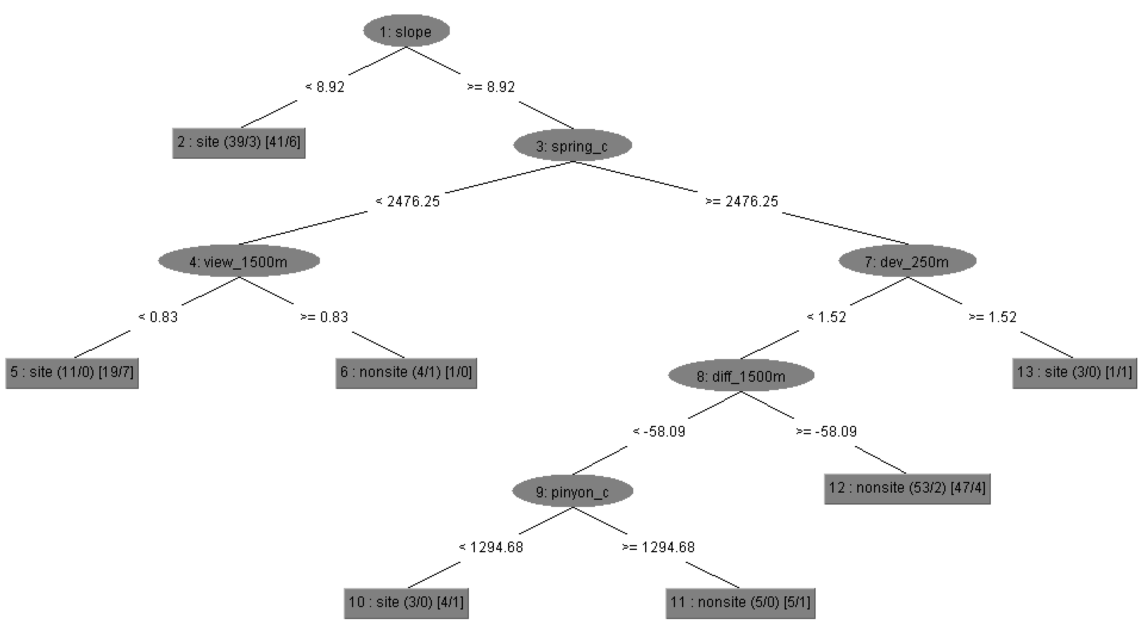


FIGURE 18: REGRESSION TREE VISUALIZED

Cross-validation was also used to prune the tree to prevent overfitting by evaluating the error on the testing data at each pair of leaf nodes with a common parent to determine whether the sum of squares would be smaller by removal of the nodes to turn the parent into a leaf. This process is repeated until pruning no longer improves the error on testing data. Using regression tree, the environmental parameters under investigation here can correctly identify approximately 80% of site presence/absence instances, although there are undoubtedly less easily quantifiable influences such as ideology and more abstract cultural practices that influence spatial behavior being picked up in this model. The model output may be less desirable than that of logistic regression, since it results in a binary outcome representing a classified landscape in which sites are either likely to occur, or not likely to occur (see Figure 19).

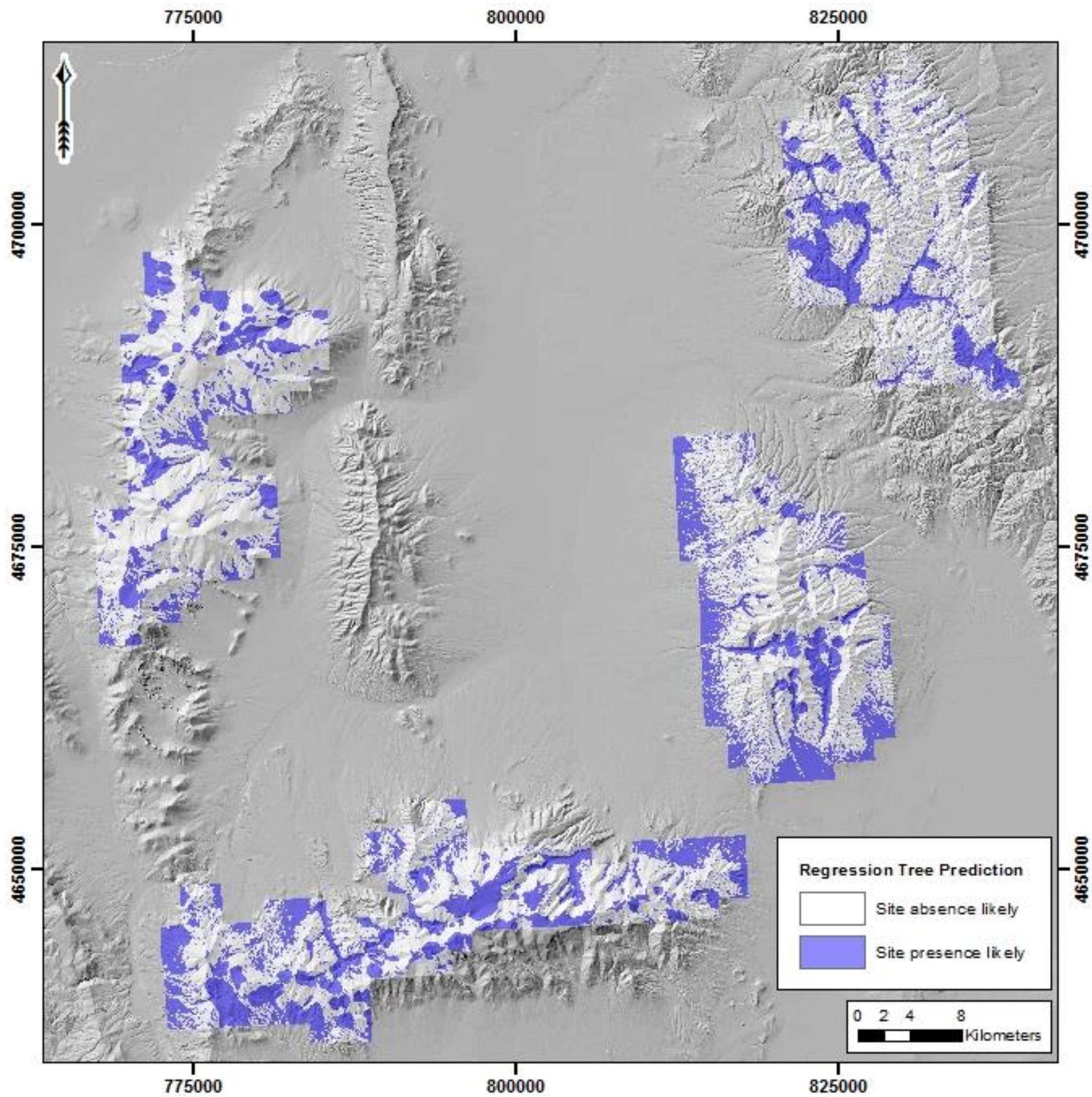


FIGURE 19: PREDICTIVE MAP GENERATED FROM REGRESSION TREE MODEL

Results from Model 3: Random Forest

Weka software was used to create a random forest model. The algorithm was executed with 13 parameters and 500 iterations. Permutation-based MDG reduction is used as the criterion of importance to rank model parameters. Random permutation of predictors demonstrates an increase in MDG positively correlated with its importance rank as a predictor. The random forest model produced an out-of-bag error of 0.1356, demonstrating its efficacy as a predictor of site presence. Run information from the model implementation is included below.

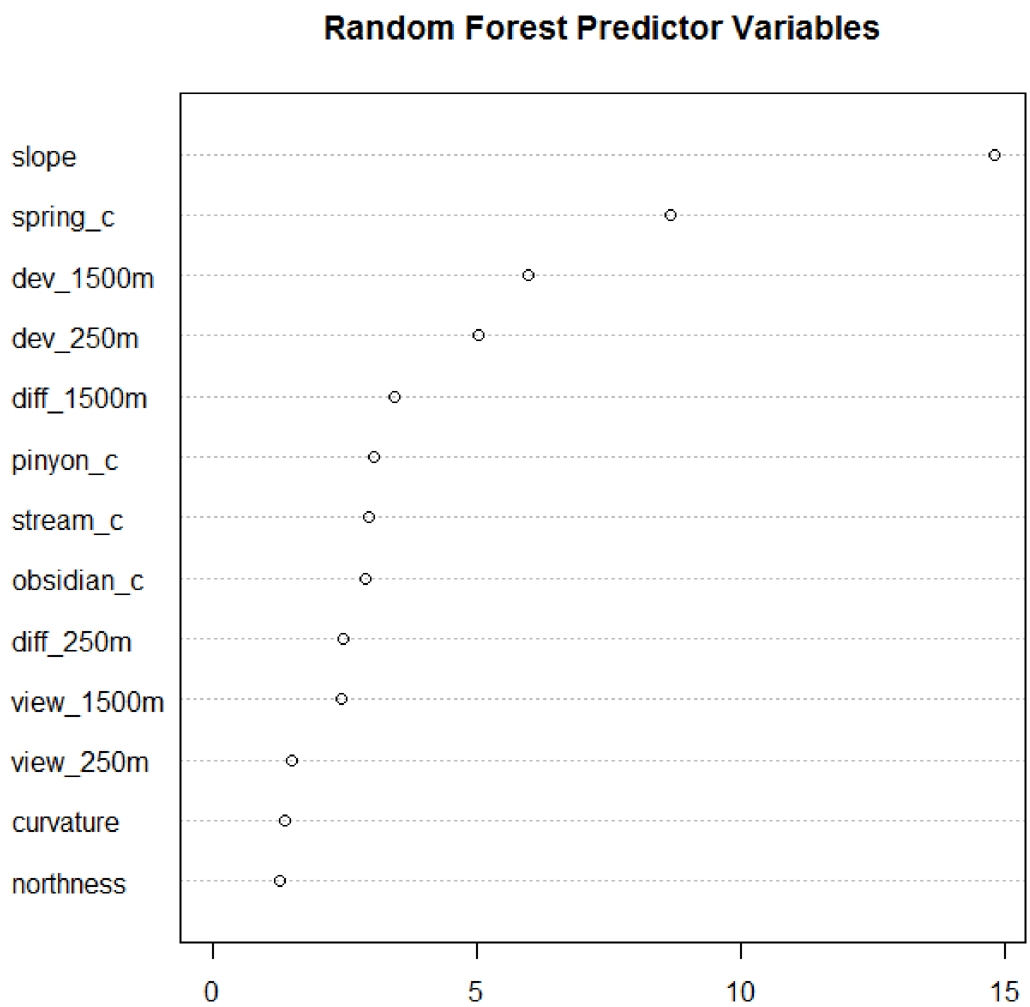


FIGURE 20: PARAMETER IMPORTANCE DERIVED FROM RANDOM FOREST ANALYSIS.

=== Run information ===

Instances: 236

Attributes:

Presence	obsidian_c
curvature	pinyon_c
dev_1500m	slope
dev_250m	spring_c
diff_1500m	stream_c
diff_250m	view_1500m
northness	view_250m

Test mode: 5-fold cross-validation

=== Classifier model (full training set) ===

Random forest of 500 trees, each constructed while considering 4 random features.

Out of bag error: 0.1356

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	206	87.2881 %
Incorrectly Classified Instances	30	12.7119 %
Kappa statistic	0.7449	
Mean absolute error	0.2278	
Root mean squared error	0.315	
Relative absolute error	45.7262 %	
Root relative squared error	63.1013 %	
Total Number of Instances	236	

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.865	0.12	0.865	0.865	0.865	0.939	Site
	0.88	0.135	0.88	0.88	0.88	0.939	Nonsite
Weighted Avg.	0.873	0.128	0.873	0.873	0.873	0.939	

TABLE 8: DETAILED ACCURACY BY CLASS FOR RANDOM FOREST

Site	Nonsite	Classified as
96	15	Site
15	110	Nonsite

TABLE 9: CONFUSION MATRIX FOR RANDOM FOREST

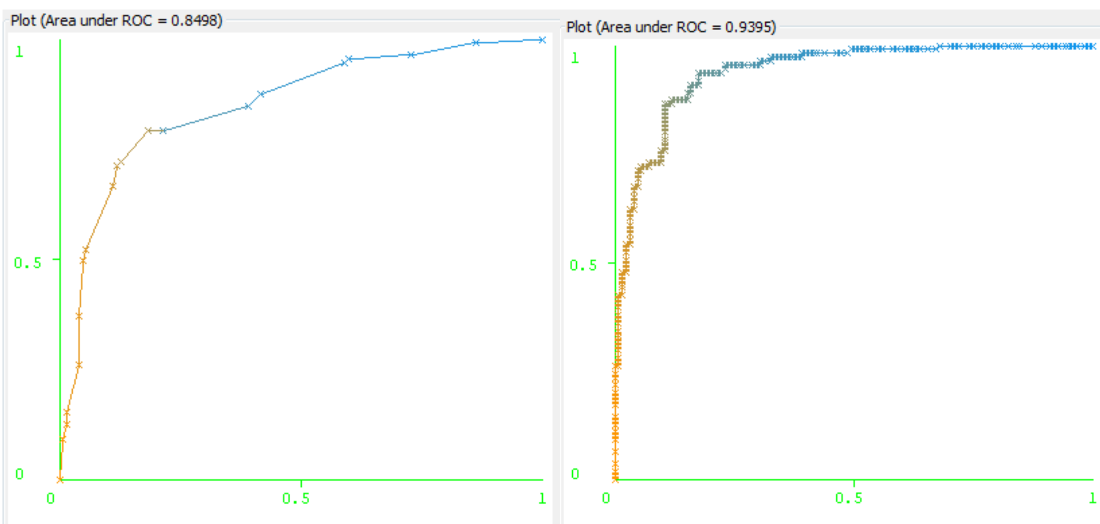


FIGURE 21: AUC RESULTS FROM REGRESSION TREE AND RANDOM FOREST MODELS; AT LEFT: REGRESSION TREE 0.85, AT RIGHT: RANDOM FOREST 0.94

The AUC results of regression tree (0.85) and random forest (0.94) demonstrate that both perform well at correctly classifying site presence when cross validated.

Results from Model Assessment

The limited testing done in 2014 provides an opportunity to compare the results of the model classifiers on novel data, although it is a clear limitation of this data that the sample size is not large enough to be statistically significant. A second limitation is that it was collected prior to model development, and in the case of both the logistic regression and regression tree outputs, only provides a comparison sample of areas classified as having a higher likelihood to bear cultural resources. Unfortunately no subsurface testing was done in any areas of low probability, so this sample may only confirm errors of omission and not errors of commission. Seven locations were visited and surveyed either through systematic transect reconnaissance, shovel testing, or a combination of the two. Of the seven, four were positive for the presence of cultural resources. Although it may appear that these results show poor model performance and contradict the cross-validation results outlined above, it is cautioned that the very small sample size limits what inferences can be made. Furthermore, even a rather disappointing 57% success rate would represent a marked improvement over the 0.03% probability that a randomly chosen pixel (approximately a 10x10m location) will contain a known site.

V. Conclusions

Research Findings

The fact that it has been possible to construct a predictive model does not in itself guarantee the accuracy of the model's predictions (Conolly and Lake, 2006). Validation of the model must be carried out by determining its predictive power above chance, in this case using k-fold cross-validation. The 0.88 AUC value from the stepped logistic regression model shows that it is performing very well at correctly classifying site presence, and the AUC values of 0.85 and 0.94 for regression tree and random forest demonstrate that all of the models examined here are suitable methods for predicting site presence when tested using cross-validation. It is the author's recommendation that the logistic regression model be utilized in future field research as opposed to the regression tree or random forest models, since it represents the most parsimonious model and reliably classifies site presence and absence.

A widely reported measure of model performance in archaeological predictive modeling is Kvamme's gain index (Balla et al., 2014a, 2014b; Brandt et al., 1992; Carleton et al., 2012; Chen et al., 2013; Ebert, 2004, 2005; Harrower, 2013; Kvamme, 1992; Verhagen and Whitley, 2011). The validity of the logistic regression and regression tree models were tested by calculating Kvamme's gain, expressed by the following:

Gain = 1− ((% of total area covered by the model)/(% of total sites within model area))

As gain approaches 1, the predictive utility of the model increases (Kvamme, 1989). The gain statistics produced by the regression tree and logistic regression models are 0.96 and 0.97 respectively, indicating that they are both excellent classifiers of site presence. This method of evaluating model performance provides a measure of the efficiency of prediction as a function of area and is useful for comparing models developed using different algorithms or techniques (Hill et al., 2005).

This study is one of a very small number that compares multiple model types directly. Given that, depending on the model used, 80-90% of the variation observed in human locational patterning can be explained by a handful of environmental attributes, the premise of using an ecological approach to studying human systems in the Northern Great Basin is supported. The hypothesis that consistency in locational behavior observed over long timescales in the Minidoka results from selective pressure that favored plasticity in cultural adaptation is supported by these results. Although it is evident that locational behavior was correlated strongly with environment, other social and ritual forces almost certainly influenced the observed variation.

Predictive models can be used in both CRM and academic research to identify areas in need of further investigation. Discovery of new archaeological sites adds to existing knowledge and deepens our understanding of past human activity. There is also great utility in potentially reducing costs by providing guidance and support for development and land use projects. Predictive modelling can be a successful tool that also advances archaeological thinking and interpretation of the past (Balla et al., 2014a). This research contributes to the understanding of hunter-gatherer adaptations in the intersection between the Great Basin and Plateau cultural areas of North America.

Results show that there is a significant relationship between site distribution and terrain characteristics and processes that can be assessed by topographic indices and environmental parameters. It was demonstrated that the modeling methodologies employed here yielded relationships that can be applied to the region under study to derive spatial archaeological site probabilities. The information gained here can be used to develop hypotheses that can be tested in further research as well as improving sampling design for future field work.

Use of statistical methods to predict site locations strikes a delicate balance; is the goal to continue to find sites that are similar in functionality and time depth to the sites already known, or is it preferable to proceed with an inductive model and include environmental parameters that may define classes of sites under-represented in the dataset? Results of analysis from the models examined here suggest that it would perform very well at predicting locations of human activity that conform to the dataset available, but it is an open question as to whether or not this dataset is truly representative. Taken together with field testing, these data will help to enhance knowledge of mobility patterns, subsistence, and economy over time. High altitude regions have been traditionally thought of as marginal and peripheral to core areas of cultural development, and so too have nomadic groups traditionally been excluded from discussions of complexity (Aldenderfer, 2006). This research helps to understand human movement across the landscape in montane regions and further general knowledge about the ecology and culture of nomadic peoples.

Overall this study contributes not only to our knowledge of culture history of the region, but to a greater understanding of human prehistory by investigating the change over time in hunter-gatherer communities in the Great Basin and Plateau cultural areas of North America. This research demonstrates that modeling human behavior as a response to environment is effective in the spatial and temporal extent studied. It also contributes to anthropological studies about human-environment interaction in general by modeling and testing variability in resource exploitation as a response to environment, and evaluates continuity in the range and variation of human locational behavior. Data generated here describes cultural practices on a local level and may be used in comparative study in a wider regional context. This research focuses on elucidating patterns of human locational behavior by using an HBE framework to draw inferences from material remains. Future work can build on these foundations to better understand human behavior and how it interacts with and is influenced by dynamic and complex socio-environmental contexts.

Future Research Possibilities

The strong negative correlation between site location and NDVI values suggests a discovery bias in survey methods. This could be corrected in future research by the inclusion of subsurface testing in areas with low surface visibility due to vegetation, potentially resulting in a more representative sample of cultural resources in the area. Future modeling efforts could be made substantially more robust by including a detailed paleoenvironmental record to reconstruct paleoscapes that more accurately represent the landscape that past humans inhabited at different points in time. Although computational resources have improved dramatically in recent years, many of the methodological processes described here remain time-consuming analyses. Further research will no doubt benefit from improved processing power in the future. Other modeling methods that could be applied to this data are spatial generalized linear mixed models, generalized linear models (GLMs) and Geographically Weighted Regression (GWR). GWR has been used to model archaeological data (e.g., Bevan and Conolly, 2009; Gkiasta et al., 2003) although is not employed as frequently as the other methods used in this study.

These results also provide many opportunities for field investigation in future seasons. Upcoming Idaho State University Field Schools may make further use of these results in testing the model's predictive validity to produce a detailed dataset of cultural resources through reconnaissance pedestrian survey, GPS mapping, and shovel testing. To uncover possible outliers or exceptions it will be necessary to employ a sampling strategy that includes survey of areas with low archaeological potential as well as those that are expected to contain sites.

Radiocarbon dating of existing materials from previous field studies could help to develop a better understanding of potential temporal variation in site attributes.

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Appendices

Appendix A: Site data used in model creation

curvature	elevation	dev 1500m	dev 250m	diff 1500m	diff 250m	northness	obsidian cost	pinyon cost	slope	insolation	spring cost	stream cost	view 1500m	view 250m
-0.67	2250.46	-1.53	-1.15	-125.02	-24.58	81.06	86679.14	1969.50	3.70	1464783.25	295.59	6021.97	0.69	0.90
-0.37	2063.11	-1.47	-0.80	-179.29	-21.00	121.48	48341.49	115.57	10.76	1479168.88	7130.16	214.62	0.68	0.54
-0.38	1714.05	-1.72	-1.08	-105.68	-18.95	54.21	81675.93	987.44	2.46	1378075.63	688.54	18.49	0.55	0.66
-0.99	1855.75	-1.44	-1.11	-69.39	-22.69	1.64	72364.76	908.56	13.80	1213348.50	900.13	17610.21	0.45	0.45
-0.12	2986.20	1.01	0.80	117.71	18.82	171.73	61816.66	7509.36	3.53	1667730.88	3070.44	2364.00	0.71	0.83
-0.60	2075.70	-1.10	-0.35	-101.12	-9.65	34.36	64428.93	720.55	16.94	1227557.75	690.98	139.67	0.83	0.93
-8.72	2166.21	-0.96	-1.00	-104.59	-28.44	90.51	76123.87	241.90	5.83	1384668.00	812.89	0.00	0.73	0.79
-0.94	2160.25	-1.07	-0.66	-127.65	-25.75	105.08	75675.08	863.07	24.69	1414103.13	345.52	322.02	0.68	0.85
0.04	1698.87	0.02	0.34	1.19	4.25	50.82	30053.35	78.45	7.42	1342099.63	8626.46	12109.42	0.50	0.76
-2.82	1803.97	-1.44	-1.33	-85.63	-23.39	3.45	80782.48	974.48	9.68	1257718.00	74.29	5767.44	0.58	0.63
-4.53	2186.00	-0.55	-1.06	-65.73	-37.40	126.47	43714.43	1312.36	15.95	1506017.50	388.32	4839.27	0.58	0.72
0.25	1778.57	0.00	0.23	0.13	2.62	136.33	47739.63	0.00	8.76	1484029.13	12961.39	380.86	0.98	1.00
3.28	1954.45	0.22	1.02	33.24	39.40	26.06	40284.93	83.21	6.57	1363510.00	12263.21	15117.74	0.61	0.37
-0.37	1838.68	-1.55	-1.04	-170.07	-43.03	175.78	50490.36	0.00	26.36	1517529.63	2383.54	747.38	0.71	0.54
-1.26	1889.74	-1.09	-1.32	-109.24	-36.89	144.43	52856.30	111.28	3.88	1422120.63	8481.63	142.85	0.88	0.85
-2.20	1911.70	-0.61	-1.30	-51.34	-30.25	56.68	54971.23	39.23	5.18	1379430.25	5710.01	4415.18	0.89	0.95
-0.76	1847.86	-1.06	-0.44	-101.60	-8.83	72.16	37633.30	364.66	6.26	1384021.63	260.33	23.11	0.45	0.37
-0.21	1877.33	-0.48	-0.16	-63.15	-3.57	19.88	63788.18	165.50	6.77	1330480.25	100.12	14045.65	0.68	0.96
-1.05	1830.12	-0.64	-0.94	-79.14	-18.33	83.52	62960.13	837.57	11.55	1380164.13	882.70	13566.59	0.66	0.94
-0.60	1958.10	-0.67	-0.83	-51.25	-12.95	34.48	59163.97	143.17	6.93	1362893.13	2116.83	27.74	0.86	0.82
-0.42	1935.60	-1.36	-0.91	-156.05	-29.52	39.55	53272.08	226.52	20.99	1128236.00	2214.32	127.39	0.74	0.78
-0.73	1999.53	-1.48	-1.37	-145.43	-25.01	140.49	50559.03	508.30	5.03	1478658.13	2827.50	46.23	0.84	0.54
-0.04	2188.33	-0.05	-0.39	-6.13	-11.50	74.78	47176.23	764.21	13.22	1401871.38	1868.07	1933.45	0.67	1.00
-1.48	2196.36	-0.01	-0.53	-1.25	-15.59	30.63	47091.83	459.50	15.84	1245652.50	2076.04	2104.25	0.66	0.97
0.38	2305.13	0.34	0.17	28.36	2.43	32.16	72646.94	770.88	7.59	1412246.00	364.80	3948.38	0.81	0.74
-0.80	2318.36	-0.69	-1.33	-59.20	-23.01	139.02	77138.03	1279.18	8.24	1557887.75	46.56	225.59	0.79	0.83
-0.17	1542.19	-0.38	-0.58	-18.84	-9.33	43.87	61250.24	27.74	7.25	1312931.75	160.22	10481.10	0.98	0.99
-1.35	1890.51	-1.10	-1.06	-76.15	-21.56	0.86	57782.46	32.36	3.74	1372080.13	367.04	0.00	0.87	0.80
-0.02	1854.69	-0.75	-1.09	-58.14	-15.70	174.73	56736.96	110.81	8.68	1508898.13	2010.06	64.72	0.85	0.87
-0.05	1898.77	-0.31	-0.61	-35.02	-11.05	76.75	78596.83	587.96	8.29	1400793.38	3407.64	3374.89	0.99	1.00
-0.18	1898.47	-0.28	-0.57	-29.90	-14.61	58.84	76251.55	235.82	21.60	1219326.88	5365.00	5391.62	0.99	1.00
0.47	2852.29	0.76	1.06	143.14	33.16	116.57	71450.50	1617.45	2.86	1611252.88	5529.15	3830.03	0.92	0.87
-4.53	1754.77	-0.74	-1.48	-73.42	-53.62	165.48	59149.71	152.88	9.11	1282667.50	23450.86	26206.04	0.07	0.15
-1.86	1929.94	-1.61	-1.25	-99.41	-32.31	56.70	73194.74	907.24	13.38	1281201.50	4035.98	18376.96	0.28	0.36

-0.49	1676.70	-0.99	-1.07	-61.91	-23.75	164.34	52058.60	66.96	7.48	1465060.25	26039.21	29788.70	0.24	0.50
-0.17	1814.74	-1.61	-0.71	-115.28	-13.39	104.87	66671.34	1113.63	1.82	1398896.50	2420.61	11510.25	0.44	0.46
0.27	1906.99	-0.85	-1.22	-44.63	-13.39	34.84	75501.12	2519.08	6.12	1368211.25	221.63	14478.93	0.56	0.80
-0.37	1888.16	-0.86	-1.01	-40.64	-15.48	160.39	73699.71	1043.03	5.03	1482052.00	245.01	18771.12	0.38	0.39
-0.46	1805.54	-1.41	-1.24	-86.34	-19.93	167.09	80739.31	957.57	8.20	1489950.50	189.40	5732.70	0.58	0.59
-0.16	1802.29	-1.54	-0.72	-121.51	-15.16	59.50	66605.88	1175.51	2.60	1383848.38	76.21	12818.61	0.44	0.54
-0.01	1484.37	-0.14	-0.08	-5.93	-0.59	110.88	26990.58	1148.40	3.50	1389520.38	1868.84	5576.79	0.74	0.96
1.47	2034.65	-1.23	-0.53	-203.84	-29.15	57.80	56628.54	3125.15	43.60	817654.00	359.58	22175.15	0.66	0.68
0.50	2021.93	-1.27	-0.68	-212.62	-35.73	74.04	56485.42	2914.49	31.53	1081601.13	403.56	22084.83	0.66	0.70
-0.04	2115.62	-0.85	-0.40	-53.27	-6.06	164.58	70741.63	952.70	14.39	1604069.50	216.68	1749.46	0.63	0.66
-0.23	1810.46	-0.42	-0.42	-50.49	-10.18	5.68	89176.98	27.74	9.71	1290608.38	2286.57	4690.62	0.28	0.44
0.07	1809.71	-0.90	-0.10	-64.23	-0.96	133.97	70358.39	926.28	3.06	1447139.88	3873.27	300.74	1.00	1.00
0.16	2053.85	-0.44	-0.27	-57.88	-4.11	115.58	60271.68	263.10	7.43	1492523.75	5758.34	8348.33	0.40	0.29
0.30	1841.75	-0.31	-0.29	-26.09	-4.01	114.37	52168.68	84.99	8.61	1456946.25	376.95	3555.17	0.32	0.44
-3.19	2036.78	-0.64	-0.37	-63.65	-9.17	175.67	60232.81	3480.32	13.72	1591325.75	91.99	5702.88	0.32	0.08
0.09	2952.98	0.80	0.48	87.73	12.00	64.39	56742.48	7063.42	3.16	1594996.00	1436.83	4209.67	0.65	0.98
-0.19	1971.37	-1.44	-0.89	-156.56	-16.21	43.31	51786.09	730.20	12.10	1289460.25	2799.30	119.73	0.80	0.62
-0.07	1770.44	-0.16	-0.32	-7.93	-3.49	165.22	47625.18	0.00	8.80	1507164.75	12872.70	235.77	0.98	1.00
0.16	2742.96	0.44	-0.53	56.81	-8.62	21.19	58645.01	3095.30	10.09	1430302.50	319.04	2956.59	0.93	0.97
-1.29	2133.33	-0.50	-0.08	-33.75	-1.69	137.63	71805.64	78.59	4.30	1512665.50	118.14	1913.83	0.60	0.34
-3.05	1709.72	-0.31	-1.07	-30.73	-16.02	115.88	37104.52	115.57	11.52	1425920.63	8587.50	11096.16	0.68	0.77
-0.04	1771.63	-0.53	-0.36	-33.10	-5.43	40.24	37621.04	55.01	2.39	1394974.88	4303.45	9.25	0.97	1.00
-0.03	1764.35	-0.45	-0.07	-26.38	-0.51	2.81	37354.02	193.23	2.04	1393855.38	4085.46	36.98	0.98	1.00
0.03	1771.72	-0.54	-0.35	-33.88	-4.88	43.20	37607.33	40.81	2.38	1396758.63	4289.72	13.08	0.98	1.00
-0.14	1772.49	-0.53	-0.39	-33.77	-6.27	49.82	37648.46	78.45	2.54	1396212.38	4320.82	0.00	0.97	1.00
-0.14	1772.49	-0.53	-0.39	-33.77	-6.27	49.82	37648.46	78.45	2.54	1396212.38	4320.82	0.00	0.97	1.00
-1.73	2904.32	0.15	-0.35	15.57	-14.17	117.78	58067.93	8197.44	18.46	1596310.00	1369.40	3821.81	0.68	0.97
0.00	2920.74	0.37	-0.20	39.10	-7.40	12.75	57471.02	7610.11	30.94	1019359.13	1685.28	4117.24	0.66	0.97
0.00	2920.74	0.37	-0.20	39.10	-7.40	12.75	57471.02	7610.11	30.94	1019359.13	1685.28	4117.24	0.66	0.97
-0.05	2028.29	-1.13	-0.15	-91.77	-1.90	34.32	62756.21	52.30	5.18	1394936.88	2572.12	328.88	0.87	0.92
1.62	2112.93	-0.10	0.39	-12.03	12.33	170.47	63303.88	0.00	5.86	1528439.25	5399.50	2132.19	0.87	0.83
0.17	1687.87	-0.21	0.05	-8.52	0.32	117.91	35323.37	0.00	6.56	1436331.00	5866.47	5862.64	0.97	0.89
-0.02	1773.52	-0.12	0.44	-9.51	5.56	123.45	40511.17	0.00	4.99	1450046.13	10013.93	9332.09	0.96	0.82
0.18	1673.57	-0.31	0.26	-21.65	3.29	104.38	30968.19	0.00	5.33	1415225.25	8055.96	11538.93	0.54	0.59
0.08	1832.99	-0.01	0.44	-1.31	9.17	139.97	32498.12	0.00	9.28	1502965.63	11699.97	13689.41	0.51	0.67
-0.16	1484.86	-0.16	-0.13	-6.63	-0.76	128.07	27284.64	821.67	2.93	1396709.75	1797.16	5272.50	0.78	0.92
0.17	1491.04	-0.08	0.02	-3.29	0.10	135.76	27597.72	403.70	1.68	1391542.38	1832.10	5180.67	0.80	0.86
0.02	1475.00	-0.14	-0.23	-5.82	-1.19	50.80	26846.62	1042.70	0.73	1369557.50	1558.78	5116.50	0.79	0.96
0.78	1713.43	0.58	0.57	50.02	18.96	51.19	32914.15	240.39	14.03	1269798.50	6311.37	9687.26	0.64	0.61
-0.11	1689.73	-0.08	0.25	-5.10	3.90	68.95	38151.52	0.00	7.66	1366015.63	9022.50	10737.36	0.76	0.80
-0.15	1675.08	-0.18	0.42	-10.47	7.58	107.03	38142.20	0.00	6.41	1421377.88	8979.91	10651.18	0.78	0.73
0.26	1644.45	-0.60	-0.49	-32.78	-7.49	35.00	37733.55	51.18	5.81	1334581.88	8580.41	10174.62	0.80	0.76

0.51	1648.07	-0.64	-0.64	-33.75	-7.37	116.99	37973.47	219.38	3.68	1415320.13	8775.95	10370.15	0.80	0.82
-1.85	1684.58	-1.45	-1.27	-76.03	-28.60	130.80	78968.40	904.42	22.96	1410697.75	1975.11	75.42	0.38	0.44
0.86	2051.21	0.49	1.70	44.05	33.99	69.46	43224.66	1630.99	14.10	1355695.13	2279.00	3588.22	0.42	0.09
0.10	1760.16	-1.29	-0.69	-68.03	-12.76	49.27	74018.81	503.16	29.28	1037073.69	2750.85	202.67	0.32	0.76
0.03	1654.50	-1.57	-0.87	-109.10	-19.16	92.90	78431.41	541.07	1.85	1378810.25	927.59	39.23	0.59	0.83
1.46	2098.50	1.75	1.82	134.24	48.87	45.40	73939.33	234.18	17.64	1263414.75	12050.04	12055.78	0.49	0.65
1.63	2102.80	1.89	1.42	141.79	40.16	57.05	74102.04	150.50	5.49	1432710.63	12729.58	12717.30	0.48	0.51
1.09	2174.78	2.85	2.10	211.37	51.69	178.03	73834.84	526.79	10.69	1601813.13	12646.67	14413.37	0.48	0.84
1.11	2087.24	1.63	1.53	132.67	28.35	171.31	75030.21	642.17	11.18	1587614.13	10291.87	11980.19	0.55	0.77
1.22	2053.91	1.31	1.83	90.57	33.09	19.77	76768.84	780.73	6.41	1384175.88	7020.90	15213.71	0.49	0.47
-0.30	2363.55	-0.46	-0.82	-68.01	-16.99	104.68	69697.30	416.06	6.88	1516861.38	5643.44	77.33	0.94	0.98
-0.44	1662.43	-1.51	-0.97	-100.99	-14.39	74.34	78947.80	975.00	5.99	1368014.25	496.49	82.42	0.59	0.75
-0.98	1665.05	-1.67	-1.23	-99.23	-27.12	11.56	80023.06	608.23	3.43	1329419.38	792.22	45.76	0.58	0.75
-0.14	1726.20	-1.67	-1.10	-101.56	-24.09	22.57	81398.07	1143.72	5.75	1316731.63	26.15	23.11	0.52	0.74
-1.88	1674.28	-1.43	-1.26	-95.98	-23.15	25.26	80101.62	717.92	8.94	1260816.50	855.95	52.30	0.58	0.67
-0.42	1682.92	-1.40	-1.22	-95.29	-37.70	169.51	81023.19	294.47	4.79	1318937.50	55.80	18.49	0.56	0.67
-1.47	1779.75	-1.41	-1.20	-125.27	-22.32	74.48	81390.65	159.75	8.37	1353647.38	1283.09	6350.39	0.62	0.55
-1.14	1838.87	-1.11	-1.34	-64.39	-21.07	145.75	79432.83	2174.74	2.49	1406799.50	0.00	4487.13	0.58	0.43
-0.33	1754.25	-1.49	-0.98	-77.70	-13.19	144.95	74232.70	387.12	2.29	1431353.13	2369.32	22.32	0.33	0.89
-0.21	1754.22	-1.55	-1.07	-82.86	-17.73	128.61	74361.22	529.97	0.88	1411618.88	2363.90	101.70	0.33	0.82
-5.05	1829.47	-0.95	-1.58	-48.52	-36.28	150.61	77310.04	1223.52	14.63	1481460.75	142.85	93.12	0.46	0.36
-0.01	1765.14	-1.17	-1.38	-75.76	-24.50	110.60	74171.66	1514.45	0.07	1396456.50	9.25	2574.17	0.43	0.53
0.69	2010.18	0.72	0.59	46.96	15.40	52.94	79287.75	1729.11	17.29	1273889.75	3190.93	14589.67	0.64	0.80
-1.86	1878.47	-1.00	-1.05	-60.94	-16.30	133.16	78047.86	1986.05	3.13	1450875.50	150.97	12776.42	0.65	0.73
-0.25	1666.69	-1.54	-0.80	-96.61	-12.92	86.72	79289.75	656.43	5.50	1384833.88	867.96	68.88	0.58	0.76
-0.43	2002.02	-1.12	-1.00	-91.52	-24.39	167.74	63463.91	794.87	15.73	1571182.25	1381.27	1381.27	0.78	0.82
0.17	2156.28	-0.78	-0.43	-44.73	-5.48	31.68	68832.53	1641.57	7.05	1393445.38	333.97	599.91	0.65	1.00
-0.23	1828.19	-0.49	-0.22	-40.72	-2.50	33.71	31946.38	212.05	2.37	1402873.38	45.76	3185.39	0.99	1.00
-0.01	1539.82	-0.40	-0.61	-19.80	-8.15	66.05	61234.77	32.69	5.48	1351674.13	266.54	10383.50	0.98	0.99
-0.02	1755.46	-0.47	-0.96	-46.58	-20.64	34.10	75923.57	488.50	7.92	1296663.75	2892.31	168.86	0.73	0.75
-2.81	1744.39	-1.05	-1.37	-88.99	-32.94	124.02	46185.35	109.36	4.28	1417858.63	6478.29	4802.25	0.89	0.72
0.19	1678.06	0.27	0.71	14.86	12.12	132.59	26343.13	73.97	11.18	1475058.63	10303.42	6808.03	0.71	0.30
-0.12	2052.28	-0.21	0.07	-32.71	1.29	152.25	79944.10	232.13	6.23	1515342.38	5158.49	5000.36	0.99	1.00
-0.41	2022.63	-0.54	-0.56	-61.09	-14.45	8.06	79545.46	1181.12	12.41	1254781.63	8507.67	6504.54	0.99	1.00
0.29	1934.21	-0.69	-0.12	-59.19	-3.50	11.94	61386.40	1640.51	11.21	1275735.13	7487.67	15369.07	0.68	0.89

Appendix B: Nonsite data used in model creation

curvature	elevation	dev 1500m	dev 250m	diff 1500m	diff 250m	diff 500m	northness	obsidian cost	pinyon cost	slope	insolation	spring cost	stream cost	view 1500m	view 250m
0.25	2554.70	-0.21	-0.28	-40.03	-19.74	-29.53	109.36	47993.18	2490.50	27.65	1507099.13	10115.39	8282.07	0.42	0.29
-0.25	2969.50	0.71	-0.19	65.65	-5.60	-3.05	91.07	60073.76	9646.68	13.05	1584096.50	2430.64	3551.38	0.61	0.68
-1.36	1903.91	-0.38	-0.78	-19.68	-12.37	-15.15	128.35	57582.83	41.61	21.65	1509693.63	6383.43	4207.02	0.44	0.49
-0.01	2320.53	0.59	0.09	44.57	1.11	10.06	122.91	72338.09	831.91	6.86	1546188.88	3212.19	3240.04	0.75	0.66
-0.72	1922.31	-0.19	-0.29	-19.40	-5.48	-8.72	27.15	37109.38	173.15	9.28	1326165.13	684.25	2401.27	0.98	1.00
-0.21	2479.11	-0.73	-0.31	-121.53	-15.70	-30.51	76.13	72251.49	1885.17	25.68	1312121.00	3875.48	2333.32	0.62	0.75
-0.30	2094.59	0.13	-0.40	17.15	-10.90	-15.79	26.46	40200.53	794.46	12.97	1287974.63	3041.12	3091.26	0.94	1.00
-0.78	1958.32	0.48	-0.18	53.94	-7.26	26.50	15.79	57583.07	0.00	23.04	1083007.00	2743.80	7067.49	0.91	1.00
0.01	2535.18	0.03	-0.06	5.01	-2.34	2.11	85.12	73634.95	1623.60	16.41	1471949.50	3326.56	3022.15	0.89	1.00
0.01	2505.14	0.01	0.19	0.95	6.73	15.46	56.12	69748.23	450.26	10.52	1438430.88	5882.00	2461.77	0.74	1.00
0.15	2103.91	0.28	0.09	34.68	2.71	11.91	20.19	65324.38	1314.39	11.84	1309095.75	3492.05	3433.35	0.93	1.00
0.25	2015.62	-0.28	0.05	-22.12	0.78	-8.38	31.81	61021.77	152.56	8.43	1354385.13	7992.77	7591.94	0.32	0.41
-0.59	1917.43	-0.69	-0.32	-47.38	-4.29	-13.43	44.53	66167.88	0.00	13.50	1277623.50	3460.02	6478.76	0.78	0.68
-0.14	2270.80	0.29	0.45	24.01	10.10	12.95	169.10	71298.73	1377.41	14.90	1644599.88	2160.73	2160.73	0.71	0.61
0.61	1976.53	0.73	0.64	63.20	22.64	30.91	70.56	28091.93	0.00	24.61	1249280.63	5165.52	10598.26	0.40	0.37
0.27	2134.07	-0.18	0.04	-20.98	1.16	-6.83	64.84	62682.70	41.61	14.25	1361189.00	8336.26	8571.71	0.90	0.98
0.68	2111.88	-0.56	0.30	-39.16	11.47	11.28	43.34	76284.65	1705.50	17.44	1251836.75	1912.50	1411.22	0.74	0.94
0.53	2917.00	1.70	1.35	195.03	16.05	38.42	35.45	67865.98	4480.22	3.66	1566639.88	4550.70	3786.33	0.68	0.97
-0.12	2139.65	-0.12	0.01	-8.81	0.45	13.15	79.81	76855.91	1514.81	14.29	1398358.00	2665.93	2043.44	0.76	0.99
-1.26	2151.52	-0.48	0.52	-38.36	15.03	4.10	100.17	75304.26	743.41	20.76	1434961.63	1411.72	1246.65	0.80	0.83
0.21	2216.05	0.72	0.32	83.47	11.22	33.92	50.86	36931.56	787.70	12.92	1356199.13	6810.30	11265.41	0.69	0.99
-0.83	1951.62	-0.28	0.27	-29.35	6.90	4.31	57.66	63295.75	0.00	11.26	1350154.50	2887.47	2433.49	0.94	1.00
-0.46	1872.17	-0.20	-0.41	-8.19	-11.27	-14.33	120.68	64443.11	0.00	27.79	1452052.50	1544.80	405.34	0.90	0.92
0.03	2043.37	-0.51	-0.33	-38.50	-8.32	-14.77	149.76	72522.02	851.77	10.01	1549122.25	3511.23	878.22	0.22	0.48
0.88	2589.50	0.77	0.78	111.72	22.89	44.70	126.91	74571.60	2248.25	13.43	1623135.63	4626.29	4735.78	0.71	0.96
-0.41	2526.89	0.44	0.11	68.37	4.61	19.11	43.21	52611.80	1187.65	17.88	1308618.13	10439.29	2272.27	0.89	0.97
-0.41	2549.91	0.25	-0.22	35.87	-7.75	-1.87	153.41	74781.22	3189.41	17.62	1680071.75	4232.42	4108.03	0.69	0.80
0.82	2676.97	0.58	0.30	116.31	16.52	46.95	148.41	64254.30	1462.32	31.11	1706833.63	7060.04	7030.39	0.18	0.12
-0.02	2236.79	-1.00	-0.19	-161.05	-10.94	-48.68	5.77	52241.55	1701.01	30.09	922771.25	9328.84	827.50	0.65	0.72
-0.60	2267.24	0.19	-0.28	20.00	-11.34	-17.42	14.35	72068.74	0.00	12.20	1308892.13	3528.87	3977.87	0.89	1.00
-0.06	2675.18	0.33	-0.16	45.89	-8.83	-19.25	13.89	49830.94	1240.86	23.41	1145452.63	7999.95	5378.55	0.73	0.98
0.51	1826.13	0.19	0.64	11.53	8.80	12.36	122.32	33791.54	126.27	13.15	1482967.13	10039.17	10031.19	0.91	0.95
0.03	1620.51	-0.28	-0.37	-8.84	-1.78	-3.98	146.44	24879.82	193.23	9.04	1470675.50	11873.17	9186.95	0.73	0.92
1.15	2075.90	0.96	1.08	95.95	44.44	96.08	4.59	51309.08	0.00	29.12	969174.00	11560.03	23740.34	0.58	0.93
-0.24	2396.82	-0.06	-0.01	-11.89	-0.68	-22.60	179.96	53250.25	3087.40	13.88	1649098.63	5505.17	5482.98	0.87	0.95
0.32	2209.80	-0.04	0.45	-7.27	18.28	17.07	101.88	66155.63	197.86	20.46	1461968.13	5961.29	11208.24	0.94	0.99
1.25	1862.77	-0.51	-0.22	-53.21	-7.34	-19.83	61.33	33971.55	106.98	25.38	1158277.50	4075.08	4713.05	0.56	0.59
-0.12	2190.62	1.16	0.34	128.31	14.77	32.10	144.47	53842.82	1901.74	24.63	1613424.00	9393.53	7911.11	0.83	0.99

0.73	2208.73	-0.02	0.15	-3.59	6.34	1.98	107.48	66455.25	966.14	16.93	1493810.75	6795.06	12020.94	0.94	0.99
-0.14	2070.02	-0.21	-0.51	-36.67	-18.50	-26.08	102.80	60642.36	989.33	25.51	1405620.50	2664.64	2526.96	0.90	0.97
-0.53	1861.72	0.03	-0.02	2.38	-0.48	0.39	156.74	38863.73	116.23	25.12	1586537.63	10982.58	10972.87	0.88	0.98
-0.73	2388.07	0.38	-0.39	68.59	-22.80	-4.61	114.53	61764.07	1201.96	33.45	1463039.63	10551.84	10517.68	0.91	1.00
-0.03	2788.26	1.63	0.48	253.49	21.58	69.67	122.46	60311.16	323.00	24.96	1640395.88	12563.57	12554.19	0.89	0.92
-0.01	2006.22	-0.32	-0.73	-54.08	-28.90	-39.41	154.25	40661.30	612.58	21.91	1567635.38	12926.33	14606.37	0.64	0.84
-0.01	2094.82	-0.42	-0.64	-87.78	-20.65	-43.33	43.84	63229.09	1658.78	36.22	855159.44	4864.33	5117.05	0.92	0.75
3.88	2685.11	0.91	0.86	155.44	46.56	54.05	85.91	62412.17	681.54	19.42	1479151.88	12395.20	15643.90	0.80	0.50
0.47	1921.64	0.07	-0.14	7.67	-4.42	2.56	89.72	60907.30	0.00	31.71	1262718.38	10935.96	12761.90	0.83	0.87
1.46	1818.11	-0.27	-0.72	-24.50	-17.15	-16.23	85.95	61401.29	101.70	19.35	1332976.13	13487.96	16225.82	0.87	0.88
0.32	1783.03	-0.10	0.38	-6.74	4.72	2.87	129.57	56709.43	176.98	11.63	1486821.38	8616.68	9497.16	0.89	0.86
-1.21	1969.41	0.21	-0.48	15.04	-10.25	-6.57	22.33	56578.14	397.95	20.79	1130548.00	12505.01	14287.22	0.76	0.89
-0.01	1822.33	-0.43	-0.82	-45.18	-20.41	-26.16	47.44	67172.87	622.10	20.27	1149654.13	5962.88	11619.16	0.59	0.77
0.98	1781.56	0.03	0.15	1.48	1.59	0.64	60.10	35214.95	0.00	7.30	1368454.50	8823.14	8819.31	0.93	0.99
-0.13	1851.87	0.25	0.62	16.09	9.26	16.33	106.84	33715.48	27.74	8.22	1450582.50	11696.82	10441.48	0.90	0.98
0.36	1760.77	0.01	0.26	0.38	2.75	6.07	5.86	57495.07	0.00	11.65	1253025.00	12533.29	11965.34	0.90	0.94
0.04	1771.98	-0.47	-0.02	-27.33	-0.08	0.62	73.83	44153.07	305.77	2.04	1413277.25	12808.20	16117.09	0.68	0.50
-2.66	1887.73	-1.27	-1.36	-110.66	-52.02	-83.31	99.12	34939.59	466.50	6.80	1324285.13	9574.33	9175.26	0.64	0.46
0.05	1975.70	-0.89	-0.02	-97.88	-1.07	-18.41	13.88	53362.49	1915.65	20.62	1109934.25	5204.86	24624.80	0.62	0.24
0.29	1711.07	-0.05	0.22	-3.27	2.79	2.50	47.35	58157.18	197.06	4.30	1373094.00	9152.57	13606.76	0.93	0.93
1.03	2037.19	-0.37	0.23	-41.32	11.02	8.33	174.98	62927.76	971.19	33.13	1627116.13	4021.66	8180.57	0.92	0.98
-0.22	2017.88	0.17	0.05	24.40	2.29	-8.42	22.83	43860.20	0.00	28.00	983548.56	11815.83	17943.42	0.65	0.75
0.38	2333.12	0.32	0.41	56.52	11.59	26.57	2.20	57390.00	3592.63	13.43	1303684.13	7540.39	1244.93	0.71	0.98
0.80	1895.71	0.45	0.58	58.46	20.44	34.65	11.42	59809.32	1169.84	17.12	1180444.25	4942.33	4552.61	0.24	0.13
0.25	2134.45	0.04	0.31	4.52	7.68	19.28	169.19	77519.84	410.10	9.22	1576183.50	1782.09	1227.54	1.00	1.00
-0.66	2394.82	-0.91	-0.48	-118.78	-13.88	-36.32	158.64	68915.75	3100.72	14.78	1637517.88	5497.43	962.53	0.87	0.93
0.12	2402.47	0.83	0.05	149.51	2.57	27.30	121.78	85156.58	2877.45	24.50	1571511.88	7898.88	7937.01	0.96	1.00
0.66	2086.57	0.58	1.09	87.51	25.38	48.15	135.97	82420.75	785.00	19.33	1555951.13	1714.03	1797.74	0.82	0.99
-0.08	1885.60	-0.01	-0.14	-1.17	-7.55	-17.36	94.91	66040.23	1562.11	21.76	1374446.75	2658.83	9866.57	0.39	0.39
0.07	2389.20	0.94	0.30	119.86	6.98	17.90	36.16	90436.45	1016.66	10.17	1396174.00	3745.68	4907.93	0.74	0.97
-0.09	2147.89	-0.40	0.03	-59.43	0.95	0.49	130.00	79634.37	2386.58	12.42	1545346.38	3013.10	1125.86	1.00	1.00
0.72	1884.48	0.32	0.77	35.10	19.34	29.04	168.81	49621.69	2428.35	17.62	1583209.50	6905.94	2779.65	0.55	0.40
-0.09	2561.76	0.44	0.03	90.46	1.59	16.12	43.27	76676.07	1044.07	26.60	1167925.00	8420.17	3901.84	0.98	1.00
0.33	1870.10	-0.20	0.41	-28.03	13.67	17.69	116.09	71229.84	1153.92	12.51	1464712.00	4399.68	2306.95	0.92	0.83
-0.65	1782.87	-0.89	-0.59	-107.86	-14.88	-38.73	174.38	56917.27	430.45	15.09	1531712.00	1336.52	73.97	0.11	0.46
0.03	1850.66	-1.01	-0.92	-55.10	-11.19	-22.82	65.11	65440.80	878.19	10.52	1354462.00	3980.65	163.44	0.96	1.00
-0.09	2034.40	0.50	0.00	76.37	0.24	12.57	78.05	53740.71	297.37	26.71	1273272.88	7126.53	7328.91	0.59	0.29
-0.31	1970.89	-0.16	0.03	-16.33	0.41	3.37	123.20	68712.80	642.31	6.23	1481708.13	7244.23	1368.52	0.94	1.00
0.64	2412.66	-0.15	0.29	-24.29	15.07	-4.57	5.64	63617.71	5239.16	23.93	1101935.63	5385.56	4658.73	0.78	0.66
0.59	2252.72	-0.22	0.53	-39.72	25.35	5.00	55.10	60451.57	7297.36	25.28	1200228.50	9253.80	5396.00	0.70	0.06
-0.09	2246.23	0.99	-0.20	127.29	-8.25	-2.74	79.79	73072.30	943.46	22.66	1351453.25	8926.38	5272.57	0.37	1.00
0.02	2063.64	-0.28	0.15	-36.72	6.70	12.59	19.70	56663.02	3246.16	17.67	1198736.00	3853.85	3661.81	0.70	0.52

0.28	2781.75	0.40	0.10	65.88	4.98	3.31	87.46	70646.79	4962.93	21.03	1487137.38	6639.72	3513.67	0.88	1.00
-0.16	1956.16	-0.12	-0.67	-12.77	-16.53	-21.16	38.38	65692.27	874.25	9.72	1329570.75	3905.52	2870.17	0.98	0.99
0.02	2452.34	0.32	0.19	46.62	6.67	25.00	10.74	81244.34	1292.80	15.80	1280700.13	2526.11	2461.20	0.71	0.55
1.48	2095.13	-0.26	0.10	-45.98	2.29	-2.57	172.25	73582.56	157.18	14.38	1601337.88	7966.14	3800.55	0.93	0.98
0.23	2829.45	0.96	0.27	147.79	8.66	24.38	5.32	72258.41	3197.06	10.68	1426758.88	12818.47	4184.62	0.92	0.96
-0.26	2062.59	0.45	-0.10	60.77	-5.04	-6.34	108.19	56068.48	2131.05	22.61	1455808.88	7169.26	7923.84	0.43	0.36
-0.08	2328.41	-0.34	-0.42	-63.19	-18.18	-47.70	63.33	81566.05	1408.24	26.70	1202327.38	4473.81	4318.16	0.65	0.45
1.01	2536.10	0.13	1.15	21.35	44.88	68.91	67.95	65535.24	6010.94	18.49	1388580.63	2248.41	1436.33	0.83	1.00
0.21	2471.55	-0.20	-0.15	-37.54	-7.75	-22.12	179.86	86534.91	2454.76	22.03	1688635.25	15681.81	7015.70	0.99	1.00
1.27	2667.55	2.02	1.51	254.66	40.63	98.92	67.04	68329.10	675.33	10.25	1494129.38	6865.56	5003.87	0.80	0.76
0.36	2057.37	0.35	0.44	52.23	20.58	30.10	54.68	55385.68	498.92	25.55	1161075.88	4376.85	6946.73	0.58	0.02
-0.44	1844.70	0.18	-0.13	25.01	-4.17	6.58	12.22	60659.50	1614.66	14.32	1219958.25	3083.35	3068.03	0.27	0.62
0.12	1934.18	-0.60	-0.18	-77.29	-4.81	-30.70	7.58	66294.48	1734.47	14.88	1214445.75	2607.33	485.52	0.98	0.93
-0.13	1719.66	-0.36	-0.51	-47.11	-14.18	-33.52	127.54	61146.49	637.69	12.24	1464011.88	4423.95	330.53	0.29	0.68
-0.15	2196.03	0.04	-0.11	6.69	-4.44	8.22	47.53	54997.00	1303.58	15.36	1309296.13	7630.64	2417.70	0.31	0.19
0.69	1907.40	0.33	1.09	25.97	25.64	53.86	158.87	69969.37	405.56	10.31	1540433.75	16218.28	12898.32	0.47	0.64
0.26	1992.17	1.68	0.38	111.96	11.59	30.16	161.00	52131.11	582.93	12.87	1566945.00	19239.40	14915.42	0.23	0.62
0.78	1831.96	-0.03	-0.38	-2.91	-9.24	-6.77	4.60	49612.56	601.61	27.95	954361.44	22540.67	18373.31	0.19	0.50
-0.35	1940.45	1.09	0.99	104.62	40.54	67.66	114.89	82069.64	104.60	35.80	1397312.75	5968.17	5644.83	0.64	0.70
-1.78	1831.65	-0.05	-0.92	-3.43	-28.09	-10.99	169.69	74724.14	1205.14	18.66	1514122.00	4208.30	4156.22	0.21	0.45
-6.36	1841.47	-0.64	-1.18	-41.06	-36.00	-43.14	1.35	76669.07	2187.24	29.54	859230.63	5140.05	5148.08	0.43	0.66
0.33	2019.44	-0.47	-0.31	-36.50	-12.31	-7.99	60.30	71526.95	2777.15	30.41	1095873.88	7939.44	18479.57	0.47	0.45
-0.12	1890.36	-0.61	-0.11	-50.33	-3.59	-17.62	94.40	59225.09	1717.76	16.07	1388096.13	10080.22	13276.00	0.61	0.64
1.96	1933.55	-0.16	0.27	-15.08	10.74	5.99	116.34	61966.11	899.33	32.20	1424918.63	23851.99	31168.41	0.21	0.22
-1.21	1966.47	-0.33	-0.90	-24.98	-36.19	-33.95	166.67	71517.65	2394.57	23.97	1564417.88	2383.54	16706.48	0.42	0.54
0.00	1848.18	-0.10	0.46	-11.85	23.58	21.09	50.07	68543.99	2849.73	28.49	1066552.13	8816.33	13510.07	0.25	0.16
-1.47	1778.51	-1.28	-0.66	-81.63	-18.89	-40.74	25.31	54542.53	594.42	40.76	742621.81	13314.20	8215.48	0.38	0.45
0.49	2062.93	0.83	1.68	67.24	35.99	58.03	149.27	64286.46	2734.85	10.30	1556818.00	7912.01	17858.22	0.60	0.59
5.14	1814.61	-0.17	0.24	-14.16	9.55	-0.28	48.65	49339.92	374.70	29.21	1054933.25	23574.39	18792.75	0.21	0.32
1.30	1973.24	0.61	0.03	53.56	0.95	-10.42	77.30	65088.91	1885.82	36.57	1113419.13	4656.32	17454.44	0.44	0.75
6.59	2023.32	0.75	0.61	68.34	19.29	25.79	76.17	59490.00	1142.30	22.39	1297275.50	14595.08	14940.13	0.49	0.82
2.97	1959.58	1.49	1.22	112.65	34.90	60.48	17.18	81849.89	319.31	14.75	1238778.00	6340.67	6217.74	0.73	0.72
-0.76	2065.36	0.18	-0.69	18.38	-31.02	-47.99	61.81	73681.29	2593.06	19.25	1263033.13	9256.29	10817.40	0.56	0.84
-0.81	1989.34	-0.24	-0.27	-29.46	-12.25	-30.84	93.40	80474.66	5099.52	26.06	1349482.75	3089.50	9061.72	0.74	0.99
-0.03	1944.16	0.58	-0.45	54.03	-18.39	-0.45	113.91	80940.59	1333.42	26.13	1440301.63	8971.00	8448.35	0.68	0.99
-1.83	1998.57	0.06	-0.92	4.48	-39.92	-23.32	135.61	72091.34	3065.08	23.53	1506859.50	3046.59	17318.67	0.40	0.64
-3.69	1927.76	1.09	0.12	84.82	3.86	23.74	85.45	81141.83	666.74	18.33	1353618.63	6791.26	6376.86	0.74	0.91
-0.04	1791.99	0.09	0.56	8.73	19.52	16.20	61.91	79250.55	1180.73	29.22	1114734.13	4919.06	2620.02	0.59	0.44
-1.67	1856.98	-0.93	-0.84	-80.87	-26.08	-42.69	94.08	77265.63	1538.42	33.14	1212023.88	6184.10	6141.70	0.56	0.61
0.07	2226.90	2.17	1.11	194.97	40.75	99.16	97.10	70464.07	509.95	28.25	1394720.13	19786.54	19061.16	0.35	0.66
0.05	2103.91	0.57	0.11	37.90	4.40	11.79	30.69	68411.77	1650.14	21.40	1150236.75	10181.81	20662.65	0.37	0.69
0.94	2000.16	0.66	0.94	62.71	27.30	56.41	99.54	78260.05	2069.02	23.84	1402257.25	7717.78	7672.67	0.59	0.52

0.62	2077.76	1.64	0.71	162.45	28.70	78.31	98.03	61159.27	1665.73	21.06	1423571.13	10868.99	15459.02	0.44	0.56
2.13	2073.65	1.37	1.29	107.12	40.93	58.16	36.69	76479.97	610.61	19.56	1206783.63	10489.81	11002.66	0.65	0.82
-1.36	2100.11	0.92	-0.65	88.51	-30.97	-17.65	136.65	67557.16	3261.45	30.21	1513042.50	20373.79	19667.69	0.34	0.65