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# A Comparison of Presence Only Suitability Models to Accurately Identify Prehistoric Agricultural Fields in Western New Mexico Through Remote Sensing

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# A Comparison of Presence Only Suitability Models to Accurately Identify Prehistoric Agricultural Fields in Western New Mexico Through Remote Sensing

BY

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**A Comparison of Presence-Only Suitability Models to Accurately Identify Prehistoric Agricultural Fields in Western New Mexico through Remote Sensing**

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## ABSTRACT

This project aims to provide greater understanding of the agricultural practices of prehistoric cultures throughout the arid and semi-arid environments of western New Mexico by developing a remote sensing suitability model that will identify prime environments for a specific form of agricultural field, ak chin, that are often difficult to locate with standard field-based archaeological methods. Remote sensing and Geographic Information Systems methods were applied to develop suitability models that will identify ideal environments for ak chin style agricultural fields based on a small training data sample. Three models: Mahalanobis Technicality, Maximum Entropy (Maxent), and Multi-Criteria Evaluation Ordered Weighted Average (MCE OWA) were used and the suitability raster results were compared. Area Under the Curve (AUC) values were calculated and used to validate model results. Although archaeological fieldwork is a required follow up to these results, technological verification methods indicate that Mahalanobis Typicality and Maxent performed well in identifying potential new prehistoric agricultural fields.

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# Chapter 1

## 1.1 Introduction

This project aims to provide greater understanding of the agricultural practices of prehistoric cultures throughout the arid and semi-arid environments of western New Mexico. It develops a remote sensing suitability model that will identify prime environments for a specific form of agricultural field, ak chin, that are often difficult to locate with standard field-based archaeological methods. Many prehistoric archaeological sites found throughout New Mexico and Arizona consist of cultural materials that indicate humans were continuously adapting to adverse conditions, including severe water scarcity and a warming climate. Archaeologists believe that prehistoric societies flourished in these difficult conditions by studying and understanding the natural hydrologic cycle. The earliest known presence of domesticated crops in the American Southwest dates back approximately 4,000 years before present (bp), but it took at least a thousand years before agriculture was widely developed and commonly practiced throughout the region, given the importance of developing a vital knowledge base that could sustain these agriculturally dependent communities. Various cultures throughout this area developed their own methods for collecting, managing, and using floodwaters and runoff for agricultural development. The presence of agriculture among archaeological sites is strongly indicative of many defining cultural traits and changes throughout time.

This research focuses specifically on ak chin style agricultural fields, which are found in locations where reliable water sources were not necessarily readily available.

Ak chin was one of several known forms of runoff/dryland agriculture that prehistoric populations used to grow crops and ultimately flourish in unwelcoming environments.

Ak chin is a Tohono O'Odham term that translates to "mouth of the arroyo." Ak chin is not only the descriptive name for this style of agricultural field, but is also the name of a Tohono O'Odham community in southern Arizona. Although other forms of prehistoric dryland farming relied on a variety of construction approaches—check dams, terraces, rock mulch fields, rock piles, or rock grid fields—to catch excess water in the immediate area, ak chin farming is unique in that it takes advantage of the natural flood patterns of arroyos and drainages. Where the steepness of the slope decreases at the mouth of the arroyos, decelerating floodwaters deposit nutrient-rich sandy sediments on the alluvial fans. The water subsequently soaks into the clay rich deposits below the sand, which act as a natural reservoir. Ak chin style fields planted on these fans enabled agriculture in otherwise arid environments (Sandor 1990). This type of field required very little manual labor to build and maintain. Some ak chin style fields include rock terracing upslope of the fields to assist in slowing down water as it moves towards the mouth of the arroyo, but terracing is not always associated with these fields. In fact, the lack of obvious landscape alterations is a signature of ak chin fields that makes them very difficult for archeologists to locate.

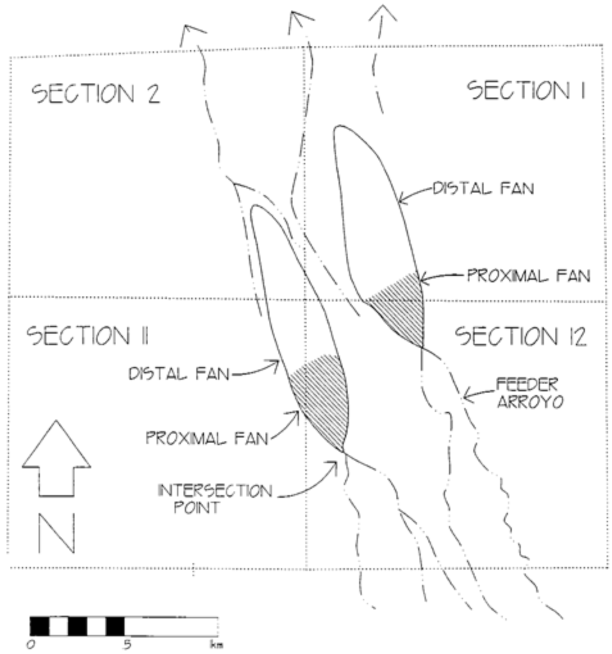


**Figure 1. How ak chin agricultural fields work.** Water is channeled down through the "feeder arroyo," and then as it decelerates, the water and soil nutrients are deposited within the alluvial fan. This is where agricultural fields were placed (Phillips et al. 1993).

Despite its minimalism, ak chin fields were effective for taking advantage of less than ideal environmental conditions to cultivate crops. The presence of ak chin fields is known within several archaeological sites throughout western New Mexico; however, the extent and density of these features throughout the region is unknown. To date, little research has been completed to further understand this type of field, partly because they are so difficult to locate. This project used remotely sensed imagery to identify a consistent spectral signature of fifteen known ak chin style dryland agricultural fields and to test the abilities of three different suitability models for identifying new agricultural fields in the future.

### 1.2 Project Description

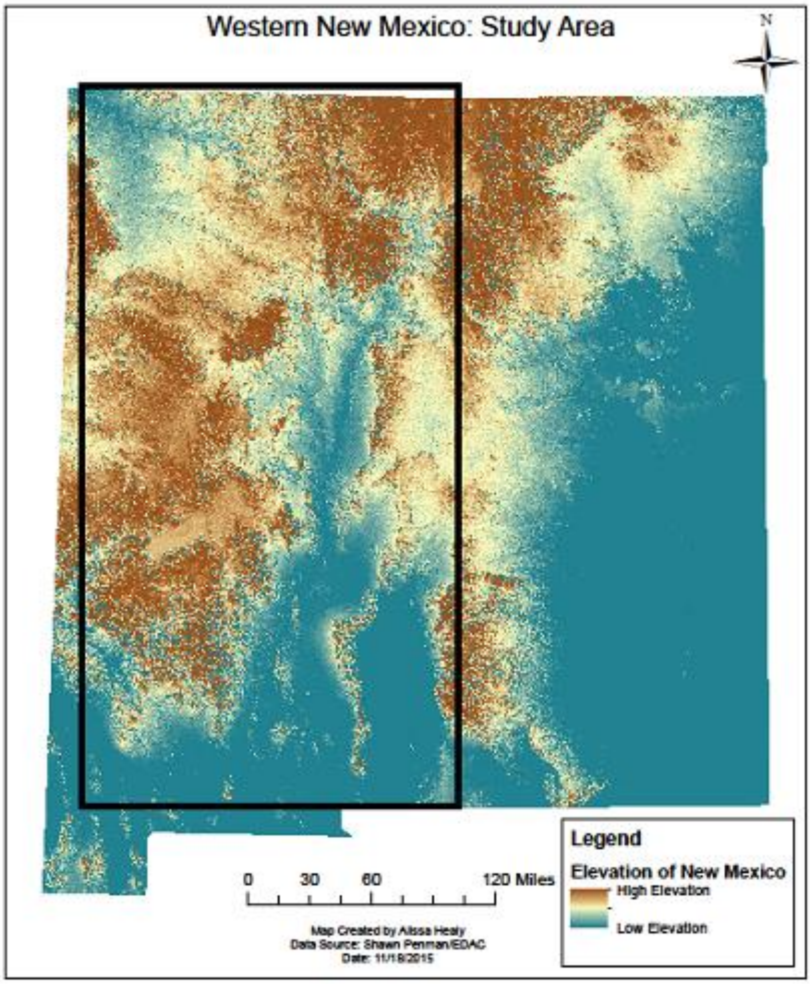


**Figure 2. Project study area.** The area outlined in black above represents the study area for this project, which includes most of western New Mexico.

This study addresses the lack of research regarding ak chin style agricultural fields by developing a suitability model to more easily locate these features. Although minimal environmental alterations are required to construct ak chin fields, I hypothesized that they could be remotely identified based on similarities in environmental composition and cultural context, as reflected in the following variables: elevation, solar radiation, Normalized Difference Water Index (NDWI), Normalized Difference Vegetation Index (NDVI), cost-distance, and slope degree. By testing the ability of suitability models to predict likely ak chin field locations based on these spatial-environmental criteria, this study contributes not only to our knowledge of prehistoric agricultural practices in the American Southwest but also to the development of new applications for remote sensing technology.

Most of the environmental variables identified above were expected to be constant at all alluvial fans throughout the study area, regardless of whether agricultural fields were present. Since it would be improbable that ak chin agricultural fields were developed at every single alluvial fan in the Southwest, however, additional variables were needed to help refine the results. To limit the suitability models' predictions to those alluvial fans most likely to have been targeted for ak chin field development, both cost distance analysis and solar radiation data were included in the modeling process.

To begin this research, known ak chin style fields were plotted in ArcMap 10.1. The locational data for known ak chin style fields were collected from various researchers throughout the state of New Mexico. This file was then used to inform three different suitability models of the appropriate spatial-environmental contexts, so that the models could identify new field candidate sites. The results of this analysis are presented as a series of suitability maps in conjunction with a discussion of what the results mean in terms of both the archaeological and geographical records.

### 1.3 Research Question

Which "presence-only" suitability models perform best in identifying ak chin style agricultural fields?

# Chapter 2

## 2.1 Background

Prehistoric habitation sites provide valuable data for furthering the knowledge of ancient landscapes, climate conditions, and land use practices. Identifying the presence of agricultural fields is extremely important in the archaeological record for understanding subsistence patterns, which in turn gives researchers information about how land was being used and what this meant in terms of the social structure. The type of environment and period of habitation can help to determine the types of households or residences that should have been present, which in turn may help to identify the social structure of a community (Chang 1958). A 1987 archaeological study regarding the cultural change from pit structures to pueblos in the American Southwest around A.D. 1150, for example, determined that climate played a large role in this transition (Gilman 1987).

Other cultural transitions were noted around this same period. Paleoindian groups were highly mobile, moving regularly to follow big game and other valuable resources. As climate changed and as domesticated crops began to spread throughout the region, archaic people became significantly more dependent on a combination of hunting and gathering. Eventually, the farming of domesticated crops became more important than hunting for many groups. This transition towards sedentary lifestyles suggests that it was considered worthwhile for communities to put in the labor efforts required to build permanent settlements (Gilman 1987).

To better understand prehistoric cultural behavior, archaeologists focus on human behavioral ecology. They study artifacts left behind hundreds to thousands of years in the past in order to reconstruct human behaviors and early cultural practices

(Res 2006). Many of the data examined in this research fall into the category of ethnoarchaeology. This field of study acknowledges that all present understandings of prehistoric cultures are based on what humans know to be true today (Huckell 1996; Res 2006). Using a behavioral ecology model, many archaeologists believe that humans adopted an "optimal foraging" practice, which suggests humans would only hunt or gather animals and plants that were most beneficial for their own livelihood. For example, if hunting an animal utilized more calories and effort to capture than it provided in sustenance, prehistoric hunters would look for something that required less effort (Res 2006). This perspective provides an introduction to the examination of human behavioral patterns that can be used as a guide to understanding prehistoric actions. Additionally, understanding prehistoric behavioral patterns may begin to shed light on the early factors that encouraged prehistoric populations to begin domesticating crops.

Prehistoric life during major droughts has been studied through the archaeological record in the American Southwest. According to various paleoclimatic and paleohydrologic models, cultures extant between 1200-650 years bp survived several detrimental droughts that caused huge problems for prehistoric populations. As climate changed, resources became less available causing major cultural changes such as temporary abandonment of certain regions during times of severe drought. Droughts caused severe lack of water, dispersal of animal populations, and reduced crop production meaning that many cultures were forced to relocate or find new methods of survival (Jones et al. 1999). Adaptations that resulted from this transformation of subsistence patterns included the development of increasingly sedentary lifestyles of late archaic to late prehistoric populations, as observed through the settlement of large groups in semi-permanent residences.

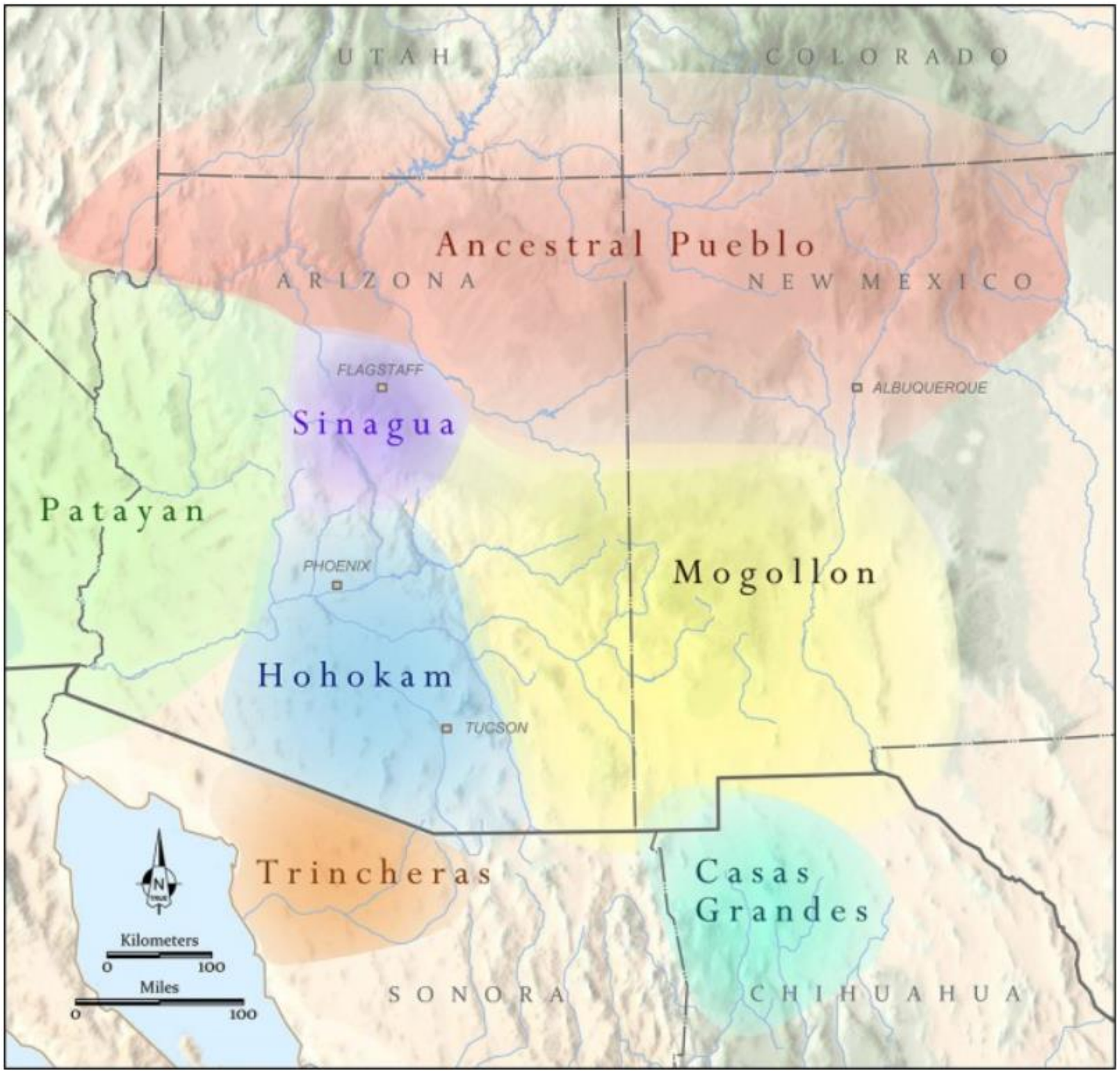


**Figure 3. Western New Mexico prehistoric culture groups.** This figure shows the major culture groups that were present in the American Southwest, from ~AD 200-1500. The groups pertinent to this research are the Ancestral Pueblo in Northwest New Mexico and the Mogollon in Southwest New Mexico (Peeples 2015).

Western New Mexico consists of two main culture areas: Mogollon and Ancestral Pueblo. Within each of these culture group areas, there are numerous different populations. In the Mogollon region, an increase in the reliance upon agriculture during the early to late pithouse periods (AD 200—1000) has been identified by archaeologists.

Cultures in this area (modern day southwest New Mexico) were generally dependent on water from the Gila River and its tributaries in the surrounding area (Hegmon and Nelson 2003).

Ancestral Puebloans were the dominant culture group in the Four Corners region of the American southwest. This region includes major cultural sites such as Chaco Canyon, Bandelier, and Mesa Verde. Early during the Archaic period, groups built pithouse structures and eventually began to develop large, permanent, above-ground structures made from masonry. Ancestral Pueblo groups were also dependent on agriculture for subsistence once the population began to grow due to an increasingly sedentary lifestyle (National Park Service 2016).

**Figure 4. Chaco Canyon.** This figure shows structural remains found within the Ancestral Pueblo region of New Mexico. Large structures, such as these, are common at sedentary agricultural sites, but settlements are not always this large. Image by author.

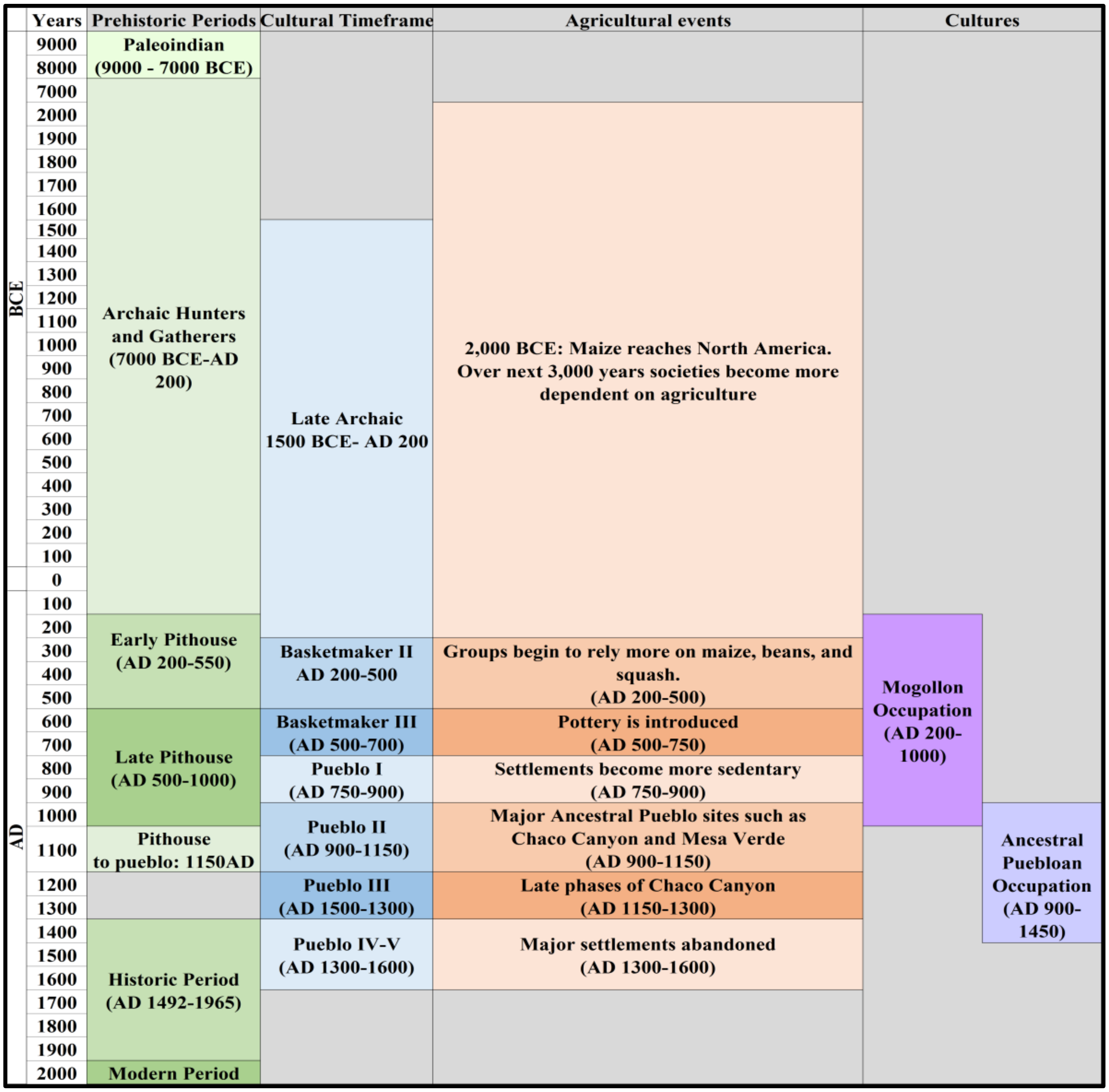


**Figure 5. Prehistoric cultural timeline.** This figure provides a timeline of prehistoric events, specifically involving the Mimbres and the Ancestral Pueblo cultures. Column 3 describes the agricultural events that have been compiled through archaeological records—describing its progression through the southwest.

All prehistoric culture groups throughout the southwest, especially in New Mexico, dealt with difficult environmental conditions and a severe lack of water. Four-thousand years ago, temperatures were beginning to warm and the environment was very similar to that which is experienced today (PHMC 2015). This changing climate may have caused major cultural changes for archaic hunters and gatherers, leading to a dependence upon agricultural practices (PHMC 2015). In this way, the development of ak chin style agricultural fields was extremely important for the survival of these prehistoric groups in areas that did not have access to a dependable water source.

# Chapter 3

## 3.1 Literature Review

Prehistoric land use can be difficult to interpret from modern field sites; however, the combination of archaeological field studies coupled with geographic information systems (GIS) and a general understanding of human responses to climate change can help researchers to better understand how prehistoric people interacted with their natural environments. The first section of this literature review will identify recent studies of the impacts of climate change on prehistoric human populations. The second section of this review will address recent data on prehistoric land use patterns, specifically focusing on researchers' present understanding of ak chin style floodplain agricultural fields. The final section will identify the most effective remote sensing data and image manipulation processes for identifying and interpreting archaeological sites.

### 3.1.1 Impact of Climate Change on Prehistoric Human Populations

Prehistoric habitation sites can be studied for evidence about ancient landscapes, climate conditions, and land use practices. Climate is a major driver of human activity and lifestyle, and can therefore be studied by archaeologists to better understand how people may have responded to past environments (Force 2004; Clevis 2006; Blinman 2008). A 1987 archaeological study regarding the cultural change from pit structures to pueblos, for example, determined that climate played a significant role in this transition. Larger and more permanent structures were built in response to groups becoming more sedentary and dependent upon agriculture for subsistence (Gilman 1987).

Current research seeks to understand the relationship between humans and their environment, and how humans have ultimately had to adapt over time to changing environmental conditions. Some of the key topics addressed in this line of inquiry include the assessment of climate and culture (Force 2004; Blinman 2008; Wills and Dorshaw 2011), the transition from hunter-gatherer to agricultural societies (Jones et al. 1999; Force 2004; Roth and Freeman 2008; Wills and Dorshaw 2011), changes in social structure (Chang 1958; Cordell 2007; Roth and Freeman 2008; Wills and Dorshaw 2011; Mabry 2008), and access to water (re)sources (Wills and Dorshaw 2011; Hall 2013).

Climate change can be studied using several methods through the archaeological record. Dendrochronology (tree-ring analysis), the generation of Species Distribution Models (SDMs), and the effects of changing water patterns are all methods used to document climate change through the archaeological record. Paleoclimate is fairly well studied on a global scale; however, impacts on individual regions are less studied. For the American Southwest, the assemblage and interpretation of tree-rings has been used to identify six major droughts (Benson and Berry 2009) and to identify climate change as a key driver in the cultural change from hunter-gatherer society to agricultural subsistence patterns (Bocinsky and Kohler 2014). Dendrochronology is a common way for researchers to observe climate patterns throughout the southwest, which could ultimately be correlated with different periods of cultural change—including the transition to agriculture and specifically maize (Alshuwaikhat and Nkwenti 2002; Banister 2011; Benson and Berry 2009; Tacoli 2009), and the change to seasonal habitation of prime cultivation and wintering locations (Huckell 1996; Hill and Holliday 2011).

For areas where prehistoric agriculture was practiced, carbon 14 dating can be used in combination with tree-ring analysis (Riede 2009; Alshuwaikhat and Nkwenti 2002; Banister 2011; Benson and Berry 2009; Tacoli 2009) to identify fluctuating cultural population densities and activities on a regional scale. These dates can be used to correlate cultural success or failure to major environmental changes (Riede 2009). Research using these techniques shows that the Archaic period was characterized primarily by aridity with minor rainy seasons (Huckell 1996).

Blinman (2008) examined pollen samples, tree core samples, and geomorphological deposition throughout the Southwest to understand what conditions were like throughout the last 12,000 years, and identified seven cultural transitions within the last 2,000 years. Cultural success can be measured by the geographic distribution and estimated population densities of various groups. For example, evidence of larger and more dispersed populations are indicative of increasingly stable societies (Blinman 2008).

Climate change can also be observed through a change in species zonation. The lowering of tree lines and changing locations of vegetation types can be observed using Species Distribution Models (SDM). As temperatures rise, tree and vegetation zones move up or down mountain slopes to relocate to a more climatically appropriate environment (Beltran et al 2014). The types of vegetation present prehistorically can be determined through both pollen and starch analysis.

Conversely, humans also impact climatic and environmental factors through the overuse of resources in certain locations which, for example, can change the natural patterns of rivers and streams. As climate continues to change and temperatures rise, it is possible for these resources to disappear completely—ultimately altering human settlement patterns, because humans will always seek out water sources. Different climatic patterns create the need for distinctly different settlement patterns. The archaeological record shows that paleo-lakes were a prime location for Paleoindian groups—this pattern has been recorded through the presence of mostly Paleoindian artifacts that were present in high density surrounding the lakes, but were completely absent in areas further away; however, as the lakes dried up and climate changed, human settlement patterns altered and Archaic groups began to migrate to locations where water was still present. This change resulted in a fairly extreme transition in land use patterns. Paleoindian hunters had to be mobile and able to follow herds of large game to retain this primary food source. As climate warmed, Archaic groups began to rely on a broad spectrum of wild food sources collected through both hunting and gathering practices. Approximately 4,000 years bp, agriculture was introduced to the Southwest and over time groups became significantly more dependent on crop cultivation. This provided greater stability and less mobility among populations (Hill and Holliday 2011).

A variety of geo-archaeological studies has been conducted on sites throughout the American Southwest (De Cunzo 2010, Sandor 1993), highlighting the importance of understanding climatic and cultural history throughout the region for predicting locations of previously unidentified prehistoric agricultural fields.

Agricultural remains are among the material culture that can be studied by archaeologists. The presence of agricultural fields is extremely important in the archaeological record for understanding prehistoric subsistence patterns, which in turn gives researchers information about how land was being used and how this may have related to social structures. Through the collection and analysis of soil samples, researchers have been able to refine their understanding of ancient agricultural fields to better understand how prehistoric people engaged in subsistence activities (Homberg et al. 2005). These authors identified definite patterns of agricultural land use along floodplains where the soil was most fertile (Clevis 2006; Gregory et al. 2008). These patterns indicate that prehistoric people were aware of the variation between land qualities and were able to identify ideal locations for growing crops—and may have even sought them out during the growing seasons. Similar studies have been conducted within the Hohokam region of southern Arizona. Certain agricultural sites within the American Southwest still reveal altered soil chemistry and soil development from centuries ago (Homberg et al. 2011; Hall et al. 2013).

Cultural response to a changing climate can easily be observed through the archaeological record in Chaco Canyon, a large Ancestral Pueblo structural site located in northwest New Mexico. Extensive research in this region has focused on the subsistence of these prehistoric Ancestral Pueblo cultures. Life in this arid zone was undoubtedly challenging and arguments have been made that trade was a primary resource through Chaco Canyon since the soil there does not hold sufficient nutritional value for crops (Cordell 2007; Wills and Dorshaw 2011).

Chaco Canyon and the surrounding region have been heavily studied and very little evidence for agricultural fields has been documented. Only one semi-confirmed agricultural field has been identified via remote sensing (Wills and Dorshaw 2011). Wills, Hall, and Force have all recognized the potential for water control systems, leading to the belief that agriculture was at least minimally occurring at the site (Force

2004; Wills and Dorshaw 2011; Hall 2013). Wills and Dorshaw (2011) state that one potential explanation for the uncertainty of agricultural presence is that the land was over-cultivated, thereby causing crops to not grow, leading to a catastrophic economic collapse and diaspora which would further exemplify the importance of agriculture and land use (Wills and Dorshaw 2011).

Human survival was largely based on the optimal use of the land by prehistoric people (Blinman 2008). Chaco Canyon populations were not the only early settlements to attempt to control water flow. The Hohokam built intricate irrigation systems to direct water towards maize and cotton crops. In fact, most early cultures had some way of efficiently diverting and using water resources; these methods include the construction of rock alignments, check dams, rock mulch gardens, and terraces in addition to the irrigation canals observed within Hohokam archaeological sites (Hall et al. 2013).

Huckell (1996) states that climate change was a major driver of a socioeconomic shift from Archaic hunter-gatherers to Middle Archaic and late prehistoric agricultural social structures. This change was accompanied by a decrease in big game and an increase in the presence of maize throughout the archaeological record. Dendrochronology (Bocinsky and Kohler 2014; Benson and Berry 2009), archaeological investigations (Alshuwaikhat and Nkwenti 2002; Bailey 2011; Bansiter 2011; Benson and Berry 2009; Tacoli 2009), and a documented increase in maize and seed grinding technology (Huckell 1996; Hill and Holliday 2011) help solidify the claims that climate change impacted prehistoric human populations.

In some ways, climate change had a positive effect on prehistoric groups by generating a more sedentary lifestyle where food resources were more regularly available, but climate has also been documented as a factor in cultural decline. The Fremont culture (primarily found throughout Utah) is an excellent example of a cultural collapse based on climate change and the fall of agriculture. The Fremont are characterized as having a complex social and economic structure; however, researchers tracked the prosperity of this culture using stable isotope analysis from bones collected at a burial site in the region and determined that due to a changing climate, crop production must have substantially decreased. There was evidence that due to the decline in agriculture, the Fremont culture could no longer trade for necessary items such as animal products and labor, and therefore, their society collapsed (Brenner and Leavitt 2002).

It is clear that climate had a lasting impact on prehistoric life and was the cause of many site abandonments throughout time. A study conducted by Jones et al. (1999) throughout western North America indicates a distinct correlation between climate change, cultural productivity, and settlement patterns from A.D. 800 to 1350. During the medieval period, several major droughts resulted in cultures having to find new areas to reside due to a lack of water or infertile soil for agriculturalists. Some areas, such as the Great Basin, are thought to have been completely abandoned during the worst droughts and repopulated when the drought receded. The study argues that climate is a major driver in the success and/or failure of cultures. When natural resources are impacted, prehistoric cultures must have also been negatively impacted since they depended so heavily on the environment (Jones et al.1999).

Due to a changing climate and a progressively more sedentary lifestyle, the study of prehistoric agriculture can bring to light deeper interpretations of ancient lifestyles, social structures, and subsistence patterns.

### 3.1.2 Prehistoric Cultures and Agriculture

Research has been conducted around the world to examine the distribution of Paleolithic to Late Prehistoric sites, noting changes in land use all the way up to the agricultural period (Rodning 2010). Roth and Freeman (2008) argue that agriculture in the American Southwest started during the Middle Archaic, based on extensive research involving ancient climate patterns observed through both pollen and plant analysis. The early stages of agriculture brought about a strong change in land use patterns of prehistoric groups (Chang 1958; Cordell 2007; Roth and Freeman 2008; Mabry 2008; Wills and Dorshaw 2011).

Hunter-gatherer societies relied on the hunting and gathering of available resources. Their lifestyle required high mobility and responsiveness to environmental factors; however, as the presence of maize and other crops grew within the American Southwest, many cultures began to adopt this new form of sustenance. The change in habitation can be determined through the construction of more permanent residences and large grinding tools (manos and metates) that indicate an agricultural yield of corn or similar crops (Roth and Freeman 2008). Ancestral Puebloan people relied upon precipitation and their trade relationships with surrounding groups during the growing seasons (Cordell 2007). Some locations were endowed with more rainfall than others; therefore, if one group had a surplus of agricultural goods, they could trade for other items that were abundant in nearby locations (Cordell 2007). This provides a strong argument for how different settlements interacted, and more specifically, suggests a change in social structure due to a change in subsistence patterns (Chang 1958; Cordell 2007).

Generally, dryland agricultural fields are fairly unpredictable. Dryland agriculture is an effective method in that it takes advantage of the natural hydrologic cycle; however, it is unreliable because it is impossible to know exactly which areas will receive the most precipitation each year. At any given time, therefore, only 15% of dryland fields were likely active (Field 2001).

Ak chin farming occurs at the terminus of arroyos within the associated alluvial fans. The water is directed down through arroyos to the base of mountains. At the mouth of the arroyo the water slows down and fans out. These fields required minimal labor to produce the most effective form of agricultural fields (Phillips et al. 1993). This type of agriculture helps to explain the presence of prehistoric people in such arid locations where few resources were present. Huckleberry and Billman (1998) state that ak chin farming is a system wherein people responded and adapted to a changing environment and brought agriculture to a landscape that would often not be considered a sustainable location for crops.

Government documentation from the late 1800s states that Ak Chin users, although intelligent about their land use practices, were malnourished because they depended so heavily on barely sufficient precipitation levels in southern Arizona. During this time, ak chin water sources were altered by Anglos, which heavily impacted the Tohono O’Odham community’s ability to farm effectively on their land. Ak chin agriculture is believed to have been extremely successful pre-contact; however, as the government began to control the land more, any individual who practiced traditional ak chin farming would be imprisoned—ultimately ending this traditional practice. The United States Government created an Ak Chin reservation in 1912 and continues to provide water to this group (Marmaduke et al. 1983).

Sediment at the base of drainages is considerably more fertile and more nutrient rich than the sediments near the top of arroyos. Research previously conducted on these fields was completed using Landsat-3 satellite imagery and Google Earth to identify these fields (Phillips et al. 1993). Some research has found that the potential exists for ak chin agriculture to have been used by the Hohokam culture as well as in the Wupatki region of Northern Arizona (Downum and Stone 1999). It is unclear if any ak chin crop fields have been verified in Wupatki; however, it is hypothesized that this type of field would be a prime source for agriculture in this type of environment (Downum and Stone 1999). Agricultural presence can be identified within the archaeological record by collecting soil samples for pollen analysis (Homberg and Sandor 2011).

Archaeological analysis can help researchers to better understand the environment. In terms of agriculture, these studies can indicate whether the soil is too degraded to grow crops or if it still has the potential for productivity (Dominguez and Kolm 2005; Homberg and Sandor 2011). The sandy sediment deposited within these ak chin style fields allows water to soak in to the more clay-rich sediments below, which subsequently prevents water from evaporating rapidly (Phillips 1993; Sandor et al. 2008). In addition to the primary environmental trademarks of ak chin style fields, there will often be a single pit house located along the edge of these ak chin style agricultural fields, most likely for the individual guarding the field and planting the crops (Mabry 2008).

### 3.1.3 Remote Sensing and GIS in archaeology

Remote sensing has become an important and valuable resource for archaeologists around the world, especially in the last five years (Parcak 2009; Giardino 2010; Harrower 2010; Hritz 2010; Pappu 2010; Lasaponara and Masini 2011; Dorshow 2012 Morehart 2012; McFeeters 2013; Chase 2014; Knott 2014). Until recently, only basic aerial imagery—typically from Google Earth—had been regularly used within archaeology. This review will examine the use of Landsat and Sentinel Imagery to identify vegetation changes over buried cultural remains (Agapiou et al. 2014), research examining the effects of prolonged human habitation within the archaeological record via aerial imagery (Parcak 2009; Dorshaw 2012; Giardino 2010; Chase 2014; Knott 2014), and specific methods that can be used to identify high moisture levels in the sediments (McFeeters 1996; 2013).

Remotely sensed imagery can be used alongside archaeological site data and climate reconstructions to assist in the identification of prehistoric habitation sites. Most analysis of archaeological sites has been done within other countries that have similarly arid and semi-arid environments as the southwestern United States, but few have actually been conducted in the Southwest (Parcak 2009; Hritz 2010; Dorshow 2012; Morehart 2012; Pappu 2010).

Remote sensing in archaeology will significantly increase the efficiency and overall understanding of the spatial characteristics of archaeological sites (Agapiou et al. 2014; Lasaponara and Masini 2011; Parcak 2009; Giardino 2010; Dorshow 2012; Pappu

2010). Recently, researchers have conducted their own experiments to better understand the altered surface vegetation patterns that appear over subsurface cultural deposits (Agapiou et al. 2014). Researchers physically buried structural materials at various depths below modern ground surface as a control sample for their study. They allowed vegetation to grow on top of the buried materials and documented the vegetation differences using temporal analysis (Agapiou et al. 2014). This research could help future archaeologists identify subsurface features before even setting foot in the field (Agapiou et al. 2014; Lasaponara and Masini 2011). Along these same lines, Lasaponara and Masini (2011) reviewed the uses Thematic Mapper (TM) in assessing soil marks and changes that are indicative of human impact. Lasaponara and Masini state that remote sensing is a non-invasive survey method to better understand the archaeological environment (Lasaponara and Masini 2011). Research conducted by Pappu (2010) primarily helped in identifying general spatial patterns of archaeological site distribution throughout south India. This research found that satellite imagery, in combination with thematic mapping, GIS modeling techniques, and field investigations, could accurately be used to develop a predictive model to help archaeologists find the most probable locations for prehistoric site placement.

In the mid 1990s, GIS modeling was a new application in the field of archaeology. Rivet (1997) discusses the value of examining archaeological sites in relationship to their surrounding environments. He states that archaeological site modeling is vital in predicting where sites would/should be located, especially in locations with heavy vegetation and alluvial deposition obscuring the ground surface. In 1997, environmental data was less widely available which made this type of modeling very challenging; however, it was clear that environmental predictive modeling was becoming a key resource in archaeological survey.

Many archaeologists feel that remote sensing is the future of archaeology, and this is demonstrated through the extensive research involved in identifying archaeological remains through the use of this technology (Parcak 2009; Giardino 2010). Some research has shown that it is possible to identify specific stratigraphic layers throughout a region that are the same as the stratigraphy containing the earliest hominids (Parcak 2009). Giardino identified Thermal Infrared Multispectral Scanner (TIMS) and the Thematic Mapper Simulator (TMS) as good sensors to use for identifying locations heavily impacted by human use. At the time of Giardino's publication, NASA was taking images from appropriate altitudes for effectively identifying archaeological sites (Giardino 2010). Knott (2014) hypothesized that known archaeological sites are not entirely random, but that their placement is predictable based on environmental components. This author used a DEM, LiDAR data, vegetation data, geomorphology, hydrological data, and a file of known archaeological sites in the study region. A weighted overlay suitability model was developed in ArcGIS software where each input raster was assigned a weighted value of importance in identifying new archaeological sites. Using this model and methodology, researchers were able to predict where sites are likely to be located in hopes that more archaeological sites may be saved from destruction through urban development (Knott 2014).

A study conducted by Merwin and Bernstein (2003) proved that predictive modeling can be used to predict the locations of archaeological sites now completely inundated by the Atlantic Ocean. This research used a variety of environmental inputs, and it was found that there is a regularity in the distribution of archaeological sites on the landscape. This means that, based on a set of known archaeological sites in the region, general locations of currently submerged archaeological sites can be predicted using this type of presence only GIS modeling (Merwin and Bernstein 2003).

Remotely sensed imagery is especially helpful in identifying and interpreting prehistoric agricultural fields (Parcak 2009; Dorshow 2012; Morehart 2012; Bauer 2014; Chase 2014). An extensive amount of work has been conducted in India in relation to agricultural soil erosion analysis; additionally, it is possible to examine the vegetation differences over a specific spatial range and to identify localities of prolonged human occupation (Parcak 2009; Chase 2014). Morehart (2012) utilized Landsat data, Quickbird, Very High Resolution (VHR) imagery and aerial photographs to identify canal systems in Mexico, but the author makes it clear that this technology is best for examining previously identified sites (Morehart 2012). A 2010 study in south India determined that LiDAR and Digital Elevation Models (DEMs) are useful for mapping archaeological sites by providing a more accurate representation and greater spatial identification of an archaeological landscape. It assists in the mapping of archaeological features that are difficult to view from ground level. It also provides a somewhat more accurate representation of the cultural materials present (Chase 2014). Some remote sensors can also pick up soil differences, river channel flooding potential, crop cultivation, and agricultural landscapes (Dorshow 2012). Bauer conducted an analysis of Neolithic impacts on land in India, and argued that agricultural processes sped up erosion. Remote sensing was used to identify change in sediment over time to help archaeologists see which locations were degrading more quickly and how specific locations have been directly impacted by human use (Bauer 2014).

GIS and remotely sensed imagery can also bring to light the extent and context of a variety of archaeological sites. The entire scope of the Hohokam irrigation canals are difficult to grasp. Aerial imagery can assist in the interpretation and identification of these large features from ground level. Researchers are beginning to use remote sensing technology to better understand prehistoric water diversion features (Harrower 2010; Hritz 210). Harrower has utilized this technology to identify prehistoric water flow systems (such as canals and irrigation systems, etc.). He was able to identify how prehistoric societies were utilizing available water resources (Harrower 2010). Hritz examined prehistoric land use and settlement patterns as well as ancient water paths using remotely sensed imagery. He argued that by using this technology to study prehistoric land use, archaeologists will have a more extensive working knowledge of prehistoric life (Hritz 2010).

When attempting to understand water catchment or agricultural features, imagery can be altered to better accentuate them. Since agricultural fields often hold water better than surrounding areas, the soil is often more rich in clay deposits. A Normalized Difference Water Index (NDWI) most effectively detects moisture that is present in the soil and is an important element to finding distinct differences between various land uses. It was introduced by McFeeters in 1996 as an effective method of illuminating open water regions throughout a landscape on an aerial image (McFeeters 1996). In 2006, Xu conducted an analysis of the levels of efficiency between using NDWI and a modified NDWI. The modified NDWI will better enhance the appearance of water (Xu

2006). An area that was once used for agriculture will be apparent with higher moisture densities being retained immediately after a precipitation event (McFeeters 2013). Li Zhang and Wylle (2009) conducted a comparative study between different methodologies for delineating water within a region and determined that NDWI was the most useful. There are still some errors in this data that researchers should be aware of, but overall the results were acceptably accurate.

Kailihiwa (2015) conducted an analysis of a rock mulch/alignment/pile agricultural fields using Maximum Entropy presence-only modeling to identify ideal geographic locations and general distributions of these features throughout the landscape. Kailihiwa used rainfall data, elevation data, slope aspect, slope degree, and soil fertility data as inputs for his modeling to help locate ideal locations for archaeological agriculture fields. The results from his research showed that Maximum Entropy, a common Habitat Suitability Model, is effective in identifying agricultural features. It also provides evidence that presence-only modeling can be effective for these purposes (Kailihiwa 2015).

### 3.2 Gaps in the Literature

A few major gaps were identified throughout all three sets of literature. Increasingly, studies are being conducted that link remote sensing and archaeology within the southwestern United States. Specific uses of remote sensing in archaeology could benefit from further analysis and a more intensive use within the field. Also, ak chin style agriculture is under-researched (Phillips et al. 1993). It is uncertain exactly where ak chin agriculture was utilized. The available research on ak chin agricultural fields fails to indicate what prehistoric period and what cultural affiliation is associated with ak chin style agriculture. Lastly, a more in depth regional study would be useful for understanding and interpreting cultural features before actually visiting the field.

My research addresses some of these remaining questions. My research is centered on prehistoric cultures and agricultural practices, specifically focusing upon the ak chin floodwater fields in the arid southwest. Agricultural practices are ultimately the result of changing climate and a need for different subsistence patterns. A greater understanding of prehistoric agricultural practices will be gained by incorporating remote sensing derived metrics of climate conditions (e.g., NDWI) into a suitability model trained on known ak chin style agricultural fields. This work could aid the archaeological community in the identification of prehistoric ak chin style agricultural fields, leading to a further understanding. Work extending beyond this thesis may further investigate the potential of using these suitability models in conjunction with archaeological field investigations.

# Chapter 4

## Research Design

### 4.1 Research Question

Which "presence-only" suitability models perform best in identifying ak chin style agricultural fields?

### 4.2 Methods

Three suitability models were selected to identify potential ak chin style prehistoric agricultural fields; these include Maximum Entropy (Maxent), Mahalanobis Typicality, and Multi-Criteria Evaluation. The results of these three models were compared and ultimately the most ideal suitability model for identifying ak chin style agricultural fields was determined.

#### 4.2.1 Data

This research required the use of mostly secondary data sources. The first step to data processing required gathering raw data, from which all spatial-environmental variables were created.

##### 4.2.1.1 Known Ak Chin Style Agricultural Field UTM data (Training data)

Training data field locations were extracted from a combination of sources: A thesis by Antonio De Cunzo (a former student at Eastern New Mexico University), records at the Office of the state Engineer, and research conducted by Dr. Jonathan Sandor (Emeritus Faculty member at Iowa State University). This data was provided in UTM format which was then used to generate a .csv file to create the Training Data raster input file.

#### 4.2.1.2 Digital Elevation Model

A 10 meter Digital Elevation Model (DEM) of the entire state of New Mexico was obtained from the New Mexico Resource Geographic Information System (RGIS) at the University of New Mexico. This raw data file was used to create the slope, elevation, and solar radiation input variables.

#### 4.2.1.3 Archaeological Site Data

A shapefile containing archaeological site locations and boundaries was obtained from the New Mexico Cultural Resource Information System (NMCRIS). This data was provided in both polygon shapefile and an excel database file and was gathered by a variety of archaeologists and archaeological companies throughout the state of New Mexico.

A specialized query was conducted of the NMCRIS database to cater directly to this research. The query conducted by NMCRIS extracted only site data that consisted of two or more room blocks, pithouses, or other structural remains that have been dated between Basketmaker II (~500 B.C.E) to Pueblo III (A.D. 1300) time periods. Additionally, the query was limited to a UTM range of 103690 mE to 419700 mE UTM zone 13N and all northing values from the furthest south portion of the study area to the Colorado/New Mexico border (along the boundaries of the study area) to help limit the search to western New Mexico.

The Cost Distance input variable was created from a combination of the archaeological site data shapefile and the 10 meter digital elevation model.

#### 4.2.1.4 Landsat 8 OLI-TIRS satellite imagery

Fourteen Landsat 8 OLI/TIRS scenes were downloaded from http://earthexplorer.usgs.gov, these included paths 33-35 and rows 34-38. All of this data was collected during a seventeen day time frame that ranged from May 31 to Jun 16, 2014. All 14 scenes were not required to cover the study area, but were downloaded to ensure all gaps were covered. This raw data was used to create the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI) input variables.

| Data | Format | Source |
|---|---|---|
| **Training data** | UTM locational data | Sandor, De Cunzo, OSE |
| **Elevation (DEM)** | Raster | RGIS |
| **Landsat 8** | Raster | Earthexplorer.usgs.gov |
| **Archaeological Site data** | Shapefile and Database | NMCRIS |

**Table 1. Raw Data**

### 4.2.2 Initial Data preparation

Since the state of New Mexico crosses a line of longitude, the downloaded imagery originated within two separate UTM zones: UTM 13N and UTM 12N. This meant that all of the scenes had to be re-projected so that they could be mosaicked into one single image. To accomplish this, all scenes were first re-projected into the Albers_Equal_Area_Conic_USGS_version EPSG: 5070 format and were then mosaicked together. All data were then converted to UTM 13N, as this is the convention in the state of New Mexico.

After all data were correctly projected, they were clipped so that each input variable contained the exact same number of columns and rows as well as the same x-and y- minimum and maximum coordinates, thereby ensuring that the models would run properly. Once complete, the raw data was processed and prepared to function as spatial-environmental input variables.

**4.3 Variable Preparation**

The raw data described above was used to create six different spatial-environmental input variables and a training data file.

**4.3.1. Dependent Variables**

Dependent variables are those which are dependent upon the values of each variable within the independent variables.

**4.3.1.1 Training Data (Known field data)**

The training data consists of a limited number of verified ak chin style agricultural fields that were used to calibrate the models to find environments similar to the known field data. Each model utilizes the information extracted from each spatial-environmental input variable at the training field locations and calibrates the model to identify other locations with the same or similar spatial-environmental characteristics.

This file was created using a UTM center point for each known field and a Comma Delimited file (.csv) was created using the Northings and Eastings of each training site. This file was imported into TerrSet using the xyz-idrisi module, which generated a TerrSet compatible vector file. This file was converted from a vector point file into a TerrSet raster Boolean file, with a value of ‘1’ representing the presence of agricultural fields, and a value of ‘0’ representing the absence of known agricultural fields.

Although a polygon format would likely have been more effective for modeling this type of agricultural field, the data collected by both archaeologists and soil specialists were provided as center points. Since these fields may range in size from 10 meters to 5 kilometers depending on the alluvial fan and the arroyo supplying water (Phillips et al. 1993), estimating boundaries would have provided more inaccurate results than simply running these models with point file training data.

Very few ak chin style agricultural fields have been identified and verified throughout the American southwest. Although only 15 total fields have been identified and verified within the study area, several others have also been found throughout Maja and Hohokam sites in southern Arizona. In an attempt to limit the total area examined for this research, the study area excluded Arizona.

| Field # | Site Description | Source | UTM East | UTM North |
|---|---|---|---|---|
| 1 | Mimbres, NM | Jon Sandor | 766172 | 3659226 |
| 2 | Mimbres, NM | Jon Sandor | 766129 | 3659481 |
| 3 | Mimbres, NM | Jon Sandor | 765842 | 3659370 |
| 4 | Zuni, NM | Jon Sandor | 719105 | 3887210 |
| 5 | Weekoty Field | Jon Sandor | 714761 | 3893965 |
| 6 | Weekoty Field | Jon Sandor | 712953 | 3893208 |
| 7 | Laate Field | Jon Sandor | 717560 | 3903984 |
| 8 | Montecello Box Canyon | Antonio De Cunzo | 263521 | 3714303 |
| 9 | Ak Chin Acoma 1 | OSE Adjudication | 265920 | 3861617 |
| 10 | Ak Chin Acoma 2 | OSE Adjudication | 259715 | 3864054 |
| 11 | Ak Chin Laguna 1 | OSE Adjudication | 273718 | 3889574 |
| 12 | Ak Chin Laguna 2 | OSE Adjudication | 273946 | 3889113 |
| 13 | Ak Chin Laguna 3 | OSE Adjudication | 244499 | 3847851 |
| 14 | Ak Chin Laguna 4 | OSE Adjudication | 269834 | 3871805 |
| 15 | Ak Chin Laguna 5 | OSE Adjudication | 292447 | 3870884 |

**Table 2. Ak Chin field training data.** The data represented in this table consists of UTM's for each reference ak chin style agricultural field. It includes the appropriate data for the 8 training site data and the 15 training site data.

The first eight training data fields (Numbers 1-8 in Table 2) consist of fields that were sampled by Jonathan Sandor and Antonio De Cunzo. This soil analysis verified the presence of *Zea Mays* (corn); this type of pollen is heavier than most others and is not often found far from actual prehistoric agricultural fields (Pfarr 2008).

The last seven training data fields (#9-15 in Table 2) consist of ak chin fields documented through Pueblo litigations from the Office of the State Engineer (OSE). Although archaeologists and soil specialists have not tested these fields for pollen, they have been officially identified as ak chin style agricultural fields by the associated pueblos (HKM Engineering Inc. 2003). All of the known fields addressed here were within the western half of New Mexico.

### 4.3.2 Independent Variables

Independent variables are those that researchers have control over and which drive the other variables in analysis.

#### 4.3.2.1 Cultural Factors (Cost-Distance)

Cost-distance analysis was the only cultural input variable created for this analysis. The cost-distance variable proved to be the most valuable resource in this analysis. This variable informs the models of the effort required to travel from the source location (known archaeological sites) to a certain distance away from these known archaeological sites. This helps to dictate feasible routes and indicates the likelihood that people would put forth the effort required to travel to a potential ak chin agricultural field. Locations that require extremely difficult climbs or go through steep environments may be eliminated from the analysis.

The results were buffered so that only locations within five miles of known archaeological sites were observed. All potential locations further than five miles from known archaeological sites were not considered because they cannot be easily associated with a specific cultural component—this is not to say that fields do not exist at a distance greater than five miles from known sites. If environmental conditions required this type of trek, fieldhouses would have been placed at the agricultural field and individuals would have stayed at the field until crops were produced.

Since the environmental variables were expected to provide an ample number of potential ak chin agricultural field locations, this input helped to define the locations where potential agricultural fields would most likely be present. To create this variable, archaeological site data and the digital elevation model were input into the cost-distance analysis module; the archaeological site data was input as a polygon shapefile and the DEM was input as a raster file.

It is important to note that not all archaeological sites have been located and recorded throughout the state of New Mexico. It is also possible that groups not residing in semi-permanent settlements were participating in agricultural practices; however, this cannot easily be verified and modeled by researchers. Additionally, site density is much greater in the northern portion of the state than it is in the southern portion of the state. This distribution may be due to the number of archaeological projects that have been completed in each region of New Mexico or is simply a reflection of the data available through NMCRIS; either way, this variable may have had an effect on the overall results by skewing the number of potential fields identified to the northern portion of the state.

#### 4.3.2.2 Environmental Factors

Five environmental variables were taken into consideration to complete the modeling process. These variables include slope, elevation, solar radiation, Normalized Difference Vegetation Index (NDVI), and Normalized Difference Water Index (NDWI). Each of the environmental input variables are discussed below.

#### 4.3.2.3: Slope

Ak chin style agricultural fields are located on very gradually sloping alluvial fans. It was expected that this analysis would easily identify all alluvial fans in the study area. This variable helped to limit the number of potential ak chin style agricultural fields that were found through this analysis by providing additional known data to calibrate the models.

The slope image was calculated using the "slope" module in Erdas Imagine. The output image is represented in slope degrees and was created using a 10 meter digital elevation model (DEM) of the state of New Mexico. Once the slope input was created it was processed through CONTRACT in TerrSet to make it a 30 meter resolution image. Ak chin agricultural fields typically exist on a 2-10 percent (1-5 degree) slope, and this input will help identify new locations with similarly shallow slopes as the training site data.

#### 4.3.2.4: Solar radiation

Solar radiation is a key variable that was expected to greatly inform researchers of where crops were most likely to grow. All newly identified fields should reflect similar solar radiation patterns as the training data sites. Solar radiation analysis takes into consideration not only the direction landforms face (aspect) but also slope, topography, atmospheric effects, and the reflectivity of different landscapes (Jenness 2007). These various elements can be vital in understanding habitat suitability. Latitude and season can impact solar radiation; therefore, based on an understanding of the general growing season in the American Southwest, specific dates were chosen to most accurately represent prehistoric growing conditions. Numerous environmental components were considered with solar radiation analysis including soil temperature regimes, evapotranspiration, snow melt, and soil moisture patterns (Esri 2013).

To develop a solar radiation map of western New Mexico several steps were taken. First, a 10 meter resolution DEM of New Mexico was imported into Erdas Imagine. Next, a grid layer consisting of 66 separate 0.5 x 0.5 degree blocks was developed in ArcMap 10.3 and imported into Erdas Imagine as a vector layer. This grid helped researchers divide up the 10 meter resolution DEM into equal sized blocks to make analysis easier. Since this is a very time consuming processes, this ensured that the solar radiation analysis could be processed quickly and successfully in a parallel computing environment.

Each half degree, 10 meter resolution block was selected individually and was clipped so that each individual block could be processed through the “area solar radiation” module in ArcMap 10.3. All 66 blocks were subsequently mosaicked back together in Erdas Imagine.

The inputs selected consist of a one month analysis from June 15, 2014 to July 15, 2014 since this range falls within the midpoint of the major growing season throughout the American southwest which is consistent with what growing seasons would have been 3,000 years ago. The sky size resolution input was set to 512—

increasing the accuracy of the process from the default setting of 200. Additionally, this input was be sufficient for mapping solar radiation over a larger region (Esri 2005). The results were mosaicked back together and converted to a 30 meter resolution to function as the solar radiation input for the suitability modeling process.

Below is an image of the 10 meter DEM of New Mexico with the grid that parsed this 10 meter resolution DEM into 66 0.5 x 0.5 degree latitude/longitude blocks overlaying it; this demonstrates how the image was divided to run solar radiation. The first six blocks from the western edge of the study area and all blocks north to south within the study area were processed (represented by the light blue outline in figure 6 below).

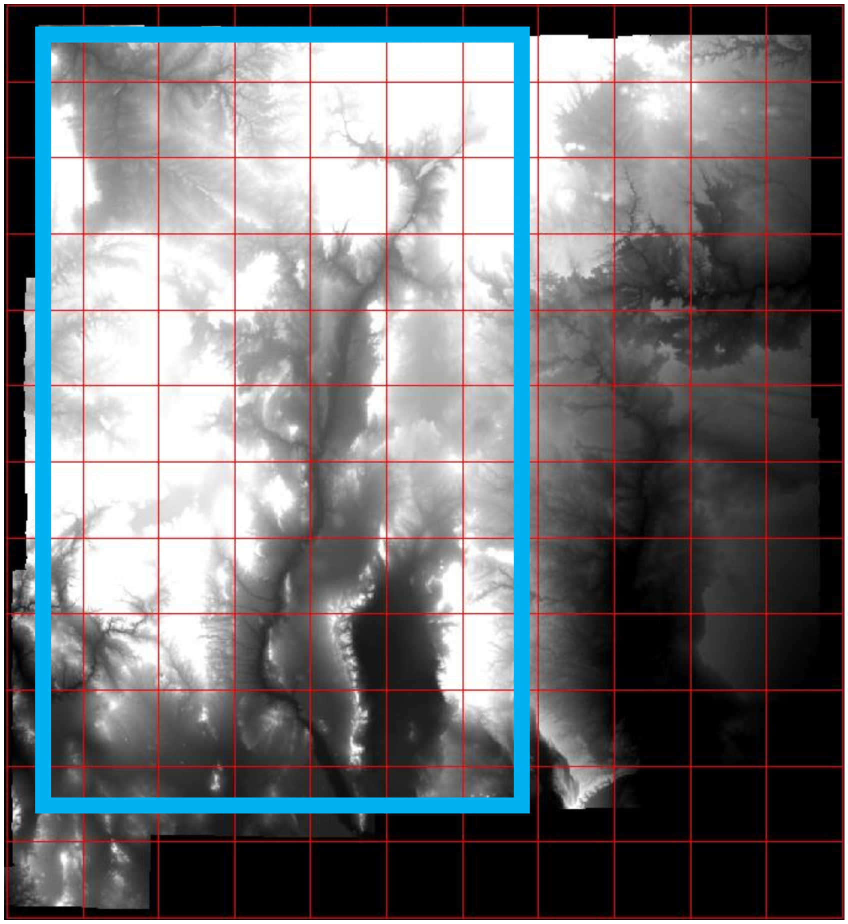

**Figure 6. Solar Radiation Analysis Grid.** This figure displays the division of the DEM for the purposes of creating an estimate of solar radiation. A total of 66 half degree blocks were clipped and separately processed through the Area Solar Radiation Graphical User Interface in ArcMap 10.3.

### 4.3.2.5: Elevation

All known ak chin style fields are located within an elevation range of 1800-2200 meters. This was an ideal range where the fields were high enough in elevation that temperatures were not too hot and water would be able to reach them, but also low enough in elevation that the fields would not freeze early in the growing season.

Based on previous archaeological studies of ak chin fields (Phillips et al. 1993), elevation is an important variable for understanding their likely locations. This data was created by simply using the DEM as the input variable.

#### 4.3.2.6: Normalized Difference Vegetation Index (NDVI)

NDVI was included to provide a measure of the physical environment associated with ak chin features. NDVI helped identify the presence of living vegetation, thereby identifying locations of greater water retention in the arid study region. It was calculated using the following equation:

$$(1)\quad \frac{\text{Band 5 (NIR) - Band 4 (Red)}}{\text{Band 5 (NIR) + Band 4 (Red)}}$$

#### 4.3.2.7: Normalized Difference Water Index (NDWI)

NDWI was included to provide data on the presence of water features and water content in the soils of the region. This image was created using the following equation:

$$(2)\quad \frac{\text{Band 3 (Green) – Band 5 (NIR)}}{\text{Band 3 (Green) + Band 5 (NIR)}}$$

| Variable | Input Source | Use |
|---|---|---|
| **Training Site Data** | UTM's created .csv file | Dependent |
| **Elevation** | 10m DEM | Independent |
| **Slope** | 10m DEM | Independent |
| **Solar Radiation** | 10m DEM | Independent |
| **NDVI** | Landsat 8 mosaicked scenes | Independent |
| **NDWI** | Landsat 8 mosaicked scenes | Independent |
| **Cost-Distance** | 10m DEM and Archaeological Site data | Independent |

**Table 3. Spatial-environmental input variables**

#### 4.3.2.8 Data Input Variable Values

The values of each input variable were extracted for each of the training sites. Field number 8 yielded an unexpectedly high slope degree, which may have adversely impacted the overall results. An ideal slope for ak chin style farming is typically no greater than 3.2% but can range between 2-10% or 1 to 5 degrees (Phillips 2006). A few other training fields fall above this mark, but are still within an acceptable range.

Essentially, ak chin fields (and most other floodwater farming fields) must be situated on a very gentle slope where water naturally slows down and pools, using the natural hydrological processes to the greatest extent possible. The values for elevation at the training sites fit the known attributes for ak chin style agricultural fields.

| 30 Meter Resolution, Training Data Locations and Original Data | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Training site #** | **UTM East** | **UTM North** | **Elevation** | **Solar Radiation** | **Cost Distance** | **NDVI** | **NDWI** | **Slope (°)** |
| **1** | **205790** | **3660283** | 1921.43 | 207948.34 | 3065811.75 | 0.17 | -0.18 | 2.12 |
| **2** | **205820** | **3660026** | 1909.49 | 210781.53 | 2904198.25 | 0.16 | -0.17 | 1.91 |
| **3** | **205495** | **3660189** | 1919.23 | 211508.23 | 24277750.75 | 0.15 | -0.18 | 3.41 |
| **4** | **172191** | **3890452** | 2073.32 | 213674.13 | 264195.53 | 0.16 | -0.22 | 0.72 |
| **5** | **168221** | **3897531** | 2094.60 | 213511.70 | 507972.03 | 0.13 | -0.19 | 0.64 |
| **6** | **165082** | **3897218** | 2078.82 | 211907.87 | 507972.03 | 0.14 | -0.19 | 0.73 |
| **7** | **171662** | **3907334** | 2074.49 | 214303.03 | 2452140.75 | 0.11 | -0.16 | 0.72 |
| **8** | **263521** | **3714303** | 1871.97 | 196124.84 | 782477.50 | 0.11 | -0.15 | 13.38 |
| **9** | **265920** | **3861617** | 1927.42 | 210877.00 | 19140142.00 | 0.10 | -0.17 | 0.30 |
| **10** | **259715** | **3864054** | 1952.99 | 210875.42 | 32793396.00 | 0.11 | -0.15 | 0.12 |
| **11** | **273718** | **3889574** | 1951.58 | 212222.39 | 426125.50 | 0.10 | -0.16 | 0.48 |
| **12** | **273946** | **3889113** | 1940.87 | 211887.94 | 4345121.00 | 0.09 | -0.15 | 0.30 |
| **13** | **244499** | **3847851** | 2420.18 | 220995.92 | 6819125.50 | 0.18 | -0.19 | 5.69 |
| **14** | **269834** | **3871805** | 1851.38 | 209956.81 | 17467916.00 | 0.13 | -0.17 | 0.35 |
| **15** | **292447** | **3870884** | 1700.06 | 207418.19 | 11958494.00 | 0.09 | -0.22 | 0.91 |

**Table 4. 30 meter training data values.** The data displayed is for each training data site.

### 4.3.2.9: Excluded Variables

Three additional environmental variables were considered but rejected due to the non-standard nature of the data. Vegetation is often different from within the ak chin agricultural field and the surrounding area; however, all current vegetation maps are grossly generalized and fine scale variations cannot not accurately be identified. Field size and shape were also considered but could not be used as input variables because not all ak chin fields are the same size or shape and the shape and size of known ak chin fields is not well understood or consistent. Both are heavily dependent on the size of the alluvial fan and the amount of rain each region receives, and these are not generalizable variables. Research conducted within various regions of southern Arizona and central New Mexico indicate that these fields were often several square kilometers in size (Phillips et al. 1993); however, without specific data indicating the exact size of each known field, it is impossible to delineate definite field boundaries.

### 4.4 Suitability Models

Three different suitability models were selected based on their potential for identifying potential new locations for ak chin style agricultural fields. These models consist of Maximum Entropy (Maxent), Mahalanobis Typicality, and Multi-Criteria Evaluation (MCE) Ordered Weighted Average (OWA). Since the training data for this research contains "presence-only" information, the selected models had to be compatible. Presence-only models utilize known location data about the variable being researched, but do not provide training information about environments where the species were *not* found.

| | Minimum # Training Data | Type | Theoretical Framework | Output | Leave one out? |
|---|---|---|---|---|---|
| **Maxent** | 15 | Presence-only | Identifies largest geographic spread of species presence based on the training data and the associated spatial-environmental values. | Raster Suitability, jackknife, response curves AUC value | No |
| **Mahalanobis Typicality** | 10 | Presence-only | Identifies how typical (how similar) each pixel is of the training data. | Raster Suitability | Yes |
| **MCE OWA** | n/a | Presence-only | Expert system. Researchers weight the model based on what is known to be the most important data. | Raster Suitability | No |

**Table 5. Brief breakdown of each suitability models requirements.**

### 4.4.1: Maximum Entropy (Maxent)

Maxent is a suitability model that uses presence-only training data. Maximum Entropy works by "finding the largest spread (maximum entropy) in a geographic dataset of species presences in relation to a set of 'background' environmental variables" (Phillips et al. 2006). Essentially it uses the presence-only data supplied by researchers to find the most suitable environments based on all additional spatial-environmental variables. It predicts where similar environments are likely to occur. The model completes multiple iterations in which it uses the training data to "learn" the ideal environmental input variables of the desired study area. These iterations begin by assuming equal distribution of potentially suitable locations and each time it runs, the model improves upon the "fit" of potentially suitable locations—eventually outputting a suitability raster that displays a range of locations from the least suitable to the *most* suitable potential field environments.

This suitability model uses all environmental inputs to define the likely distribution of agricultural fields. This model, though typically used for identifying species distribution, will be used to identify environmental and cultural signatures of ak chin fields. Maximum Entropy is especially designed to work with small training samples (Phillips et. al 2006). Many settings are available for this model; however, for the purposes of this project, the default settings were utilized (described in model parameterization in section 4.5.1. page 48 below).

For this analysis, a minimum of 15 training sites were required to obtain appropriate results. As with any suitability model, a higher sample size provides a greater accuracy of results (Phillips et al. 2008). Training data containing 15 or more training fields utilizes a combination of linear, hinge, and quadratic computational features. Each additional computational feature utilized during model analysis constrains the overall output for the Maxent Model to provide increasingly more accurate results (Kailihiwa 2015). Linear features utilize the spatial-environmental variable values at each training field to find locations throughout the data that have the exact same spatial-environmental values as the training data. These linear features consist of all continuous inputs—i.e. slope, elevation, etc. Categorical input variables such as soil data would not be useful in this context (Kailihiwa 2015). Variables are not weighted based on importance, rather they are considered equally for the output suitability distribution of potential agricultural fields (specifically for this research).

The quadratic features further constrain the linear feature output distribution suitability file for agricultural fields by accounting for a variance in the data. A margin of error is calculated and any pixels within a specific range of the expected data values are analyzed more extensively (Kailihiwa 2015; Phillips et al. 2006).

Hinge features further constrain linear distributions by identifying even more complex relationships between the training data and the spatial-environmental input variables. The suitability results are constrained by developing a binary probability grid that identifies ideal locations based on the training data. A threshold of a certain distance from most suitable environments is calculated using values from the linear function (described above), and more accurate/extensive processing is conducted on these more ideal locations within the data. (Phillips and Dudik 2008). The additional output features, while all still dependent upon linear features, help to further restrain the model results.

In addition to a raster suitability map, Maxent results consists of response curves and jackknife results that help researchers to interpret and understand the use of the input variables in the overall outcome of the model. Response curves allow researchers to understand the probability that a species will be present. The model provides two sets of response curves—one provides the average values identified for each variable and the second set displays the response of each individual variable when all other variables are excluded from the analysis. These response curves assist researchers in understanding how much each independent variable effected the overall suitability results.

The Jackknife results provide a bar graph representation of how well each model performs when run using all input variables, when using all but one variable, and lastly when using only one variable. This helps to determine which variable had the greatest impact on the overall outcome of the Maxent suitability model ("Presence-Only Modeling with Maxent" 2016).

**4.4.2: Mahalanobis Typicality**

Mahalanobis Typicality is also a presence-only model that accepts only continuous data. Continuous data—which defines all input variables in this research—cannot be quantified or divided into distinct groups (whereas categorical data, such as a soil map, can be).

Mahalanobis Typicality works by assessing how "typical" each pixel is within the study area. Typicality in this context refers to how similar each pixel is to the pixels on which the model was trained. The results of this model are provided in the form of a suitability raster that consists of a range of decimals between 0 and 1, where values closer to 1 are considered more likely to be more suitable environments for ak chin style agricultural fields and decimals closer to zero represent locations that are less suitable environments. The results from this model require careful interpretation since all values fall between 0 and 1—and the suitability of each pixel is relative to the rest of the image, making it easy to erroneously interpret the results (Eastman 2015).

Mahalanobis Typicality assesses each individual pixel and determines how typical each one is in terms of the training site data (Clark Labs 2015); whereas, Maxent begins by assuming that there is an even distribution of suitable environments across the grid and as the model runs, it "learns" from the training data and identifies increasingly more suitable environments ("Presence-Only Modeling with Maxent" 2016). The results for both models are provided as a suitability raster. Each pixel is assigned a suitability rating between 0 and 1, and the pixels with values closer to 1 indicate that that pixel is more typical of the training environments. However, the interpretation of Mahalanobis typicality results are far more general than those of the Maxent suitability model because the Maxent model provides AUC data, response curves, and jackknife graphs in addition to the suitability raster.

### 4.4.3: Multi-Criteria Evaluation, Ordered Weighted Average

As an expert system, Multi-Criteria Evaluation (MCE) Ordered Weighted Average (OWA) evaluates a combination of criteria to develop a single composite based on researcher designations of factor weights. This model is designed to work with data sets that do not have training data available. This model was chosen for the purposes of this research to compare the differences between models that train on ak chin style agricultural field locations and one based on expert opinion based primarily on the literature (Philips 1993; Sandor 2008). Since these fields have specific elements that can be somewhat generalized, researchers were interested in understanding if expert knowledge on these fields was sufficient for identifying ak chin style agricultural field environments or if additional data was extracted when using the training data with Maxent and Mahalanobis typicality.

The MCE OWA model uses a decision making algorithm based in the input variables that requires a certain degree of risk-taking and tradeoffs. These risks and trade-offs help to evaluate a wide range of possibilities when the inputs and criteria are uncertain (Gorsevski et al. 2012). Risk is the potential that a decision made by the model for any particular locations may be incorrect (Drobne and Lisec 2009). Trade-off is dependent on the factor weights and ordered weights. When one variable is deemed more important than another, the ordered weights will make a decision for which variable will be given greater consideration. For example, if there is low risk and no tradeoff, then the model will search for locations that have high values for each input variable. If there were high risk, then the suitable environments identified may only be ideal for one or two of the input variables because the model had to decide which variable was most important for the analysis (tradeoff).

All variables are used as inputs and each variable is assigned a factor weight that indicates how important researchers believe each variable to be in identifying the suitability based on the literature regarding ak chin style agricultural fields. Factor weights are applied to each variable and must sum to 1 among all inputs; the factor weights that are applied to each input variable are assigned to every pixel within that specific variable. MCE-OWA utilizes a second set of weights called “ordered weights” which introduces a degree of trade-off between each of the input variables (or factors).

Ordered weights are assigned on a pixel by pixel basis rather than a variable by variable basis—as the factor weights are. The ordered weight is directly correlated to the amount of trade-off experienced by the model (Drobne and Lisec 2009). When ordered weights of [1, 0, 0…] are applied, this results in a “minimum operator of fuzzy sets”—the author refers to this as “ANDness” (Eastman 1999; Drobne and Lisec 2009) and consists of no trade-off among variables. As these ordered weights are altered, and various values are utilized—such as [0.5, 0.3, 0.2…] or [0.3, 0.3, 0.3…] different degrees of trade-off are introduced into the model. These different ordered weights effect the degree of trade-off and risk that are being implemented in the processing of the model.

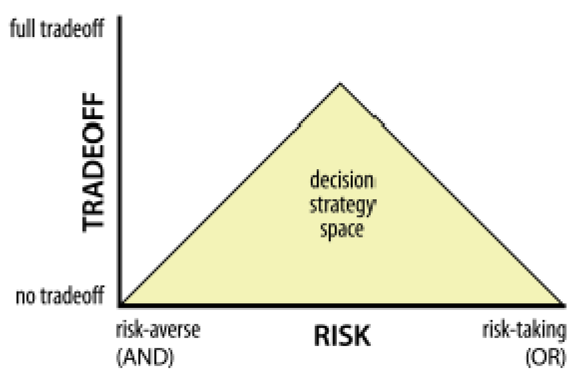


**Figure 7. MCE-OWA Risk and tradeoff graph.** MCE-OWA involves a series of risks and tradeoffs when calculating which variables are the most important (Eastman 2015). When there is an equal amount of risk (i.e. the ordered weights are all equal), there is potential for full trade-off of the importance of each variable. When there is either no risk (Ordered weight: 1, 0, 0…) or full risk (Ordered weight: ...0, 0, 1), there is little to no potential tradeoff between each variable.

### 4.5 Model Parameterization

Each of the three models were run with all six of the environmental and cultural input variables with somewhat unique input selections based on model requirements. The resulting suitability models were visually assessed and then processed through a verification module to interpret the accuracy of the results.

#### 4.5.1 Maxent

The defaults for this model were selected for the purposes of this analysis. These default settings require the model to produce the "auto features"—for 15 training data sites this includes Linear, Quadratic, and Hinge computational features. Additionally, the model is set to produce logistic results that will also result in response curves and a jackknife test graph. It is set to run 500 iterations with a convergence threshold of 0.00001. All input variables were of a continuous format and the training data file with 15 known ak chin style agricultural fields was used.

#### 4.5.2 Mahalanobis Typicality

The parameters for this model consist of six raster input variables and the raster training data file. The output file was named appropriately and the model was run.

#### 4.5.3 MCE-OWA

Multi-Criteria Evaluation Ordered Weighted Average required the six input variables to be added and factor weights were assigned to each. The exact values assigned are displayed in table 6 below. Cost-distance was considered the most important input variable and the best limiting factor for ak chin style agricultural fields because it identified a cultural component for this research—therefore, this variable was assigned the highest factor weight. Slope and elevation both consist of known values in which ak chin style agricultural fields should be found and therefore these values were assigned the second highest factor weights. There are not previously determined values or a solid background literature describing specific values expected for NDWI, Solar radiation, and NDVI within ak chin agricultural environments and therefore these variables were assigned the lowest factor weights.

The Ordered weights of [1, 0, 0, 0, 0, 0] were then selected. This set of ordered weights applied all weight to the variable with the lowest factor weight. Variables with higher factor weights received no weight. This means that factor weights are not contributing much in this scenario and that no trade-off was applied to this model when it was run, meaning that all factors were taken into consideration and only locations that included all variables were considered suitable. The values for both the factor weights and ordered weights are displayed in table 6 below.

| Variable | Factor Weights | Ordered Weights |
|---|---|---|
| **Cost Distance** | 0.25 | 1 |
| **Slope** | 0.2 | 0 |
| **Elevation** | 0.2 | 0 |
| **NDWI** | 0.15 | 0 |
| **Solar Radiation** | 0.1 | 0 |
| **NDVI** | 0.1 | 0 |
| **Total** | **1** | **1** |

**Table 6. MCE-OWA input weights.** The Factor weights indicate that the Cost Distance variable holds the greatest importance for the outcome of the model. By placing a value of 1 in the first ordered weight and zeros for the remaining variables, this results in a low-risk analysis of the input data. No Training data is required for this type of analysis.

### 4.6 Model Validation

In order to test the accuracy of the suitability models, several steps were taken. Each model had slightly different input requirements and therefore, the process to analyze the accuracy for each of the results varied slightly.

First, a "leave one out" method was completed in order to begin verifying the Mahalanobis Typicality results. This model was run fifteen separate times, each time excluding one of the training data sites from the file. The UTM location for the excluded training site was located on the resulting image and the suitability value was recorded, as displayed in table 7 below. These values are what ROC works with to interpret model accuracy.

| Mahalanobis Typicality Suitability Values | |
|---|---|
| **Field # excluded** | Mahalanobis Typicality 30m |
| **1** | 0.215616 |
| **2** | 0.339474 |
| **3** | 0.204086 |
| **4** | 0.17923 |
| **5** | 0.753231 |
| **6** | 0.542683 |
| **7** | 0.636428 |
| **8** | 0.0001 |
| **9** | 0.843656 |
| **10** | 0.000152 |
| **11** | 0.727655 |
| **12** | 0.371858 |
| **13** | 0.0001 |
| **14** | 0.749466 |
| **15** | 0.0001 |

**Table 7. This table displays the suitability results of Mahalanobis Typicality.** The decimals values indicate suitability values extracted directly from the Mahalanobis Typicality suitability image. These values do not represent the accuracy of the model—each value is relative to the rest of the image. The highest possible value in each suitability result was 1.0.

Once all suitability maps were created, the results were validated using the Receiver Operating Characteristic (ROC) module. ROC was chosen as a validation method because it evaluates the predictive abilities of a suitability model without introducing any external bias. Researchers specified ROC to run 100 thresholds to compare the two Boolean images. This method identifies the true presence or false presence of suitable environments (Lippitt et al. 2008). ROC is the best method for verifying these presence-only models.

ROC calculates the Area Under the Curve (AUC), which indicates how accurately the model performed. It takes into consideration the suitability model maps and the Boolean training data image that informs ROC of where the class (ak chin agricultural fields—in the case of this research) likely exists. ROC values are based on a random prediction trajectory (0.5); therefore, values that fall between 0.5-0.6 indicate that the model failed and values between 0.9-1.0 indicate that the model performed well; the intermediate values are ranked appropriately between these two extremes.

The initial suitability images for all models had too large of a gap between the number of pixels in the image to the number of training data pixels available. To correct for this, the overall study area was reduced to surround only the 15 known training sites. This made the pixel ratio more manageable for ROC, but still included the entire range of resulting suitability values. The AUC results are listed in table 8 below. Since the leave-one-out method could only be used for Mahalanobis Typicality, these are the most comprehensive AUC results. Maxent, while appearing to perform well, requires additional fieldwork to verify potential ak chin fields because without a leave-one-out verification process, we can only know that it is finding the training field environments with great accuracy. This value is directly comparable to the Mahalanobis 15 site ROC value, but it cannot be assumed that this model is finding other locations with the appropriate environmental characteristics without running leave-one-out.

Lastly, Suitability results from each model were run through TOPRANK. This module allows researchers to display only the locations with the top 1% suitability ratings from the MCE module. The locations for the top 1% of pixels for each model were found in significantly different locations. This process is most useful for visually interpreting the results and understanding what types of environments are being found with each suitability model. All analyses conducted for this research were processed on the initial suitability results, *not* the top 1% images.

# Chapter 5

## Results and Discussion

### 5.1 Results

Maxent, Mahalanobis Typicality, and MCE-OWA models all produced suitability maps that consisted of varying decimal values for each pixel. For all three models, the resulting values ranged from 0 to 1; the closer the value was to 1, the more similar the pixel was considered to be to the training fields for ak chin style agricultural fields. Any value that is greater than zero contains some degree of similarity to the training pixels used in the analyses; however, as values approach zero, they are considered increasingly dissimilar to the training pixels. These suitability results identify locations that are the *best* fit for the appropriate environmental conditions based on the analysis (Eastman 2015). The values for each unique suitability map are relative to the rest of the image and the highest value for a suitability result may actually be lower than 1; additionally, the highest value will often be different for each suitability image.

A common theme noted among all model results is that there was a higher density of newly identified potential ak chin style fields noted in the northern half of the study area. This is directly correlated to the elevation differences between the northern and southern portions of the state, as elevations fall far below the acceptable range in the southern half of the study area and the northern portion has more acceptable elevation ranges for this type of field. These results may further correlate to the distribution of recorded archaeological sites throughout the state of New Mexico.

| ROC AUC Results for each model Includes "Leave-One-Out Results" | | | |
|---|---|---|---|
| **Training Sites** | **Mahal. Typicality 30m** | **MCE 30m** | **Maxent 30m** |
| **All Training sites** | 0.893000 | 0.562333 | 0.922 |
| **1st Out** | 0.885667 | | |
| **2nd Out** | 0.888334 | | |
| **3rd Out** | 0.885000 | | |
| **4th Out** | 0.888334 | | |
| **5th Out** | 0.891667 | | |
| **6th Out** | 0.890334 | | |
| **7th Out** | 0.895000 | | |
| **8th Out** | 0.883667 | | |
| **9th Out** | 0.896334 | | |
| **10th Out** | 0.895000 | | |
| **11th Out** | 0.892334 | | |
| **12th Out** | 0.889667 | | |
| **13th Out** | 0.937000 | | |
| **14th Out** | 0.887667 | | |
| **15th Out** | 0.902333 | | |

**Table 8.** This table represents the accuracy rating calculated using ROC based on the suitability results of each model. Mahalanobis Typicality is the only model that could use a leave-one-out process.

### 5.1.1 Mahalanobis Typicality

The suitability results from Mahalanobis Typicality when using 15 training sites had an AUC result of 0.893000. This ROC value indicates that this model performed well, and potential new fields were likely accurately identified. The "leave one out" analysis determined the lowest AUC value to be 0.883667 and the highest value was 0.937000. All values calculated are presented in table 8 above.

The ROC results indicated that this model performed very well in identifying potential new ak chin style agricultural field environments; however, this analysis does not replace the need to conduct fieldwork to further validate the results.

A histogram analysis of the initial suitability raster revealed that only three potential fields were identified among the highest suitability range (0.9999-1.0099). This further suggests that the model performed well in identifying ideal locations since the highest suitability range did not include hundreds of top potential locations for ak chin style agricultural fields.

A visual assessment of the Mahalanobis Typicality results supports the claim that this model performed well in identifying potential new ak chin style agricultural fields. Potential locations appear to fall generally within alluvial fans and the appropriate environmental ranges—based on what is known about ak chin fields (Philips 1993).

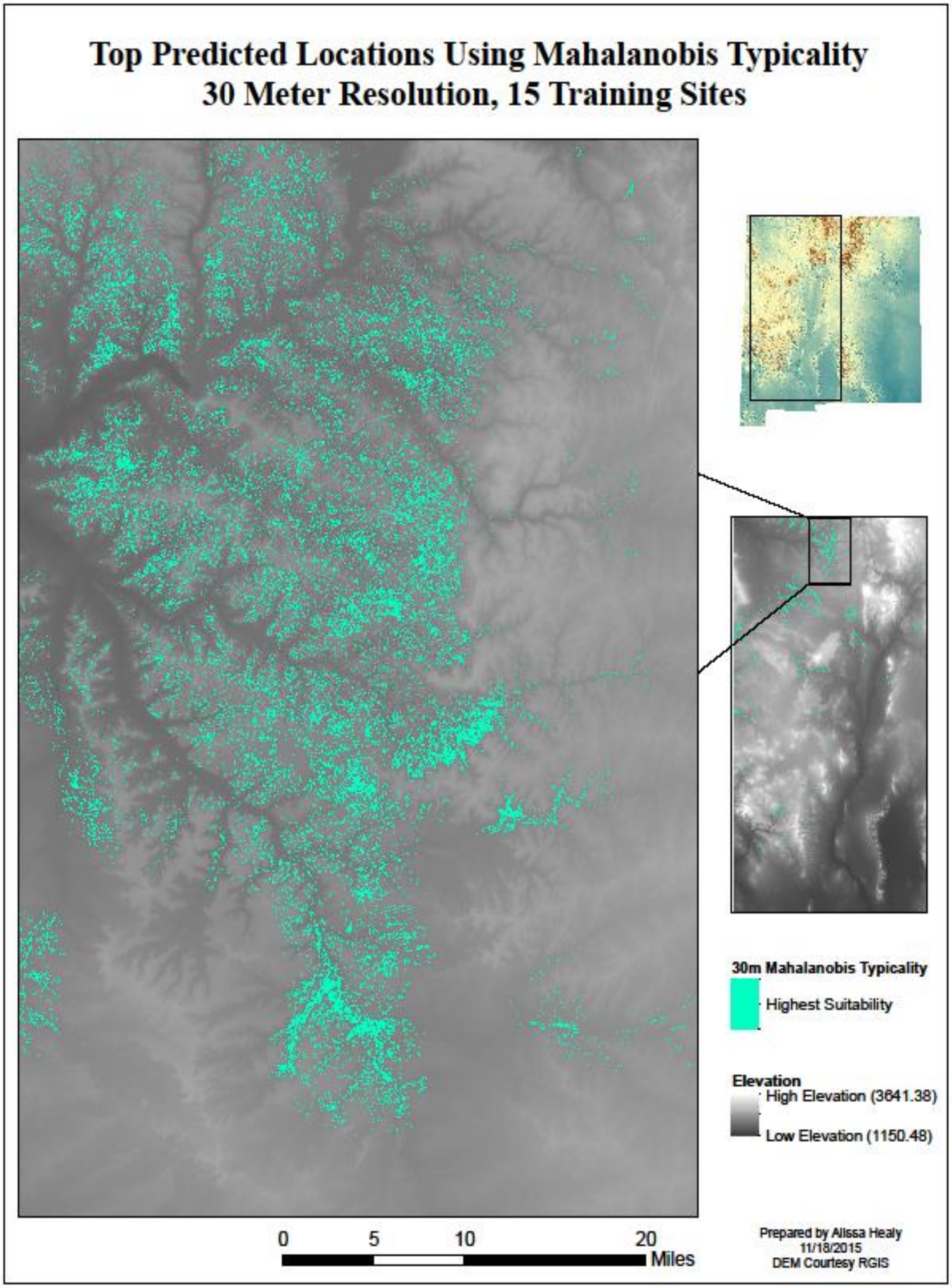


**Figure 8. Potential field locations identified using Mahalanobis Typicality.** These results were created using 30 meter resolution data and 15 training sites. The turquoise dots represent potential ak chin style agricultural field environments.

### 5.1.2 Maximum Entropy (Maxent)

The AUC value is 0.922 and is based on 500 iterations of this model. This indicates exceptional accuracy for these results. A value of 0.922 was calculated through the Maxent model as well as the ROC module in TerrSet as a verification method. It was derived from the suitability model resulting from all 15 training sites. Since less than 15 training sites cannot be used for this model (due to a difference in features that would limit the results) this AUC value is only comparable to Mahalanobis Typicality 15 site ROC results. Since all 15 training fields were used in the ROC analysis this value says that Maxent can fit the training fields well, but does not necessarily indicate that it can perform well in identifying potential new field environments. The initial suitability results for Maxent indicated that only one potential new ak chin style agricultural field was identified within the highest suitability range (0.9730-1.9727).

The first set of response curves (figure 10)—or marginal response curves—describes the average response of each variable when all variables were processed simultaneously. These response curves indicate that the model identified locations that range in elevation from 1400 to 2800 meters, with a spike in new potential locations between 1800-2200 meters in elevation. The slope and cost-distance response curves had similarly accurate responses. The graphs display ideal environmental conditions that align with the known attributes of ak chin style agricultural fields.

NDWI seems to have identified a certain signature that is common among the most suitable environments based on the training data. This is data that researchers did not have specific value ranges for and were therefore not well understood. The marginal response curves indicates that ideal values for NDWI range from -0.1 to 0.1. The outliers—NDVI and solar radiation—provide some uncertainties.

Neither NDVI nor solar radiation provide much information in the marginal response curve; however, the second set of response curves (figure 11) shows the greatest amount of change in the solar radiation and NDVI variables. Somehow during the processing of this model, these two variables were marginalized to the point that they did not have a significant impact on the overall outcome. The second set of response curves has identified specific range of values that are applicable to primarily solar radiation and NDVI, but this is not apparent when all six spatial-environmental variables are processed together. The other four variables—cost-distance, slope, elevation, and NDWI had similar response curves that were simply more exaggerated than they were in the marginal response curves.

The jackknife results presented in figure 9 below allow researchers to further understand the impact of each individual input variable on the overall results of this suitability model. The jackknife results indicate that cost-distance was the most important input variable. It consists of the most data that is not present in any other input variable and without it, the results would change more drastically than when any other variables were omitted. This graph also shows that if NDVI and solar radiation were completely excluded from the analysis, the results would not be different—which supports the response curve analysis. NDWI does not appear to have had a significant impact on the final results, but removing it from the analysis does change the overall results slightly. Slope, elevation, and cost-distance had the greatest impact on the results of this analysis.

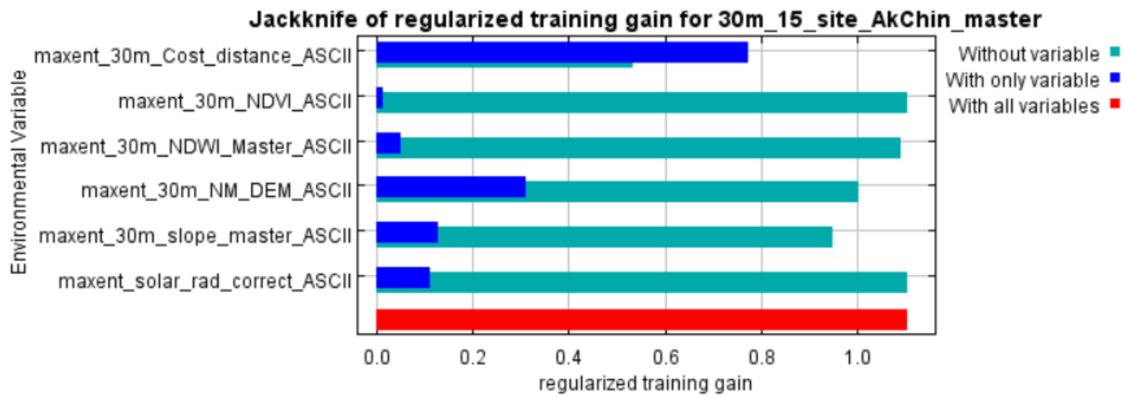


**Figure 9. 30 meter Maxent Jackknife results**. The jackknife graph above represents different responses for each variable; the blue bar displays the response when only that variable is used, and again with all variables included (red bar), and the impact of the results when each variable is left out (green bar). The red bar at the bottom shows the response when all six input variables were used, meaning that none of the green bars should extend past this point.

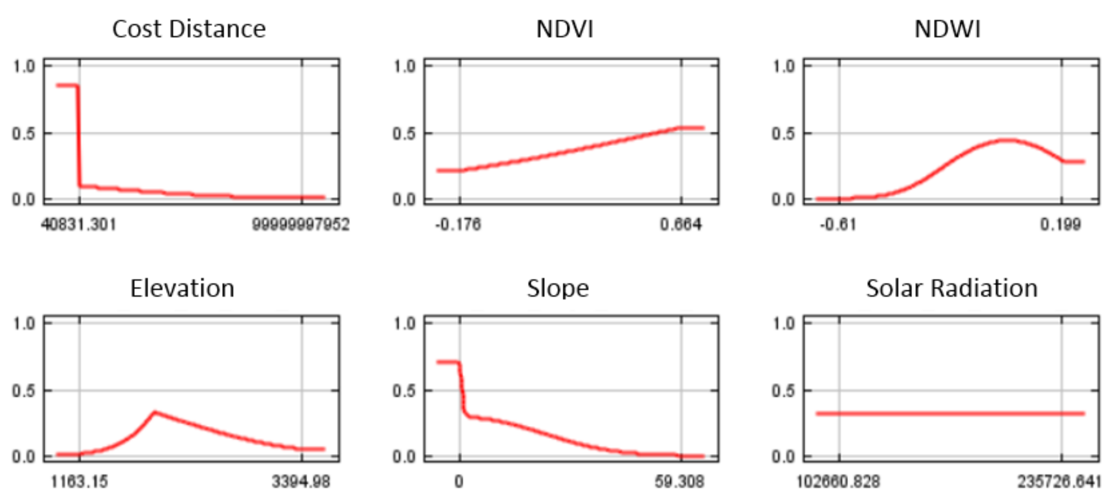


**Figure 10. Marginal response curves.** The six graphs above illustrate the response of each input variable when all other variables are changed slightly.

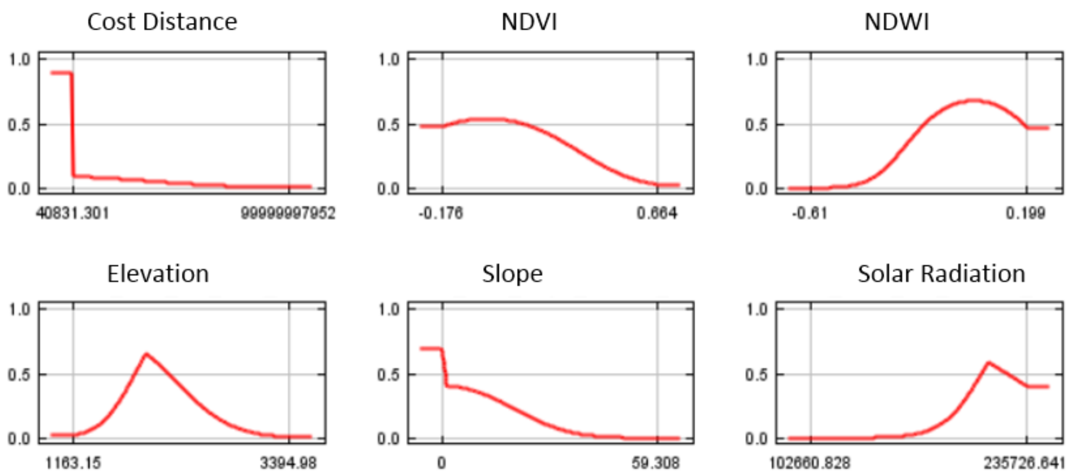


**Figure 11. Individual Response Curves.** This figure shows the response curves when the model was run six different times, each time using only one variable. The biggest differences observed are with the NDVI and solar radiation variables.

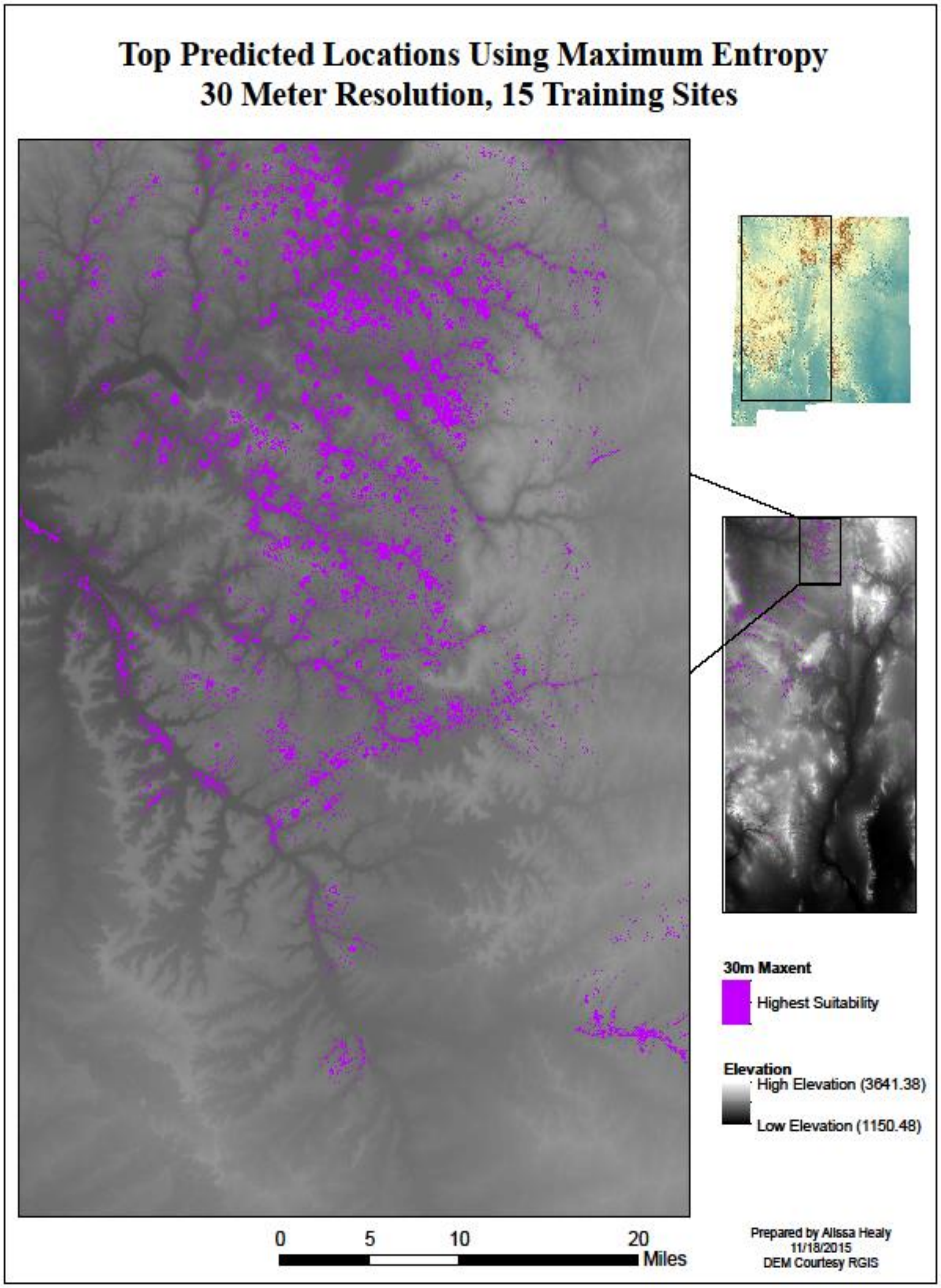


**Figure 12**. **The map above shows the potential field locations identified using Maxent with 30 meter resolution input imagery.** The purple dots represent the top 1% of the most suitable locations identified with this model.

### 5.1.3 Multi-Criteria Evaluation-Ordered Weighted Average

Multi-Criteria Evaluation Ordered Weighted Average (MCE OWA) did not perform well in terms of identifying potential new locations for ak chin style agricultural fields. The ROC result for MCE OWA was 0.562333, meaning that this model failed in identifying potential agricultural fields. The ROC value is only slightly better than random prediction; this low accuracy rating is interesting in that it indicates that either researchers chose to weight the model incorrectly or that using training data is truly the most effective way to predict ak chin style agricultural field locations. The initial suitability model results indicated that only one potential new ak chin style agricultural field was identified within the highest suitability range (0.0697-0.07674).

The initial results of this model are somewhat difficult to interpret and therefore the results were processed through the TOPRANK module in TerrSet to extract only the top 1% for visual interpretation. The results of this model primarily displayed locations that fell within river and drainage beds. Visual inspection of MCE OWA results support the argument that this model did not accurately identified potential ak chin style agricultural field environments.

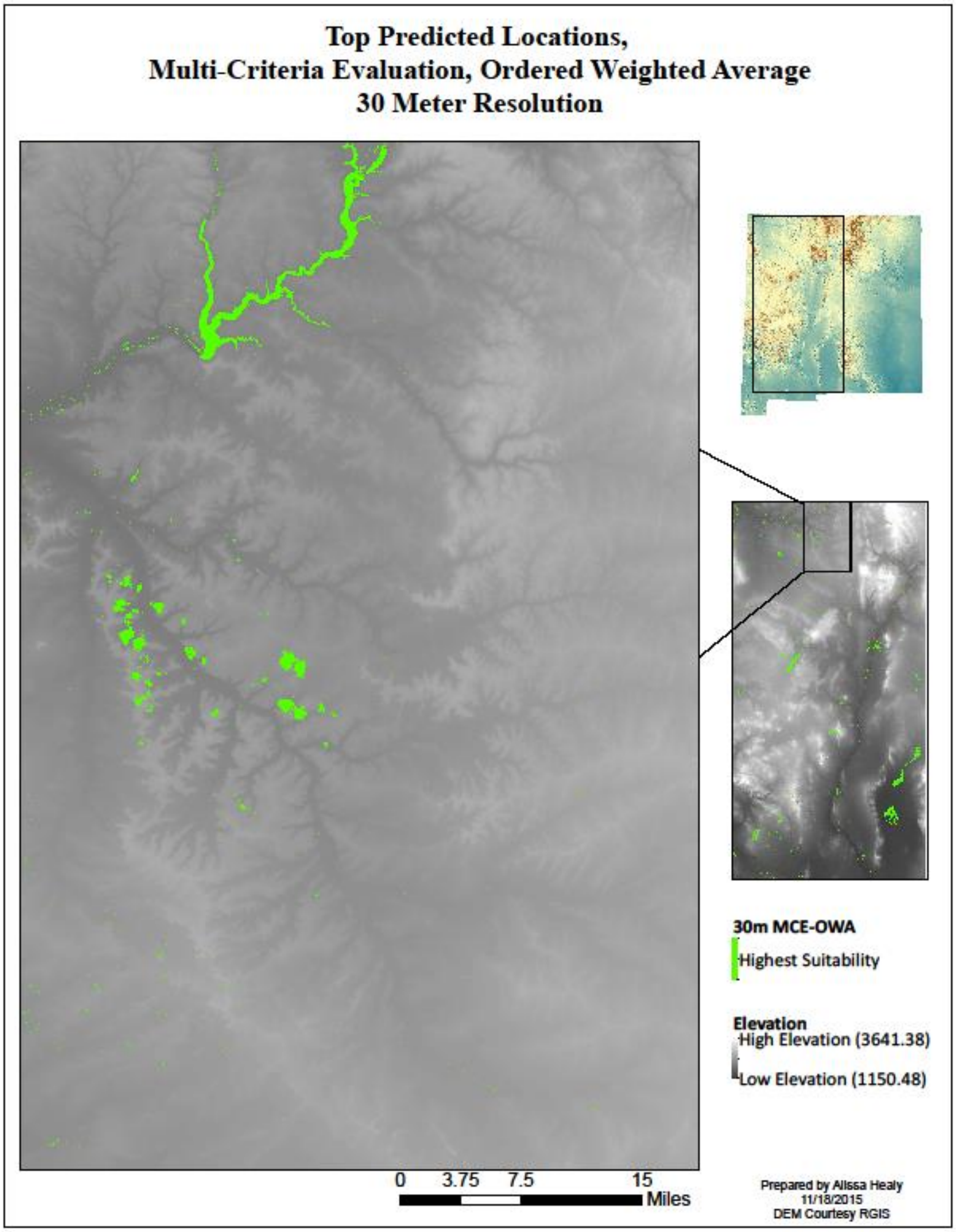


**Figure 13**. **The map displayed above displays the results of MCE-OWA with 30 meter resolution input data.** The green dots represent the top 1% of the most suitable locations identified using this model.

**5.2 Model Comparisons**

The following maps allow for a visual comparison between the results from all three suitability models. For display purposes, the top 1% of locations are shown. The variations between each model are clear; MCE OWA (green) follows the paths of drainage beds, whereas Mahalanobis Typicality (turquoise) and Maxent (purple) results are scattered among likely alluvial fan locations, with more results from Mahalanobis Typicality than Maxent.

In an attempt to find similarities between all three of the suitability model results, a query was conducted to identify all overlapping locations among all three suitability results if any exist—none were identified. The query formula is indicated below.

*(3) "30m Mahalanobis Typicality" & "30m Maxent" & "30m MCE"*

Second, comparisons were then made between two models at a time. MCE and Maxent had 45,140 overlapping points and Mahalanobis Typicality and Maxent had 62,454. No overlap was found between Mahalanobis Typicality and MCE-OWA.

It is interesting to note that the results from MCE-OWA and Maxent identified locations in the river/drainage beds, which are not ideal environments for ak chin style agricultural fields. While some potential fields identified through Maxent were found within drainages it is visually clear that the majority did not; however, most potential fields found through MCE OWA were located in drainage beds. Maxent still appears to have performed better than MCE OWA.

Figures 15 and 16 display the potential field locations identified through the overlap analysis of model results, and are defined by the title of each map.

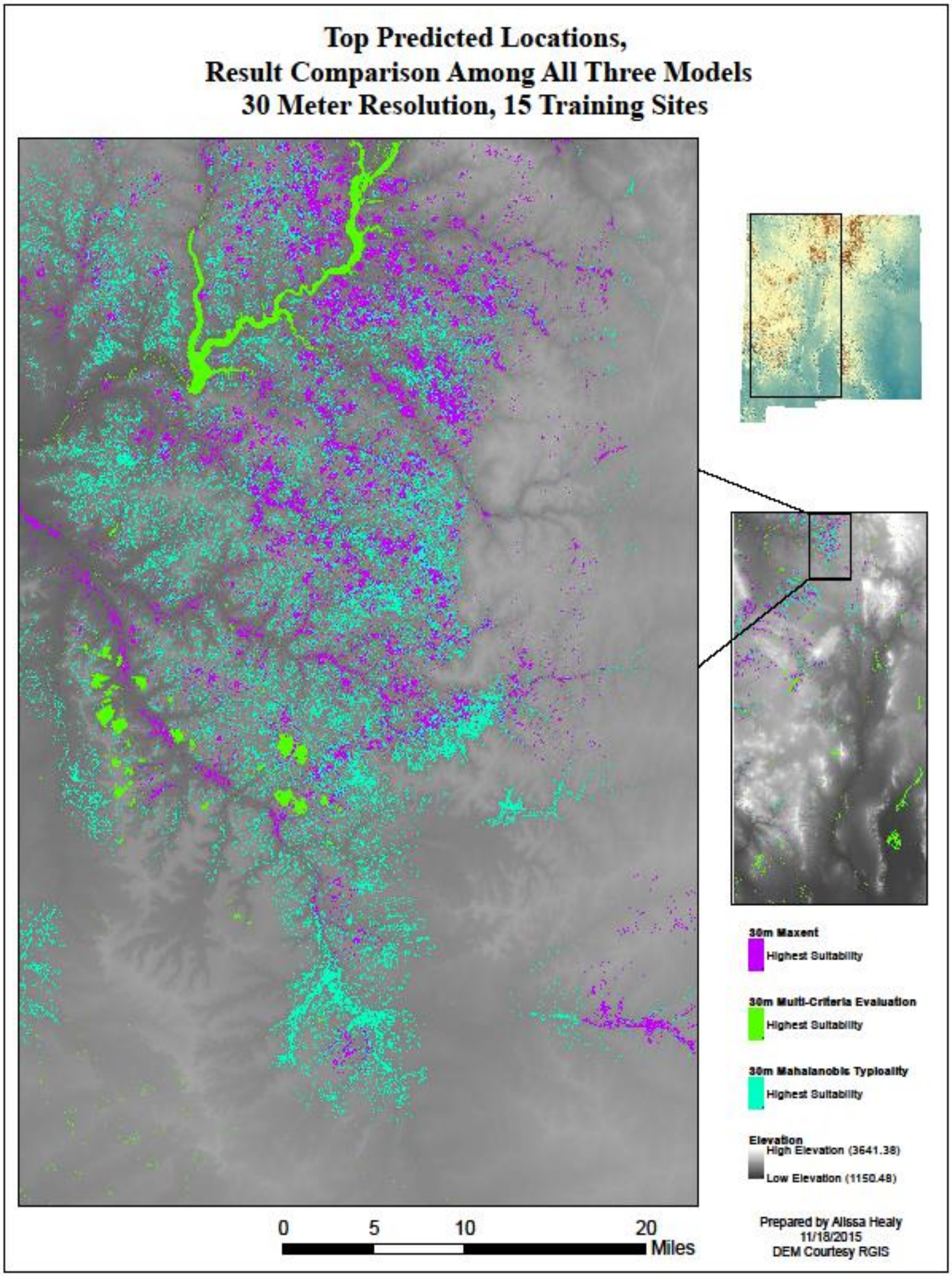


**Figure 14. The map displayed above shows the top 1% of results from all three suitability models.** Purple represents Maxent, green represents MCE-OWA, and turquoise represents Mahalanobis Typicality.

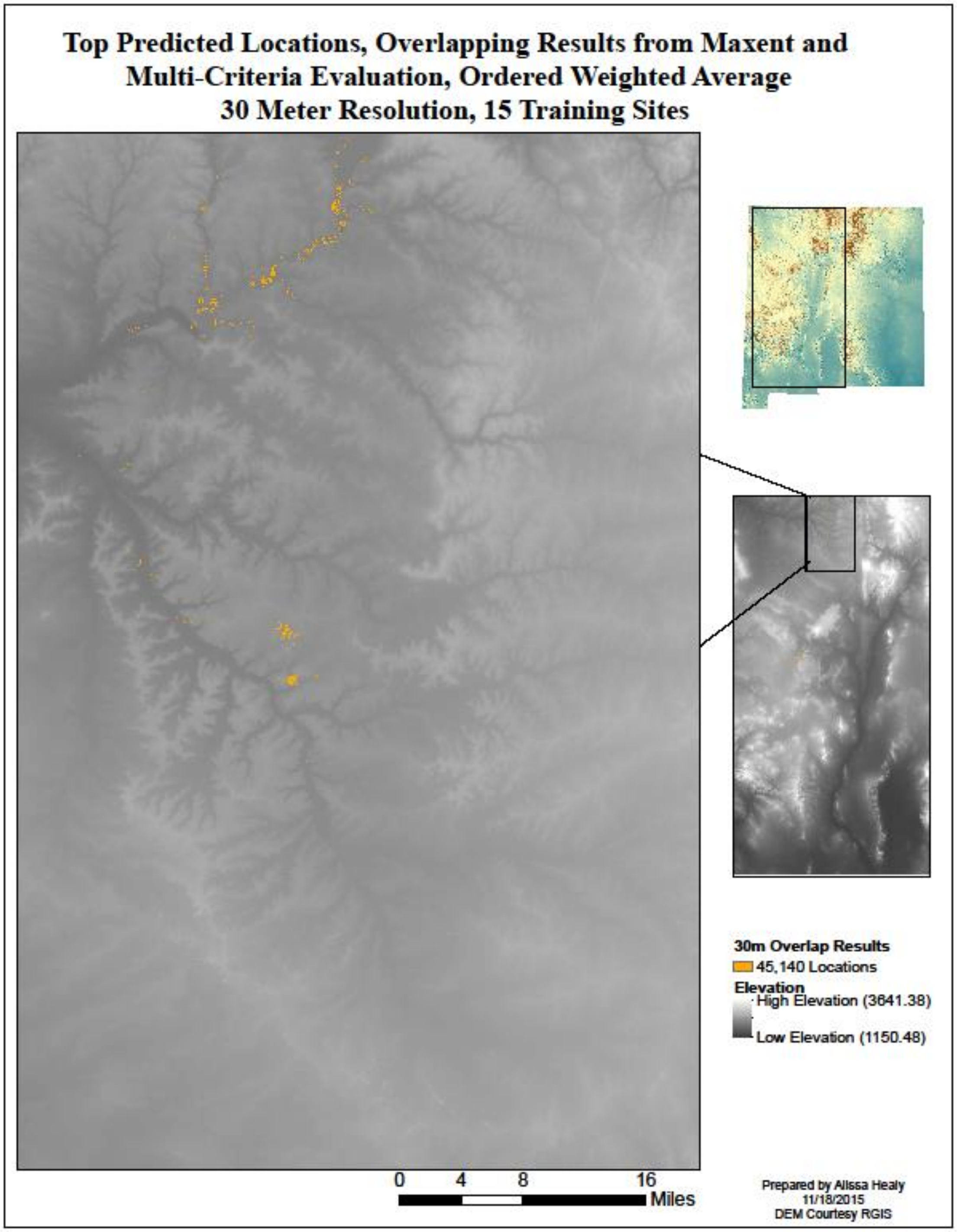


**Figure 15. The map displayed above displays the overlapping potential field locations between MCE-OWA and Maxent.** There are 45,140 locations that overlap between these two models.

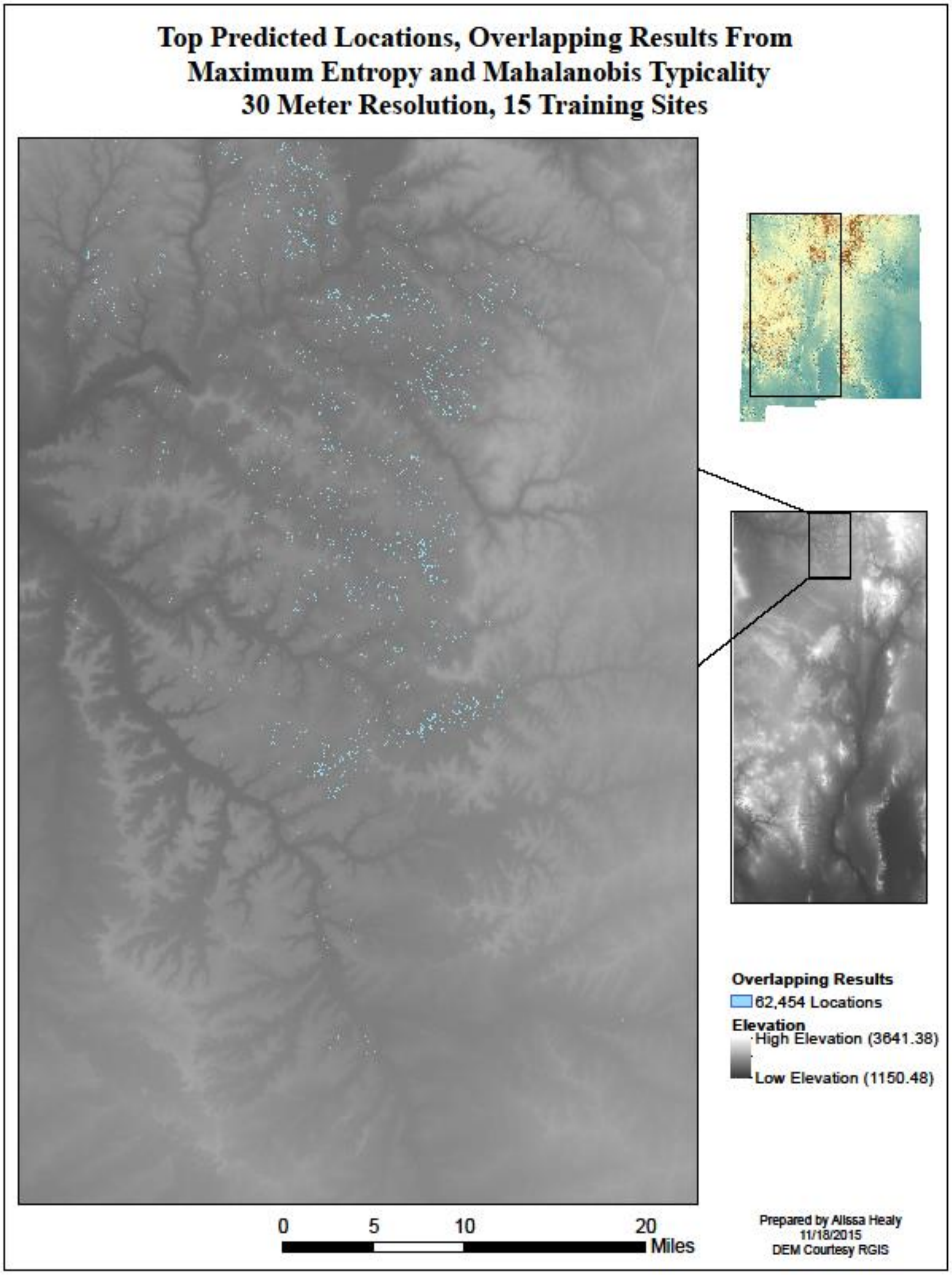


**Figure 16. The map above displays the overlapping potential field locations between Maxent and Mahalanobis Typicality.** There are 62,454 potential locations that overlap.

## 5.3 Soil Data

Soil data was extracted post processing of each model as an additional check on whether the locations identified as highly suitable are found within the expected soil types. The soil data is not very detailed because it is a general dataset with a 1:100,000 scale and fine scale differences between soil types were not distinguishable.

When examining soil types from these agricultural fields, it is important to remember that the soils being discussed are those that exist within the fields today; 3,000-1,000 years before present these soils may have been somewhat different depending on the type of soil development found. Ideally the types of soil found at prehistorically cultivated fields consist of an older colluvium soil that consists of Argiustolls with clay-rich soils found underneath sandier soils. Argiustolls can be up to 50 centimeters thick and are indicative of prehistoric agricultural practices because they take a very long time to develop; it is likely similar in composition today to what it was 3,000 years ago. Less stable soil development such as that found in Torriorthents and Haplustolls provides less ideal agricultural environments (Sandor et al. 1990). These types of soils are likely not the same as the soils present 3,000 years before present.

Where disturbed features are identified, there is some degree of instability in the soil—meaning crops are less likely to grow. Overall, these results do not aid the suitability results presented here at all. In the future, a more precise soil map should be used to locate specific soil types.

Table 9 describes the five different soil types found among all 15 training sites and the number of sites found on those particular soils. These soil types were then sorted and the number of fields found on each soil type from the training data were tabulated (table 10).

The fifteen training sites for the models were located on five different soil types: Haplustolls-Argiustolls-Rockland, Torrifluvents-Haplargids-Haplustolls, Argiustolls-Haplargids-Rockland, Rockland-Torriorthents-Argiustolls, and Rockland-Torriorthents-Haplargids.

Rockland is an unexpected result for ak chin style agricultural fields. Generally in New Mexico, this indicates a lava flow where very little soil or sediment development exists and plants do not grow as easily; however, when Rockland environments are combined with various types of soil development, such as Argiustolls or Haplargids which commonly have subsurface clay accumulation and fairly stable alluvium soil, they may have been more ideal for growing crops.

Locations with predominately Torriorthents and Haplustolls have little to no subsurface development, so when they are associated with Rockland deposits, it is unlikely that agriculture would be successful in such an environment. The soils associated with the training sites consist of a wide range of soil types, from stable environments that have been around for thousands of years and considerably less stable lavaflow environments.

| SOILTYPE | COUNT |
| --- | --- |
| **Haplustolls-Argiustolls-Rockland** | 4.00 |
| **Torrifluvents-Haplargids-Haplustolls** | 6.00 |
| **Argiustolls-Haplargids-Rockland** | 1.00 |
| **Rockland-Torriorthents-Argiustolls** | 2.00 |
| **Rockland-Torriorthents-Haplargids** | 2.00 |

**Table 9. Training site soil types.** Two of the training sites were found on Rockland-Torriorthents-Haplargids soil, whereas the highest count of newly found sites were found on this same soil.

| **Top Soil Types from Training Data** | | | | | |
| --- | --- | --- | --- | --- | --- |
| | Haplustolls-Argiustolls-Rockland | Torrifluvents-Haplargids-Haplustolls | Argiustolls-Haplargids-Rockland | Rockland-Torriorthents-Argiustolls | Rockland-Torriorthents-Haplargids |
| **30m Mahalanobis Typicality** | 19750 | 22901 | 13545 | 8131 | 195278 |
| **30m MCE** | 74294 | 26238 | 48798 | 80665 | 108587 |
| **30m Maxent** | 2880 | 33932 | 2356 | 7426 | 52200 |

**Table 10. Number of potential new fields on each of the top five soil types.** This table is based on the results in table 13. The soil types present at the 15 training sites were examined individually and the counts of all newly identified potential agricultural fields were assessed and tabulated.

### 5.4 Discussion

The suitability models and the verification module ROC suggest that potential new fields are likely being identified; however, it is also likely that other environmental characteristics not associated with ak chin style agricultural fields are also being identified. One potential error in the models and/or the data may include the finding of *all* alluvial fans within a five mile radius of known archaeological sites within the study area. It is possible that certain input variables have the greatest effect on the results. Short of individually analyzing each alluvial fan in the study area, it is hard to say for certain if this is occurring. If this is in fact occurring, it is highly likely that the various alluvial fans are just being identified with varying suitability ratings—some more suitable than others.

A second possible error involves the over dependence on a single input variable. Maxent indicated that the cost-distance variable had the most impact on the model results and researchers decided that the input factor weights of MCE OWA should put the most emphasis on the cost-distance variable. It is possible that the results are simply reflecting this variable. The literature for cost-distance does not address the impact that cost-distance may have for suitability modeling purposes, and therefore the overall effect is currently unknown. The locations being found may just be alluvial fans that meet all of the same criteria, but may not be associated with any cultural developments.

Third, a different soil map should be used in the future. A better scale is necessary to identify minor changes in the soil within these ak chin agricultural fields.

Fourth, the potential field locations identified might not all fall within agricultural contexts. Since field work has not yet been conducted alongside the model results, it is hard to know for certain what the models are identifying. While accuracy ratings appear to be good, researchers will remain uncertain about the actual accuracy of the models until potential fields are visited and assessed for pollen residue or cultural modifications to the land.

Fifth, the training data is represented only as point data, not as polygon data. The point data limits potential field locations significantly since it only trains the models on one 30 x 30 meter pixel. These fields are potentially much larger or much smaller than one pixel, and with the appropriate training data, model accuracy would greatly improve. Until more data is collected, it will be difficult to determine which variable impacts the results most.

Lastly, Maxent ROC values only indicate that the training data fields are a good fit for ak chin style agricultural fields. Since a leave-one-out verification method could not be used on this dataset, these results are not indicative of model fit and are also not indicative of the entire field population for this type of agricultural field. Without developing a larger training data file (by visiting potential fields and conducting analysis on the soils) it will be hard to know whether this model is working to fit a general population of potential ak chin style agricultural fields or if it is only identifying the 15 training fields.

Initially, this research had intended to use both 30 meter resolution and 10 meter resolution data. Upon analysis it was discovered that the 10 meter resolution needed to begin at a higher resolution. Initial analysis was conducted with imagery displayed at a 10 meter resolution (from the 30 meter Landsat scenes) and the combination of too few training sites paired with too large of a study area led to significantly inaccurate ROC results. The settings programmed in TerrSet required a mask to process the 10 meter resolution images, which also impacted the overall results. When these ROC results from TerrSet were compared with the ROC results from the Maxent model 10 meter results, the discrepancy was clear. Maxent produced an AUC of 0.912 whereas the ROC result calculated for the same image through TerrSet was 0.526667. It is expected that the 10 meter resolution would likely be more precise for this type of analysis and all future work should consider using a higher resolution image set. Sentinel-2 recently came online with good 10 meter resolution imagery that would work well for this analysis. Additionally, if more training fields are identified through this analysis, a larger training set will assist in improving future results/accuracy.

The results obtained from the 30 meter resolution data are believed to be fairly accurate as far as the suitability models are concerned. This does not mean that true ak chin style agricultural fields have actually been identified. The most suitable potential fields will need to be visited and soil samples will need to be collected and analyzed for agricultural remains. The environments surrounding these potential fields should also be surveyed to identify any cultural modifications made to the land surrounding the features. This will help to further suggest that the land was used for prehistoric agricultural purposes.

## Chapter 6

### 6.1 Limitations

The most significant limitation associated with suitability modeling is that the models are identifying sites that share characteristics with known sites. This may not capture the full range of variability among different ak chin style agricultural fields since there may be many other axes of variables that are unknown to researchers. These suitability models are not necessarily predicting where sites exist, they are simply predicting locations where similar spatial-environmental attributes exist.

A second limitation was that the amount of validation data available was extremely limited. Since Mahalanobis typicality could be run with less than 15 training data fields, a leave-one-out verification method was used to help validate the results. When ROC is run using all 15 training data sites on the initial suitability result, it is simply saying that the fields that the model trained on are a good fit. It does not tell us a lot about how well potential new fields were identified. This could not be done with Maxent because less than 15 training sites—as would be necessary for a leave-one-out assessment—would provide results based on a different set of output features.

This work was also limited by the site data currently available. NMCRIS site records are limited to the data that has been collected and submitted by field archaeologists. This type of data collection is completed in survey transects that only represent a sample of the study area—therefore every site that exists within New Mexico has not been identified and recorded. It is unknown to what extent this may adversely affect the results of this research. This archaeological site data, though collected from a specific timeframe with certain structural features present points towards agricultural practices, it does not guarantee that these groups were growing crops. This is based on educated estimations.

Additional limitations are introduced with the training data. It is expected that better results could be obtained from a polygon shapefile of the known ak chin style agricultural fields rather than the point file used. In the future, known fields should be physically visited and mapped with polygon shapefiles prior to running more suitability models.

# Chapter 7

## 7.1 Conclusions

The results of these suitability models indicate that there is great promise for modeling the potential locations for ak chin style agricultural fields. The methods may be improved upon (as indicated in the “future work” section—section 8.1 on page 79), but overall the input variables for the models have sufficiently zoned in on ideal environmental and cultural contexts where these fields are expected to be present. As more fields are found and verified, the training data will significantly improve. With more detailed training data, the number of potentially suitable field locations is expected to decrease and the accuracy of the model is expected to increase.

Until actual soil samples are collected from potential new fields and analyzed for pollen residue, it is impossible to know if these models are actually finding agricultural fields or just prime environments for ak chin agricultural fields. But visual and algorithmic data suggest Maxent and Mahalanobis Typicality performed well. Table 11 lists the northings and eastings for the top 10 potential ak chin style agricultural fields from the Mahalanobis Typicality and Maxent suitability model results. It is suggested that researchers visit these fields first to test for agricultural presence.

Upon comparison of the three suitability model results, it is clear that Multi-Criteria Evaluation Ordered Weighted Average results are the least accurate and in the future should not be consulted. This model identified primarily environments in arroyos and river beds and although this type of environment does allow for growing crops in some contexts, these are not the environments that are in question. This does, however, demonstrate the effectiveness of the training data input into the other two models. MCE OWA focuses solely on environmental features that align with the input variables indicated as the most important to least important and does not take into consideration any training data. In some cases, it appears that appropriate environments were identified, but these were few and far between.

The results from the two models that utilized training data found much more select environments primarily within alluvial fans. The importance of training data is made clear with these models. Overall, it is clear that Mahalanobis Typicality is more effective than MCE OWA. The true accuracy of Maxent is unknown due to the inability to run a leave-one-out analysis. The response curves and jackknife results indicate that Maxent was the most effective of all three models.

Table 11 displays the top ten potential ak chin style agricultural fields that should be visited first, based on these suitability model results.

| Top Potential Ak Chin Style Agricultural Fields to Visit | | | | |
|---|---|---|---|---|
| | Mahalanobis Typicality | | Maxent | |
| | **Easting** | **Northing** | **Easting** | **Northing** |
| **1** | 229335.69 | 4090709.82 | 286437.06 | 4098430.90 |
| **2** | 229546.58 | 4090728.00 | 275612.48 | 4045124.95 |
| **3** | 230715.99 | 4091649.19 | 248900.08 | 3997370.33 |
| **4** | 231425.31 | 4092051.78 | 248993.87 | 3997244.38 |
| **5** | 255533.47 | 4091387.72 | 252139.68 | 3985992.66 |
| **6** | 255519.93 | 4071079.44 | 251959.33 | 3985687.94 |
| **7** | 259075.94 | 4069640.11 | 251928.23 | 3985691.05 |
| **8** | 260515.28 | 4067862.11 | 159477.13 | 3953611.32 |
| **9** | 290320.06 | 4045019.26 | 157637.61 | 3930617.25 |
| **10** | 284121.62 | 4017901.11 | 260068.58 | 3884632.77 |

**Table 11. UTM's for the top 10 potential ak chin style agricultural fields.** UTM's have been extracted for both the Mahalanobis Typicality and Maxent model results. UTM's were not extracted from MCE, OWA since the results were not considered valuable.

## Chapter 8

### 8.1 Future Work

The suitability model results of this project may be greatly improved upon if the known agricultural fields were fully mapped with polygon shapefile data. This would increase the accuracy of the model predictions. Additionally, this project would be considerably improved upon by completing fieldwork to support the analysis conducted in this research. A selection of the most suitable field locations should be sampled and tested for the remains of *Zea Mays*. Table 11 above lists the top 10 field locations for both Mahalanobis Typicality and Maximum Entropy. The suitability model results were reclassified and only the top 10 potential field locations from each model were presented. The UTM's were then extracted from these images and fall within a 30 meter radius of potential fields. When visiting these fields it is recommended to bring an expert to help verify the presence of these fields.

This modeling process can easily be applied to different forms of agricultural fields—such as rock mulch gardens and rock grid fields, both of which have strong environmental signatures and definite shapes. This type of analysis would accurately identify prehistoric fields. This has recently been done in Hawaii (Kailihiwa 2015), but has not yet been practiced in the southwest.

## References


1. Agapiou, Athos, Dimitrios D. Alexakis, Apostolos Sarris, and Diofantos G. Hadjimitsis. 2014. "Evaluating the Potentials of Sentinel-2 for Archaeological Perspective." *Remote Sensing*, no. 6: 2176–94. doi: 10.3390/rs6032176.

2. Alshuwaikhat, Habib M., and Danjuma Nkwenti. 2002. "Developing Sustainable Cities in Arid Regions." *Elsevier Science Ltd.* 19 (2): 85–94.

3. Arias, Veronica Maria. 2013. "Application of GIS and Spatial Data Modeling to Archaeology: A Case Study in the American Southwest." Dissertation, Albuquerque: The University of New Mexico.

4. Bailey, Adrian. 2011. "Population Geographies and Climate Change." *Progress in Human Geography* 35 (5): 686–95.

5. Banister, David. 2011. "Cities, Mobility, and Climate Change." *Journal of Transport Geography* 19: 1538–46. doi:10.1016/j.jtrangeo.2011.03.009.

6. Bauer, Andrew M. 2014. "Impacts of Mid- to Late-Holocene Land Use on Residual Hill Geomorphology: A Remote Sensing and Archaeological Evaluation of Human-Related Soil Erosion in Central Karnataka, South India." *Holocene* 24 (1): 3–14. Doi: 10.1177/0959683613512165.

7. Beltran, Bray J., Janet Franklin, Alexandra D. Syphard, Helen M. Regan, Lorraine E. Flint, and Alan L. Flint. 2014. Effects of climate change and urban development on the distribution and conservation of vegetation in a Mediterranean type ecosystem. *International Journal of Geographical Information Science* 28, (8) (Aug 03): 1561-1589, http://search.proquest.com/docview/1534819914?accountid=14613 (accessed November 13, 2014).

8. Benson, Larry, and Michael S. Berry. "Climate Change and Cultural Response in the Prehistoric American Southwest." *USGS Staff Published Research*, 2009, 89–119.

9. Bentley, Michael. 2007. "Healthy Cities, Local Environmental Action and Climate Change." *Health Promotion International* 22 (3): 246–53.

10. Bird, Douglas W., and James F. O'Connell. "Behavioral Ecology and Archaeology." *Journal of Archaeological Resources* 14 (2006): 143–88. Doi: 10.1007/s10814-006-9003-6.

11. Blinman, Eric. 2008. “2000 Years of Cultural Adaptation to Climate Change in the Southwestern United States.” *Royal Swedish Academy of Science* 37 (14): 498–487. Doi: http://dx.doi.org/10.1579/0044-7447-37.sp14.489.

12. Bocinsky, R. Kyle, and Timothy A. Kohler. “A 2,000-Year Reconstruction of the Rain-Fed Maize Agricultural Niche in the US Southwest.” *Nature Communications*, 2014, 1–12. Doi: 10.1038/ncomms6618.

13. Bolten, Andreas, Olaf Bubenzer, and Frank Darius. 2006. “A Digital Elevation Model as a Base for the Reconstruction of Holocene Land-Use Potential in Arid Regions.” *Geoarchaeology: An International Journal* 21 (7): 751–62. doi:DOI:10.1002/gea.20137.

14. Brenner, Coltrain, and Steven w. Leavitt. “Climate and Diet in Fremont Prehistory: Economic Variability and Abandonment of Maize Agriculture in the Great Salt Lake Basin.” *Society for American Archaeology* 67, no. 3 (2002): 453–85.

15. Chang, Kwang-Chih. “Study of the Neolithic Social Grouping: Examples from the New World.” Harvard University, 1958.

16. Chase, Arlen F., Diane Z. Chase, Jaime J. Awe, John F. Weishampel, Gyles Iannone, Holley Moyes, Jason Yaeger, et al. 2014. “Ancient Maya Regional Settlement and Inter-Site Analysis: The 2013 West-Central Belize LiDAR Survey.” *Remote Sensing*, no. 6: 8671–95. Doi: 10.3390/rs6098671.

17. “Clark Labs.” 2015. Org. *Species Distribution Modeling with TerrSet’s Habitat and Biodiversity Modeler*. https://clarklabs.org/species-distribution-modeling-in-terrsets-land-change-modeler/.

18. Clevis, Quintijn, Gregory E. Tucker, Gary Lock, Stephen T. Lancaster, Nicole Gasparini, Arnaud Desitter, and Rafael L. Bras. 2006. “Geoarchaeological Simulation of Meandering River Deposits and Settlement Distributions: A Three-Dimensional Approach.” *Geoarchaeology: An International Journal* 21 (8): 843874. Doi: 10.1002/gea.20142.

19. Cordell, Linda S., Carla R. Van West, Jeffrey S. Dean, and Deborah Muenchrath. “Mesa Verde Settlement History and Relocation: Climate Change, Social Networks, and Ancestral Pueblo Migration.” *Kiva: The Journal of the Southwestern Anthropology and History* 72, no. 4 (2007): 391–417.

20. De Cunzo, Antonio. “A Geoarchaeological Investigation of Linear Rock Features at the Victorio Site (LA 88889), Canada Alamosa.” Master of Arts, Eastern New Mexico University, 2010.

21. Dominguez, Steven, and Kenneth E. Kolm. “Beyond Water Harvesting: A Soil Hydrology Perspective on Traditional Southwestern Agricultural Technology.” *Society for American Archaeology* 70, no. 4 (2005): 732–65.

22. Dorshow, Wetherbee Bryan. 2012. “Modeling Agricultural Potential in Chaco Canyon during the Bonito Phase: A Predictive Geospatial Approach.” *Journal of Archaeological Science* 39: 2098–2115. doi:10.1016/j.jas.2012.02.004.

23. Downum, Christian E., and Glenn Davis Stone. 1999. “Non-Boserupian Ecology and Agricultural Risk: Ethnic Politics and Land Control in the Arid Southwest - Stone - 2008 - American Anthropologist - Wiley Online Library.” *American Anthropologist* 101 (1): 113–28.

24. Drobne, Samo, and Anka Lisec. 2009. “Multi-Attribute Decision Analysis in GIS: Weighted Linear Combination and Ordered Weighted Averaging.” *Informatica* 33 (4). http://wen.ijs.si/ojs-2.4.3/index.php/informatica/article/download/263/260.

25. Eastman, J. R. 1999. “Multi-Criteria Evaluation and GIS.” *Geographical Information Systems* 1: 493–502.

26. Eastman, J. Ronald. 2015. “TerrSet Manual: Clark Labs.” Clark Labs. http://planet.botany.uwc.ac.za/NISL/BDC332/Terrset/TerrSet%20Manual.pdf.

27. EPA. 2016. “Summary Table: Characteristics of the Ecoregions of New Mexico.” Government. Accessed January 12. ftp://newftp.epa.gov/EPADataCommons/ORD/Ecoregions/nm/nm_back.pdf.

28. Esri. 1995–2013. “ArGIS Resources.” Commercial. *ArcGIS Help 10.1*. http://resources.arcgis.com/EN/HELP/MAIN/10.1/index.html#//00qn0000001p000000.

29. “Eureka Cartography.” 2015. *Eureka Cartography*. http://www.maps-eureka.com/gallery.php?galleryID=42&galleryIndex=35.

30. Field, John J. “An Evaluation of Alluvial Fan Agriculture.” The University of Arizona Press, 2001. http://www.uapress.arizona.edu/onlinebks/Fish/chapter5.htm.

31. Finlayson, Clive, and Jose S. Carrion. “Rapid Ecological Turnover and Its Impact on Neanderthal and Other Human Populations.” *Trends in Ecology and Evolution* 22, no. 4 (2007): 213–22. doi::10.1016/j.tree.2007.02.001.

32. Force, Eric R. 2004. “Late Holocene Behavior of Chaco and McElmo Canyon Drainages (Southwest U.S.): A Comparison Based on Archaeologic Age Controls.” *Geoarchaeology: An International Journal* 19 (6): 583–609. Doi: 10.1002/gea.20013.

33. Giardino, Marco J. 2010. “A History of NASA Remote Sensing Contributions to Archaeology.” *Journal of Archaeological Science* 38: 2003–9. doi:10.1016/j.jas.2010.09.017.

34. Gilman, Patricia A. “Architecture as Artifact: Pit Structures and Pueblos in the American Southwest.” *Society for American Archaeology* 52, no. 3 (1987): 538–64.

35. Gorsevski, Pece V., Katerina R. Donevska, Cvetko D. Mitrovski, and Joseph P. Frizado. 2012. “Integrating Multi-Criteria Evaluation Techniques with Geographic Information Systems for Landfill Site Selection: A Case Study Using Ordered Weighted Average.” *Waste Management* 32 (2): 287–96. doi:doi:10.1016/j.wasman.2011.09.023.

36. Gregory, David A., Fred L. Nials, and J. Brett Hill. 2008. “Early Agricultural Period Settlement Strategies in the Southern Southwest.”

37. Hall, Sharon J., Jolene Trujillo, Dana Nakase, Colleen Strawhacker, Melissa Kruse-Peeples, Hoski Schaafsma, and John Briggs. 2013. “Legacies of prehistoric agricultural practices within plant and soil properties across an arid ecosystem.” *Ecosystems* 16, (7) (11): 1273-1293, http://search.proquest.com/docview/1549666620?accountid=14613 (accessed October 26, 2014).

38. Harrower, Michael J. 2010. “Geographic Information Systems (GIS) Hydrological Modeling in Archaeology: An Example from the Origins of Irrigation in Southwest Arabia (Yemen).” *Journal of Archaeological Science* 37: 1447–52. doi:10.1016/j.jas.2010.01.004.

39. Hegmon, Michelle, and Margaret Nelson. 2003. “The Archaeology and Meaning of Mimbres.” *Archaeology Southwest: Exploring and Protecting the Places of Our Past* 17 (4): 13.

40. Hill, Matthew E., and Vance T. Holliday. “Paleoindian and Later Occupations along Ancient Shorelines of the San Agustin Plains, New Mexico.” *Journal of Field Archaeology* 36, no. 1 (2011): 3–20. Doi: 10.1179/009346910X12707321242557.

41. HKM Engineering Inc. 2003. “Rio San Jose Stream System Laguna Pueblo Water Use Survey: Supplemental Surface Water Irrigation Uses.” Office of the State Engineer.

42. Homburg, Jeffrey A., Jonathan A. Sandor, and Jay B. Norton. 2005. “Anthropogenic Influences on Zuni Agricultural Soils.” *Geoarchaeology: An International Journal* 20 (7): 661–93. Doi: 10.1002.

43. Homberg, Jeffrey A., and Jonathan A. Sandor. “Anthropogenic Effects on Soil Quality of Ancient Agricultural Systems of the American Southwest.” *Catena* 85 (2011): 144–54. doi:10.1016/j.catena.2010.08.005.

44. Hritz, Carrie. 2010. “Tracing Settlement Patterns and Channel Systems in Southern Mesopotamia Using Remote Sensing.” *The Journal of Field Archaeology* 35 (2): 184–203. Doi: 10.1179/009346910X12707321520477.

45. Huckell, Bruce C. “The Archaic Prehistory of the North American Southwest.” *Journal of World Prehistory* 10, no. 3 (1996): 306–73.

46. Huckleberry, Gary A., and Brian R. Billman. “Floodwater Farming, Discontinuous Ephemeral Streams, and Puebloan Abandonment in Southwestern Colorado.” *Society for American Archaeology* 63, no. 4 (1998): 595–616.

47. Jenness, Jeff. 2007. “Some Thoughts on Analyzing Topographic Habitat Characteristics.” Jenness Enterprises. http://www.jennessent.com/downloads/topographic_analysis_online.pdf.

48. Jones, Terry L., Gary M. Brown, L. Mark Raab, Janet L. McVickar, W. Geoffrey Spaulding, Douglas J. Kennett, Andrew York, and Phillip L. Walker. “Environmental Imperatives Reconsidered: Demographic Crises in Western North America During the Medieval Climatic Anomaly.” *Current Anthropology* 40, no. 2 (1999): 137–70.

49. Kailihiwa, III, Soloman Ha’aheo. 2015. “Using Maxent to Model the Distribution of Prehistoric Agricultural Features in a Portion of the Hokuli’a Subdivision in Kona, Hawai’i.” Master of Science, University of Southern California. http://spatial.usc.edu/wp-content/uploads/2014/03/KailihiwaSolomonThesis.pdf.

50. Knott, Leanne D. 2014. "GIS Predictive Model of Potential Undiscovered Native American Archaeology Sites for the Red Wing Locality, Red Wing Minnesota." *Papers in Resource Analysis* 16: 13.

51. Lasaponara, Rosa, and Nicola Masini. 2011. "Satellite Remote Sensing in Archaeology: Past, Present, and Future Perspectives." *Journal of Archaeological Science* 38 (9): 1995–2002. doi:10.1016/j.jas.2011.02.002.

52. Li Zhang, Lei Ji and Bruce Wylle. "Analysis of Dynamic Thresholds for the Normalized Difference Water Index." *Photogrammetric Engineering and Remote Sensing* 75, no. 11 (2009): 1307–17.

53. Lippitt, Christopher D., John Rogan, James Toledano, Florencia Sangermano, J. Ronald Eastman, Victor Mastro, and Alan Sawyer. 2008. "Incorporating Anthropogenic Variables into a Species Distribution Model to Map Gypsy Moth Risk." *Ecological Modelling* 210 (3): 339–50. doi:10.1016/j.ecolmodel.2007.08.005.

54. Mabry, Jonathan B. 2008. "Irrigation, Short-Term Sedentism, and Corporate Organization during the San Pedro Phase," 293–327, n.d.

55. Maetstri, Nicoletta. 2015. "Anasazi Timeline - Chronology of the Ancestral Pueblo People." *Anasazi Timeline - Chronology of the Ancestral Pueblo People*. http://archaeology.about.com/od/americansouthwest/a/anasazi_timeline.htm.

56. Marmaduke, W. S., C. F. Berry, L. Conway, and D. G. Robinson. *The Ak Chin Farm Project: Intensive Archaeological Survey of the Ak Chin Indian Reservation, West Half*. Ak Chin Community: Bureau of Land Management, 1983.

57. Mas, Jean-François, Britaldo Filho, Robert Pontius, Michelle Gutiérrez, and Hermann Rodrigues. 2013. "A Suite of Tools for ROC Analysis of Spatial Models." *ISPRS International Journal of Geo-Information* 2 (3): 869–87. Doi: 10.3390/ijgi2030869.

58. McFeeters, S.K. "The Use of Normalized Difference Water Index (NDWI) in the Delineation of Open Water Features." *International Journal of Remote Sensing* 17, no. 7 (1996): 1425–32.

59. McFeeters, Stuart K. 2013. "Using the Normalized Difference Water Index (NDWI) within a Geographic Information System to Detect Swimming Pools for Mosquito Abatement: A Practical Approach." *Remote Sensing* 5 (7): 3544–61. www.mdpi.com/journal/remotesensing.

60. Merwin, Daria E., and David J. Bernstein. 2003. “A GIS-Based Model for Predicting the Location so Submerged Prehistoric Archaeological Sites in New York Harbor.” State University of New York at Stony Brook.

61. Morehart, Christopher T. 2012. “Mapping Ancient Chinampa Landscapes in the Basin of Mexico: A Remote Sensing and GIS Approach.” *Journal of Archaeological Science* 39: 2541–51. doi:10.1016/j.jas.2012.03.001.

62. “National Park Service.” 2016. Government. *Bandelier*. http://www.nps.gov/band/learn/historyculture/ancestral-pueblo-people.htm.

63. National Park Service. 2015. “Ancestral Puebloans and Their World.” Accessed May 9. http://www.nps.gov/meve/learn/education/upload/ancestral_puebloans.pdf.

64. Office of the State Engineer. n.d. “Rio San Jose Water Rights Adjudication Process.” State. *New Mexico Office of the State Engineer/Interstate Stream Commission*. http://www.ose.state.nm.us/Legal/Adjudication/SanJose/adj_sj.php.

65. Pappu, Shanti, Kumar Akhilesh, Sudha Ravindranath, and Uday Raj. 2010. “Applications of Satellite Remote Sensing for Research and Heritage Management in Indian Prehistory.” *Journal of Archaeological Science* 37: 2316–1331. doi:10.1016/j.jas.2010.04.005.

66. Peeples, Matt. 2015. “Preservation Archaeology”. Organization. *Archaeology Southwest: Exploring and Protecting the Places of Our Past*. http://www.archaeologysouthwest.org/2013/11/25/back-to-basics-part-1/.

67. “Pennsylvania Historical & Museum Commission (PHMC).” 2015. State. *Transitional Period--4,000-3,000 Years Ago*. http://www.portal.state.pa.us/portal/server.pt/community /native_american_archaeology/3316/transitional_period/405752.

68. Pfarr, Joshua M. “Geoarchaeological Investigations of Floodwater Farming at Canada Alamosa, New Mexico.” Master of Arts, Eastern New Mexico University, 2008.

69. Parcak, Sarah H. 2009. *Satellite Remote Sensing for Archaeology*. New York, NY: Routledge.

70. Phillips, Jr., David A., Thomas R. Motsinger, and Heidi M. Roberts. 1993. *Excavations at the Maja Site: A Tanque Verde Phase Field House in the Avra Valley, Pima County, Arizona*. Archaeological Report 93-2. SWCA.

71. Phillips, Jr., David A. 2006. "Agriculture at Pottery Mound: A Working Hypothesis." *The Archaeological Society of New Mexico: Southwestern Interludes* 32: 119–28.

72. Phillips, Steven J., Robert P. Anderson, and Robert E. Schapire. 2006. "Maximum Entropy Modeling of Species Geographic Distributions." *Ecological Modelling* 190: 231–59. doi:10.1016/j.ecolmodel.2005.03.026.

73. Phillips, Steven, Miro Dudik, and Rob Schapire. 2008. "Help for Maximum Entropy Species Distribution Modeling." AT&T Labs-Research and Princeton University.

74. "Presence-Only Modeling with Maxent." 2016. Education. Accessed February 22. http://plantecology.syr.edu/fridley/bio793/maxent.html.

75. Riede, Felix. "Climate and Demography in Early Prehistory: Using Calibrated 14C Dates as Population Proxies." *Human Biology* 81, no. 2–3 (2009): 309–37.

76. Rivett, Paul. 1997. "Conceptual Data Modelling in an Archaeological GIS." *Proceedings of GeoComputation*, 15–26. http://www.geocomputation.org/1997/papers/rivett.pdf.

77. Rodning, Christopher. 2010. "Place, Landscape, and Environment: Anthropological Archaeology in 2009." *American Anthropologist* 112 (2): 180–90. Doi: 10.1111/j.1548-1433.2010.01217.x.

78. Roth, Barbara J, and Andrea Freeman. 2008. "The Middle Archaic Period and the Transition to Agriculture in the Sonoran Desert of Southern Arizona" *Kiva: The Journal of the Southwestern Anthropology and History* 73 (3): 321–53.

79. Sandor, J.A., P.L. Gersper, and J.W Hawley. 1990. "Prehistoric Agricultural Terraces and Soils in the Mimbres Area, New Mexico." *World Archaeology* 22 (1): 70–86.

80. Sandor, Jonathan A., John W. Hawley, Robert H. Schiowitz, and Paul L. Gersper. 2008. "Soil-Geomorphic Setting and Change in Prehistoric Agricultural Terraces in the Mimbres Area, New Mexico." *New Mexico Geological Society* 59: 167–75.

81. Strange, Niels, Bo Jellesmark Thorsen, Jesper Bladt, Kerrie A. Wilson, and Carsten Rahbek. 2011. "Conservation Policies and Planning under Climate Change." Biological Conservation 144 (12): 2968–77. doi:10.1016/j.biocon.2011.08.022.

82. Tacoli, Cecilia. 2009. "Crisis or Adaptation? Migration and Climate Change in a Context of High Mobility." *Environment and Urbanization* 21 (2): 513–25.

83. Thompson, Robert S., and Katherine H. Anderson. 2013. "Past Climate and Vegetation Changes in the Southwestern United States." USGS. *Impacts of Climate Change and Land Use in the Southwestern United States*. http://geochange.er.usgs.gov/sw/impacts/biology/pastclim/.

84. Wills, W.H., and Wetherbee Bryan Dorshow. 2011. "Agriculture and Community in Chaco Canyon: Revisiting Pueblo Alto." *Journal of Anthropological Archaeology* 31: 138–55. doi:10.1016/j.jaa.2011.11.002.

85. Xu, Hanqiu. "Modification of Normalized Difference Water Index (NDWI) to Enhance Open Water Features in Remotely Sensed Imagery." *International Journal of Remote Sensing* 27, no. 14 (2006): 3025–33.