EXPLORING THE USE OF FINE RESOLUTION NESTED ECOLOGICAL NICHE MODELS TO IDENTIFY GREATER SAGE-GROUSE (*CENTROCERCUS UROPHASIANUS*) HABITAT AND CONNECTIVITY POTENTIAL ACROSS A DIVERSE LANDSCAPE

by

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ABSTRACT

Suitable habitat for greater sage-grouse (*Centrocercus urophasianus*) has been greatly reduced over a relatively short ecological scale (1800s – Present). This reduction of habitat has had a negative impact on the current distribution and connectivity of the species. There has been work to map sage-grouse distribution at small ecological extents with fine resolution, and at broad extents and coarse resolutions. There is a current need to identify sage-grouse habitat at a fine ecological scale across a broad extent. This information will help researchers and land managers to better understand spatial patterns and connectivity associated with sage-grouse habitat and the processes that drive them. I focused my dissertation on testing the feasibility of developing broad spatial extent and fine resolution predictive habitat models for sage-grouse nest and brooding habitats. By using fine resolution mapping, I was able to capture more subtle variation in potential habitat; by using a broad extent I was able to apply these findings at a landscape scale. I also proposed a method of using nested ecological models blended together to predict potential habitat. In order to best predict habitat potential, multiple modeling techniques were applied (nonparametric multiplicative regression, maximum entropy distribution, random forest and generalized additive model). These methods were used to create independent sagebrush presence and total vegetation cover models and these were combined to create sage-grouse habitat predictive models. The statistical strength of each model was tested (logβ, R^2 and AUC) as well as their predictive ability (overall accuracy and RMSE). The results of this work produced fine resolution (30m) models, predicted across a broad extent (Utah, 21.9 million ha). The overall accuracy for the final sagebrush model was 72%. The RMSE for the vegetation cover MODEL was between 6.6 and 7.6% cover. In addition to model creation, potential research and management applications for these models are discussed. These models will provide baseline habitat estimations that could be used for better understanding past distributions of sage-grouse and improving current and future management planning. Furthermore, these same techniques could be applied to other species across multiple spatial and temporal scales

I would like to dedicate this dissertation to my wife, Marie Barrett Balzotti, who has always supported me in my educational pursuits. She has made sacrifices in her own career goals and provided valuable feedback and direction to this and my previous work.

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CHAPTER 1

INTRODUCTION

Problem Statement

Suitable habitat for greater sage-grouse (*Centrocercus urophasianus,* sage-grouse) has been greatly reduced since the early 1800's (Schroder et al., 2004). Reduction of this habitat, primarily woody *Artemisia* L (sagebrush), comes in multiple forms such as total loss, fragmentation and degradation. Due to this habitat reduction, sagebrush dominated ecosystems are considered by some as one of the most imperiled ecosystem in North America (Noss et al., 1995). Many factors, natural and anthropogenic, contribute to the range-wide loss and degradation of sage-grouse habitat. However, there is strong evidence that the greatest impact to sage-grouse and their habitat comes from anthropogenic-assisted disturbances (Braun, 1998; Connelly et al., 2011; Aldridge et al., 2003). Regardless of the cause, vast amounts of sage-grouse habitat has been lost or degraded making the remaining habitat more ecologically important for conservation and long-term survival of the species.

Sage-grouse and their habitat needs are a multiscale issue. For example, Doherty et al. (2010) found that combined local and landscape-scale features were important in sage-grouse nesting habitat selection, emphasizing the need to document and manage sage-grouse habitat at multiple ecological scales. The benefits of identifying, monitoring, and protecting sage-grouse habitat go beyond the individual species. Due to sage-grouses' habitat requirements and spatial distribution, some researchers have designated them as an umbrella species for other sagebrush associated organisms (Hanser and Knick, 2011; Rowland et al., 2006).

Because sage-grouse and their habitat span an ecologically broad area, their decline is a landscape-scale issue (Doherty et al., 2010; Aldridge, 2007). Additionally, sage-grouse cross diverse political boundaries that oftentimes have differing management objectives that are prone to change with political cycles. Sage-grouse currently occupy habitat owned and managed by private, state, federal, military, tribal and other land use groups in the western United States and Canada (Aldridge et al., 2008). Despite sage-grouses' geographic extent, the majority of past research has focused on site level attributes (Yost et al., 2008). Recently, there has been a great deal of effort to synthesize the current knowledge about sage-grouse and their habitat (Knick and Connelly, 2011 and others). This work has given researchers and land managers a better understanding of sage-grouse habitat requirements thus improving our ability to create ecological niche models. The objective of this dissertation was to test the feasibility of creating a fine resolution predictive landscape-scale sage-grouse habitat model. This model will add a new perspective (scale) to the conservation tool box that will allow researchers and managers to assess sage-grouse habitat selection, distribution and connectivity at the sub-population (Utah) level. Additionally, the influence of spatial extent used in model creation was assessed. Furthermore, multiple modeling techniques were tested and combined. Finally, the question of management application beyond model creation was discussed.

Sage-grouse Life History

The focus of this dissertation was on predicting nest and brooding habitat with some work in winter habitat, thus a brief description of the life history of sage-grouse is necessary. Sage-grouses' habitat requirements vary depending on where they are in their life history. Although there is variation in habitat selection and movement patterns across the population as a whole, there are some commonalities that exist. In general, nest habitat is made up of large sagebrush patches with cover between 15 and 25% but can be as low as 5% (Connelly et al., 2000). Additionally, nests are found in close proximity to winter and summer habitats. In most studies it was observed that sage-grouse preferred to nest at the base of sagebrush plants over other available shrubs or grasses (Connelly et al., 2011). In general, brood rearing (brooding) refers to early care of the sage-grouse chicks. Brooding habitat is a combination of early and late brood rearing. Early brooding habitat is defined by Connelly et al. (2000, 2011) as sagebrush-dominated habitat near the nest. Early brooding habitat is typically occupied for several weeks after the chicks hatch (Berry and Eng, 1985; Connelly et al., 2011). These areas are usually rich in insects and forbs. Late brooding coincides with a diet transition from predominantly insects to forbs and sagebrush (Connelly et al., 2011). Sagebrush cover for late brooding (summer) habitat is usually >20% (Braun et al., 2005). Winter habitat is dominated by taller woody sagebrush that is available as a food source above the snow. During this time, sage-grouse almost exclusively feed on sagebrush (Crawford et al., 2004). Sagebrush cover in winter habitat can vary from 6% to 43% but tends to be on the higher side (Connelly et al., 2011; Braun, 2005; Schroeder et al., 1999). In summary, an underlining theme of sage-grouse habitat selection is large intact heterogeneous sagebrush stands. Sage-grouse dependence on large habitat patches is one of the reasons broad scale ecological models are an important tool for capturing and understanding sage-grouse habitat requirements across their life history.

Ecological Niche

The exact definition of an ecological niche is a controversial topic (Godsoe, 2010) and is beyond the scope of this dissertation. However, the predictive models presented here were created using niche theory. These model predictions are based primarily in Hutchinson's (1957) fundamental niche concept. In short, the fundamental niche is made up of the abiotic conditions driving a species occupation and survival in an area. Fundamental niche was defined by Kearney and Porter (2004) as "the set of conditions and resources that allow a given organism to survive and reproduce in the absence of biotic interactions."

It is not possible to ascertain all requirements (abiotic or biotic) that make up sage-grouses' ecological niche with our current knowledge. Therefore, sage-grouses' ecological niche is defined here as an incomplete combination of Hutchinson's (1957) fundamental and realized niches. Overall, the model assumes more of a fundamental niche. However, the response (dependent) variable used to create the models (sage-grouse presence) is a subset of the population, driven by realized niche interactions. Furthermore, due to the lack of complete sampling and the availability of spatial layers for model creation, the model cannot encompass all the fundamental niche criteria. Therefore, the output model in geographic space may be more conservative than a fundamental niche, more liberal than the realized niche and more robust than the standard distribution map. Semantics aside, this lack of a niche definition does not reduce the value of the models; however, it is important to state the limitations and understand that the models are predictions based on good, but incomplete data. Many authors refer to models such as these simply as species distribution models to reduce confusion (Elith and Leathwick, 2009).

Why Use Predictive Ecological Models for Sage-grouse Habitat?

Sage-grouse are an ideal candidate for predictive ecological modeling, for a variety of reasons. These reasons include sage-grouses' obligate relationship with sagebrush, their broad distribution, the large body of available literature on habitat requirements, the existence of long-term locational data sets and a current need to assess large areas in a relatively short time period, due to immediate threats to the species and their habitat.

It has long been known that sage-grouse are a sagebrush obligate species. Sage-grouse prefer sagebrush for cover during nesting and early brooding and as their primary food source in the fall and winter (Braun et al., 1977; Crawford et al., 2004; Connelly et al., 2011 and others). This relationship with sagebrush strengthens the ability to model sage-grouse habitat. Areas that contain sagebrush can be used to narrow the sage-grouse predictive habitat model. Furthermore, sagebrush could be modeled as a proxy for potential habitat in areas that sage-grouse are known to occur, but where there is a lack of ground collected presence data for modeling.

Sage-grouse are a landscape-level species (Schroder et al., 2004; Yost, 2008; Aldridge et al., 2008; Doherty et al., 2010; Knick and Connelly, 2011; Connelly et al., 2011 and others). Due to the vast area utilized by sage-grouse, ecological models become a valuable tool in understanding distribution and connectivity. Many areas may be difficult to obtain ground data due to cost or accessibility. In areas where ground data are feasible, cost and time are limiting factors in the amount of data that can be taken. Models can assist in connecting the information spatially from these limited data sets.

Selecting appropriate predictor variables is a limiting factor to any ecological model's performance. For example, if temperature was a critical component for survival of species X, than it (or a suitable proxy) should be included in the predictive model. Ecological model performance is restricted to the input variables used. Sage-grouse habitat requirements have been relatively well studied compared to most organisms. Connelly et al. (2011) argues that we know more about sage-grouse than any other North American game bird. This repository of knowledge has been used to create predictive sage-grouse habitat models at a variety of scales and life stages including nesting (Yost et al., 2008; Aldridge and Boyce, 2007), brooding (Aldridge and Boyce, 2007), winter (Dzialak et al., 2012), range wide (Schroder et al., 2004; Aldridge et al., 2008) and connectivity (Harju et al., 2013). Additionally, Schroder et al. (2004) produced a series of maps showing range-wide historic and current distribution of sage-grouse. This was accomplished using past studies, historic documents and museum records. The models in this dissertation will add to the existing models by providing additional scales and modeling techniques.

Predictive Modeling

Species distribution models are a tool using species locations or abundance combined with environmental variables to explain or predict presence (Elith and Leathwick, 2009). Since their origins in the 1970s, species distribution models have been a growing component of ecological and conservation sciences as well as land management (Schwartz, 2012; Zimmerman et al., 2010). The ability to create meaningful species distribution models has dramatically improved over this relatively short period of time. This improvement is driven, in part, by increased data availability and advancements in computer processing (Zimmerman et al., 2010). Never before has there been so much data available, knowledge on the subjects of ecological models and sage-grouse habitat or computer processing power. There is a vast number of modeling methods and software now available to implement predictive models. After reviewing the literature, four methods were chosen for implementation and model creation. The four methods selected were generalized additive models (GAM; Hastie and Tibshirani, 1986), nonparametric multiplicative regression (NPMR; McCune and Mefford, 2004), maximum entropy distribution (Maxent; Phillips et al., 2004) and random forest (RF; Breiman, 2001).

GAMs have a relatively long history with ecological modeling dating back to the 1980s (Guisan et al., 2002). GAMs are a semiparametric method that is an extension of generalized linear models, with functions that are combined additively and components that are smoothed (Yee and Mitchell, 1991). One of the strengths of GAMS is their ability to deal with nonlinear relationships between response and predictor variables (Yee and Mitchell, 1991; Guisan et al., 2002). This is important because many interactions in nature are nonlinear. GAMs were implemented using Marine Geospatial Ecology Tools (MGET; Roberts et al., 2010) and ArcMap (ESRI; Redlands, California). GAM models were used in Chapter 3 to predict total vegetation cover.

NPMR was also selected for its ability to model nonlinear interactions between species abundance and their habitat. However, NPMR identifies complex nonparametric ecological interactions in part by combining the predictors effects multiplicatively, rather than additively (Grundel and Pavlovic, 2007). An additional strength of NPMR is that if a single, highly correlated, predictor variable is lacking at a particular location, then the model will not predict that location as potential habitat. NPMR was implemented with the software package Hyperniche (McCune and Mefford, 2004; Gleneden Beach, Oregon). NPMR was used to model sagebrush presence in Chapter 2, total vegetation cover in Chapter 3 and sage-grouse habitat in Chapter 4.

Maxent was selected specifically for its ability to model presence only data. Maxent is a form of machine learning that makes inferences or predictions based on incomplete information (Phillips et al., 2006). Maxent compensates for the lack of absence data by comparing presence data to the background of the predictor variables. In order to make predictions, multiple transformations are done to find if there is agreement between the response and predictor variables. Maxent has been extensively used in the scientific literature to model a variety of species habitat distributions based on presence only data, including other avian species (Warren and Seifert, 2011; Elith et al., 2011; Moreno et al., 2011; Papes, 2012 and others). Maxent was used in Chapter 2 to create current and future climate envelopes for sagebrush and in Chapter 4 to predict sage-grouse habitat.

Although RF, a form of machine learning, has been around for some time, its use in ecological studies is relatively new (Cutler et al., 2007; Prasad et al., 2006). RF uses bootstrap samples and a randomized subset of the predictor variables to create a series of classification trees (a forest) that predict species presence. These trees (typically over 500) are then combined for the final model prediction. Unlike many of the modeling methods available, RF has the ability to create accurate predictions without over fitting the data (Cutler et al., 2007; Prasad et al., 2006). The software used to implement RF was R 2.15.1 (R development core team, 2008) and ModelMap (Freeman and Frescino, 2009). RF was used to create the sage-grouse habitat models in Chapter 4.

Chapter Overviews

The main objective of this study was to test the feasibility and accuracy of using multiple fine scale ecological niche models, projected across a broad spatial extent, to better understand sage-grouse brooding and nest habitat selection (Chapter 4). Sagebrush presence and vegetation cover are important components in sage-grouse brooding and nest habitat selection (Braun et al., 1977; Connelly et al., 2000, 2011; Crawford et al., 2004; Hagen et al., 2007 and others), and were a major component of this study (Chapters 2 and 3). Chapter 2 focused on creating an accurate sagebrush presence map. Chapter 3 explored creating multispatial and multitemporal total vegetation cover models. Chapter 4 utilized the models from Chapters 2 and 3 along with additional predictor variables to model potential sage-grouse habitat and connectivity.

There were three primary objectives for the sagebrush predictive model work, found in Chapter 2. The first was to test the feasibility of creating an accurate, cost-effective, and easily updatable sagebrush distribution model, relevant to sage-grouse, for the state of Utah. Projects such as the USGS Gap Analysis Program (GAP) have produced land cover maps at the desired 30m spatial resolution that contain sagebrush cover classes (Lowry et al., 2007). However, the percent sagebrush cover is unknown. In order to better tie sagebrush cover to sage-grouse distribution, a sagebrush presence model was created for woody sagebrush cover >5%. This threshold was chosen because sage-grouse have been observed nesting and utilizing winter sagebrush cover at 5% and higher (Connelly et al., 2011). The second objective was to assess how the model changed with more area and more training locations added. This scaling was done in each chapter to answer the question: if a model is trained at a smaller extent (one Landsat TM scene, Figure 1.1), can it be applied to a broader area (the state of Utah)? The third objective was to create current and future climate envelopes for sagebrush. These climate envelopes allowed us to identify sagebrush habitat patches most likely to change with future climate. This information will be valuable for long-term management of current sagebrush patches utilized by sage-grouse.

Although sagebrush is a habitat requirement for sage-grouse persistence, other factors such as overall vegetation cover are also important. Vegetation cover and type play a role in food availability, refuge from predators and movement. Total vegetation cover model creation, found in Chapter 3, also had three objectives: first, to assess if multitemporal *in situ* data, taken by the Utah Division of Wildlife (UDWR), could be used in conjunction with Landsat Thematic Mapper (TM) imagery to model total vegetation cover across a relatively broad spatial extent and time. Second, to use past vegetation cover models, in combination with sage-grouse ground data, to identify if sage-grouse habitat utilization is more likely to occur in habitat with minimal vegetation cover change over time, or in dynamic habitat types. Finally, similar to the sagebrush model, the influence of scale on model creation was assessed.

The final chapter focuses on utilizing predictive niche models to understand sage-grouse habitat patch connectivity and potential movement. Chapter 4 explored creating a sage-grouse nest and brooding habitat model by identifying areas of agreement between Maxent, RF and NPMR. Two of the top variables in model creation were the sagebrush presence and total vegetation cover models from Chapters 2 and 3. Once an acceptable habitat model was created for the state of Utah, that model was combined with a human impact layer (Leu et al., 2008) to predict sage-grouse corridor potentials on a more coarse scale, between currently utilized habitat patches. Despite the fact that all models are imperfect, best stated by Box (Box and Draper, 1987) when he wrote "essentially, all models are wrong, but some are useful," the models presented here will improve our ability to predict current sage-grouse habitat. Furthermore, they will expand the current understanding of the habitat spatial dynamics such as the juxtaposition of habitat patches to other spatial variables at the landscape scale.

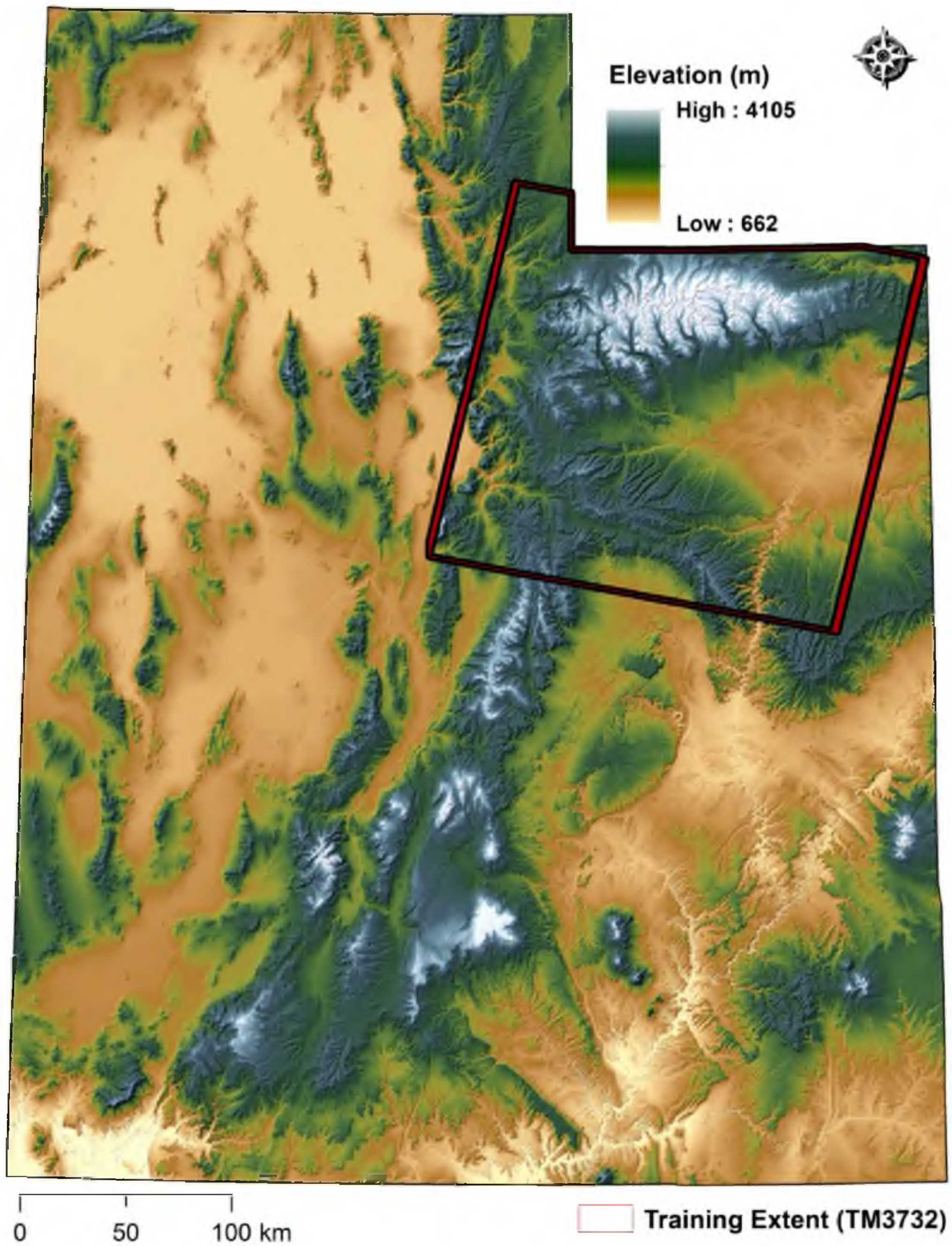

Figure 1.1: The first extent outlined in red represents the training area, Landsat TM scene 3732, used in all models. The final extent in all models was the entire state of Utah.

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CHAPTER 2

EVALUATION AND APPLICATION OF MULTISCALE FINE RESOLUTION ECOLOGICAL NICHE MODELING OF SAGEBRUSH PRESENCE IN UTAH

Abstract

There is a scientific consensus that sagebrush ecosystems extent and health as a whole have declined drastically, negatively impacting associated flora and fauna. Identification and documentation of existing sagebrush stands is an important component to protecting and managing the many species that rely on sagebrush for survival. The objective of this study was to create a management level woody sagebrush model with existing data sets. Additionally, it was our goal to identify sagebrush stands that, despite a changing climate, have a potential to persist. These objectives were realized by creating sagebrush niche models at multiple spatial scales and creating a climate envelope for woody sagebrush. It was found that a statewide sagebrush model with management level resolution (30m) is possible with acceptable model creation (Logβ 5.02) and overall accuracy (72%).

Introduction

Estimates of presettlement area within western North America dominated by sagebrush (*Artemisia* L.) range from 36 to 109 million ha (Connelly et al., 2004; Evers et al., 2011; Knick et al., 2003; Beetle, 1960; McArdle et al., 1936). Results from past sagebrush cover estimates are difficult to compare due to varying methods of assessment, species inclusion/exclusion, spatial scale of output maps, and areas included (Tisdale et al., 1969, 1981; Schroeder et al., 2004). However, there is a scientific consensus that sagebrush ecosystems extent and health as a whole have declined drastically and are currently in decline, negatively impacting associated flora and fauna (Anderson and Inouye, 2001; Connelly et al., 2004; Evers et al., 2011; Knick et al., 2003; McArdle et al., 1936; Miller and Eddleman, 2000). Previous studies in the sagebrush steppe have estimated that only 50-60% of this pre settlement sagebrush cover remains unaltered (Knick et al., 2003; Beck et al., 2012; Schroeder et al., 2004; West, 2000). Noss et al. (1995) concluded that sagebrush ecosystems are among the most imperiled ecosystems in North America.

Decline in sagebrush ecosystems has negative implications for obligate species, including greater sage-grouse (*Centrocercus urophasianus*). Beck et al. (2003) estimated that in the state of Utah alone, sagebrush habitat suitable for greater sage-grouse habitat has declined by at least 60% since pre-European settlement. There is a need to better identify and document sagebrush stands at the landscape level to better protect and manage sagebrush obligate species. Knowing where existing sagebrush occurs and studying it at a macro-ecological scale will provide additional insight into past, present and future sagebrush connectivity, patch dynamics and potential home ranges and corridors for sagebrush-associated species. The objective of this study is to test the feasibility of creating an accurate, cost-effective, and easily updatable sagebrush distribution model. This work focused on model development and evaluation for the state of Utah, USA, which possesses a wide range of sagebrush habitat types and spread across the landscape, possessing substantial elevation and precipitation gradients. Model results depict overall distribution patterns and identify areas of spatial connectivity of woody sagebrush throughout the state of Utah. Furthermore, I attempted to identify future sagebrush habitat in Utah, areas that will be less susceptible to future predicted climate changes.

Background

Sagebrush Range and Loss

Sagebrush, as defined by McArthur (2000), are woody *Artemisia* of the subgenus *Tridentatae*, indigenous to North America. Using this definition and McArthur's systematic taxonomic treatment of sagebrush, there are 11 species and 14 subspecies of sagebrush (McArthur 2000). Sagebrush is found primarily in western North America, with its pre-European distribution covering western portions of the Dakotas, southern Saskatchewan and Alberta, into Montana, Idaho, Washington, southern portions of British Columbia, Oregon, northern California, Nevada, Utah, Wyoming, Colorado, as well as northern Arizona and New Mexico (Baker et al., 1976; Beetle, 1960; Connelly et al., 2004; McArthur and Plummer, 1978). A more in-depth review and maps specific to *Artemisia* species can be found in McArthur (1978, 2000). Definitions of past sagebrush habitat coverage have varied drastically, making assessment of total loss and decline extremely difficult. Additionally, very few studies have actually created original sagebrush cover estimates. In 1936, McArdle et al. estimated sagebrush coverage in the United States to be 39 million ha. Twenty four years later, Beetle (1960) assessed sagebrush cover for the western United States to be as high as 109 million ha. One discrepancy, suggested by Beetle, was that McArdle et al. (1936) only assessed one *Artemisia* species, big sagebrush (*Artemisia tridentata* Nutt.). However, even if that were the case, Beetle's big sagebrush estimates were over 20 million ha higher than the McArdle et al. estimates. Tisdale et al. (1969) stated that Beetle's estimates included areas that sagebrush was not the dominant vegetation, making Beetle's estimates higher. Tisdale et al. (1969) further suggested that the total sagebrush cover was a value between Beetle's and the McArdle et al. estimates. Another source often used to determine past sagebrush cover is Küchler's potential natural vegetation maps (Küchler 1964, 1970). West (1983), using Küchler's maps, assessed sagebrush cover to be approximately 62.7 million ha (Great Basin Colorado- Plateau sagebrush $19.9X10^6$ ha and Western Intermountain sagebrush steppe $44.8 \text{ X } 10^6$ ha).

According to Beetle (1960), the overall distribution (not health) of sagebrush has changed very little since presettlement times. However, more recent work has described changes in the quality, connectivity and total coverage of sagebrush (Anderson and Inouye, 2001; Connelly et al., 2004; Evers et al., 2011). Sagebrush loss and degradation ranges from easily identifiable factors such as anthropological conversion (e.g., crops, cities, infrastructure), to complex factors that vary over spatial and temporal scales (e.g., fire regime alterations, invasive species, grazing, disease, and climate change). Although sagebrush ecosystems, like any ecosystem, are constantly changing due to non-anthropogenic factors such as drought and natural disease, human activities have been, and continue to be the greatest threat to sagebrush dominated ecosystems (Connely et al., 2004). Roads, irrigation, fertilization, fire regime alteration, urban and exurban sprawl, invasive species (nonnative and native) facilitation and introduction, soil erosion and other activities associated with human occupation within sagebrush ecosystems can have negative impacts on the sagebrush, as well as other associated species. Braun (1998), assessing the reasons for the decline of greater sage-grouse across the west, suggested that one contributing factor was irrigation projects, because they allowed "intensified land use" that opened up more sagebrush lands for conversion for crops and livestock, that may have otherwise not been accessible due to lack of available moisture. Gelbard and Belnap (2003) found that in southern Utah, improving and creating roads increased the spread of exotic species, degrading natural desert ecosystems at the landscape scale. The fastest growing form of land use in the US is exurban expanse (low-density home development; Hansen et al., 2005). Hansen et al. (2005) concluded that although the impacts of "exurban" development were understudied, this development can negatively impact native ecosystems. Leu et al. (2008) used a model to assess combined human impacts in the west (Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming) and found that in 2003, 13% of the land area was occupied by anthropogenic features (homes, roads, power lines etc.). Furthermore, the human assisted introduction of invasive species (such as cheatgrass [*Bromus tectorum* L.]) have altered the sagebrush ecosystem fire regimes with fires in lower elevations being larger, more frequent, and earlier in the growing season compared to historic levels (West et al., 2000). One of the consequences of the fire regime change is increased soil erosion that degrades many sites which can lose their potential to return to native ecological states (West et al., 2000).

Sagebrush Habitat

Sagebrush provides habitat for a diverse array of animal species. Vertebrate species known to be sagebrush obligates include, but are not limited to, the following: greater sage-grouse (*Centrocercus urophasianus*; Braun et al., 1976; Connelly et al., 2004), Gunnison sage-grouse (*Centrocercus minimus*), Brewers sparrow (*Spizella breweri*), sage sparrow (*Amphispiza belli*; Braun et al., 1976; Reynolds, 1981), sage thrasher (*Oreoscoptes montanus*; Braun et al., 1976), pygmy rabbit (*Brachylagus idahoensis*; Knick et al., 2003; Rich et al., 2005), sagebrush vole (*Lemmiscus curtatus*; Paige and Ritter 1999), pronghorn (*Antilocapra americana*), and sagebrush lizard (*Sceloprus graciosus*; Paige and Ritter, 1999). Additionally, there are over 350 species of concern that rely on sagebrush to some degree during their life cycles (Wisdom et al., 2005; Davies et al., 2011). Suring et al. (2005) identified 207 species of concern associated with sagebrush habitats in the Great Basin alone. Baker et al. (1976) estimated that there are over 100 bird species that forage or nest in sagebrush communities.

Pressures on Sagebrush Ecosystems in Utah

Beetle estimated in 1996 that 10.7 million ha of sagebrush existed in the state of Utah at that time (Table 2.1). While Utah has a human history dating back to prehistoric times, it can be argued that anthropogenic removal and degradation of sagebrush on a landscape scale did not begin until the arrival of early pioneers in the mid-1800s. Sagebrush in and around settlements was seen by the early pioneers as a nuisance that needed to be removed to make way for houses, crops, and forage for livestock. Claims made about the goals of dry farming included the following statement: “To make the waving fields of grain replace the worthless sage brush [sic] is work of the efforts of those who truly love Utah…" (Deseret Evening News, 1906). According to census data, 6.5% of the state had been converted to farmland by 1910 with Davis County leading the state at 72% (USDA Census of Agriculture, 2007). As of 2007, 21% of the state was farmland. Although much of the farmland was (is) necessary for human and livestock subsistence, the negative effects to sagebrush ecosystems go beyond the initial land conversion.

Utah's population has grown rapidly and exponentially, from approximately 11,000 people in 1850 to over 2.7 million people today (US. Census Bureau, 2012). With increased population often comes increased use of natural resources for humans and their livestock. Since pioneer settlement, agricultural use of Utah's lands has intensified. Much of this intensification has taken place in areas formerly dominated by sagebrush. In1850, Utah possessed 12,350 ha of farmland, 12,607 cattle and oxen, and 3,262 sheep (USDA Census of Agriculture, 1850). Utah cattle by the 1880s had as many as 160,000 head. Utah's sheep reached an estimated 2.9 million head by 1901 (McArdle et al., 1939). According to the latest agricultural census (2007), Utah had 843,474 cattle and 277,635 sheep. Farmland has changed slowly in more recent decades, increasing by less than 1% from 1950 (20.6%) to 2007 (21.1%).

Utah sagebrush ecosystems have also faced impacts from energy development, both from traditional fossil fuel (oil, gas, coal etc.) as well as renewable energy (wind, solar, geothermal etc.). Despite the fact that energy development has been a part of Utah history from the early 1900s, there are very few studies that quantify the impacts of energy development on sagebrush ecosystems (Walston et al., 2009). The infrastructure necessary for energy development (roads, pads, power lines, and other critical components) is known to alter sagebrush ecosystems (Walston et al., 2009; Knick et al., 2003). This alteration comes in many forms including fragmentation, exotic species introduction, loss of vegetation cover, fire alteration, hydrological changes, soil degradation and others (Doherty et al., 2011; Gelbard and Belnap, 2002; Walston, 2009; Knick et al., 2011).

Methods

Study Area

The state of Utah was chosen as the study area due to its sagebrush species diversity, wide range of habitat types and data availability. Landsat 5 Thematic Mapper (TM) data were used to further subdivide the state into several spatial extents in order to assess the influence of scale on the model. Landsat TM data are broken down into a grid, defined by paths (a repeating orbit path that varies east to west) and rows (latitudinal center line of image). A path and row number are assigned to TM scenes, with each scene covering a 185 km by 172 km area (more than 3 million ha) (NASA, http://landsat.gsfc.nasa.gov/about/tm.html). The objective of the differing spatial scales was to assess if sagebrush models trained at the smallest spatial scale (a single TM scene) could be used to model sagebrush presence across multiple spatial scales. Path 37 Row 32 (S1) was selected as the training scene (Figure 2.1). Total area covered within this scene is roughly 3 million ha and ranges from the forested Uinta Mountains (~ 3400-4123 m) to the Uinta basins (~1400 – 3100m). Land ownership within the area of the scene includes federal (50%), private (31%), tribal (11%) and state (7%). The training area was chosen due to its geographic and vegetation diversity, sagebrush cover, imagery availability, and known sage-grouse habitats. Modeling was applied to three additional regions to assess how the analysis could be extended to larger spatial scales: 1) TM Path 37 Rows 32 and 33 (S2, 6.5 million ha), 2) TM Path 37 Rows 32, 33, and 34 (S3, 8.6 X 10^6 ha), and 3) the state of Utah (ST, 21.9 million ha; Figure 2.2).

Predictive Modeling Methods

The modeling methods utilized in this study were nonparametric multiplicative regression (NPMR) and maximum entropy distribution (Maxent). The modeling techniques and software packages used to implement them were chosen based on previous use in the literature and availability.

Nonparametric multiplicative regression (NPMR; McCune and Mefford, 2004) was used due to its potential to identify complex ecological interactions by combining terms multiplicatively rather than additively, and its nonparametric abilities. NPMR uses a leave-one-out cross validation and a multiplicative smoothing function to predict the response variable. The software package Hypernich 2.0 (McCune and Mefford, 2004, Gleneden Beach, Oregon) was used in this study to implement NPMR. For a list of publications that have used NPMR see http://home.centurytel.net/~mjm/nichepublications.htm.

Maxent (Phillips et al. 2004) is one of the most commonly used methods for species distribution based on presence only data (Warren and Seifert, 2011). Maxent is a machine learning modeling tool that uses multiple transformations to fit the data. Maxent was used because of its wide use in landscape scale studies (Elith et al., 2011) as well as its straightforward interface with the ability to modify with simple code.

Model Creation

Predictive models were created at multiple scales using the response variable sagebrush presence (quantitative and binomial). Model creation followed six basic steps (Figure 2.3). First, response and predictor variables were determined using known sagebrush variables as well as suspected variables described below. Second, the values of the predetermined variables were extracted from existing remote sensing/GIS data sets or, if not available, they were created using ESRI (Environmental Systems Research Institute, Redlands, CA) and ENVI (Exelis Visual Information Solutions, Boulder, Colorado) software packages. Third, model lists were created for both quantitative and categorical approaches. Fourth, best fit models based on xR^2 and $\log\beta$ as well as number of variables included in the models were selected for visualization and further validation. Fifth, models were created using the prescreened lists in 2D space using NPMR. Predictive models were created for S1and then scaled up spatially to include S2, S3 and ST. Model outputs were then validated for overall accuracy.

In addition, separate sagebrush potential habitat models, using climate data alone (climate envelopes), were created for the state of Utah. Predictor variables used were the 19 Bioclim variables (Table 2.2) obtained from the WORLDCLIM data set (Hijmans et al., 2005). Model creation and validations were done using the area under the receiver operating characteristic curve (ROC), known as the AUC. Similar to the Wilcoxon test of ranks, the AUC classifier is the probability that the classifier will rank a randomly chosen positive instance higher than a negative one (Fawcett, 2006). An AUC value of 0.5 represents random guessing. Model output validation was done by withholding 25% of the data and producing an output AUC. The objective of the climate models was to identify areas that have the most potential to maintain sagebrush cover in future climate conditions.

Input Data

One of the aforementioned objectives of this study was to find appropriate data to create a sagebrush model that could be continually updated so that as additional information becomes available, the model could be improved. The data used in this study were broken down into three broad categories: *in situ*, remotely sensed, and climate. Remotely sensed data were further broken into two sub categories: digital elevation model (DEM) derived and Landsat-derived.

***In situ*.** Most of the *in situ* data used in this study were provided by the Utah Division of Wildlife Resources (DWR) Range Trend Project (RTP). The RTP collects vegetative and soil data across the state of Utah. RTP data used in this study were sagebrush type and percent cover. RTP data were chosen to create the landscape level models due to their temporal and spatial extent. Ground sites are generally re-visited every five years and many have been sampled over multiple decades. Furthermore, the coverage of the RTP sites is state-wide with hundreds of site locations distributed throughout the state. RTP data collection biases are reduced by averaging 100 quarter m square quadrates along a 152m transect, collected by multiple field technicians on each site (Figure 2.4).

The objectives of the RTP are to monitor and conduct a statewide evaluation of Utah's rangelands. RTP sites are established on state, federal, and private lands in correlation with big game habitat, as defined by biologists from the DWR, BLM and USFS. (For more information on RTP data and collection go to http://wildlife.utah.gov/range/methods.html)

Remotely sensed data. Due to the relatively large spatial extent, multiple landownerships, and diversity of terrain occupied by sagebrush in Utah, remotely sensed data were used. In general, topographic params such as slope, aspect, and relative elevation are important drivers of a plant's spatial distribution (Strahler et al., 1978; Franklin, 1995). More specifically, sagebrush spatial patterns and type are known to be associated with topographic gradients (Burke, 1989; Wang et al., 1977). DEMs for this study were available for the entire state. These models provided a continuous relative elevation layer that allowed not only for the elevation data to be represented, but multiple elevation associated layers to be created.

DEM derived data. DEM derived data were created using 30 m DEMs obtained from the United States Geological Survey (USGS, Gesch, 2007). Layers created included slope, aspect, curvature, curvature direction of slope IMI, TPI and ruggedness index (Table 2.3). Slope is defined here as a calculation of maximum rate of change in elevation between the cell and its eight neighbors. Aspect is the direction of the slope. Curvature defines the slope characteristics of drainage basins and is often used to understand erosion and runoff processes. Curvature direction of slope is the direction of the maximum slope. A modified version of the Iverson et al. (1997) Integrated Moisture Index (IMI) model was created using ArcMap (ESRI, Redlands, California) to assess topographically influenced moisture availability using the DEM derived layers: hillshade, flow accumulation and curvature. The curvature layer values were inverted and all the layers were normalized and reclassified on a scale of 0-100. The reclassified layers were then combined in a weighted fashion to create an IMI with a 0-100 scale, 0 indicating no moisture retention and 100 representing the maximum moisture retention (Davis, 2009; Yost et al., 2008).

IMI= (hillshade x 0.5) + (curvature x 0.15) + (flow accumulation x 0.35)

Landsat derived data. Landsat derived data were created using Landsat 5 Thematic Mapper (TM) imagery, downloaded from the USGS (http://www.usgs.gov/). TM bands 1-5 and 7% reflectance were included in the models and have spatial resolutions of roughly 30m. Band 6, the thermal infrared band, was not included due to spatial resolution (120m; Jensen, 2005; JPL, 2009; Mladinich, 2006). All TM scenes obtained from the USGS had undergone basic (level 1) preprocessing such as georeferencing. Further preprocessing to account for atmospheric interference was done on a pixel by pixel basis using Fast Line-of-site Atmospheric Analysis of Spectral Hypercubes (FLAASH, Air Force Phillips Laboratory, Hanscom AFB and Spectral Sciences, Inc (Adler-Golden et al., 1999)) and ENVI software. TM bands were first converted from digital values to radiance using the ENVI calibration utility. The bands were converted to reflectance using the FLAASH atmospheric correction model. The FLAASH model incorporates moderate resolution atmospheric transmission (MODTRAN4) radiative transfer code to assist in generation of the final reflectance layers.

Vegetation indices were created to better detect vegetation signatures associated with sagebrush in the TM data. These were applied using ENVI software and are described below. Normalized Difference Vegetation Index (NDVI) was proposed early on in remote sensing with its first written credit given to Rouse et al. (1973; Bannari et al., 1995). NDVI continues to be used for an array of applications in range ecology, including change detection and time series analysis (Fuller, 1998; Evans and Geerken, 2004), biomass production (Reeves et al., 2001; Moleele, 2001), land cover classification (Evans and Geerken, 2006; Geerken, 2005) and carbon flux and sequestration (Wylie et al., 2003). NDVI values range from -1 to 1 with higher values associated with greater difference between red and near infrared (NIR) reflectance. NDVI is calculated as:

$$\mathrm{NDVI} = \frac{(\rho_{NIR} - \rho_{red})}{(\rho_{NIR} + \rho_{red})}$$

where ρ indicates reflectance.

Two vegetation indices using longer wavelength infrared bands are referred to as Normalized Difference Infrared Index (NDII_5 and NDII_7, where the subscript refers to the TM band number). NDII has a similar form to NDVI, using a band from the shortwave infrared (SWIR) and a NIR reference band (Hardiskey et al., 1983; Hunt and Rock, 1989). Formulas for the two indices are:

$$\mathrm{NDII}_5 = \frac{(\rho_{b4} - \rho_{b5})}{(\rho_{b4} + \rho_{b5})}$$

$$\mathrm{NDII}_7 = \frac{(\rho_{b4} - \rho_{b7})}{(\rho_{b4} + \rho_{b7})}$$

where b indicates the band number.

Landsat 5 TM wavelengths for bands 4, 5, and 7 are 0.76- 0.90µm, 1.55-1.75µm and 2.08 – 2.35µm, respectively. NDII has been used in remote sensing to detect forest stress (Lasaponara, 2006; Souza et al., 2005), fuel types (Riaño, 2002) and insect infestation (White et al., 2007) among other applications.

Modified Soil-Adjusted Vegetation Index 2 (MSAVI2) is a vegetation index designed to improve vegetation cover estimates within areas with high amounts of exposed soil surfaces. Qi et al. (1994) developed the MSAVI2 from a modification of their earlier MSAVI. Since its creation, MSAVI2 has been used for vegetation cover (Senseman, 1996) and biomass estimations (Phillips et al., 2009) among other applications. Due to the large amounts of bare ground found in the selected training scene, the MSAVI2 was hypothesized to be useful in identifying sagebrush. MSAVI2 is calculated as:

$$\text{MSAVI2} = \frac{\left(2 \times \rho NIR_{b4} + 1 - \sqrt{\left((2 \times \rho NIR_{b4} + 1)^2 - 8 \times (\rho NIR_{b4} - \rho RED_{b3})\right)}\right)}{2}$$

The tasseled cap transformation appeared first in the remote sensing literature in Kauth and Thomas (1976), and is thus sometimes referred to as a “K-T transform.” Similar to a principal components analysis, tasseled cap transformations use linear combinations of the input bands in conjunction with a constant to produce new output bands (Crist and Kauth, 1986). The three outputs bands are referred to as “brightness,” “greenness” (indicative of photosynthetic vegetation), and “wetness” (indicative of water content).

Climate. The purpose of including climate data in this study was two-fold: first, to identify if any of the climate variables were helpful in combination with other variables to predict sagebrush presence and second, the climate data were used as a stand-alone data set to identify areas that potentially support sagebrush based on current and future climate conditions.

Precipitation and temperature. Precipitation data were obtained from the Oregon State University PRISM group (http://www.prism.oregonstate.edu/). The spatial resolution of the PRISM data is approximately 800m. Precipitation data were created using the Param-elevation Regressions on Independent Slopes Model (PRISM). The PRISM method uses a regression model with weighted weather station points combined with weighted elevation, coastal proximity, and other variables as well as atmosphere to create seamless climate models (Daly et al., 2002). Data used represented the monthly averages from 1971-2000 for both precipitation and average max temperature. Preprocessing of the PRISM data included converting text files to raster format as well as resampling to 30m and projecting the files. Resampling to 30m was done with ESRI software using the nearest neighbor method.

Bioclim. In the 1980s Nix, McMahon, Hutchinson and others created bioclimatic variables to be used in species distribution modeling (Lindenmayer et al., 1991; Nix, 1986; Busby, 1986; Booth et al., 1987). The objective of these 19 variables was to predict a species spatial distribution based in homoclime matching, identifying areas with similar climate conditions (Lindenmayer et al., 1991). Bioclim data (roughly 1 km resolution) were obtained from the WorldClime data set (Hijmans et al., 2005, http://www.worldclim.org). The WorldClime data used were created with thousands of weather stations that have been checked for quality and developed into continuous climate surfaces, applying a thin spline algorithm (delta) method (Jarvis et al., 2012; Hutchinson, 1995). Gross assumptions made by the delta method are 1) changes in climate vary only over large distances and 2) relationships between variables in the baseline are likely to be maintained towards the future (Ramirez-Villegas and Jarvis, 2010). Specific data obtained included the 19 bioclim variables for “current” conditions (1950-2000) and future conditions: 2020 (2010-2039), 2050 (2040-2069), and 2080 (2070-2099). The future conditions were created applying the current conditions to three different emission scenarios described below.

Other climate variables. The Global Climate Model (GCM) Canadian Center for Climate Modeling and Analysis third generation atmospheric climate model CCMA_CGCMA3.1 (Scinocca et al., 2008) was used to create all future predictive climate models. The objective of the sagebrush climate models was to provide visual representation of sagebrush areas which will be more likely to persist despite changing climate. Models for the current conditions were run in both Hyperniche (McCune, 2004) and Maxent (Phillips et al., 2004). However, future models were only run in Maxent due to the similarities in the models and the ease to incorporate future predictions offered by Maxent. The GCM for each future prediction data was run with three different emission scenarios. The scenarios used SRES A1B, A2A and B2. Each SRES scenario is complicated and assumes a "storyline." Additional information can be found at the Intergovernmental Panel on Climate Change website (http://www.grida.no/ specifically Nakićenović, 2000). In general, SRES A1B assumes rapid global population growth (reaching 9 billion in 2050) followed by a slow decline. SRES A1B applies a maximum energy requirement, global technological cooperation, with balanced emissions between fossil fuel and nonfossil fuel sources. SRES A2A assumes a more regional rather than global cooperation with technologies. SRES A2A follows a continuously growing population, high energy requirements and emissions less than a globally cooperative economy that is fossil fuel intensive. SRES B2 focuses on local environmental stability with a continually growing population with lower energy requirements and greater emissions.

The Bioclim data were clipped and projected, but not resampled. All models created using the Bioclim data were done at the 1 km resolution.

Model Creation

Sagebrush presence models. RTP ground data were divided into presence and absence for sagebrush. Presence data were defined as sites that contained a minimum of 5% sagebrush cover of woody *Artemisia* species. The newly classified ground data were used as the binomial response variable. A total of 33 GIS/remote sensing variables were screened as potential predictor variables. The model type was Gaussian and the over fitting controls were set to medium. Sagebrush presence models were created for S1 (S1_SAGE), S2 (S2_SAGE), S3 (S3_SAGE), ST (ST_SAGE). Model strength was assessed using the log β value. The scale for log β interpretation that was incorporated in this study was suggested by Jefferys (1961) and outlined by Kass and Raftery (1995) and used by Yost (2008; Table 2.4). After model creation, a Monte Carlo test was run using 100 iterations to compare the newly created model against random combinations of the input variables. The models were then validated using RTP data that had been randomly withheld from the model creation. To assess the influence of the withheld random points, 10 iterations were done withholding different selections of random points. Validation was an overall accuracy based on a threshold for presence. In the training data scene S1, an additional independent data set of 517 random points collected in the Strawberry Valley in 2009 was used for further validation (described in Westover 2012).

Sagebrush climate envelopes. Using the same presence data as the sagebrush models, response variables were created for the climate models. Climate models were created using Maxent software and the Bioclim data. To reduce the number of predictor variables (19) used in model creation, predictive models were created using the baseline data (1950-1999) and input variables were screened. This was done by withholding different combinations of 25% of the data (20 iterations). The top 5 predictor variables of the averaged models were determined, and climate models were created using these variables for the baseline data (1950-1999) and future dates 2020 (2010-2039), 2050 (2040-2069), and 2080 (2070-2099).

Results and Validation

Sagebrush Presence

S1_SAGE. The S1_SAGE model included 91 samples for model creation and 30 random samples withheld for validation. The best fit binomial model for S1_SAGE had a log β value of 5.04 (Figure 2.5A) and was considered a decisive model according to Kass and Raftery's (1995) model (Table 2.5). The results from the Monte Carlo test (100 runs) produced no randomly created models that were equal to or better than the best fit with a p-value of < 0.01 (p in this case is the proportion of randomized runs with a fit greater than or equal to the observed fit). The mean log β after 10 iterations was 6.34 with a standard deviation of 2.05. Three of the 33 predictor variables were considered statistically relevant in the best fit model. A sensitivity test was used to create the final predictor variable order of importance based on relative influence after more than 300 nudges. The predictor variable order is as follows (sensitivity values and tolerances listed in parentheses): curvature direction of slope (3.72, 0.05), TM band 4 (0.62, 231.2) and elevation (0.05, 731.63). The model's accuracy was an improvement of 71.4% over the naïve model. On the ground, validation (n=30) was done as an overall accuracy using a threshold of 0.6. The overall accuracy was 66.66%. The independent Strawberry Valley data set (n=517) validation had an overall accuracy of 67.31% using the same threshold as above.

S2_SAGE. The S2_SAGE model included 145 samples for model creation and 40 random samples withheld for validation. The best fit binomial model for S2_SAGE had a log β value of 4.68 (Figure 2.5B). The results from the Monte Carlo test (100 runs) produced no randomly created models that were equal to or better than the best fit with a p-value of < 0.01. The top three predictor variables were the same as the S1_SAGE model. The model's accuracy was an improvement of 74.2% over the naïve model. On the ground, validation (n=40) was done with an overall accuracy of 65% using the threshold of 0.6.

S3_SAGE. The S3_SAGE model included 189 samples for model creation and 40 random samples withheld for validation. The best fit binomial model using the same predictor variables as above had a log β value of 4.81(Figure 2.5C) with no randomly created models that were equal to or better than the best fit with a p-value of < 0.01. The model's accuracy was an improvement of 61.90% over the naïve model. On the ground validation (n=40) was done with an overall accuracy of 67% using the threshold of 0.6.

ST_SAGE. The ST_SAGE model included 402 samples for model creation and 36 random samples withheld for validation. The best fit binomial model for ST_SAGE had a log β value of 5.02 (Figure 2.5D) The results from the Monte Carlo test (100 runs) produced one randomly created model that was equal or better than the best fit with a p-value of < 0.02. The three predictor variables from the ST_SAGE model were used in the creation of this model. The predictor variable order differed from the other models with elevation as the strongest predictor variable: elevation (1.01, 224.3), TM band 4 (0.5, 490), and curvature direction of slope (0.06, 1.06). The model's accuracy was an improvement of 67.6% over the naïve model. On the ground validation (n=40) was done with an overall accuracy of 72.22% using a threshold of 0.6.

Climate Envelopes

The initial sagebrush climate models included all 19 bioclim predictor variables. After 20 iterations, the top 5 predictor variables were chosen based on percent contribution to the model. The final model included the top 5 predictors: max temperature of warmest month (42.3%), annual precipitation (18.5%), precipitation driest quarter (7.5%), mean temperature of wettest quarter (6.6%) and precipitation of warmest quarter (5.6%). Using the top 5 predictor variables the AUC was 0.90. The AUC of the withheld test data average after 20 iterations was 0.84 with a standard deviation of .018. Suitable climate for sagebrush habitat is shown for current conditions (Figure 2.6) and future time points: 2020, 2050 and 2080, under the aforementioned climate scenarios (Figure 2.7). Due to the temporal nature of the climate models, no on the ground validation was done. The main objective of these models was to visually represent potential future trends in sagebrush habitat patches.

Discussion

We may never fully know what historic sagebrush cover and distribution was, due to a lack of validation data. However, with improved ecological modeling tools and information availability, we are able to create and validate current sagebrush cover in the west. The Utah sagebrush presence model (ST_SAGE) predicted just over 2.0 million ha of land in the state of Utah to contain sagebrush. The current climate envelope model predicted 6.6 million ha of potential habitat suitable for sagebrush (sagebrush cover over

5%). The general distribution for sagebrush within the climate envelope and the predictive model was similar. Both models predicted the bulk of sagebrush cover to be found in the mountain foothills and plateaus. The climate model predicted suitable climate in higher and lower elevations than the ST_SAGE predictive model. The actual amount of land containing sagebrush in the state of Utah is most likely closer to that predicted by the Utah sagebrush presence model. With sagebrush's wide distribution across the state, it is expected that the potential coverage based on climate variables alone would be much higher.

Overall, the models presented here assigned the highest probability of sagebrush for midelevation valleys, foothills and plateaus. The strongest predictors for sagebrush cover in the models, generated by this study, were curvature direction of slope (profile curvature), TM band 4 and elevation. It is important to note that the output of these models was based on the interaction of the top predictors. However, there is value in assessing the individual predictor influences. Curvature direction of slope had the most influence on sagebrush cover with the exception of the statewide model. The curvature direction of slope is most likely an indication of water movement. The response curve showed a peak at 0.2 indicating that the surfaces most associated with sagebrush in this study are upwardly concave (foot slopes and toe slopes) and linear (lower back slope). TM band 4 reflectance had a linear relationship with sagebrush probability. Near infrared reflectance increases with vegetation cover and leaf area index, so it was expected that sagebrush dominated areas would have lower band 4 reflectance values than forest and wetland areas but higher than other many desert shrub communities. However, exposed dry soils with no vegetation, depending on type, can also have higher reflectance values than sagebrush areas. Elevations between 2200 and 2600m had the strongest influence in predicting sagebrush. This is consistent with elevations where many woody *Artemisia* spp. are generally found (Welsh et al. 2003). This elevation range may be tied to both precipitation and temperatures that are more optimal for sagebrush growth and germination. However, if the binomial ST_SAGE model where to be applied to other geographic regions, elevation thresholds may need to be adjusted. The combination of curvature direction of slope and elevation indicate that large amounts of Utah sagebrush are currently found in the foothills. Within the models, the reduced probability for sagebrush in lower elevation valleys (where precipitation would permit) may be due to anthropogenic factors. For example, in developed areas such as Salt Lake and Utah Valleys, small remnant sagebrush patches are found in contrast to the extensive sagebrush range of the same area in presettlement times (Brotherson and Brotherson, 1981; Beck et al., 2003). By using the temporal component of Landsat band 4, the models are restricted to current sagebrush cover.

The climate models help to identify areas which, under changing climate conditions, have the highest probability to maintain sagebrush populations, anthropogenic factors aside. Identifying areas that are most likely to support sagebrush habitat in the future also provides information about where sagebrush obligates are most likely to persist or migrate in the face of climate change. These models, then, may be used as management tools in assisting long-term protection and management plans of species dependent on sagebrush. All three climate model series showed extreme reduction of potential climate for sagebrush by the year 2080 with a slight shift to higher elevations. Of the climate models, series A2 showed the greatest loss (using the 10 percentile training threshold) with current potential decreasing by approximately 72% by 2080. Series B2 showed the least amount of loss with a reduction of approximately 50% by 2080. The models do not account for plant resilience to change and therefore the reduction may be less. However, while sagebrush cover change may vary according to various applied future scenarios, it is evident that loss to sagebrush ecosystems due to climate change will occur across its range.

The models presented here can be used as rapid assessments for sagebrush cover. Combined with ground validations and expert knowledge, these maps, if updated regularly, could provide a valuable tool in landscape management of sagebrush ecosystems. As range trend data continue to be collected on an annual basis, the sagebrush models could be updated to reflect changes to sagebrush cover frequently. Additionally, other data sets (areas burned etc.) could be incorporated into model updates, as long as spatial and temporal components were compatible. The models presented here were not intended to be used over long periods of time. Rather, they were designed to be a starting sagebrush cover map for future revisions and enhancement with other data sources.

Conclusions

It was found that a statewide sagebrush model with management level resolution (30m) is possible. Furthermore, with the ease of replication, availability of the data, and the low costs of software, sagebrush models could be produced at regular intervals and could be continually improved upon. DWR's big game range trend data may prove to be a valuable asset in future habitat modeling on the statewide scale. Although the sagebrush models did not fully cover all areas within the state, the overall coverage provides valuable information that could be utilized for sagebrush patch dynamics and landscape level corridor studies. In conjunction with climate envelope models and field biologists, at risk and more stable sagebrush areas could be identified and tracked at the landscape scale. Sagebrush and its obligate species go beyond the borders of Utah. The models presented here were trained in one Landsat TM scene and spatially scaled up to cover the entire state without a decrease in accuracy, suggesting the possibility to extend the model to cover the extent of sagebrush range in western North America.

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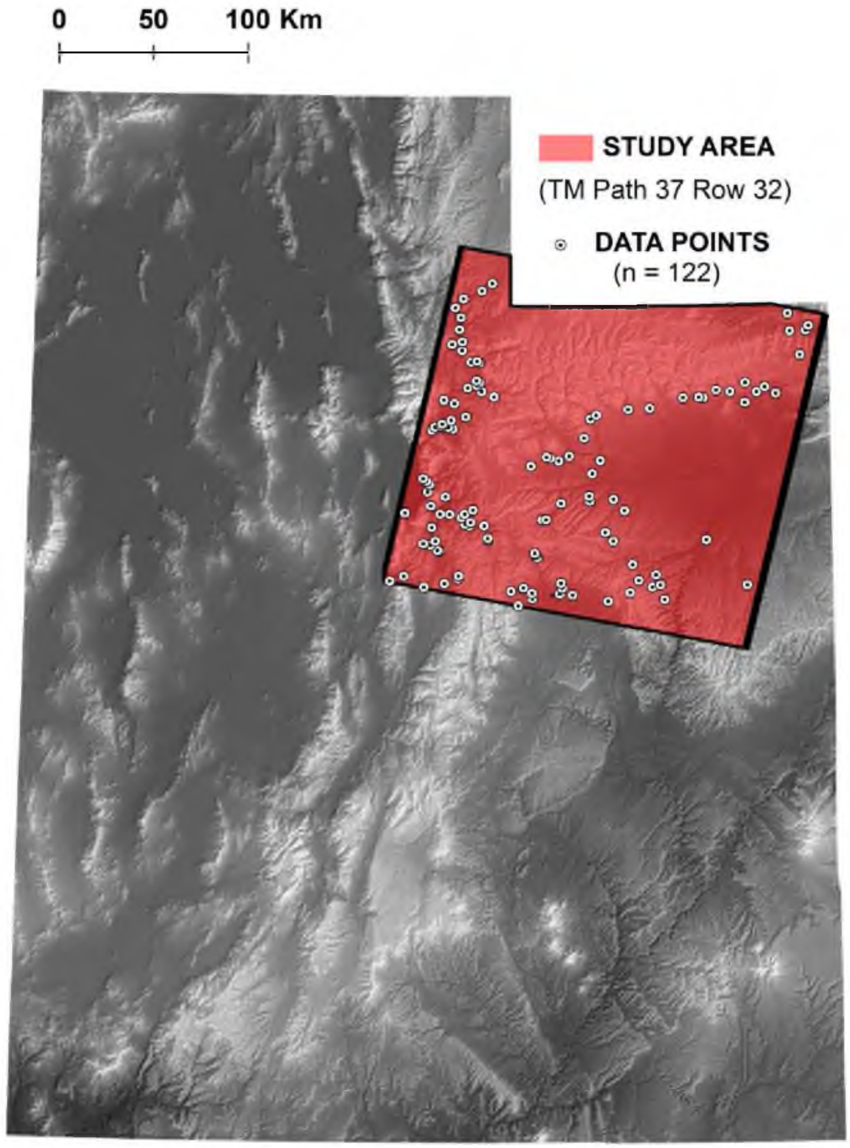

Figure 2.1: Landsat TM training scene 3732 (S1). Data points represent Utah Big Game Range Trend study sites found in S1.

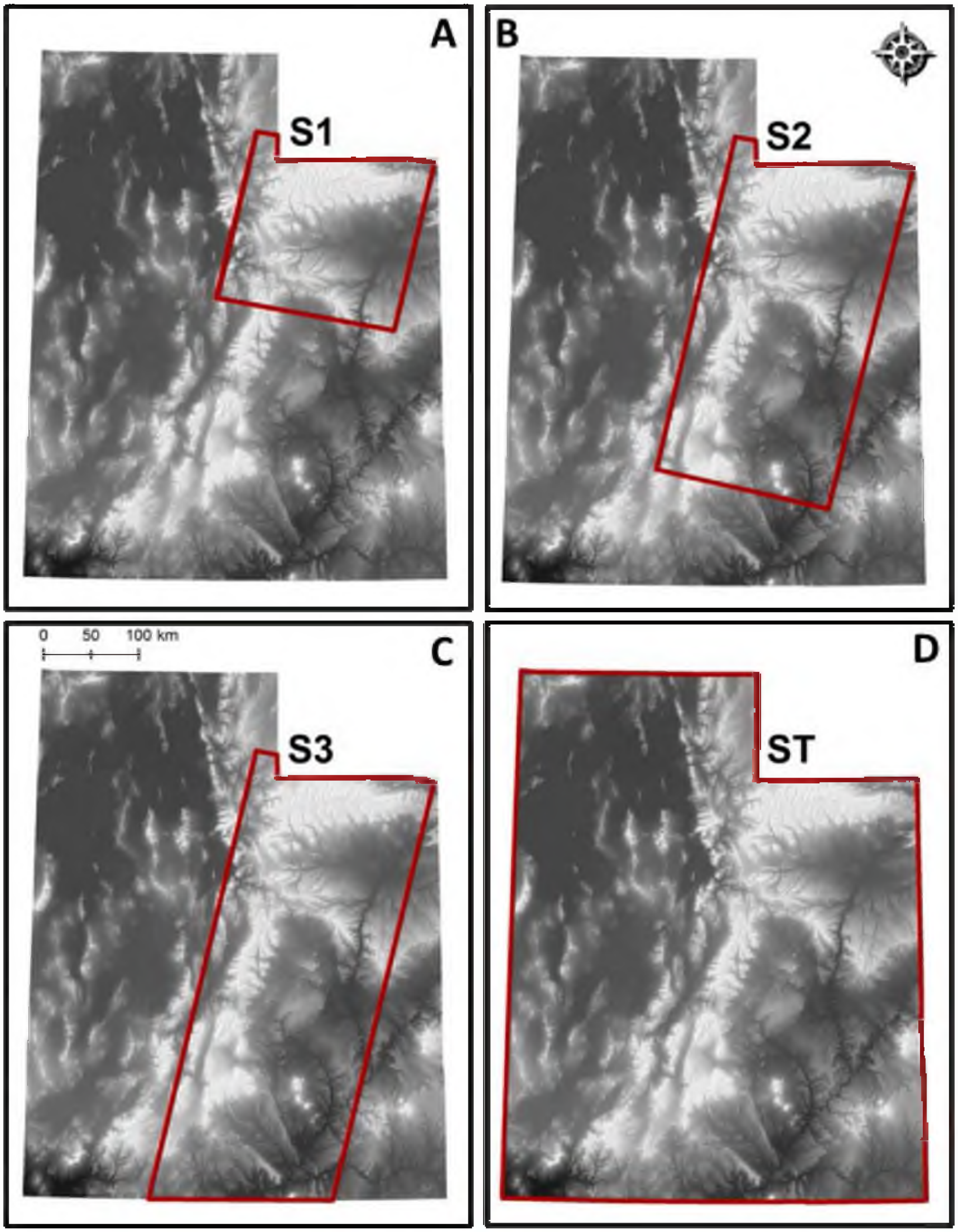

Figure 2.2: Spatial extents that the sagebrush predictive models were applied to. A) TM Path 37 Row 32 (S1). B) TM Path 37 Row 32 and 33 (S2). C) TM Path 37 Rows 32, 33, and 34 (S3). D) The entire state of Utah (ST)

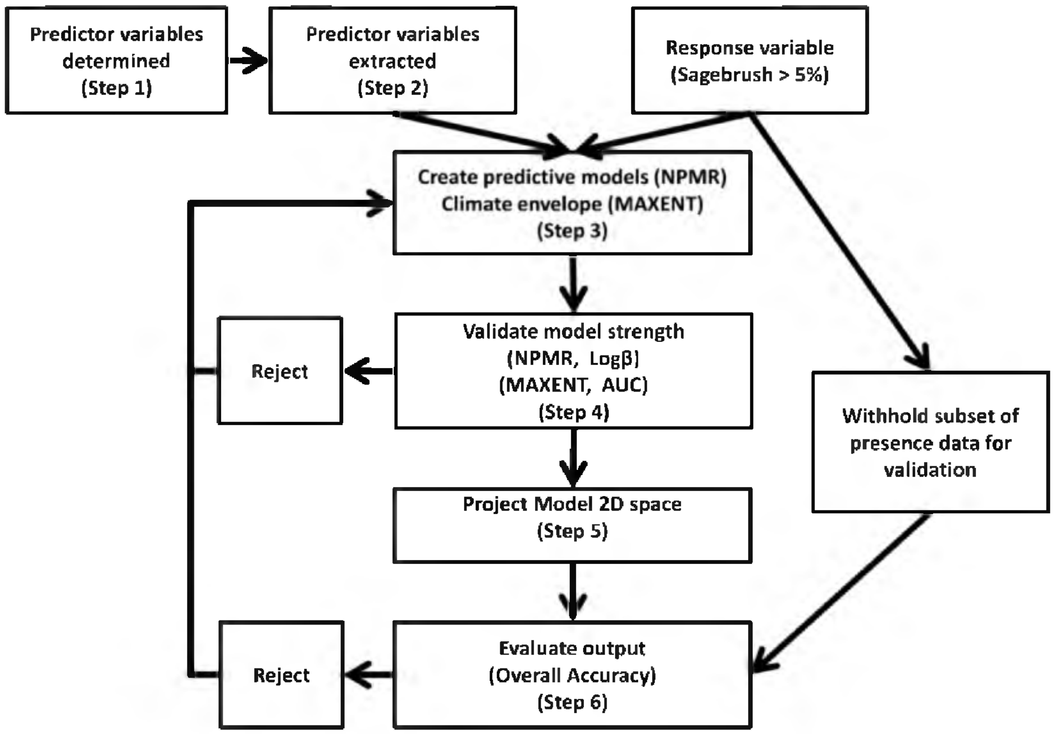

Figure 2.3: General model workflow.

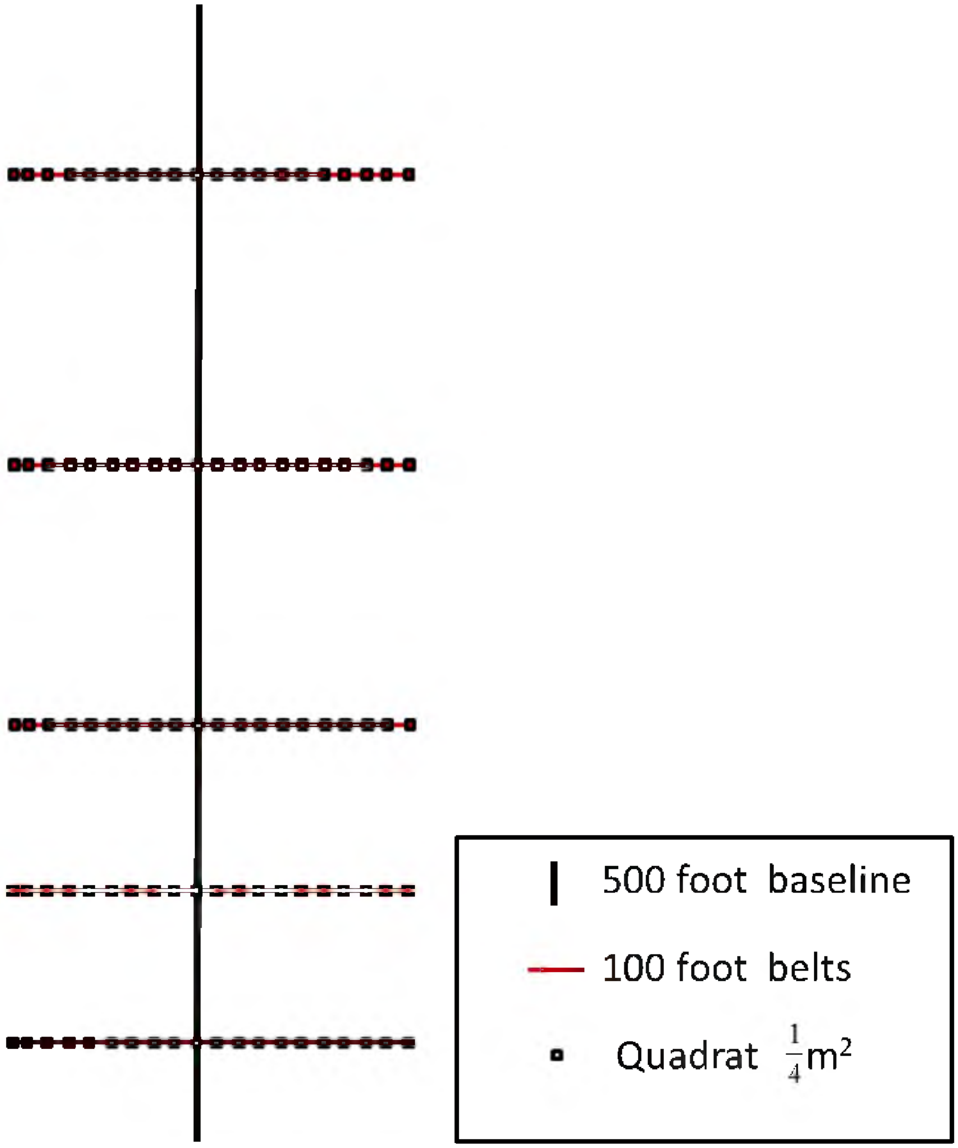

Figure 2.4: Range trend project sites are set up along a 152m transect, each with 5 30m perpendicular transects (belts) placed randomly on the baseline centering on the 15m mark of the perpendicular belt. A quarter m squared quadrat is placed every 1.5m along the belt for a total of 20 quadrates for each belt, totaling 100 quadrates for the site.

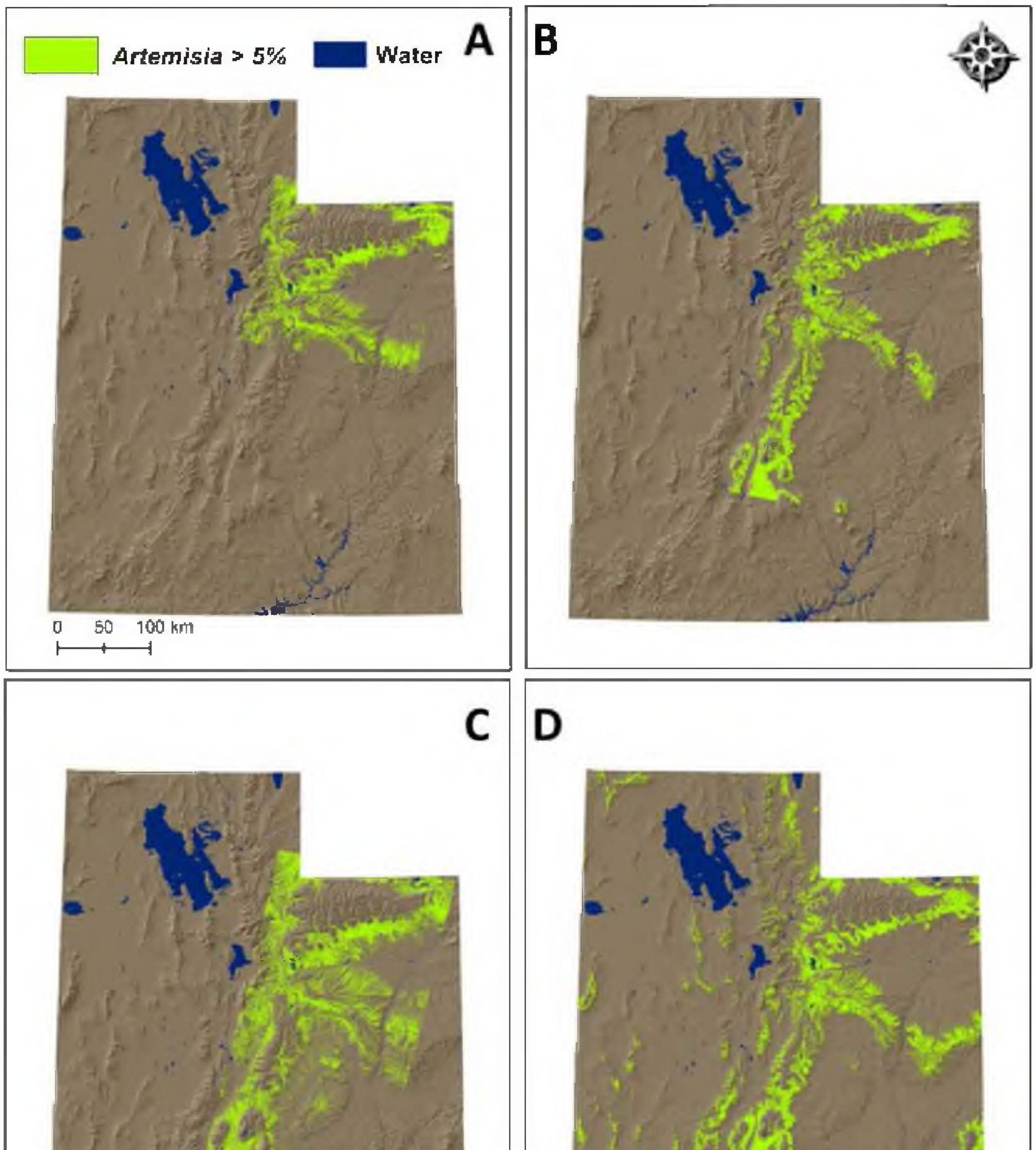

Figure 2.5: Sagebrush presence models: A) S1_SAGE, B) S2_SAGE, C) S3_SAGE and D) ST_SAGE.

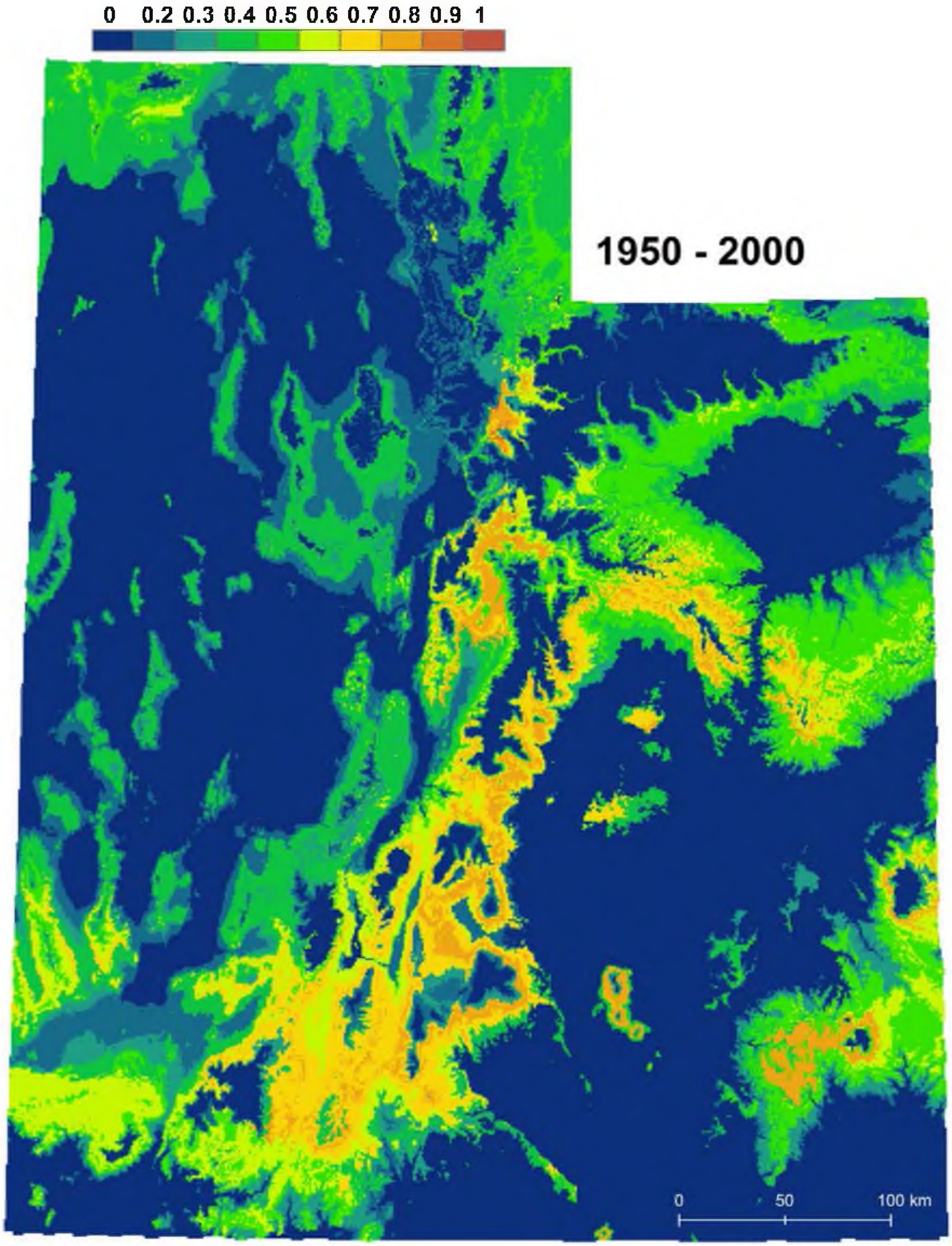

Figure 2.6: Predicted climate envelope for woody sagebrush (1950-2000).

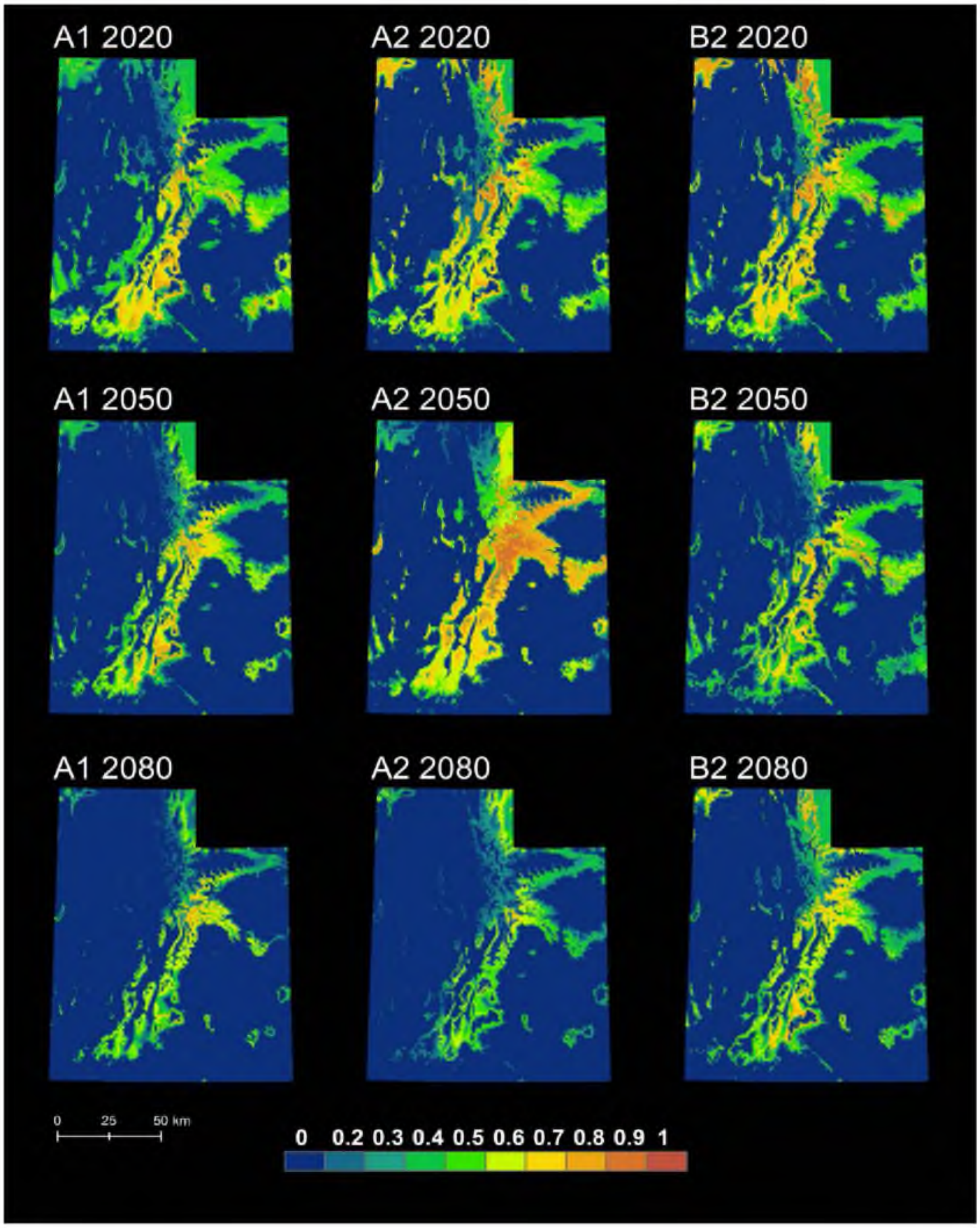

Figure 2.7: Future projections for suitable sagebrush climate for 2020, 2050 and 2080 across three climate scenarios: A1, A2 and B2.

Table 2.1: Estimated cover of sagebrush species and subspecies within the state of Utah, USA, from Beetle (1960). Scientific names are taken from http://plants.usda.gov/java/. * Wyoming big sagebrush was not listed separately in the original estimation, but was a substantial part of the Basin big sagebrush estimates.

UTAH SAGEBRUSH (1960)		
Scientific Name	**Common Name**	**Estimated cover (hectare)**
Artemisia tridentata Nutt. ssp. tridentata **Artemisia tridentata* Nutt. ssp. *wyomingensis*	Basin big sage *Wyoming big sagebrush	3,366,984
Artemisia nova A. Nelson	black sagebrush	2,589,988
Artemisia bigelovii A. Gray	Bigelow sage	2,071,990
Artemisia tridentata Nutt. ssp. *vaseyana* (Rydb.) Beetle	mountain big sagebrush	1,812,992
Artemisia cana Pursh ssp. viscidula (Osterh.) Beetle	silver sage	776,996
Artemisia arbuscula Nutt. ssp. longiloba (Osterh.) L.M. Shultz	little sage	25,899
Artemisia tridentata Nutt. ssp. *spiciformis* (Osterh.) Kartesz & Gandhi	big sage	2,590
Artemisia pygmaea A. Gray	pygmy sagebrush	2,590
Artemisia arbuscula Nutt. ssp. *Arbuscula*	little sagebrush	2,590
Artemisia tripartita Rydb. ssp. *tripartita*	three tip sagebrush	259
Artemisia arbuscula Nutt. ssp. *thermopola* Beetle	little sagebrush	259
		Total 10,653,137

Table 2.2: Bioclim climate variables used in creating the sagebrush climate envelopes.

Bioclim Variables Used in Climate Envelopes	
Name	**Description**
BIO1	Annual Mean Temperature
BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp))
BIO3	Isothermality (BIO2/BIO7) (* 100)
BIO4	Temperature Seasonality (standard deviation *100)
BIO5	Max Temperature of Warmest Month
BIO6	Min Temperature of Coldest Month
BIO7	Temperature Annual Range (BIO5-BIO6)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO10	Mean Temperature of Warmest Quarter
BIO11	Mean Temperature of Coldest Quarter
BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Month
BIO14	Precipitation of Driest Month
BIO15	Precipitation Seasonality (Coefficient of Variation)
BIO16	Precipitation of Wettest Quarter
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter
Table data from Bioclime website (http://www.worldclim.org/bioclim)	

Table 2.3: DEM derived data used in the habitat models.

DEM Derived Data	
Name	Description
Relative Elevation	Digital elevation model (DEM)
Slope	Slope assessed at 30 m intervals created from the DEM. Slope is a calculation of maximum rate of change in elevation between the cell and its eight neighbors.
Aspect	Aspect assessed at 30 m intervals created from the DEM. Aspect is the direction of the slope.
Curvature	Curvature derived from a DEM was used to identify the physical characteristics defining drainage basins often used to understand erosion and runoff processes.
Curvature Direction of Slope	The direction of the maximum slope derived from a DEM
Iverson Moisture Index (IMI)	Used to asses topographically influenced moisture availability using the DEM derived layers hillshade, flow accumulation and curvature.

Table 2.4: The scale for log β interpretations from Kass and Raftery (1999).

Value	Interpretation
0 - 0.5	no worth
0.5-1.0	Substantial
1-2.0	Strong
>2	Decisive

Table 2.5: Sagebrush presence models by spatial extent. * The 517 validation points are from the independent data set that came from Westover (2012).

Sagebrush Presence Models					
Model Name	Training Locations	Logβ	Predictor Variable Order (sensitivity, tolerances)	Improvement Over Naïve Model	Overall Accuracy
S1_SAGE	n = 91	5.04	curvature direction of slope (3.72, 0.05), TM band 4 (0.62, 231.2) and elevation (0.05, 731.63)	71.40%	(n = 30) 66.66% (n = 517)* 67.31%
S2_SAGE	n = 145	4.68	curvature direction of slope (2.62, 105.1), TM band 4 (1.18, 281) and elevation (1.06, 277.7)	74.20%	(n= 40) 65%
S3_SAGE	n = 189	4.81	curvature direction of slope (0.86, 272.3), TM band 4 (0.64, 449.1) and elevation (0.46, 458.3)	61.90%	(n = 40) 67%
ST_SAGE	n = 402	5.02	elevation (1.01, 224.3), TM band 4 (0.5, 490), and curvature direction of slope (0.06, 1.06).	67.60%	(n=40) 72.22%

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CHAPTER 3

A METHOD FOR CLASSIFYING AND MONITORING TOTAL VEGETATION COVER ACROSS SPATIAL AND TEMPORAL SCALES WITH AN APPLICATION TO SAGE-GROUSE HABITAT

Abstract

The objective of this paper was to create and validate a total vegetation cover model that could be applied across a diverse landscape with a spatial resolution of 30m. In addition, the model was created across multiple temporal periods in the same area to identify locations of total vegetation cover change over time. Model creation was accomplished with a generalized additive model (GAM). When compared to ground data, the best model for the entire state of Utah had a root mean square error (RMSE) between 6.6 and 7.6% cover. Furthermore, an application was tested using total vegetation cover models to identify areas of vegetation cover change within sage-grouse habitat. It was found that, across all sage-grouse life stages, the majority of areas in which sage-grouse were located had increased in vegetation cover between 1988 and 2009.

Introduction

Understanding the distribution of vegetation cover is an important component in many scientific studies and management applications These range from creation of global climate models to identification and management of individual species' habitats

(Pettorelli et al., 2005; Zeng et al., 2000; Gregg et al., 1994). Furthermore, accurately mapping the change in vegetation cover over multiple temporal periods can be used to identify seasonal and annual vegetation variability within a range of a species habitat. Traditionally, before the advent of aerial photography and other remote sensing platforms, vegetation type and cover estimates had been limited to *in situ* studies at relatively small spatial scales. Often data collection and scaling up of ground estimates are further restricted by limited budgets, land ownership permissions and safe accessibility of rugged terrain. These obstacles further constrain the connectivity and completeness of these data at the landscape level. With the introduction of remote sensing data, many ecological assessments done on the ground, such as biophysical characteristics of species habitat, can be augmented, minimizing the influence of these limitations at a variety of spatial scales (Kerr and Ostrovsky, 2003).

Remote sensing data allows for continuous information to be taken across vast areas at a variety of spatial scales. Remote sensing, in conjunction with well placed *in situ* data and effective use of Geographic Information Systems (GIS) makes for a set of powerful ecological tools (McVicar and Jupp, 1998). The use of remote sensing to document and determine vegetation cover, biomass and ecosystem health at a variety of spatial scales is rapidly growing (Ramsey et al., 2004). The objective of this study was to assess if multitemporal *in situ* data, measured by the Utah Division of Wildlife (UDWR), could be used in conjunction with Landsat Thematic Mapper (TM) imagery to model total vegetation cover across a relatively broad spatial scale (the state of Utah). The target accuracy was set at a root mean square error (RMSE) of < 10% compared to the ground collected vegetation cover estimates. Additionally, for a case study, change in cover was estimated across two decades of TM images. Multiple greater sage-grouse (*Centrocercus urophasianus*, hereafter referred to as sage-grouse) habitat patches were assessed. The focus of the change analysis application was to identify if sage-grouse habitat utilization occurred in habitat with minimal to no change, or in dynamic habitat types.

Sage-grouse habitat type in this study is broken down into three broad categories based on the life stages: nest, brood rearing and winter. Nests are typically found under sagebrush plants in areas dominated by woody sagebrush within or close to winter and early brood habitat (Connelly et al., 2011). Management suggested sagebrush cover for nest habitat is between 15 and 25% (Connelly et al., 2000). In general, brood rearing (brooding) refers to early care of the sage-grouse chicks. Brooding habitat is a combination of early and late brood rearing. Early brooding is defined by Connelly et al. (2000, 2011) as sagebrush-dominated habitat near the nest. Early brooding is typically occupied for several weeks after hatching (Berry and Eng, 1985; Connelly et al., 2011). These areas are usually rich in insects and forbs. Late brooding coincides with a diet transition from predominantly insects to forbs and sagebrush (Connelly et al., 2011). Sagebrush cover for late brooding (summer) habitat is usually >20% (Braun et al., 2005). Winter habitat is dominated by taller woody sagebrush. During this time, sage-grouse almost exclusively feed on sagebrush (Crawford et al., 2004). Sagebrush cover in winter habitat can vary from 6% to 43% but tends to be on the higher side (Connelly et al., 2011; Braun, 2005; Schroeder et al., 1999). I predicted that nest location selection would be more sensitive to vegetation cover changes than brooding or winter habitat due to its tighter sagebrush cover window.

Methods

Study Area (Total Vegetation Cover)

The state of Utah was selected as the study area for the production of a vegetation cover model because of the vegetation diversity, wide range of habitat types, data availability and presence of sage-grouse habitat in the region. Landsat 5 Thematic Mapper (TM) data were used to subdivide the state into four spatial extents (Figure 3.1). The objective of identifying different spatial scales was to assess if vegetation cover models trained at a smaller spatial scale with a smaller data set, such as a single TM scene, could be used to model vegetation cover across larger areas.

The model training site was defined by Landsat TM Path 37 Row 32 clipped to Utah (TV1; Figure 3.1). TV1 was chosen due to its geographic and vegetative diversity, sagebrush cover, imagery availability, and identified sage-grouse habitat patches. Modeling was applied to three additional spatial extents: 1) TM Path 37 Rows 32 and 33 (TV2, 6.5 million ha), 2) TM Path 37 Rows 32, 33 and 34 (TV3, 8.6 X 10^6 ha), and 3) the entire state of Utah (TVST, 21.9 million ha; Figure 3.1).

Study Area (Vegetation Cover Change)

The change in vegetation cover analysis study area was defined as the Fruitland sage-grouse brooding nest and winter habitat found northeast of Strawberry reservoir, Utah, characterized by the 2013 Utah greater sage-grouse land use plan (UDWR/BLM/USFS draft; Figures 3.2 and 3.3). This area was chosen to determine if there were any patterns associated with sage-grouse location and past vegetation cover change. Change in vegetation cover models created across multiple time periods were utilized to identify and quantify areas of predicted changing vegetation cover. The final model assessed change between 1988 and 2009

To assist in the interpretation of the modeled vegetation cover change, the following graphs were created: annual precipitation, spring precipitation, winter precipitation and the Palmer Drought Severity Index (PDSI; Figures 3.4-3.6). The PDSI was first introduced by Palmer (1965) and is now a widely used metric to identify periods of drought in the United States (Heim, 2002). The PDSI is an approximate measure of the departure from the expected cumulative effects of the atmospheric moisture supply and the soil water demand (Dai et al., 2004).

Model Creation

Model creation followed three general steps, broken into multiple processes (Figure 3.7). To begin, response and predictor variables were obtained or created. Second, a statistic model was generated and validated. If the model was statistically accepted ($R^2 > 0.5$), then a predictive model was projected in 2D space across the study area and validated. Vegetation cover modeling was done utilizing a semiparametric generalized additive model (GAM, Hastie & Tibshirani, 1986) and Nonparametric Multiplicative Regression (NPMR; McCune and Mefford, 2004). The GAM models were created with Marine Geospatial Ecology Tools (MGET; Roberts et al., 2010) and the NPMR models were created with the software package Hyperniche 2.0 (MJM Software, Glendale Beach, Oregon). The response (dependent) variable, vegetation cover, was obtained from the UDWR big game range trend data (range trend). These data were used as the ground data for all model creation and validation.

Twenty-five remote sensing GIS derived predictor (independent) variables were generated for this study. To reduce the total number of predictor variables in model creation, NPMR was used to screen the top variables. Using the prescreened predictor variables, GAM and NPMR models were created. Model creation was based on R^2 (GAM) and the more conservative cross R^2 (xR^2, NPMR). Variable importance was based on p-values (GAM) and sensitivity (NPMR). To find the strongest predictive models within the available data, multiple approaches were tested. First, TV1 was used to train the models, after which the model rules were applied to the larger areas. Once acceptable, models were identified, the results were compared and smoothing splines added. Alternatively, the same areas were modeled, but instead of using scene TV1 as a training site, each new area was modeled independently.

Once predictive models were made, validation was done by using random points that had been withheld from the original model creation. It was expected that the modeled vegetation cover would vary slightly from the ground collected data. This variation is due in part to the fact that the ground data used an average of several different human observers' interpretations of the multidimensional vegetation cover. The remote sensing derived data is created with one sensor and in many cases, assesses only the top, or a cumulative reflectance pattern. This view may not penetrate all the layers of the vegetation canopy. Additionally, the sensor is limited to an average value found within a 30m cell, not always centered on the ground data. The actual vegetation cover at the proposed 30m resolution cells may, in fact, be a value between the ground collected data and the modeled data. The overall accuracy was evaluated using RMSE. Influence of the random points withheld was minimized by performing 10 iterations of differing random points for each model. In addition, smoothing splines were also assessed for three of the four areas modeled: TV1, TV3, and TVST. Overall performance for the final model selection was judged on a combination of model creation (R^2), validation (RMSE), and coverage (ha modeled).

Change Analysis

Due to data and time constraints, change in vegetation cover was assessed on one sage-grouse habitat patch located in TV1 (Figures 3.2 and 3.3). Prior to any change analysis, images were co-registered to the 2009 image (RMSE < 1 pixel) and atmospherically corrected. The change method used was a form of post classification comparison (Singh, 1989) using GAM vegetation cover models. Past vegetation cover models were created using the training data from the 2009 model in conjunction with TM data from fall 2005, 1998, 1993 and 1988. Original dates were chosen based on a five year interval, with some adjustment made due to availability of suitable TM imagery. Ground validation data for vegetation cover and change were available for 1998 and 2005. However, due to a lack of sufficient range trend data for the other years within the study area, validation was not possible for all years. Model outputs were validated using RMSE between the vegetation cover models and the ground data.

It is important to note that vegetation cover change does not equate vegetation type change. Furthermore, increased cover is not the same as improved cover. For example, a sagebrush stand that increased in invasive species may also have increased in overall cover (Ramsey et al., 2004).

Input Data

Response variable. Vegetation cover at each ground location was estimated by the UDWR Big Game Range Study. This study is a long-term monitoring program that collects vegetation and soil data across the state of Utah. Range trend data are used by researchers and land managers to make informed decisions on long-term range management. Vegetation cover is defined as the total contribution of all vegetation types. At each site, ocular cover estimates were made on 100 quarter m^2 quadrats across a 152 two m transect. The average vegetation cover obtained across the site was defined as total vegetation cover (UTDWR, retrieved 11/2012). For a more in depth description of the ground data methods see http://wildlife.utah.gov/range/pdf/2011%20Methods.pdf

Predictor variables. Despite the relatively large number of predictor variables prescreened, the top variables were Landsat 5 TM band 7, normalized difference infrared index ($NDII_5$; Hardiskey et al., 1983; Hunt and Rock, 1989), the second modified soil-adjusted vegetation index (MSAVI2; Qi et al., 1994) and digital elevation (DEM) derived aspect.

TM imagery was downloaded for 9/11/2009, 8/31/2005, 8/28/1998, 9/15/1993, and 9/01/1988 from the USGS server in 2012 (http://www.usgs.gov/). All TM scenes were preprocessed by converting digital numbers to radiance values and then atmospherically correcting to percent reflectance. Percent reflectance conversion for TM bands 1-5 and 7 was done in ENVI using the atmospheric correction algorithm FLAASH, developed by the US Air Force Philips Laboratory (Hanscom AFB, Bedford, MA) and Spectral Sciences, Inc. (Burlington, MA). For additional FLAASH information, see Adler-Golden et al. (1999). Following atmospheric correction, TM images were used to create the vegetation indices. $NDII_5$, was one of several vegetation indices proposed by Hunt and Rock in 1989 as a means to identify water content in vegetation. $NDII_5$ here, used TM bands 4 (0.76- 0.90μm) and 5 (1.55-1.75μm).

$$\text{NDII}_5 = \frac{(\rho_{b4} - \rho_{b5})}{(\rho_{b4} + \rho_{b5})}$$

MSAVI2 is a modification of Huete's Soil-Adjusted Vegetation Index (Huete, 1988; Seseman, et al., 1996; Qi et al., 1994). MSAVI2 was designed to reduce the influence of exposed soil when estimating vegetation cover with remote sensing. Senseman et al. (1996), assessing vegetation cover, found that MSAVI, when compared to other vegetation indices, had a higher correlation with ground collected data than other similar indices. MSAVI2 here used TM bands 4 and 3 (0.63 – 0.69).

$$\text{MSAVI2} = \frac{\left(2 \times \rho NIR_{b4} + 1 - \sqrt{\left((2 \times \rho NIR_{b4} + 1)^2 - 8 \times (\rho NIR_{b4} - \rho RED_{b3})\right)}\right)}{2}$$

Results and Validations

The NPMR model for TV1 study area used 67 samples for creation and 30 samples for validation. The model had an xR^2 value of 0.706 (Figure 3.8, Table 3.1). The average xR^2 value after 10 iterations was 0.705 with a high of 0.850 and a low of 0.614 and a standard deviation of 0.07. The results from a Monte Carlo test (100 runs) produced no randomly created models that were equal to or better than the best fit with a p-value of < 0.01. Four of the 33 screened predictor variables were relevant to the model creation. A sensitivity test was used to create the final predictor variable order of importance based on relative influence after more than 300 nudges. The predictor variable order was as follows (sensitivity values and tolerances listed in parenthesis, respectively): MSAVI (1.89, 0.07), B7 (1.40, 410.1), aspect (0.20, 138.7), and NDII5 (0.17, 0.13). Thirty validation points were withheld; however, five of the withheld points fell in areas not modeled leaving 25 validation points. On the ground, validation (n=25) provided an RMSE of 7.7% cover (Table 3.1).

The GAM model for the TV1 area used the same samples for creation and validation as the NPMR model (Figure 3.8, Table 3.1). Models were created both with and without splines. The R^2 value for model creation was 0.58 without splines. After 10 iterations of random samples withheld, the average R^2 was 0.60 with a high of 0.64 and a low of 0.55 and a standard deviation of 0.03. After splines had been added, the model improved to a R^2 of 0.70. The 4 variables identified by the NPMR model were used with the order of importance based on p values. The order without splines was as follows, with the p-values in parenthesis: MSAVI2 (1.19E-07), NDII5 (6.09E-06), B7 (0.02), and aspect (0.72). With the addition of splines, the order and p-values were MSAVI2 (5.90E-06), NDII5 (1.52E-4), B7 (0.291) and aspect (0.81). Of the 30 validation points withheld, all fell within the area modeled. The RMSE for the GAM TV1 was 7.3% cover. The RMSE with splines was 7.2% cover.

Only GAM models were scaled up due to overall area covered and similarity in results. The NPMR TV1 area modeled with vegetation cover was roughly 1,100,852 ha compared to the TV1 (without splines), 2,561,753 ha (Table 3.1). The NPMR had a RMSE of 7.7% cover and the GAM (without splines) was 7.3% cover. Furthermore, 200 random points were generated within the training area of TV1 to compare how similar the two model outputs were. Of the 200 points, 119 (60%) fell in areas not modeled by the NPMR model. Only 45 fell outside the GAM model (22%). A total of 68 points fell within both. Using a matched pairs t-test, the random points were compared. It was found that the mean difference in vegetation cover estimates across data points found in both models was only 0.7% with a standard error of 0.53 and correlation coefficient of 0.92. The null hypothesis that there is a difference between the two models' means is rejected with a p value of 0.19. It is important to note that this does not demonstrate which model is more similar to the actual (ground) data, merely that the GAM and the NPMR models are similar to each other.

The GAM model TV2 extent was created using the training data from scene 3732 (Figure 3.9, Table 3.1). Randomly withheld validation points (n=82) were used for accuracy assessment. Because the same model creation data were used from TV1, the R^2 and predictor variables are the same. The RMSE was 5.7% cover. Splines were not created for this model.

GAM models for the TV3 extent were created using the training data from scene TV1 (Figure 3.9, Table 3.1). Additionally, TV3 models were created using additional data points located within the TV3 area. Randomly withheld validation points (n=130) were used for accuracy assessment. Model creation using data from TV1 had the same R^2 and predictor variables. After splines had been added, the model improved to a R^2 of 0.70. Not trained in 3732, the model had an R^2 of 0.49. The RMSE for TV3 trained with TV1 was 7.3% cover. With splines, the RMS was slightly worse at 8.6% cover. Not trained in 3732, the RMSE improved slightly to 7.0% cover.

GAM models TVST were created using the training data from scene 3732 as well as training the model using the entire state (Figure 3.9, Table 3.1). Randomly withheld validation points (n=399) were used for accuracy assessment. After splines had been added, the model improved to a R^2 of 0.70. Not trained in TV1, the model had an R^2 of 0.39. The RMSE was 7.6% cover. With the addition of splines, the RMSE improved to7.1%. TVST not trained in 3732 had RMSE of 6.7% cover.

Change Analysis

Coverage and RMSE for the validated past GAM vegetation cover models were similar to the original 2009 model (Figure 3.10, Table 3.2). The RMSE for 2005 and 1998 was 5.6% cover.

Total vegetation cover changes (at each pixel) were used to compare to sage-grouse locations (Figure 3.11, Table 3.3). Sage-grouse brood and nest locations were more associated with areas that have increased in vegetation cover from 1988 to 2009 with mean vegetation cover increases of 3.9% and 3.7%, respectively. The mean percent vegetation change for sage-grouse winter locations was an increase of 1.2% and the change in vegetation cover for 100 random points was an increase by 0.1%. Nest, brood and winter means were significantly different than the random points with p values $< .005$. However, these changes are all less than the RMSE of the models and should be interpreted with caution.

Discussion

The main objective of this study was to assess if multitemporal *in situ* data, taken by the Utah Division of Wildlife (UDWR), could be used in conjunction with TM imagery to model total vegetation cover across a relatively broad spatial scale. This was accomplished by statewide total vegetation cover models with a RMSE between 6.6 and 7.6% (Table 3.1). It was found that vegetation cover can be accurately modeled at the statewide extent. Although Utah has a diverse landscape when assessing total vegetation, it is reasonable to use one Landsat TM scene (TV1) to train a model that could be applied across the state of Utah, as well as other similar areas, potentially. There did not seem to be a clear trend in model improvement (as defined as decrease in RMSE) with the addition of more training data points beyond the initial 67 for model creation in TV1. This lack of trend is demonstrated by scaling up the models without training in 3732 and using additional data points in model creation. It was also found that it is possible to train a vegetation cover model in one temporal period and apply it across multiple years without sacrificing accuracy.

In regards to using vegetation cover models for change in vegetation cover, GAM models could be useful tools in assessing changes in cover within sage-grouse habitat.

Vegetation cover models such as the one presented here, can be used as meaningful change analysis tools. These models can provide information on amount and type of change (increase, decrease, other). Vegetation cover models used as a metric for change analysis allows for relevant intuitive thresholds to be applied. For example, if a particular species is sensitive to a decrease in vegetation cover of 10%, the models could be adjusted to identify only areas that fit those criteria directly.

The change in cover between time periods, aside from the agricultural areas, seemed to be predominately increasing or decreasing in vegetation cover throughout the study area. One reasonable explanation for this would be that climate variables such as temperature and precipitation are the major drivers of the vegetation cover change seen in the models. This would be manifested by years with more water availability having higher vegetation cover values overall (increased forbs, more leaf production etc.). However, vegetation cover from one year is also influenced by the preceding years' moisture amount and timing (Figures 3.9-3.11). For example, the vegetation cover of a wet year that was preceded by several consecutive dry years (1993) may still appear less, than a wet year proceeded by several wet years (1998). Additionally, one slightly wet year found in the middle of a dry period (2005) may have similar total vegetation cover as one of the following dry years (2009). Bates et al. (2005) manipulated precipitation patterns in a sagebrush steppe community and found that many vegetation cover and biomass shifts did not begin until after four years of treatment. They also demonstrated that when the precipitation was received (spring or winter) influenced the overall vegetation cover of the site. After reviewing the precipitation and PDSI charts, it is plausible that the modeled change in vegetation cover is tied to water availability. Therefore, areas that showed little to no change may be dominated by more drought resistant shrubs (masking the influence of the present forb and grass components), contain very little forb/grass understory or have access to other moisture sources such as a springs. Additionally, some of the modeled change may be an artifact influenced by differences in the anniversary dates of the images used or errors in the model due to the changes being less than the RMSE.

Change analysis provided some insight to sage-grouse habitat selection patterns based on areas of total vegetation cover changes. The processes that form these patterns may be important to future long-term management of sage-grouse. In the example given, the spatial resolution of 30m was sufficient for mapping and monitoring. This resolution agreement is due to the large spatial range occupied by sage-grouse. However, it is difficult to know the optimal temporal interval to detect meaningful change for this species and additional studies are needed. Furthermore, it was difficult to find cloud free imagery for any interval for the habitat patch selected. Areas of decreased total vegetation cover were not heavily utilized by sage-grouse, as demonstrated by their distribution. By identifying areas of change in relation to habitat we can now work to better understand these patterns and the processes, natural or otherwise, that drive them. In some cases the changes that occurred were obvious, as well as the causes (i.e., human altered croplands). In other instances, areas within the sagebrush stands showed change that may have been a result of drought stress or other natural influences.

With the growing availability of GIS and remote sensing data, vegetation cover models could be applied in multiple ecosystems across a variety of temporal periods. Vegetation cover models could be used as a tool for a variety of research and management questions beyond what was presented here. For example, aspen leaf drop or stand death could be tracked from year to year. Additionally, vegetation monitoring could be supplemented with monthly or even daily (depending on the sensor used) modeled vegetation cover estimates. Multitemporal vegetation cover models could potentially be used to identify influences of annual species on overall vegetation cover over time. Future work will focus on applying similar modeling techniques to finer and broader areas as well as application to other sensors.

Conclusions

GAMs can be used to create landscape level vegetation cover models at multiple temporal scales with a reasonable error. Landsat TM was an important sensor for this study providing long-term remote sensing layers at a 30m resolution. Although ground data specifically taken for the purpose of remote sensing analysis are preferred, long-term vegetation monitoring data sets such as the Utah range trend data can be valuable for ecological modeling. Total vegetation cover models that span multiple years can be used as an additional tool in understanding past and current wildlife habitat selection. Future work will focus on creating finer resolution models that predict cover across the same broad scale. Change in cover models created at the seasonal level (spring, summer, winter) rather than annually will also be explored, to improve the interpretability and use of these models.

Acknowledgements

The Bureau of Land Management, The Utah Division of Wildlife, Utah Big Game Range Trend (Federal Aid Grant W-82-R), The Nature Conservancy, Utah State University and the many others who have contributed time, money, data and support.

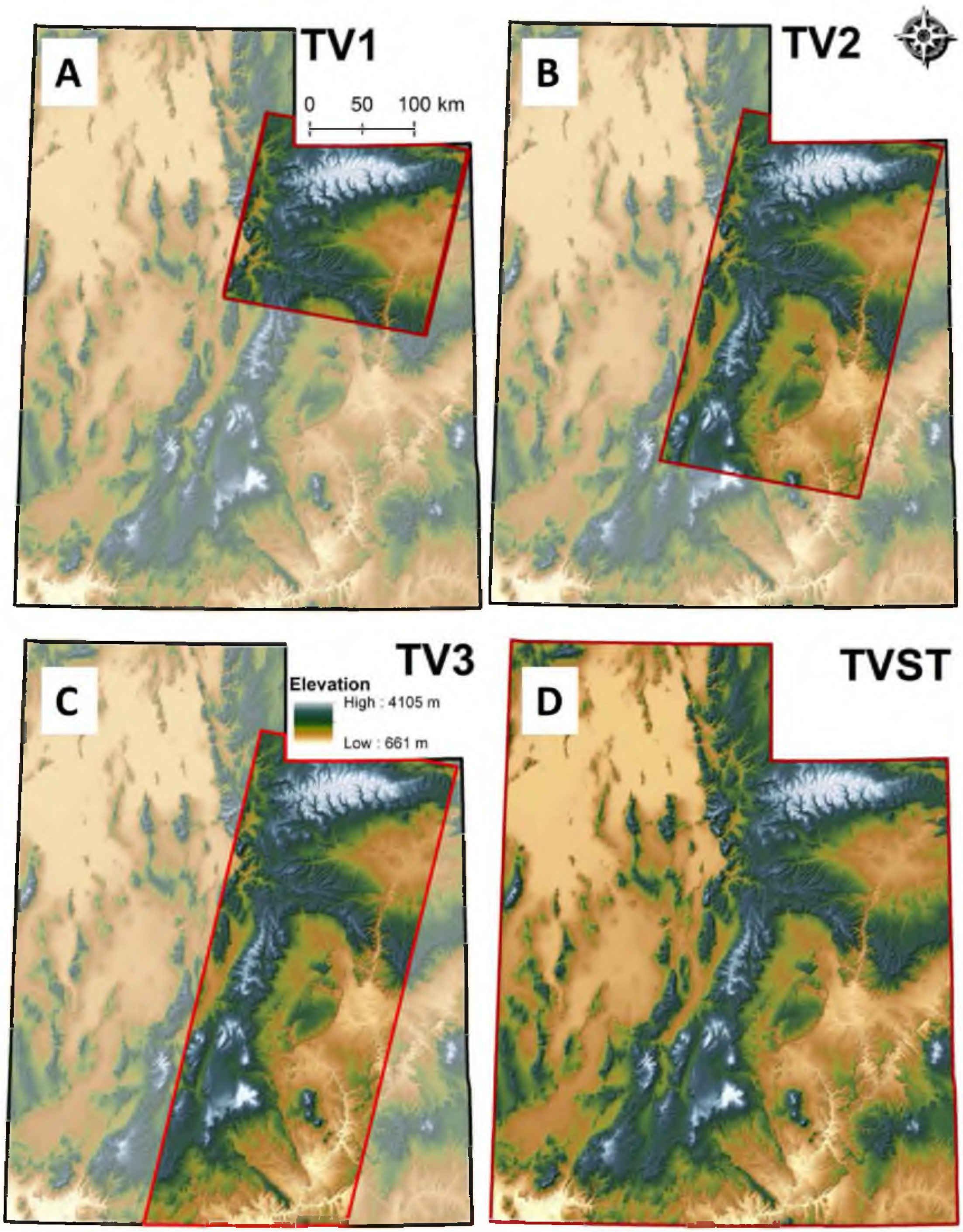

Figure 3.1: Four spatial extents used to create total vegetation cover models. Spatial extents are defined by areas within the red boxes. A) is TV1, B) TV2, C) TV3 and D), the state of Utah.

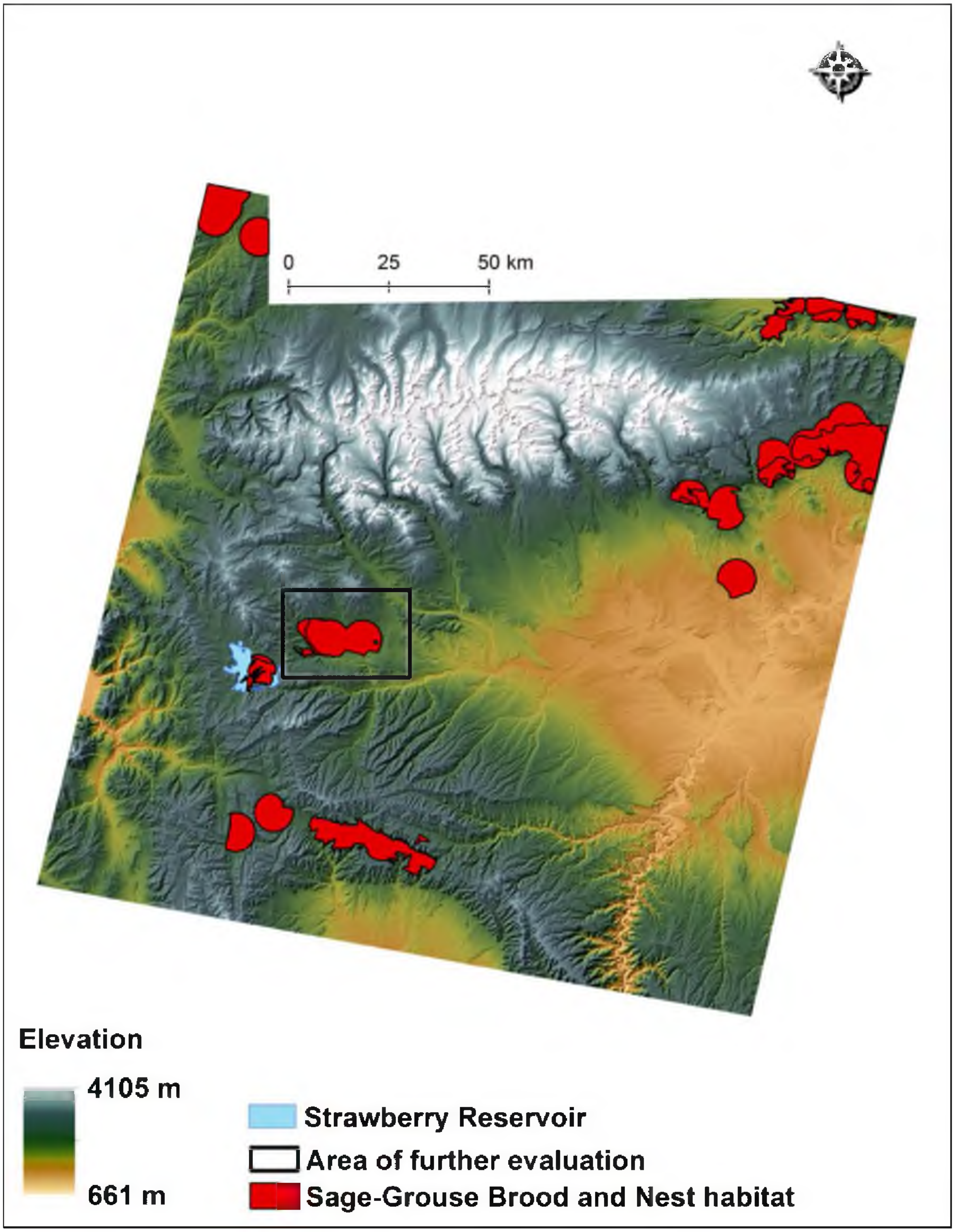

Figure 3.2: Sage-grouse brooding and nest habitat patches as defined by the 2013 Utah greater sage-grouse land use plan. The area in the black box is the Fruitland sage-grouse habitat patch near Strawberry Reservoir that has overlapping nest brooding and winter habitat.

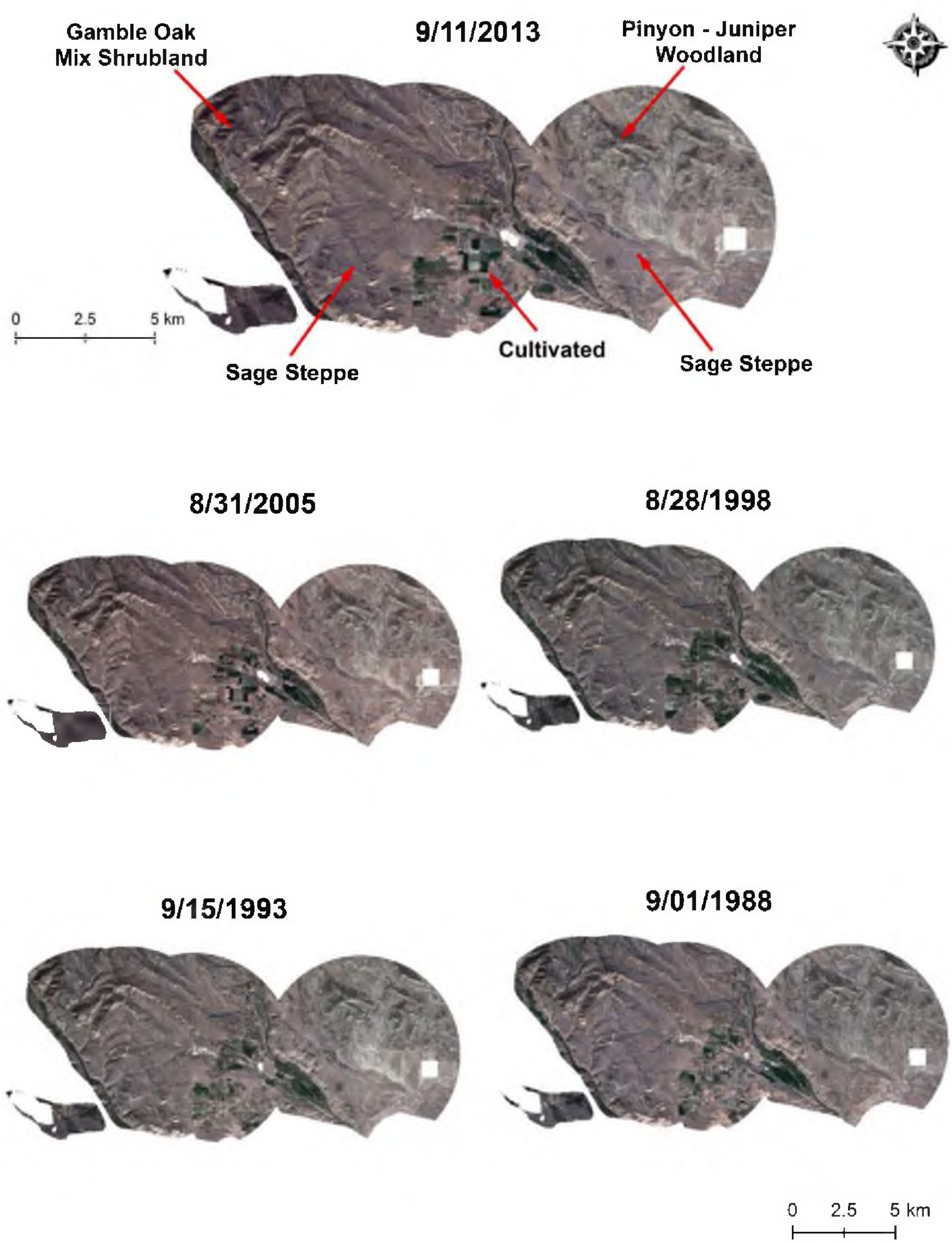

Figure 3.3: Fruitland habitat patch. Landsat TM bands 321.

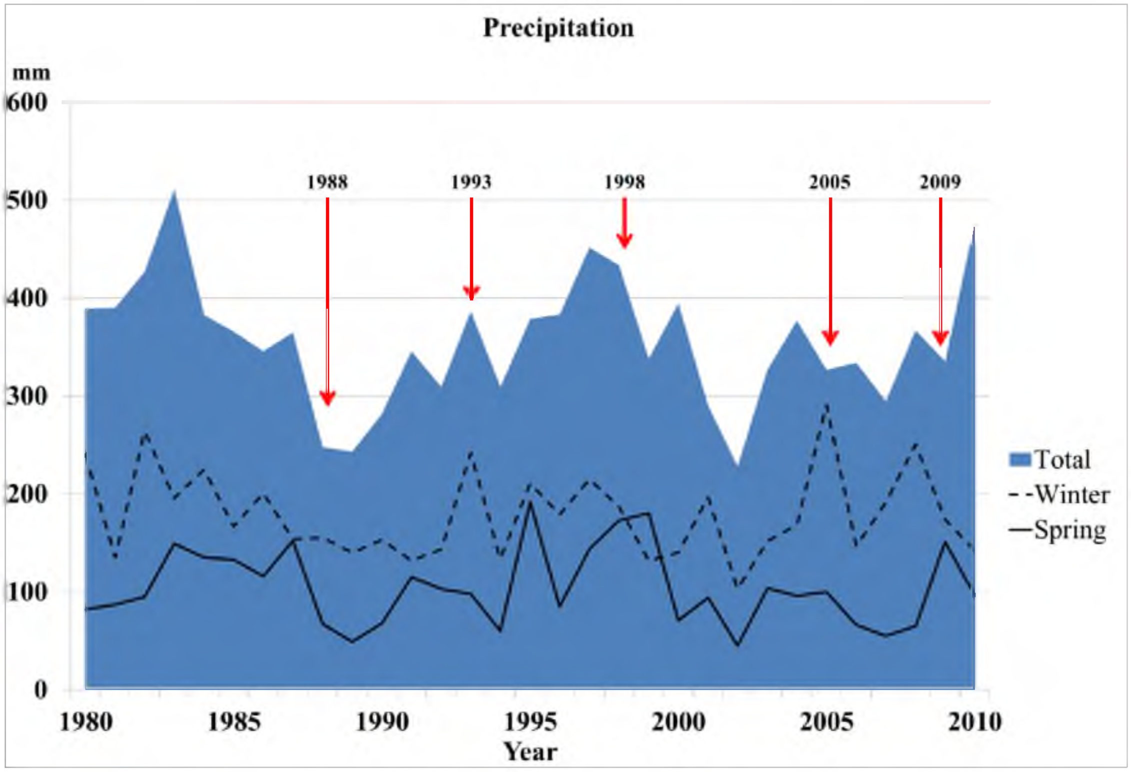

Figure 3.4: Total annual precipitation in mm for case study area. Spring is defined as April – July and winter is defined as October-March. Data obtained from the Western Regional Climate Center.

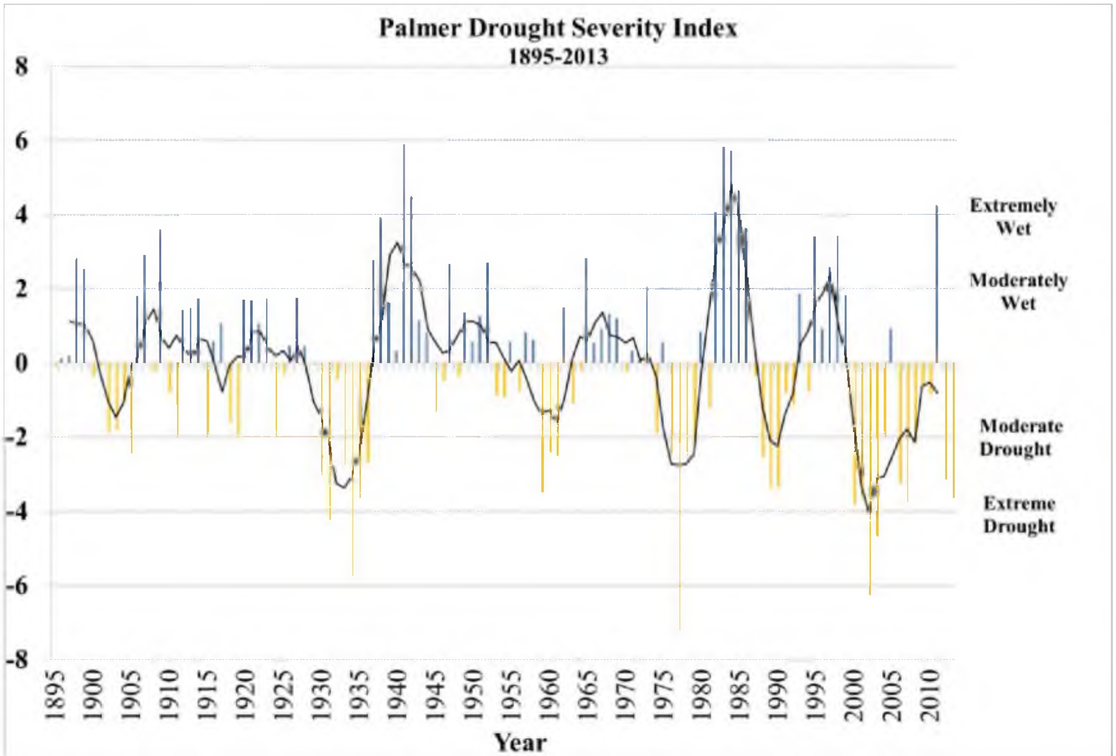

Figure 3.5: Palmer Drought Severity Index for case study area 1895-2010. Values below -2 are considered moderate drought or worse. Values above 2 are modernly wet or wetter. The dark line is a five year smoothing curve. Data obtained from the Western Regional Climate Center.

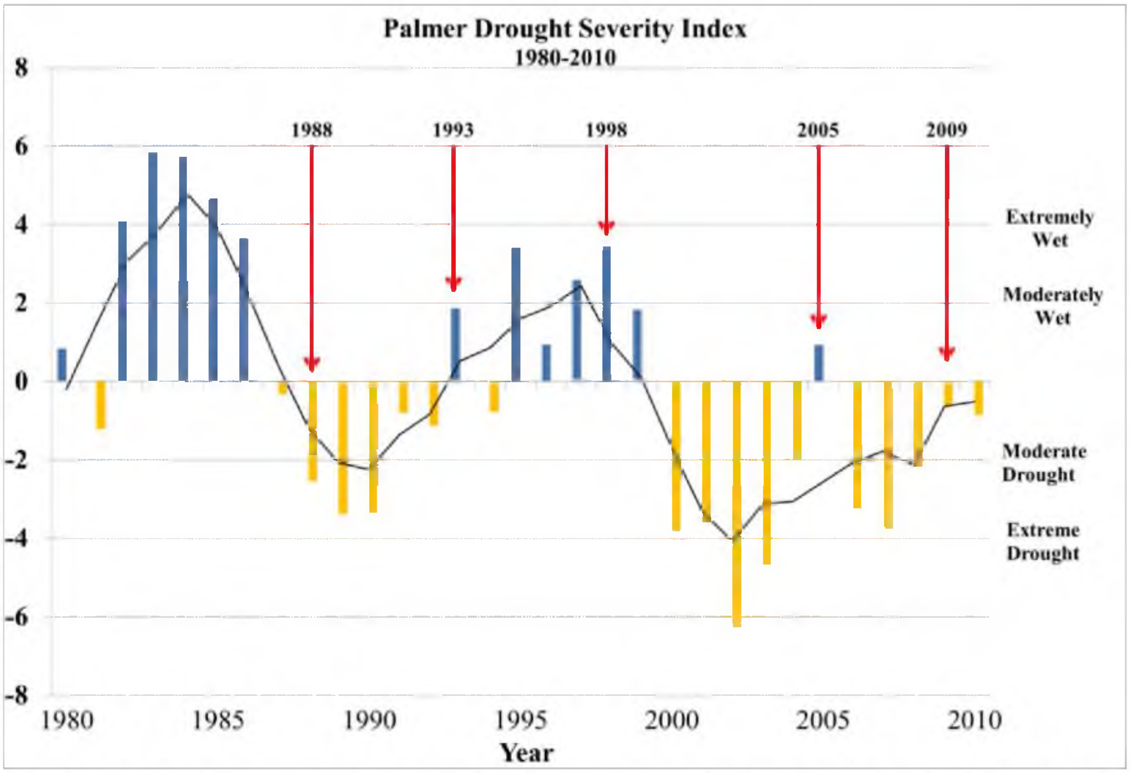

Figure 3.6: Palmer Drought Severity Index for case study area 1980-2010. Values below -2 are considered moderate drought or worse. Values above 2 are modernly wet or wetter. The dark line is a five year smoothing curve. Data obtained from the Western Regional Climate Center.

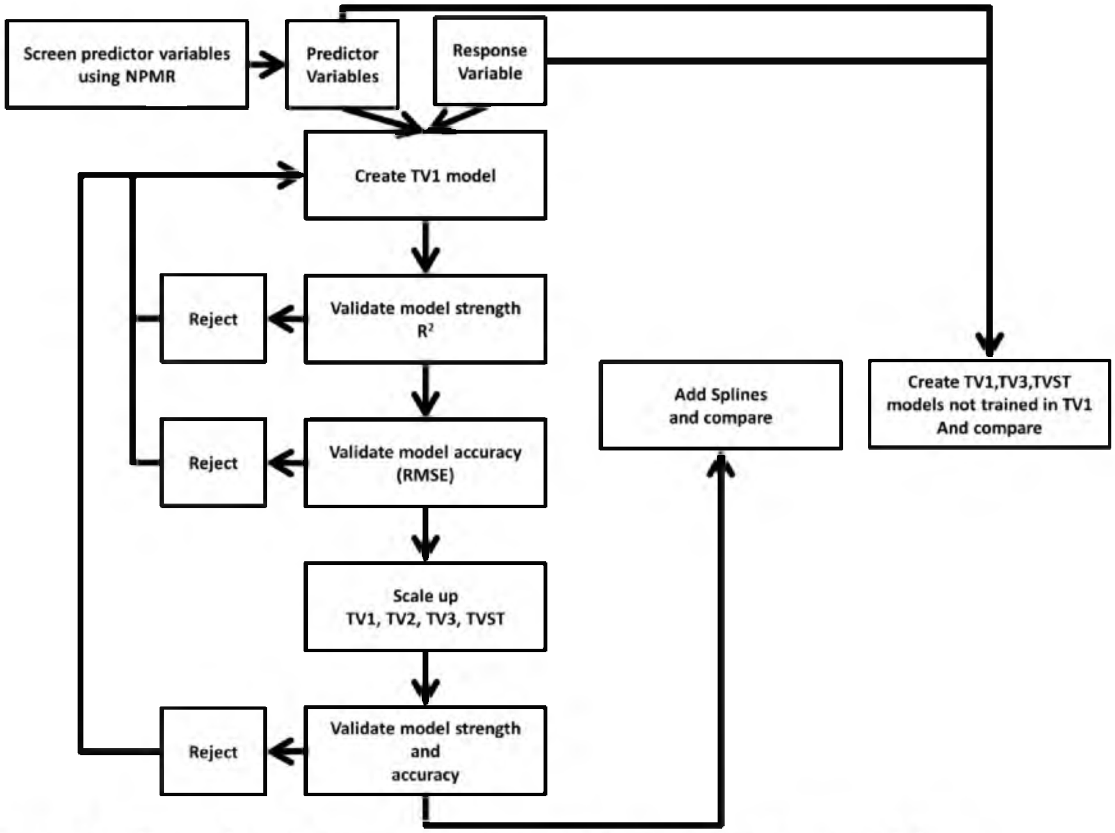

Figure 3.7: General workflow used to create total vegetation cover models.

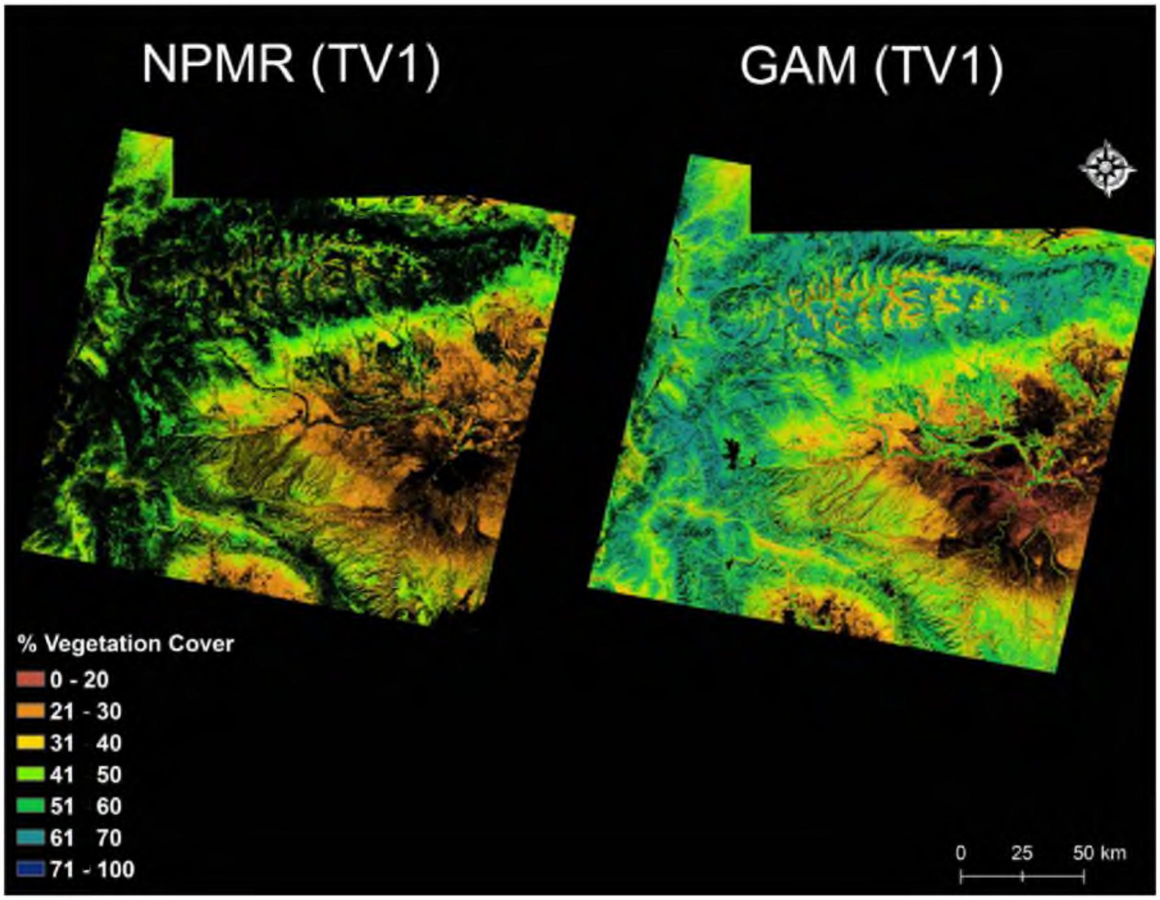

Figure 3.8: NPMR (left) and GAM (right) model outputs for TV1. Areas left black are not modeled.

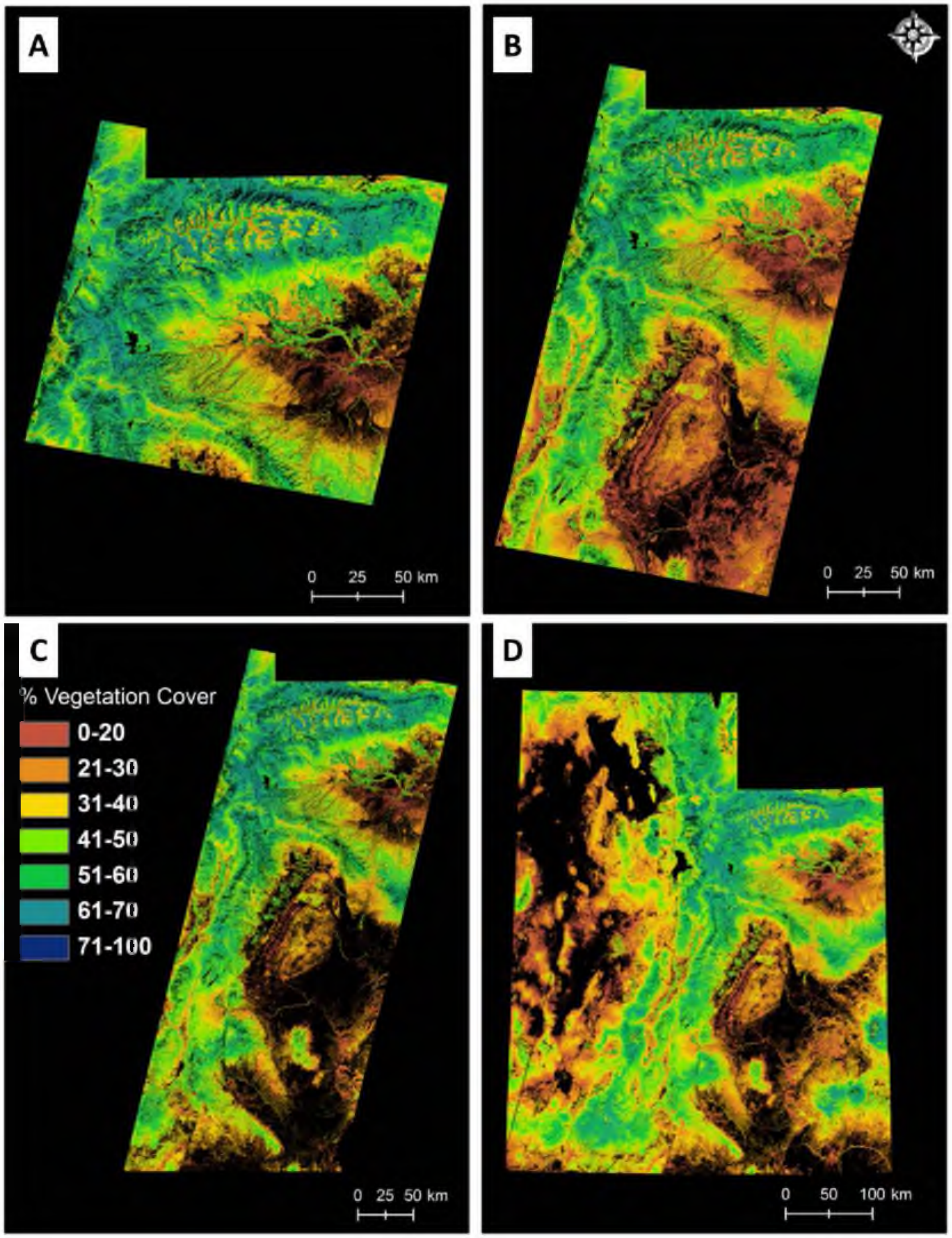

Figure 3.9: Vegetation cover models for A) TV1, B) TV2, C) TV3 and D) TVST.

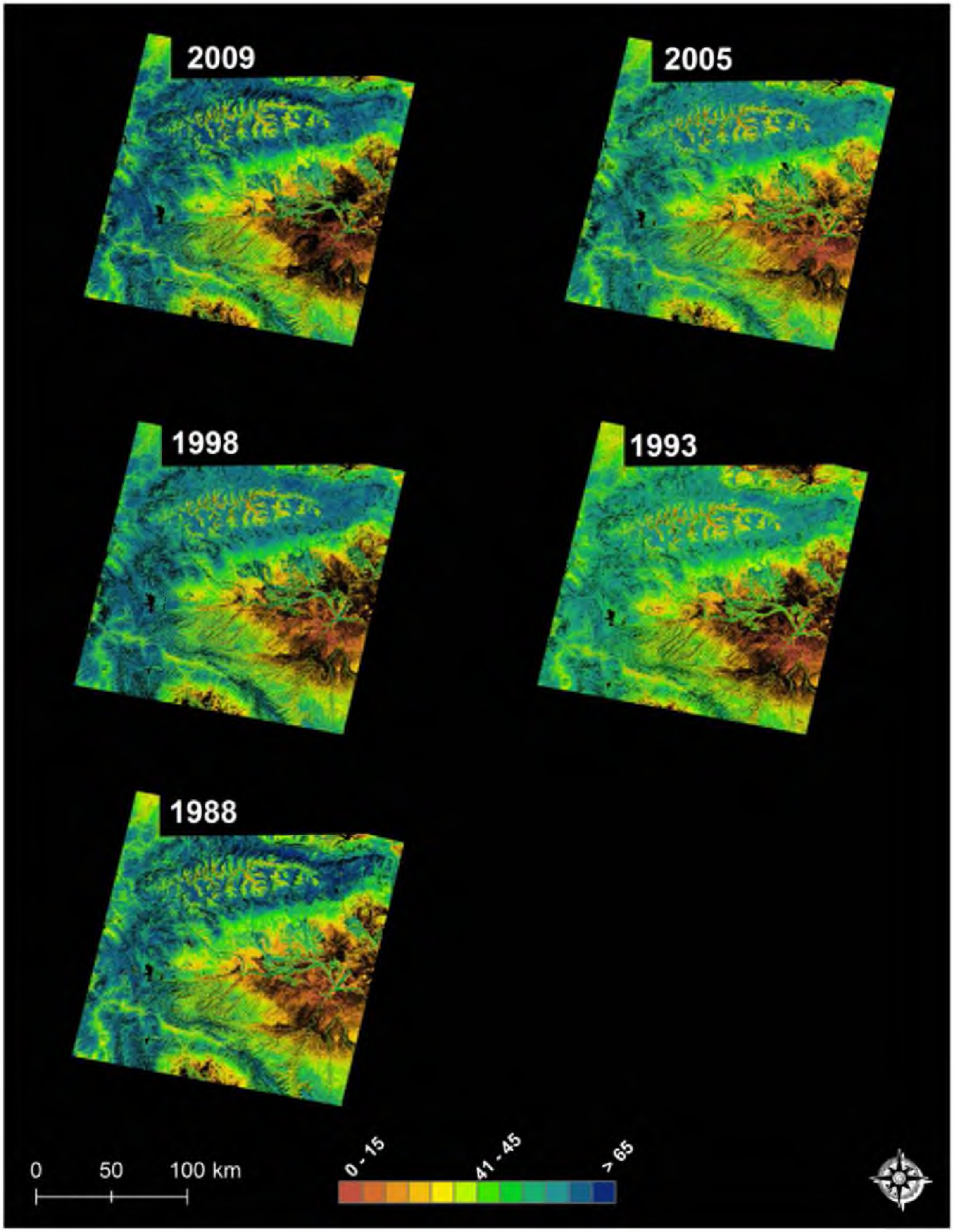

Figure 3.10: GAM total vegetation cover models for years used in this study.

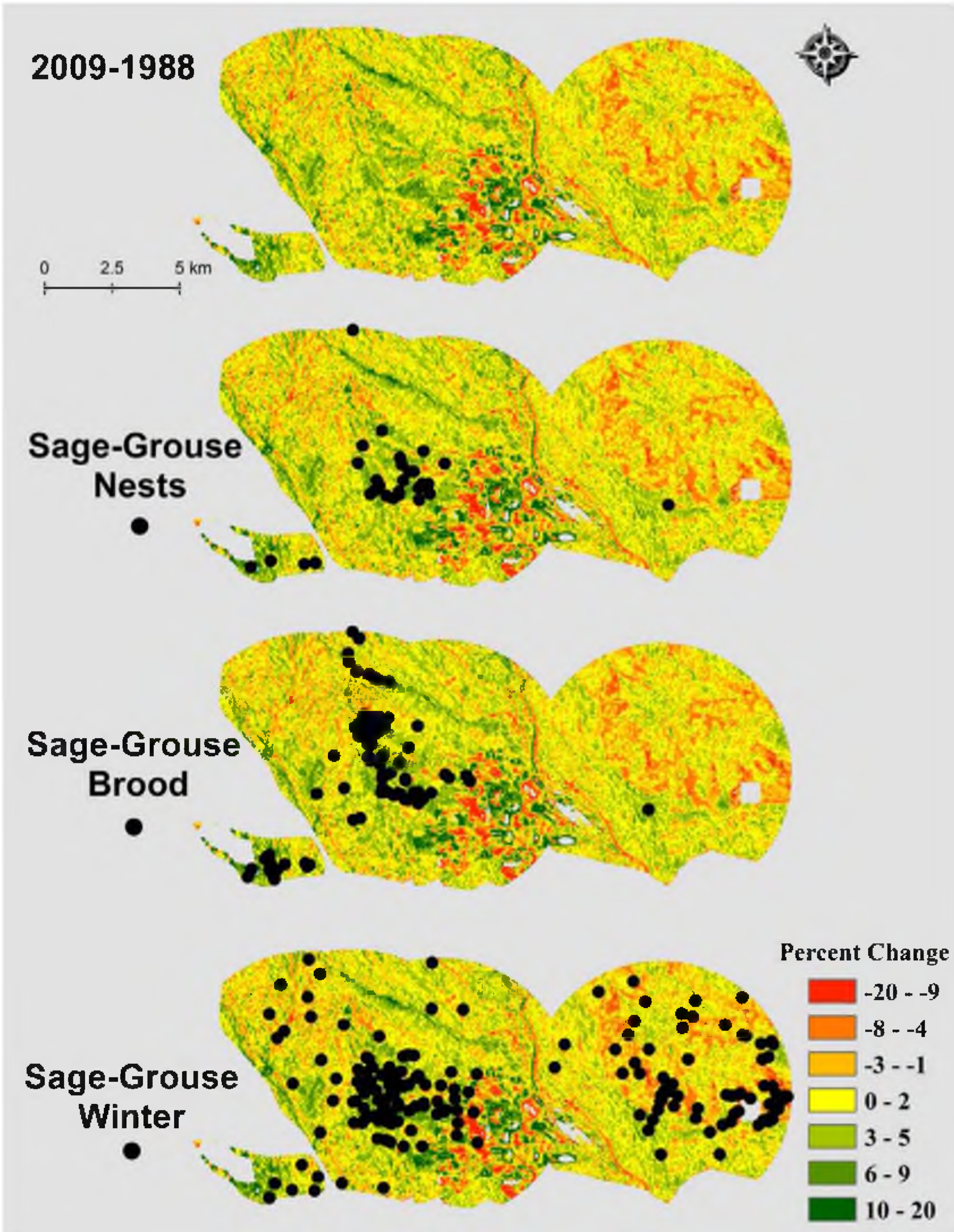

Figure 3.11: Fruitland habitat patch, total vegetation cover change between 1988 and 2009. Sage-grouse locations are represented as black dots.

Table 3.1: Results for total vegetation cover model creation and validation.

Total Vegetation Cover Validation					
Model	Test Points	Validation Points	R^2	RMSE	Area modeled (ha)
TV1 (NPMR)	n = 67	n = 30	$xR^2 = 0.70$	7.73%	1,100,852
TV1 (GAM)	n = 67	n = 30	0.58	7.34%	2,561,753
TV2	n = 67	n = 82	0.58	5.68%	4,243,425
TV3	n = 67	n = 130	0.58	7.31%	5,435,047
TVST	n = 67	n = 399	0.58	7.60%	13,223,921
TV1	n = 67	n = 30	0.58	7.30%	2,561,753
TV2	n = 67	n = 30	0.58	6.40%	4,243,425
TV3	n = 67	n = 30	0.58	6.34%	5,435,047
TVST	n = 67	n = 30	0.58	6.60%	13,223,921
With Splines					
	Test Points	validation			
TV1	n = 67	n = 30	0.7	8.43%	2,518,892
TV3	n = 67	n = 130	0.7	8.62%	5,421,237
TVST	n = 67	n = 399	0.7	7.19%	13,188,084
Not Trained in 3732					
	Test Points	Validation			
TV1	n = 67	n = 30	0.58	7.34%	2,561,753
TV3	n = 190	n = 39	0.49	7.06%	4,952,227
TVST	n = 400	n = 40	0.39	6.70%	19,468,309

Table 3.2: GAM past vegetation cover models creations and validations.

GAM Total Vegetation Cover Validation (TV1)		
Month/Day/Year	Validation Points	RMSE
9/11/2009	30	7.34%
8/31/2005	45	5.59%
8/28/1998	30	5.64%
9/15/1993	no data	no data
9/1/1988	no data	no data

Table 3.3: Sage-grouse location and change in vegetation cover statistics between the years 1988 and 2009. Nest, brood, and winter change in vegetation cover means were all significantly different than the random points with a p value < .005

Sage-Grouse Life Stage	**Mean Vegetation Cover Change**	**Standard Error**
Nest (n=30)	+3.78%	0.47
Brood (n=109)	+3.94%	0.35
Winter (n=187)	+1.25%	0.24
Random (n=100)	+0.07%	0.45

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CHAPTER 4

USING BLENDED NESTED ECOLOGICAL NICHE MODELS TO IDENTIFY GREATER SAGE-GROUSE HABITAT AND CONNECTIVITY POTENTIAL ACROSS A DIVERSE LANDSCAPE

Abstract

Recently, a great deal of attention has been given to greater sage-grouse (*Centrocercus urophasianus*) and their habitat. This attention is due, in part, to a US. Fish and Wildlife Service (USFWS) 2010 finding that sage-grouse warranted a range-wide listing under the 1973 Endangered Species Act (ESA). Although sage-grouse were not listed at that time, land managers are working to reevaluate current sage-grouse protection and management plans. Sage-grouse are a landscape species, making habitat assessment and documentation difficult and costly. Sage-grouse brooding and nest habitat predictive models were created for the state of Utah. This was done to assist with understanding past, present and future sage-grouse habitat distribution. Three modeling techniques (nonparametric multiplicative regression, maximum entropy distribution and random forest classification) were combined and validated to identify potential sage-grouse habitat. The combined model had an overall accuracy greater than 90% for brooding and nest models across the state. Additionally, the combined model was used to

identify potential sage-grouse corridor habitat (for movement and expansion). These corridors can be used to highlight potential management priority areas

Introduction

Concern over the loss of greater sage-grouse (*Centrocercus urophasianus*; hereafter referred to as sage-grouse) and their habitat dates back to the early 1900s (Visher, 1913; Hornaday, 1916; McArdle et al., 1936; Griner, 1939). Despite early concern, sage-grouse and their habitat continued to decline. Sage-grouse have received increased attention over the past decade (both in the scientific and political realms). This is in part due to the US. Fish and Wildlife Service (USFWS) 2010 finding that sage-grouse warranted a range-wide listing under the 1973 Endangered Species Act (ESA). However, due to other species facing more immediate threats, sage-grouse were precluded from listing in 2010, and continue to be considered a candidate species for future listing. Following a lawsuit in 2011, the USFWS was given until 2015 to determine if sage-grouse will be listed under the ESA. Despite the limited timeframe, there has been a great effort by biologists and land managers (nongovernmental organizations as well as state and federal agencies) to better understand sage-grouse and their habitat. A major component to sage-grouse conservation is identifying where sage-grouse habitat is located (past, current and future). Additionally, connectivity of populations (oftentimes by means of suitable habitat) is important for genetic diversity, adaptability and overall long-term survival of the species.

In order to add to the growing sage-grouse research and assist researchers and land managers, I wanted to test the feasibility of using relatively fine scale (30m) remotely sensed data to predict potential sage-grouse habitat across an ecologically broad and diverse landscape. This was accomplished using four objectives. First, fine scale predictive sage-grouse brooding and nest ecological niche models, applied at a landscape level were created. Second, multiple modeling techniques were compared and combined to assess if a combination of models predicted sage-grouse habitat better than any one individual model. Third, the predictive strength of the habitat models was tested. Finally, applications of the predictive models beyond model creation were explored, by utilizing them to identify potential corridors and additional habitat.

Background

Sage-grouse is a woody sagebrush (*Artemesia* L.) obligate found primarily in western North America, with their pre-European distribution covering western portions of the Dakotas, southern Saskatchewan and Alberta, into Montana, Idaho, Washington, southern portions of British Columbia, Oregon, northern California, Nevada, Utah, Wyoming, Colorado, as well as northern Arizona and New Mexico (Baker et al., 1976; Beetle, 1960; Schroeder, 2004; Connelly et al., 2004). It has been estimated that sage-grouse populations as a whole are only found in just over half of their historic range (Schroeder et al., 2004). However, at the northern peripheries of their range, in southern Canada, sage-grouse have declined by as much as 80%, prompting its listing as endangered in 1998 by the Committee on the Status of Endangered Wildlife in Canada (COSEWIC; Aldridge and Brigham, 2003). Similarly in the south central portion of their habitat, sage-grouse have declined at a greater rate than the range-wide estimates. For example, Beck et al. (2003) determined that sage-grouse in Utah were only occupying 40.9% of their historic range with an overall population decline of 50% compared to pre-European estimates.

Sage-grouse are an ideal species for landscape scale habitat modeling, due to the large expanse of their range and their dependence on sagebrush. Because of sage-grouses' habitat requirements and spatial distribution, some have designated them as an umbrella species for other shrubland avian species (Hanser and Knick, 2011; Rowland et al., 2006). There have been multiple range-wide sage-grouse distribution maps and habitat predictive models created in the recent past (Schroeder et al., 2004; Knick et al., 2013). In addition to the range-wide estimations, site specific finer scale models have been created (Aldridge and Boyce, 2007; Onyeahialam et al., 2005; Atamian et al., 2009; Doherty et al., 2009; Yost et al., 2008, to name a few). In most cases, if the area assessed was large, then the resulting model resolution was coarse, usually with individual map units $\geq 1 km^2$. What is currently lacking is sufficient sage-grouse potential and distribution models at the finer (map unit) scale, predicted across geographically large areas.

Sage-grouse ecological niche models for brooding and nest habitat using 30 m resolution data across the state of Utah (21.9 million ha) were created. In general, nest habitat is made up of large habitat patches with sagebrush cover between 15 and 25% (Connelly et al., 2000). Additionally, it is found in close proximity to winter and summer habitats. In most studies, sage-grouse preferred to nest at the base of sagebrush plants (Connelly et al., 2011). Brooding habitat is broken into late and early brooding in many studies. Early brooding is frequently near nest habitat, but with slightly lower sagebrush cover. After several weeks the birds' diets shift from insects to forbs. This shift usually coincides with the landscape getting dryer, prompting the brooding birds to shift to late brooding habitat. Late brooding habitat is often associated with wet meadows and in some cases cropland (Connelly et al., 2011).

Sage-grouses' ecological niche is defined here as a blending of Hutchinson's (1957) fundamental and realized niches. Overall, the model creation follows more of a fundamental niche. However, the response variable (sage-grouse presence) driving the model is a subset of the population, influenced by realized niche interactions. Furthermore, due to the lack of complete sampling of the population and the limited availability of spatial layers for model creation, the model creation does not encompass all the fundamental niche criteria. Therefore, the output model in geographic space may be more conservative than a fundamental niche, more liberal than the realized niche and more robust than a standard distribution map. It is important to state the limitations and understand that these models are predictions based on good, but incomplete data.

The state of Utah was chosen, in part, due to its diversity of landscapes along with its dispersed and patchy sage-grouse habitat distribution. Sage-grouse in Utah are found at the southernmost extent of the current species habitat and make up roughly 10.6% of the overall range-wide population (Beck, 2003; Braun, 1998). Understanding the Utah sage-grouse population distribution and connectivity can provide insight into similarly dissected populations across their range.

Methods

Study Area

The study area was broken into two spatial extents. The first extent (training area) was a smaller area that was used to develop the models (Figure 4.1). The second extent was the state of Utah and was utilized to test the ability to spatially scale up the predictive models. The training area was chosen due to its geographic and vegetative diversity as well as its previously defined sage-grouse habitat patches. Landsat 5 Thematic Mapper

(TM) data were used to subdivide the state into the two spatial extents. Path 37 Row 32 clipped to Utah (TM3732) was selected as the training extent (Figure 4.1). Total area within this scene is roughly 3.2 million ha. TM3732 covers a diverse landscape including mountains, valleys and plateaus.

Modeling Methods

Three separate modeling methods were compared and combined in this study. They were chosen primarily due to their abilities to deal with the complex multidimensional, nonlinear nature of ecological modeling and include the following: nonparametric multiplicative regression (NPMR; McCune and Mefford, 2004), maximum entropy distribution (Maxent; Phillips et al., 2004) and random forest (RF; Breiman, 2001; Cutler et al., 2007; McCune, 2006; Elith et al., 2011 and others). Additionally, they were chosen due in part to their current use in landscape scaled ecological studies (Nelson et al., 2013; Elith et al., 2011; Bradter et al., 2011 and others).

NPMR identifies complex nonparametric ecological interactions in part by linking terms multiplicatively rather than additively. Model creation based on a response variable is accomplished with a leave-one-out cross validation and a multiplicative smoothing function. NPMR was implemented with the software package Hyperniche (McCune and Mefford, 2004; Gleneden Beach, Oregon). For additional information, visit http://home.centurytel.net/~mjm/nichepublications.htm.

Maxent was selected specifically for its ability to model presence only data. Maxent has been extensively used in the scientific literature to model species distribution based on presence only data including avian habitat studies (Warren and Seifert, 2011; Elith et al., 2011; Moreno et al., 2011; Papes, 2012 and others). Maxent uses machine learning modeling through multiple transformations to find if there is agreement between the response and predictor variables.

RF use in ecology is still relatively new (Cutler et al., 2007; Prasad et al., 2006). RF uses bootstrap samples and a randomized subset of the predictor variables to create a series of classification trees (forest) that predict species presence. The trees (typically 500 to 2,000) are then combined for the final prediction. One of the strengths of RF is the ability to create accurate predictions without over fitting the data (Cutler et al., 2007; Prasad et al., 2006). The software used to implement RF was R 2.15.1 (R development core team, 2008) and ModelMap (Freeman and Frescino, 2009).

Model Creation

Nested predictive habitat models were created in ecological space using the response (dependent) variable defined as sage-grouse brood or nest presence. Presence was compared against an equal or greater number of random locations (pseudo absence), rather than true absence due to the inability to define true absence for sage-grouse. Model creation followed ten basic steps (Figure 4.2). Predictor (independent) variables (Tables 4.1, 4.2 and 4.3) were determined. Values of the predetermined variables were than extracted from existing remote sensing/GIS data sets or, if not available, they were created using ESRI (Environmental Systems Research Institute , Redlands, CA) and ENVI (Exelis Visual Information Solutions, Boulder, Colorado) software packages. Model lists were created using Maxent, RF and NPMR. Best fit models were determined based on the area under the receiver operating characteristic curve (AUC) as well as number of variables included in the models. These models were selected for further evaluation and validation. The top models created in ecological space where transferred to geographic space. The newly created predictive models were validated for overall accuracy. The top models from each method were combined to highlight areas of agreement. The combined models where classified into three groups: habitat determined by a minimum of one of the three models, in other words the agreements added together (ADD), agreement between two or more (M2+) and all three model methods agree (M3). The combined models were re-evaluated for overall accuracy. Finally, a low pass smoothing function was run on the combined models to reduce noise and fill holes for display (sADD, sM2+ and sM3).

To assess the various models' ability to predict habitat in the absence of any close training data, one full population's data points for brooding and nest locations were withheld from model creation and used as a validation. Supplementary to the Diamond Mountain points, two alternative data sets were used for validation. The additional data sets were made up by randomly withholding data points for brood and nest sites across the state.

In order to define area as suitable habitat versus not, thresholds were used in the final models. It is difficult to define optimal threshold as there is not a consensus on what is suitable for a habitat presence threshold (Tinoco et al., 2009; Lui et al., 2005; Loiselle et al., 2003; Jiménez-Valverde, 2007). The 10 percentile threshold was applied (90% of the training points were located within the predicted area) despite the potential for increased omission (sites predicted as negative for habitat that are positive). By using this threshold, the models were more conservative (Tinoco et al., 2009).

Corridor Creation

To more fully utilize the presented habitat models, the best performing model was incorporated into a resistance layer used to assess potential sage-grouse movements and population expansion corridors. A map of greater sage-grouse brooding habitat patches produced by the Utah Division of Wildlife Resources (UDWR, 2009) was used to delineate brooding habitat. The UDWR brooding habitat patches are similar to a conservation buffer and include more area than what may be suitable habitat. In some cases, the areas encompass farm land and housing developments. Despite the increased habitat, they were used to define sage-grouse brooding and nesting habitat patches to address connectivity and potential expansion.

Two types of theoretical corridors were created. The first is defined here as an expansion potential corridor (EPC). This is potential habitat (able to support brooding and/or nest) between populations. This may represent habitats that are occupied, remnant (historic), undocumented current or degraded habitats. The second is a movement potential corridor (MPC). The main difference between the two in this study is that EPC requires the corridor to be located within the highest potential (sADD) habitat with minimal human impacts (described below). However, the MPC model assumes only movement through and not occupation of habitat.

For both the EPC and the MPC, the sADD potential habitat was converted into a movement resistance layer with the highest resistance (no agreement by any model as potential habitat) given the lowest probability of use. This was further supplemented with a human footprint layer developed by Leu et al. (2008). This human footprint layer was used because anthropogenic disturbance and human occupation have been shown to have a negative impact on sage-grouse survival (Connelley et al., 2011). The MPC corridors were mapped using Linkage Mapper (McRae and Kavanagh, 2011). The corridor models created were to demonstrate the potential for using ecological niche models for sage-grouse movement assessment. The corridor models were to demonstrate potential and were not fully developed or validated due to the limited data on sage-grouse movement.

Input Data

Response variables. Sage-grouse brooding and nest GPS locations were provided by the Utah Division of Wildlife, Utah State University and Brigham Young University. These data were obtained from past and current studies in the state of Utah. In most cases, brooding birds and nests were located with radio collars and their GPS locations recorded. Potential GPS inaccuracies where minimized in this study by using 30 m resolution data layers to define the locations within the models.

Predictor variables. Predictor variables were broken into three general categories: Digital elevation model (DEM) derived (Table 4.1), Landsat-derived (Table 4.2) and Vegetative Cover models (Table 4.3). DEM-derived data were created using 30 m DEMs obtained from the United States Geological Survey (USGS; Gesch, 2007). Simple layers derived from the DEM were slope, aspect, curvature and curvature direction of slope (profile). More complex layers created were the Integrated Moisture Index, Topographic Position Index and the Terrain ruggedness index. Environmental Systems Research Institute (ESRI, Redlands, California) software was used to create the additional DEM layers. Slope and aspect where created based on the Horns method. Slope is a calculation of the maximum rate of change in elevation between a cell and its eight neighbors and aspect is the direction of the slope (Horn 1981; Jones 1998; Burrough and McDonell

1998). Curvature of the slope was used to define potential drainage basins. Curvature direction of slope (profile curvature) is the direction of the maximum slope. A modified version of the Iverson Moisture Index (IMI; Iverson et al., 1997) model was created using ESRI ArcMap to include topographically influenced moisture availability into the modeling. The IMI was created following Davis (2009) using the DEM derived layers: hillshade, flow accumulation and curvature (Davis, 2009; Iverson et al., 1997; Yost et al., 2008). Topographic position layers were created using tools designed by Jenness (2006). This index compares the elevation of each cell to the average surrounding cells and can be used to define topographic positions such as canyons valleys or plateaus (Jenness, 2006). Terrain ruggedness is a measure of terrain heterogeneity and was created following Riley et al. (1999). The ruggedness index compares each cells elevation to the surrounding eight cells to determine a rugosity score.

Landsat 5 Thematic Mapper (TM) 30m resolution imagery was downloaded from the USGS (http://www.usgs.gov/). Individual TM bands 1-5 and 7% reflectance were used as individual predictor variables. In addition, the bands were combined to create vegetative indices. Atmospheric absorption and scattering was corrected using Fast Line-of-site Atmospheric Analysis of Spectral Hypercubes (FLAASH; Air Force Phillips Laboratory, Hanscom AFB and Spectral Sciences, Inc (Adler-Golden et al., 1999)) and ENVI software. Several vegetation indices were also applied using ENVI software (Table 4.2).

Two vegetation cover models were created, sagebrush presence (Chapter 2) and total vegetation cover (Chapter 3) , to help capture potential sage-grouse habitat (Table 4.3). Due to sage-grouse dependence on sagebrush, a sagebrush presence model was created using NPMR. Presence was defined as 5% or more woody sagebrush. The overall accuracy for the model across the state of Utah was 72%. In addition to the sagebrush presence model, a total vegetation cover model was created using a generalized additive model (GAM), implemented with Marine Geospatial Ecology Tools (MGET; Roberts et al., 2010). The overall accuracy of the total vegetation model ± 10% of the ground data was 70%.

Results

3732 Model Creation

NPMR, Maxent and RF all created models that performed better than a randomly generated model. NPMR, Maxent and RF AUC values for model creation were 0.80, 0.87 and 0.96, respectively (Table 4.4). The top predictive variables for sage-grouse nest and brooding habitat were elevation, slope, total vegetation cover, and sagebrush presence (sagebrush). It is important to note that the model outputs are based on combining the individual predictive variables and that looking at each predictor independently can be misleading in the absence of the other variables. However, knowing the individual relative influence/importance can assist in better understanding the processes driving suitable habitat.

NPMR order of variable influence was based on two sensitivity tests, one using mean absolute values (S^1), the other root mean squared difference (S^2). This was done by adjusting the observed values for each predictor variable and assessing the change to the model response at that location. Higher sensitivity indicates greater influence (McCune, 2006). NPMR variable order of influence with both S^1 and S^2 was elevation, sagebrush presence, slope and total vegetation cover (Table 4.4).

Maxent influence was based on two estimates: percent contribution and permutation importance. Percent contribution is the increase in regularized gain added to or subtracted from the corresponding variable in each of the training algorithm iterations. Permutation importance takes the final model created and evaluates the importance of each variable by randomly permutating the values of the variable with the training and background points. The resulting change in AUC values for the model is used to determine variable importance. A large drop in AUC values when a variable is randomized indicates the model is strongly influenced by that variable. The amount of change is normalized and reported as a percent (Phillips, 2011). Maxent predictor order was similar to NPMR with the exception of sagebrush having less influence than slope (Table 4.4).

RF variable influence was based on mean decrease accuracy (MDA) and mean decrease Gini (statistical measure of equality among values used to identify incorrectly labeled elements; MDG). MDA is a measure of the normalized difference of the classification accuracy for the out-of-bag (not cross validated) data included as observed and as randomly permutated (Cutler et al., 2007). MDG is a measure of node (a junction that random variables are chosen to build each decision tree) impurity and is a sum of the Gini decrease per each variable, per node in the classification trees; the higher the mean decrease, the greater the influence of the variable (for more information, see RF manual http://stat-www.berkeley.edu/users/breiman/RandomForests). The order of influence for MDG followed the same order as the NPMR. However, the MDA differed with the order of elevation, slope, total vegetation and sagebrush. MDA was the only measure to list sagebrush as the least important of the four. The most probable order of variable influence has elevation as the top predictor and total vegetation as the bottom with slope and sagebrush interchangeable in the middle (Table 4.4).

3732 Models Output Validation

Multiple models were projected into geographic space and validated. In addition to each method's top model, a series of combination models were evaluated. Percent overall accuracy (OA) for NPMR was 84%. Maxent and RF had OA's of 89%. The ADD model had a value of 98%. The M2+ models OA was 90% and M3 was 79%. After a smoothing function was run on the combined models, all three had improved OA values (Figure 4.3, Table 4.5).

Statewide Model Creation

As the models were spatially scaled up, there was very little change in the AUC values for model creation. Both RF (0.95) and Maxent (0.82) decreased, and NPMR (0.92) improved slightly. However, the order of variable importance changed with total vegetation cover becoming the second most influential variable compared to the fourth in the 3732 models (Table 4.6).

Statewide Validation

Similar to the TM3732 models, the top statewide models as well as the combined models were projected into geographic space and validated (Figures 4.4-4.7, Table 4.7). Of the individual models, RF (Figure 4.4) had the highest OA for statewide brood (93%) and nest (100%) data sets. However, the NPMR model (Figure 4.5) had a higher OA for the DM data set for both brood (83%) and nest (90%). The sADD model (Figure 4.6) was an improvement over the individual models for OA with the exception of the state nest data set, where both sADD and RF (Figures 4.7 and 4.4) models performed equally. However, despite the improved overall accuracies of the sADD model compared to the individual models, the sM2+ model (Figure 4.7) may be a more conservative model with acceptable accuracies (state brood: 77%, state nest: 87%, DM brood: 87%, DM nest: 92%). The sM2+ model predicted half as much area as habitat, compared to the sADD model.

Corridors

The EPC shows the amount of resistance for potential population expansions or movement, based on potential habitat and human impact (Figure 4.8). Many areas modeled as low resistance are not currently utilized habitat patches. However, they may be suitable for temporary occupation or small population subsistence based in part on juxtaposition to currently utilized patches. The EPC output map shows that much of the current area in the east of the state predicted to have low resistance (outside of defined brooding habitat) is found in historic sage-grouse habitat (Schroeder, 2004; Figure 4.8). In the west many areas of least resistance are found in current Gunnison sage-grouse (*Centrocercus minimus*) habitats (Figure 4.8). Additionally, there are some habitat complexes, such as the Uintah patches, that show a reduction in size and overall connectivity in relation to historic habitat estimations (Figures 4.9-4.13). Reduced patch size and expansion potential in these areas is complex and are a combination of low habitat potential (natural barriers) and high human impacts (cities, agriculture, energy development etc.). With a reduced expansion potential, many of these Uintah patches are more susceptible to current habitat loss or disturbance (i.e., catastrophic fire). These limitations stem in part from a large natural barrier to the north. For example, much of the area north of the existing Uintah habitat patches is low human impact, but also has low habitat potential. These sage-grouse habitat patches have had very little change to their northern extents compared to their historic habitat. (Uintah Mountains, Figure 4.10). Another contribution to habitat limitations to the Uintah patches is anthropogenic impacts. Areas found outside the existing sage-grouse habitat patches to the east have high human impact and low habitat potential (Figure 4.11). To the west there is a moderate habitat potential and moderate human impact (Figure 4.12). In the south it is a mix of natural (extremely xeric landscapes) and anthropogenic factors (Figure 4.13).

The MPC shows some potential routes for genetic flow (Figure 4.14). The routes with the lowest cost of movement (high potential habitat and low human impact) help to highlight areas that may be currently isolated, from historically connected habitat patches, for example, the now isolated Sheep Rock habitat patches (Figure 4.15). In addition, the MPC identifies each habitat patch's number of potential (least cost) corridors. For instance, the Strawberry habitat complex has multiple interconnecting corridors in addition to 7 MPC corridors connecting it directly to four additional habitat patches (Figure 4.16).

Discussion

Predictive models can be an important tool in future sage-grouse habitat management, both in the short and long-term. Conservation and management of any species is complex, involving ecosystems that are dynamic and unpredictable in their own right. This combination of variables, coupled with our inadequate understanding of ecological principals, limited budgets and human interests, is why Francis and Goodman (2010) appropriately labeled the science of conservation as a "post-normal science."

Sage-grouse fit directly into this description with a great deal of the work being done, after much of the habitat has been lost over a geologically short period of time (~100 years). As we gain more insight into sage-grouse habitat patches across multiple spatial and temporal scales, we can make better informed management decisions in regards to natural and anthropogenic impacts to the species survival. The initial creation of a predictive model is only one of the steps in better understanding species habitat patches and their connectivity. In many studies, the initial models are the end point rather than the beginning of management and application. Continual refinement is necessary and should be done on a regular basis for the model to remain relevant. Here, several potential uses beyond the academic exercise of model creation are presented.

Corridor Application

One of the difficulties with any corridor assessment is the assumption that if the area meets the predefined criteria for potential habitat, than the species will use it (Hobbs, 1992). There is an increased likelihood that sage-grouse will be more prone to use predicted corridors with suitable sagebrush stands, due to their reliance on sagebrush. Currently, there is very little data on acceptable migratory and seasonal corridor sizes required for sage-grouse sustainability (Connelly Rinkes and Braun, 2011).

There is a temporal component to any habitat patch connectivity that is worth noting. Some potential barriers are temporary on an ecological scale while others are more lasting. Some populations may have experienced past barriers and bottlenecking events prior to large scale anthropogenic impacts. For example, the previously mentioned Sheep Rock habitat patch complex connectivity would have been influenced by the presence of Lake Bonneville (32,000-14,500 years ago, Figure 4.17), if sage-grouse were found there at the same time as the lake.

Distance restrictions, specific to sage-grouse, were not assessed here due to the high degree of variability of movement in sage-grouse (Connelly Hagen and Schroeder, 2011), but could be implemented as each population's movements are better understood. The corridors presented here were general in their assumptions of restrictions, but could be easily adapted by local wildlife managers and conservation biologists. For example, the human disturbance weight in the model could be adjusted based on perceived on the ground impacts. In areas where human disturbance is isolated and minimal (few isolated structures) the weight of the human impact habitat resistance component in the model could be reduced in contrast to areas with high use and continual expansion (roads, houses, etc.). Additionally, with the limited resources allocated to species protection and management, potential corridors could be used to prioritize habitat for future restoration projects (McRae et al., 2012).

Finding Historical Habitat

Historical habitat is often defined as pre-European settlement. However, historic can also represent areas where the species more recently was extirpated. Historical habitat is difficult to estimate and even more difficult to validate. Using a species, current predicted ecological niche can assist in locating undocumented or poorly documented historic habitat. For example, Cedar Mountain (Emery county Utah) in the models showed potential for sage-grouse habitat. This small mountain is a habitat island surrounded by salt desert shrubs with minimal suitable habitat connecting it to current known sage-grouse habitat patches. Due to the lack of current connectivity and modeled potential, a ground survey was conducted in 2012 to visually assess habitat potential. The top of the mountain contained heterogeneous sagebrush stands with available wet springs and a beneficial forb understory. However, it had been heavily managed for livestock production with much of the sagebrush converted to grasses. Interviews were conducted in the nearest town (Cleveland, Utah). It was found that at least one population of sage-grouse occupied that area in the past and had been hunted out in the 1950s. It is unlikely the area supported a large population in recent times due to its geographic isolation. However, it may provide insight into past distributions under cooler climate conditions.

Identifying Potential Habitat for Relocation or Expansion

Although much of the current work in sage-grouse habitat is in documentation, maintenance and protection of currently occupied habitat, it is important to address potential unoccupied areas for natural or forced expansion. This need to expand or move from current habitat patches in the future may be due to climate change, natural disasters or human assisted habitat degradation. These models help to identify potential expansion areas and their juxtaposition to current habitat. In conjunction with EPC corridors, relocation sites could be identified and assessed not only at the site level, but at the landscape scale. It is difficult to assign habitat value if the species is absent. However, using historic distributions, current niche models and on the ground assessments, potential sage-grouse habitat could be better identified, protected and managed.

Conclusions

It was found that a 30m resolution sage-grouse brood and nest habitat model predicted across a geographically large area performed well with acceptable accuracies. Visually, all three modeling methods were very similar. However, there were differences in the overall accuracies. For example, RF performed better in the statewide brood and nest categories. Conversely, NPMR performed better in the extrapolation (DM) categories. It was assumed that the agreement (all three models agree, sM3) would represent areas that have the highest probability for suitable habitat. However, using overall accuracy as a performance measure, the sM3 under predicted the new population of DM. This implies that the model may be too conservative. It is suggested here that the sM2+ model may be a good balance between accuracy and coverage with over 75% agreement in all overall accuracy categories. In order to add strength to ecological models, application beyond model creation is necessary. One area that this can be accomplished is in habitat patch connectivity. With the current state of sage-grouse conservation, many land managers have created priority areas. Potential corridors and patch expansion models such as the ones presented here can help to identify, within the priority areas, habitat patches that may be at risk of losing natural genetic flow due to patch isolation. Additionally, these models can be used to identify habitat patches that have little potential for future expansion and are therefore more prone to disturbances and habitat loss.

Acknowledgements

The Utah Division of Wildlife Resources, The Bureau of Land Management, Utah Big Game Range Trend (Federal Aid Grant W-82-R), The Nature Conservancy, Utah State University and the many others who have contributed time, money, data and support.

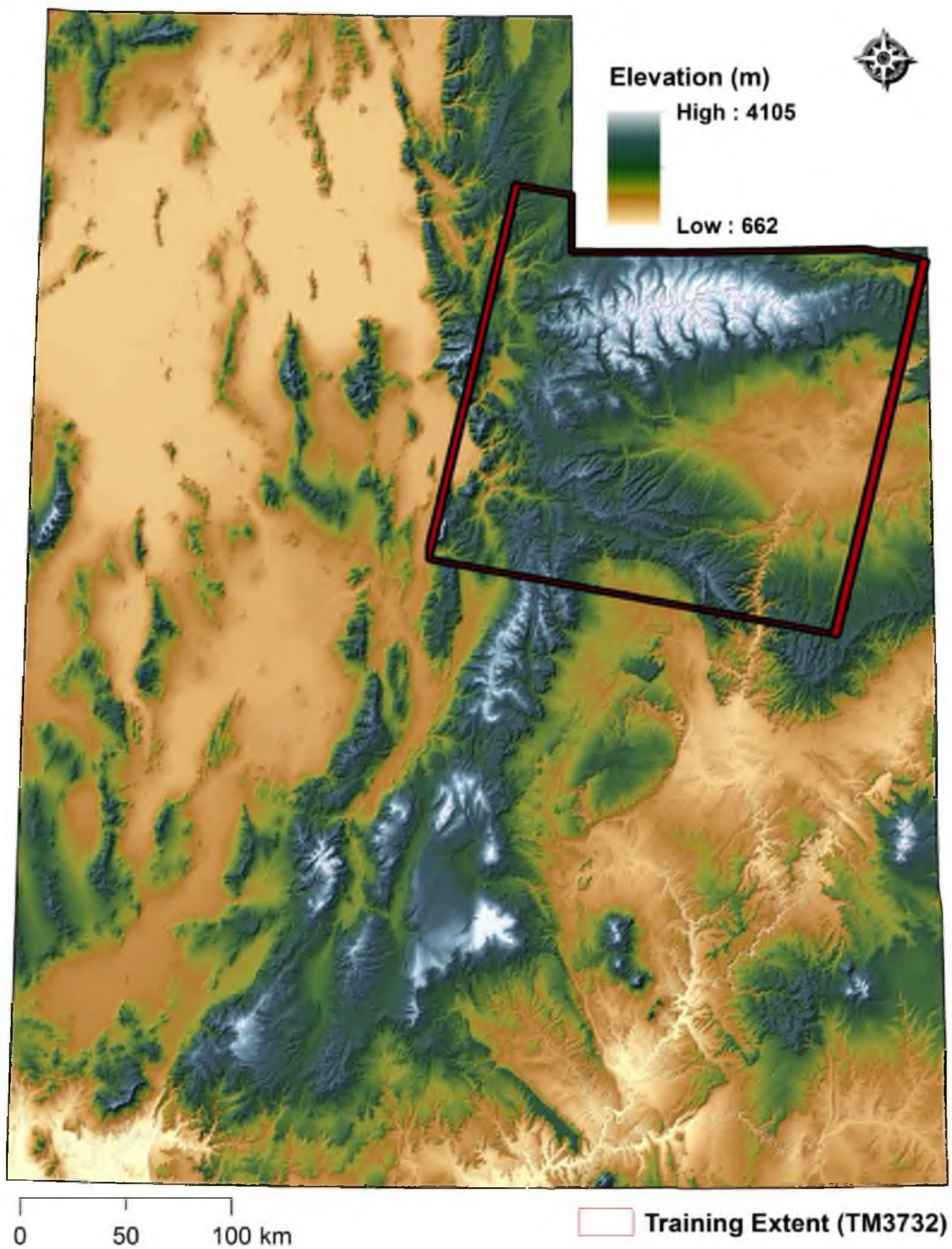


Figure 4.1: Study area. The first extent outlined in red represents the training area (TM3732). The second extent is the entire state of Utah.

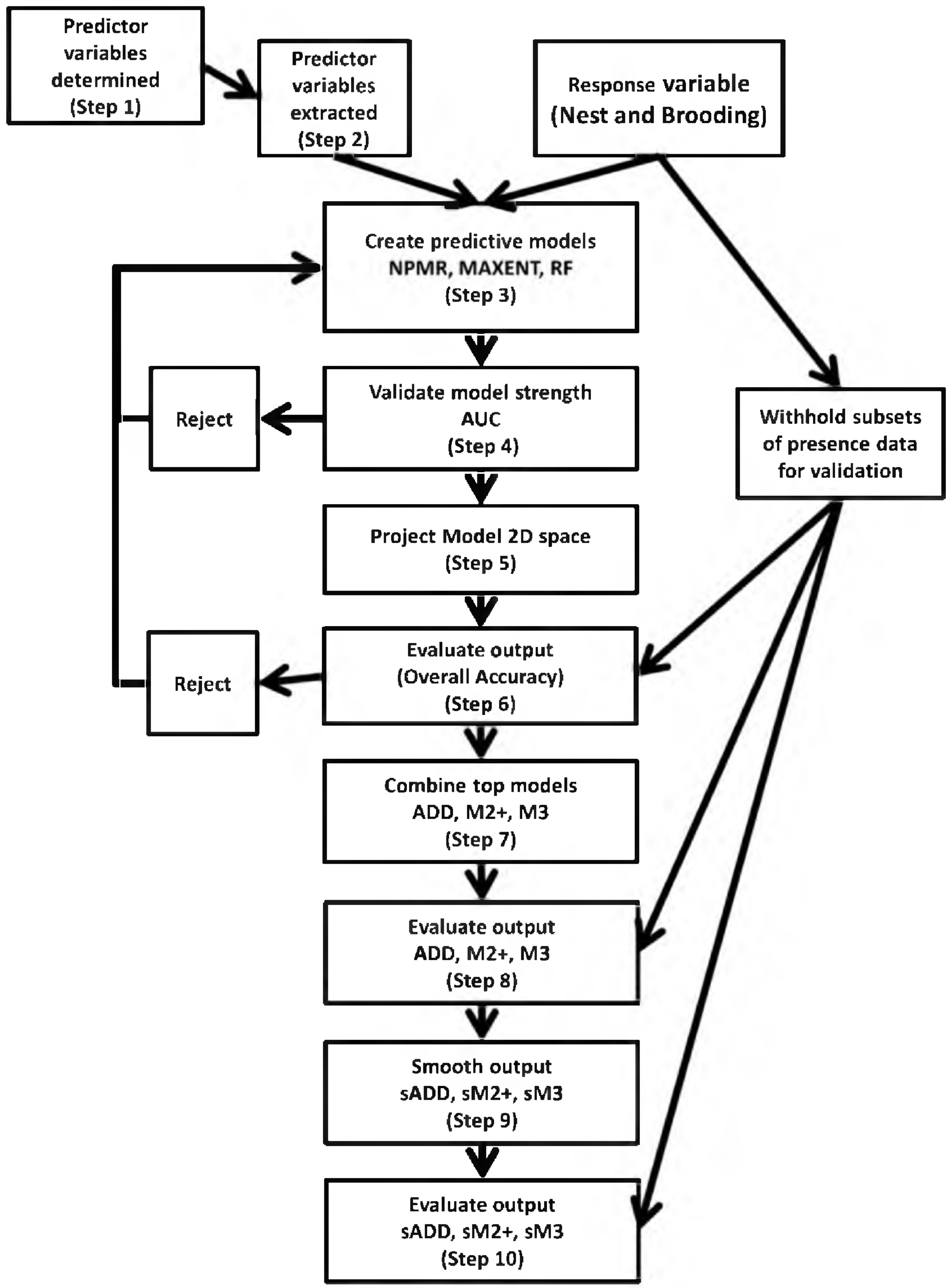


Figure 4.2: General workflow for model creation and validation.

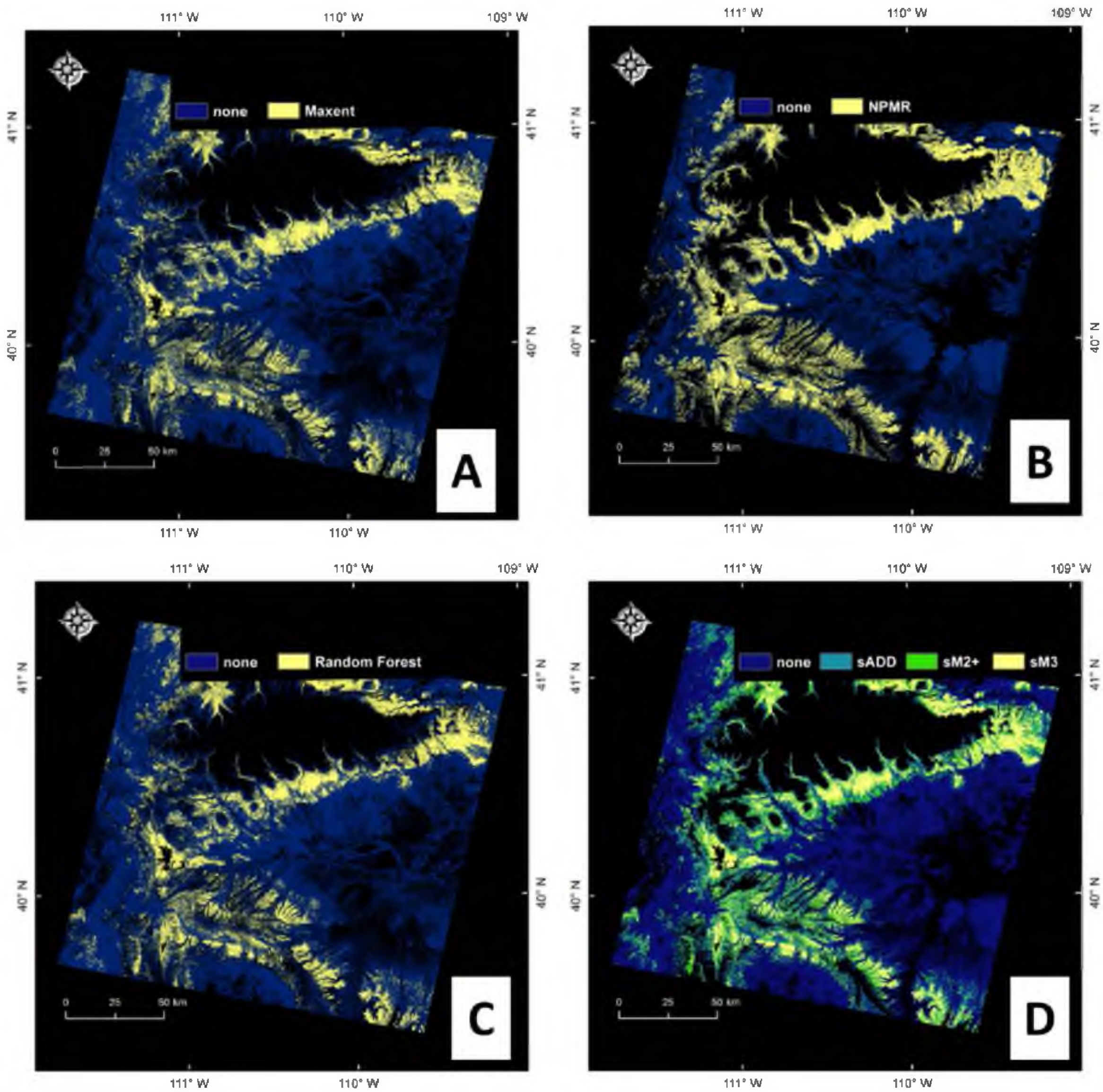


Figure 4.3 TM3723 brooding and nest predictive models. A) Maxent, B) NPMR, C) RF and D) the combination models.

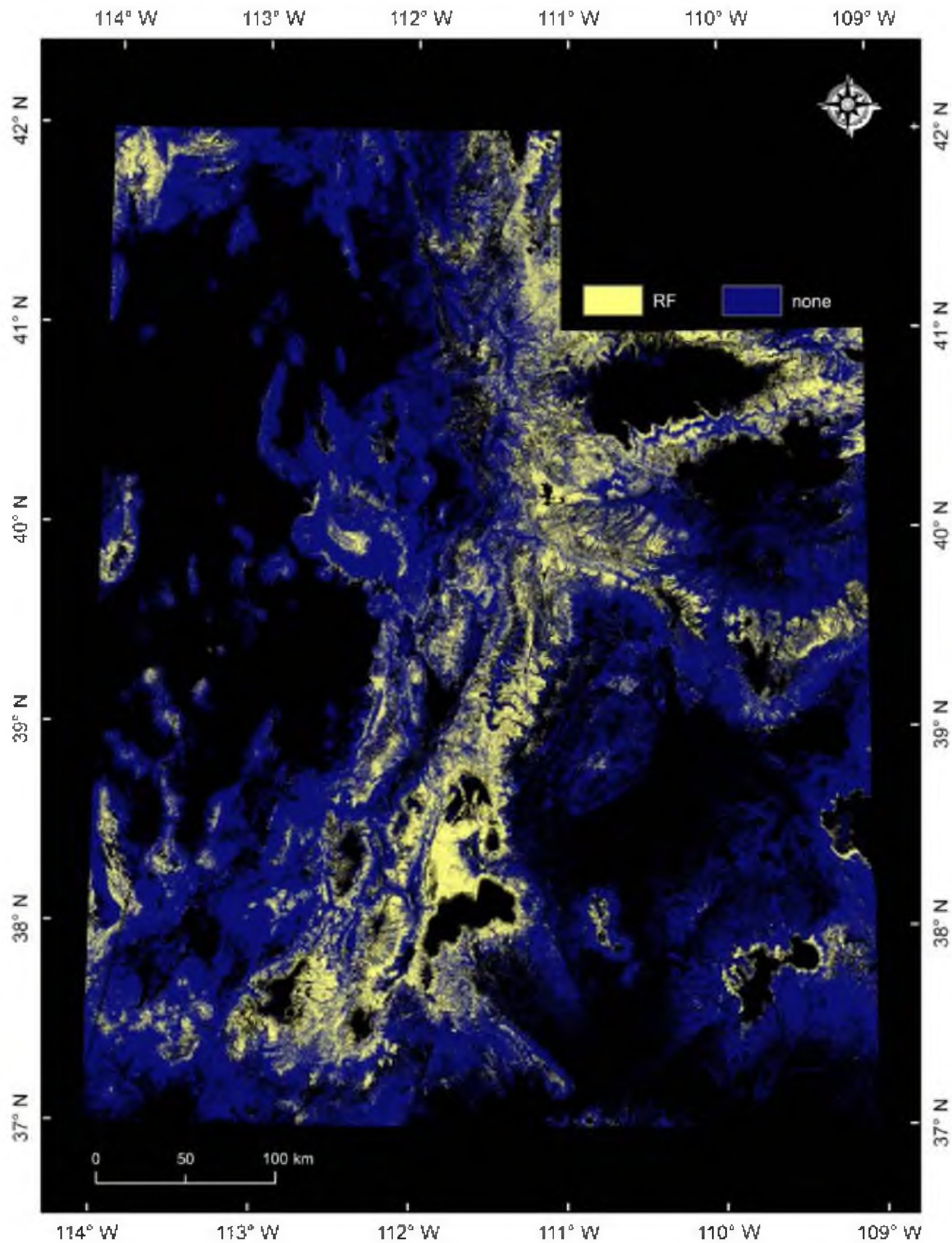


Figure 4.4: Random forest predictive model. Model creation had an AUC of 0.95. Statewide overall acuracy was 93% for brooding and 100% for nesting.

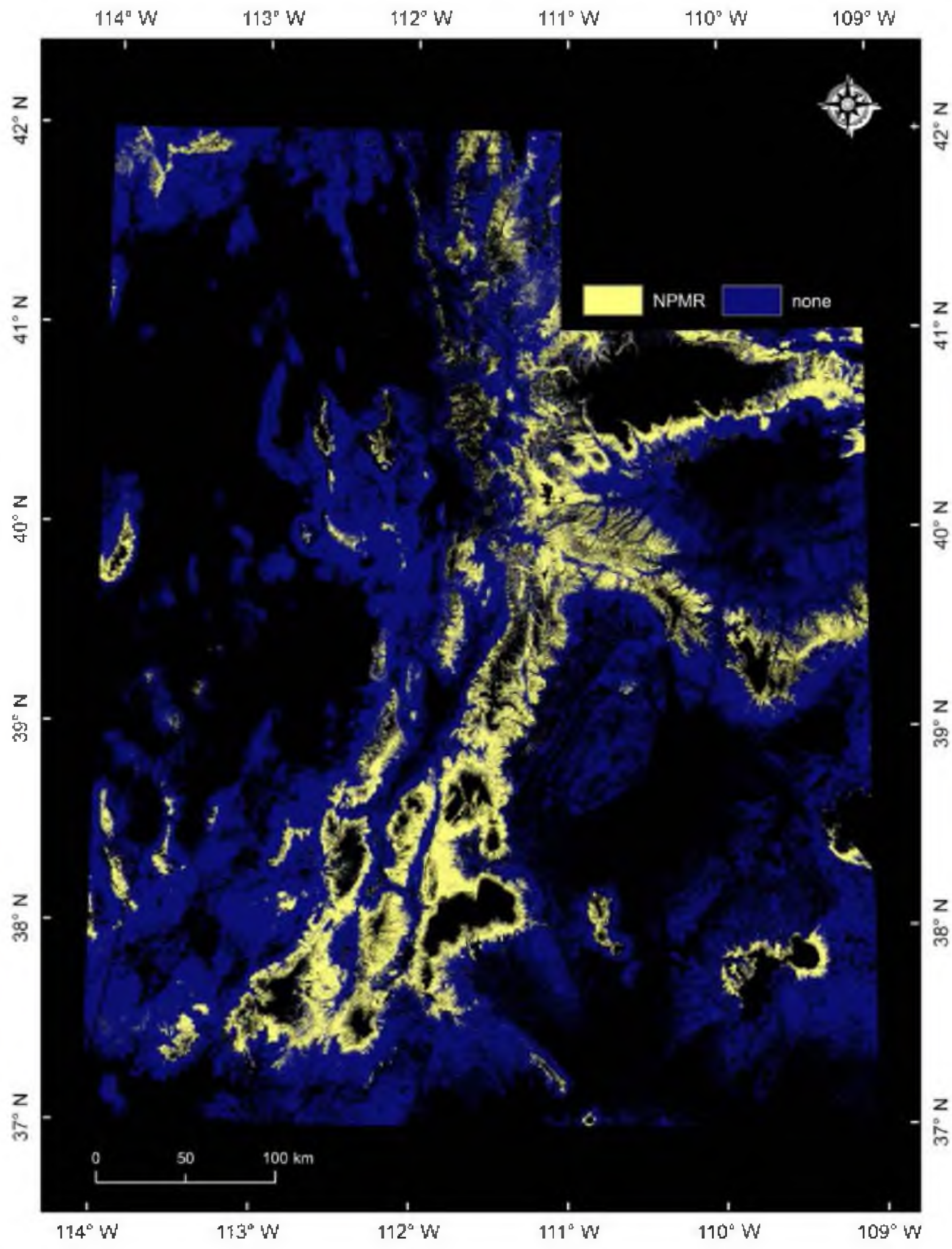


Figure 4.5: Top NPMR predictive model. Model creation had an AUC of 0.92. Statewide overall acuracy was 72% for brooding and 83% for nesting.

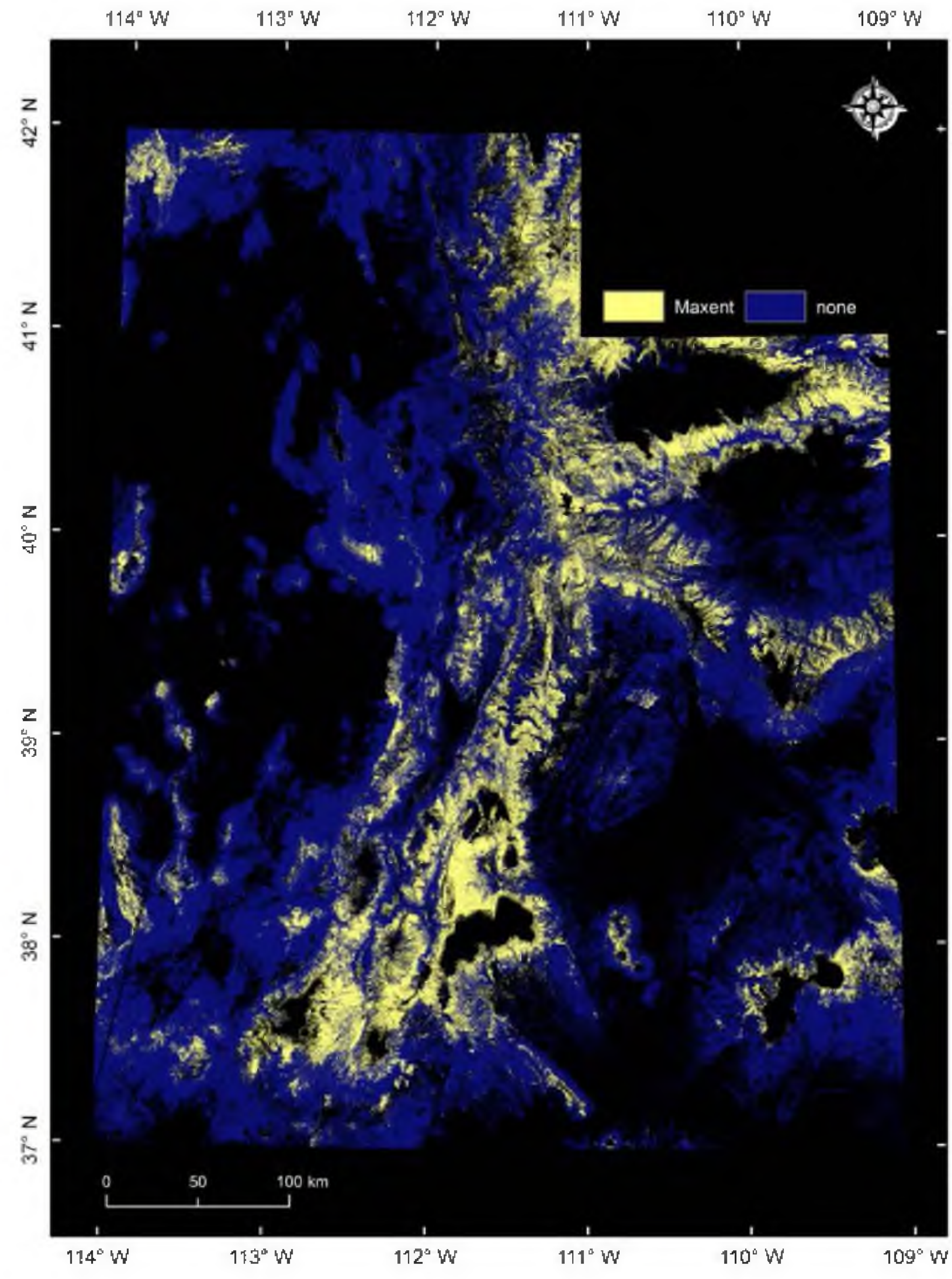


Figure 4.6: Maxent predictive model. Model creation had an AUC of 0.82. Statewide overall acuracy was 72% for brooding and 86% for nesting.

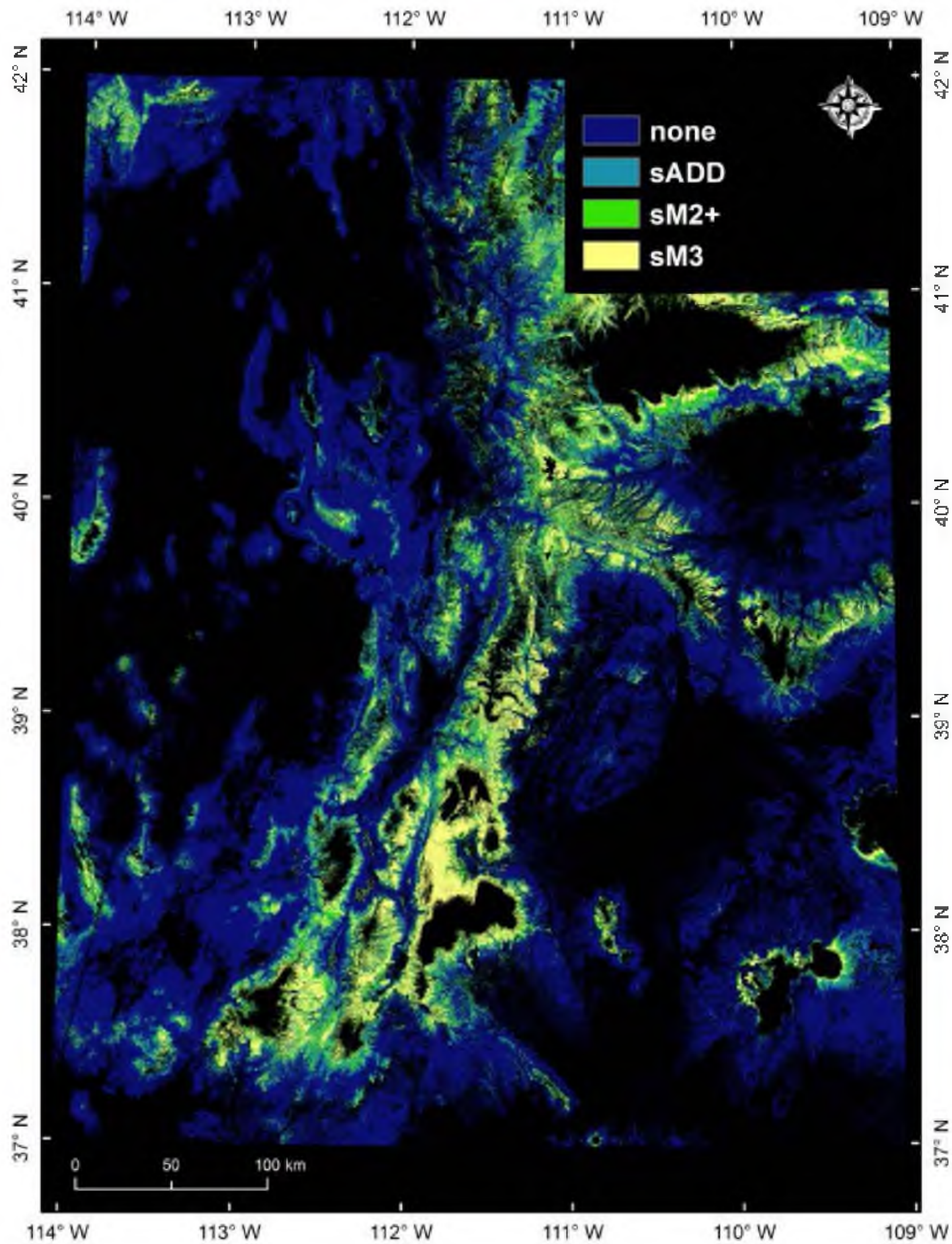


Figure 4.7: Combined predictive model. Statewide brooding overall acuracy was 92%, 77% and 66% for sADD, sM2+ and sM3, respectively. Nest was 100%, 87% and 77% for sADD, sM2+ and sM3, respectively.

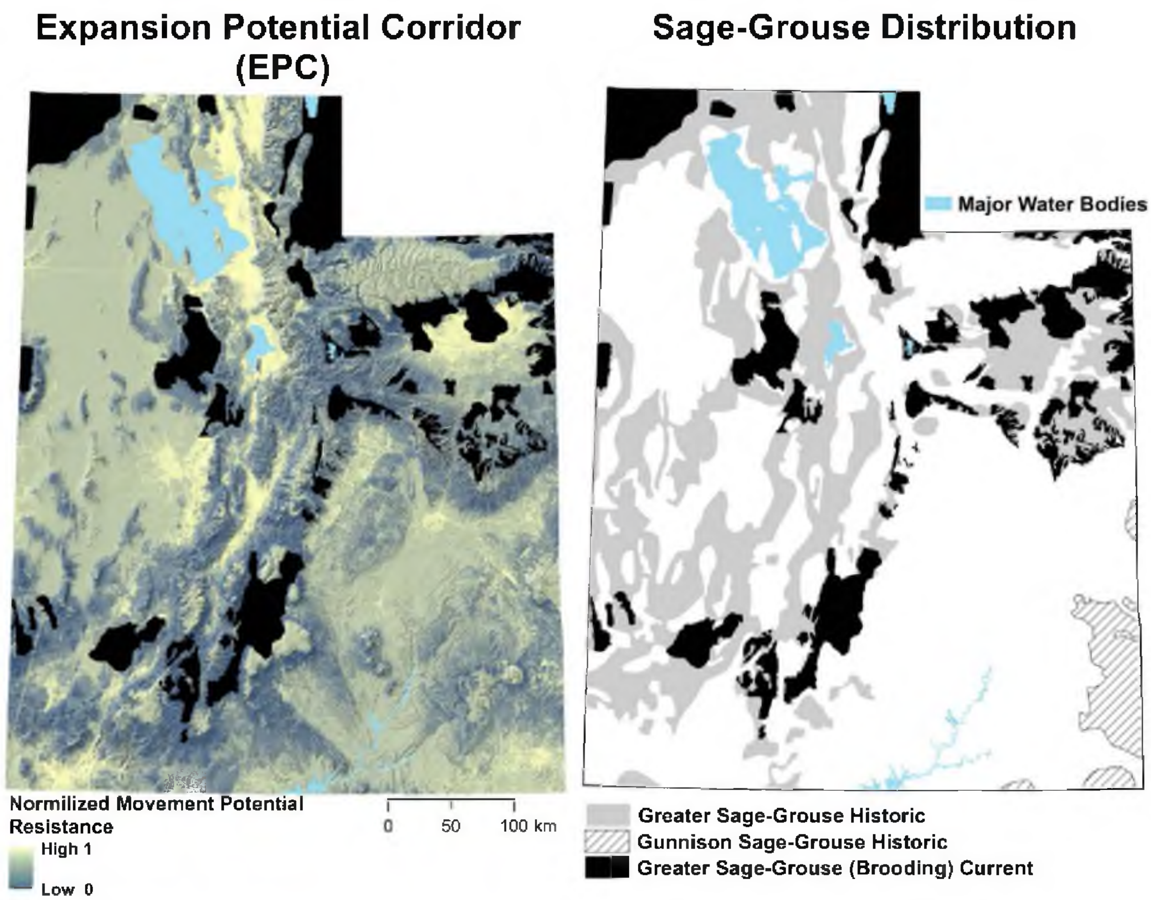


Figure 4.8: Statewide EPC and sage-grouse past and current distribution maps. Past distribution represents pre-1800 distribution (Schroeder et al. 2004).

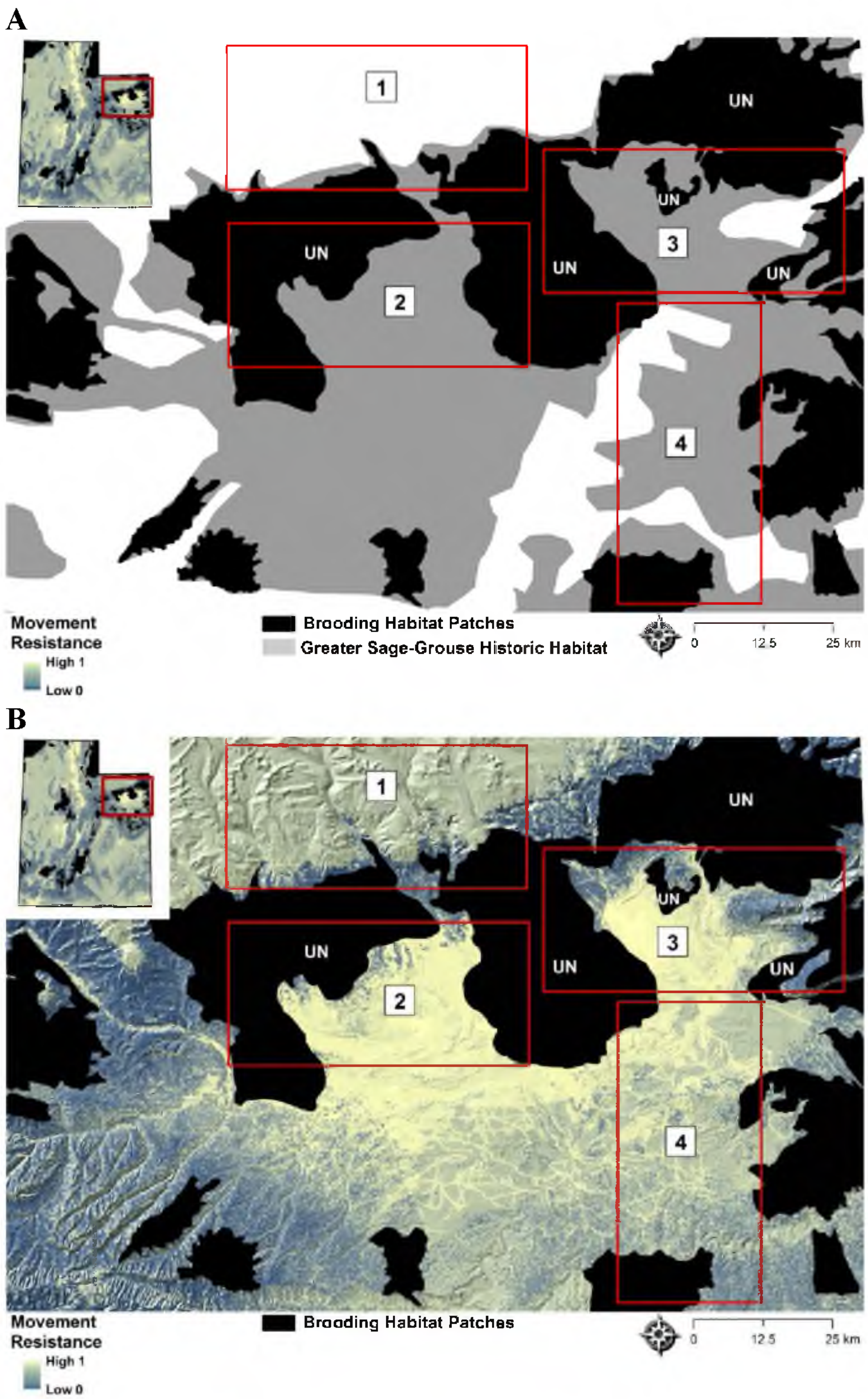
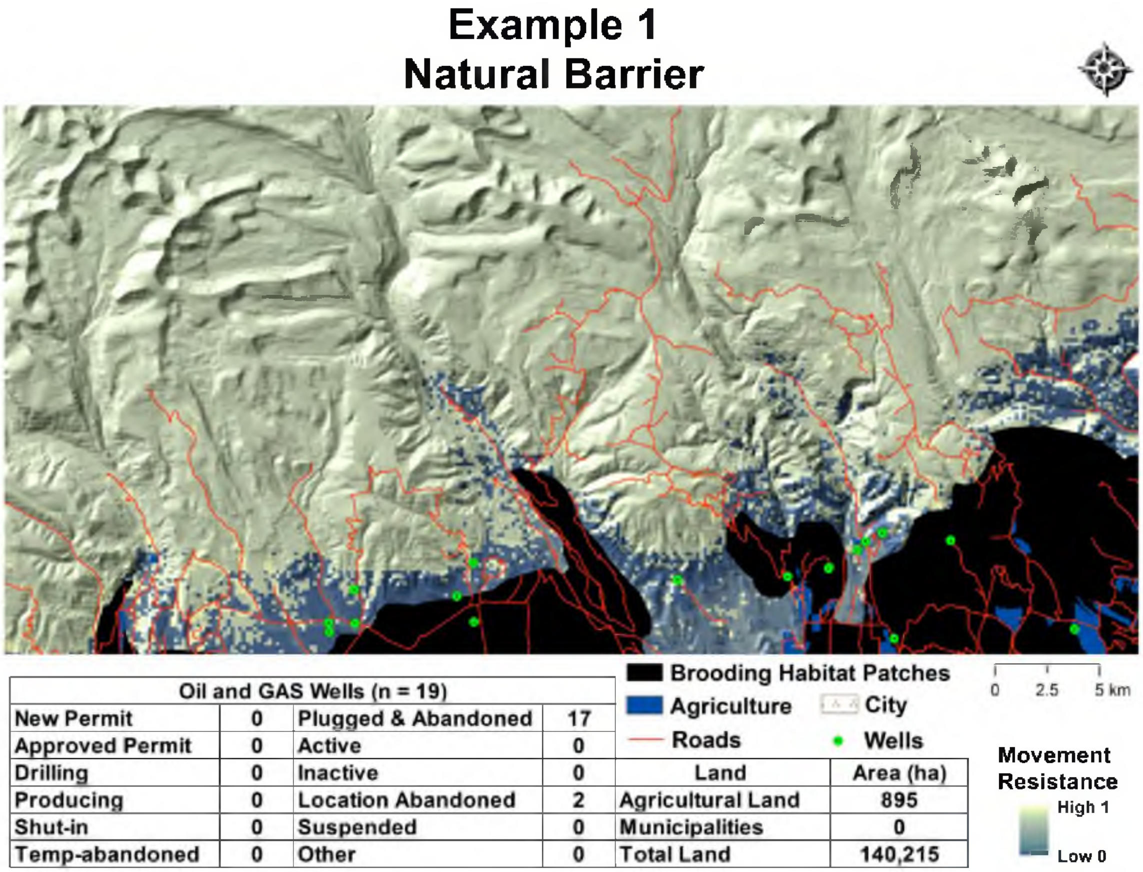


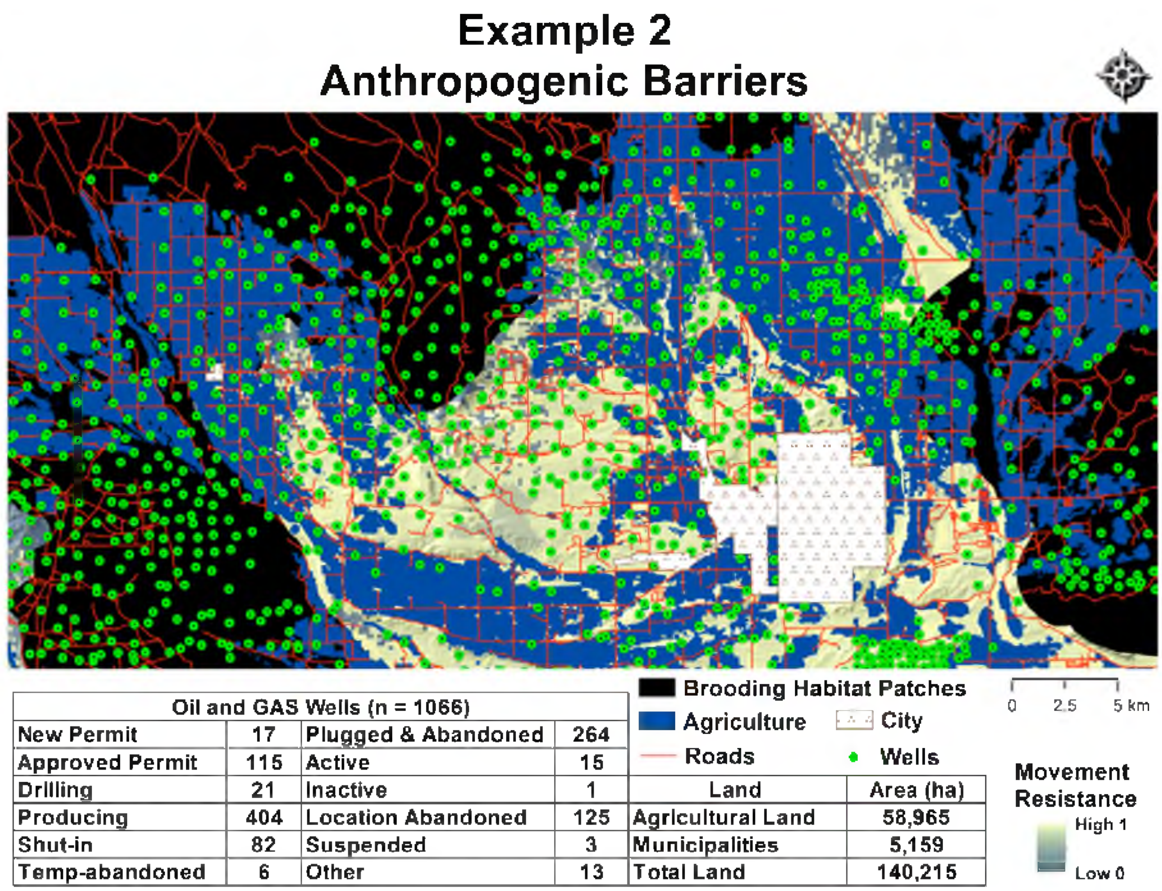
Figure 4.9: Example sage-grouse habitat barriers. A) Sage-grouse distribution in the Uintah basin. B) EPC map of the Uintah basin. UN identifies habitat patches considered here as the Uintah complex. Number one is an example of a natural expansion barrier (see Figure 4.10). Two, three, and four are examples of anthropogenic barriers (Figures 4.11 -4.13).



Oil and GAS Wells (n = 19)			
New Permit	0	Plugged & Abandoned	17
Approved Permit	0	Active	0
Drilling	0	Inactive	0
Producing	0	Location Abandoned	2
Shut-in	0	Suspended	0
Temp-abandoned	0	Other	0

Land	Area (ha)
Agricultural Land	895
Municipalities	0
Total Land	140,215

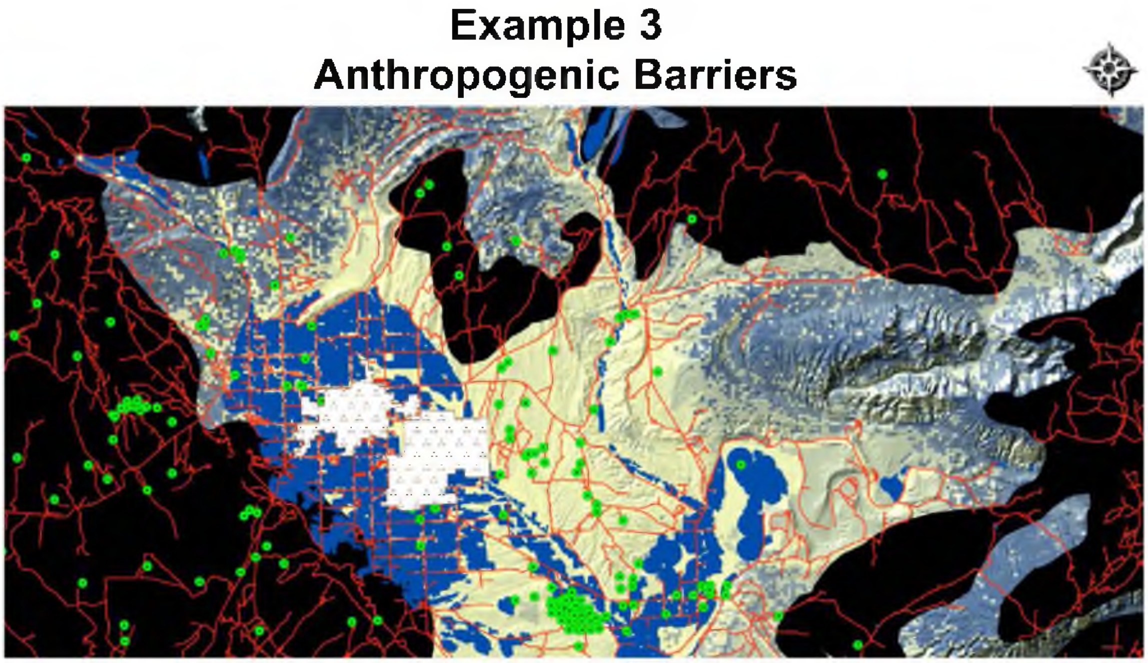
Figure 4.10: Example of a natural barrier for expansion. This area has low habitat probability and low human impact. In comparison to the historic distribution, there is very little change to the northern extent of these patches.



Oil and GAS Wells (n = 1066)			
New Permit	17	Plugged & Abandoned	264
Approved Permit	115	Active	15
Drilling	21	Inactive	1
Producing	404	Location Abandoned	125
Shut-in	82	Suspended	3
Temp-abandoned	6	Other	13

Land	Area (ha)
Agricultural Land	58,965
Municipalities	5,159
Total Land	140,215

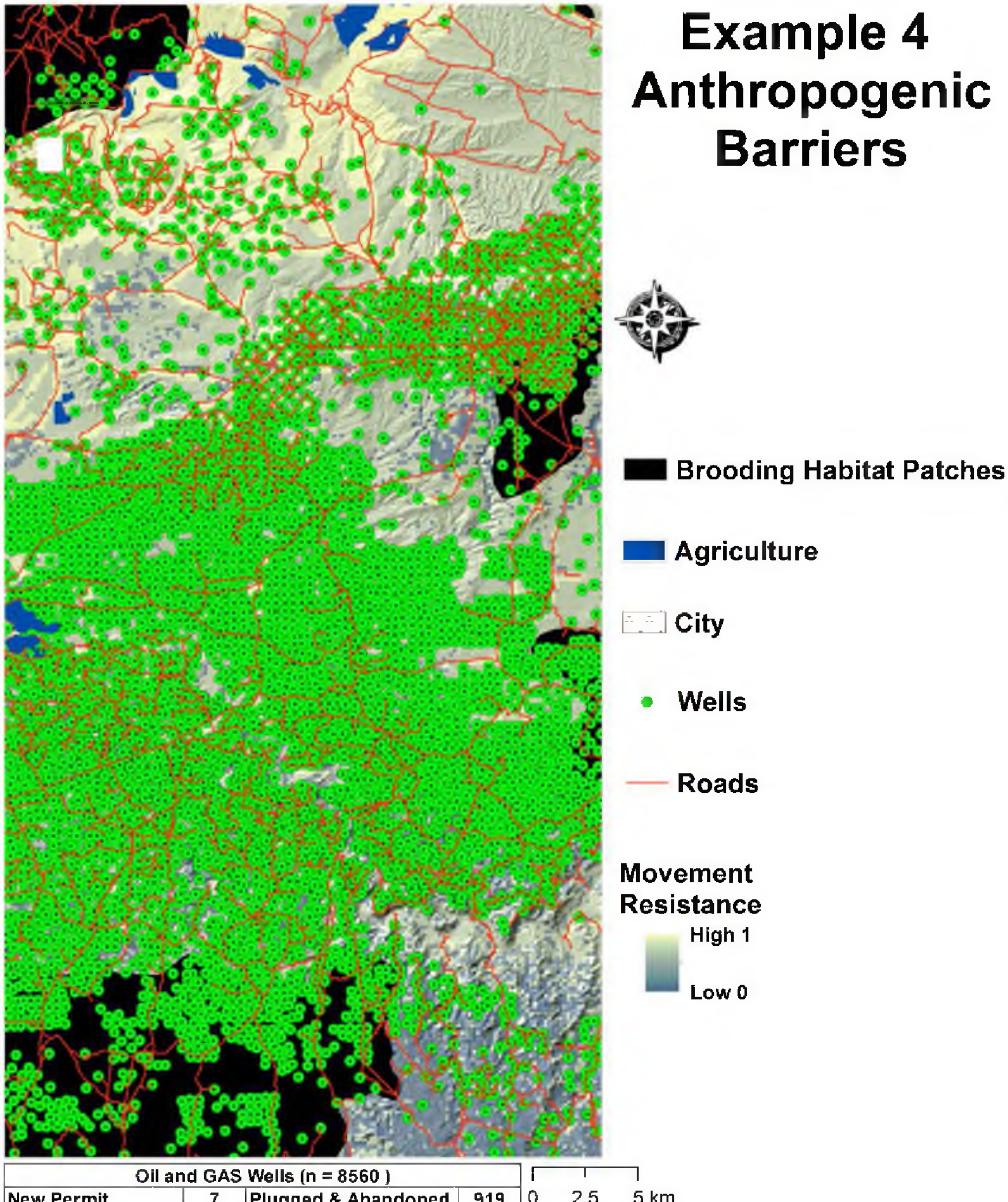
Figure 4.11: Example 2 demonstrates a complex series of anthropogenic barriers on potential habitat expansion. In this relatively small area, potential barriers include cities, farms, energy development and infrastructure such as roads and power lines. Example 2 has low habitat probability and high human impact. Additionally, the entire area was potential habitat at one time.



Oil and GAS Wells (n = 177)			
New Permit	0	Plugged & Abandoned	145
Approved Permit	0	Active	1
Drilling	0	Inactive	0
Producing	13	Location Abandoned	15
Shut-in	1	Suspended	1
Temp-abandoned	0	Other	1

Land	Area (ha)
Agricultural Land	14,570
Municipalities	2,828
Total Land	140,215

Figure 4.12: Example 3, similar to example 2, demonstrates how complex the human barriers can be. However, unlike example 2, there is still a fair amount of potential expansion habitat. Additionally, the human occupied footprint is smaller. Example 3 has moderate habitat potential and moderate human impact.



Oil and GAS Wells (n = 8560)			
New Permit	7	Plugged & Abandoned	919
Approved Permit	1185	Active	119
Drilling	213	Inactive	5
Producing	4353	Location Abandoned	1329
Shut-in	283	Suspended	33
Temp-abandoned	46	Other	68

Land	Area (ha)
Agricultural Land	925
Municipalities	0
Total Land	140215

Figure 4.13: Example 4 is unique with the majority of the anthropogenic impact seen as energy development. It is important to note that the dots that represent the well locations are not to scale of actual impact. This example also has some natural barrier components in the more xeric areas that may have never been suitable habitat (see historic habitat, Figure 4.9). Example 4 is an example of low to moderate habitat potential and medium to high human impact.

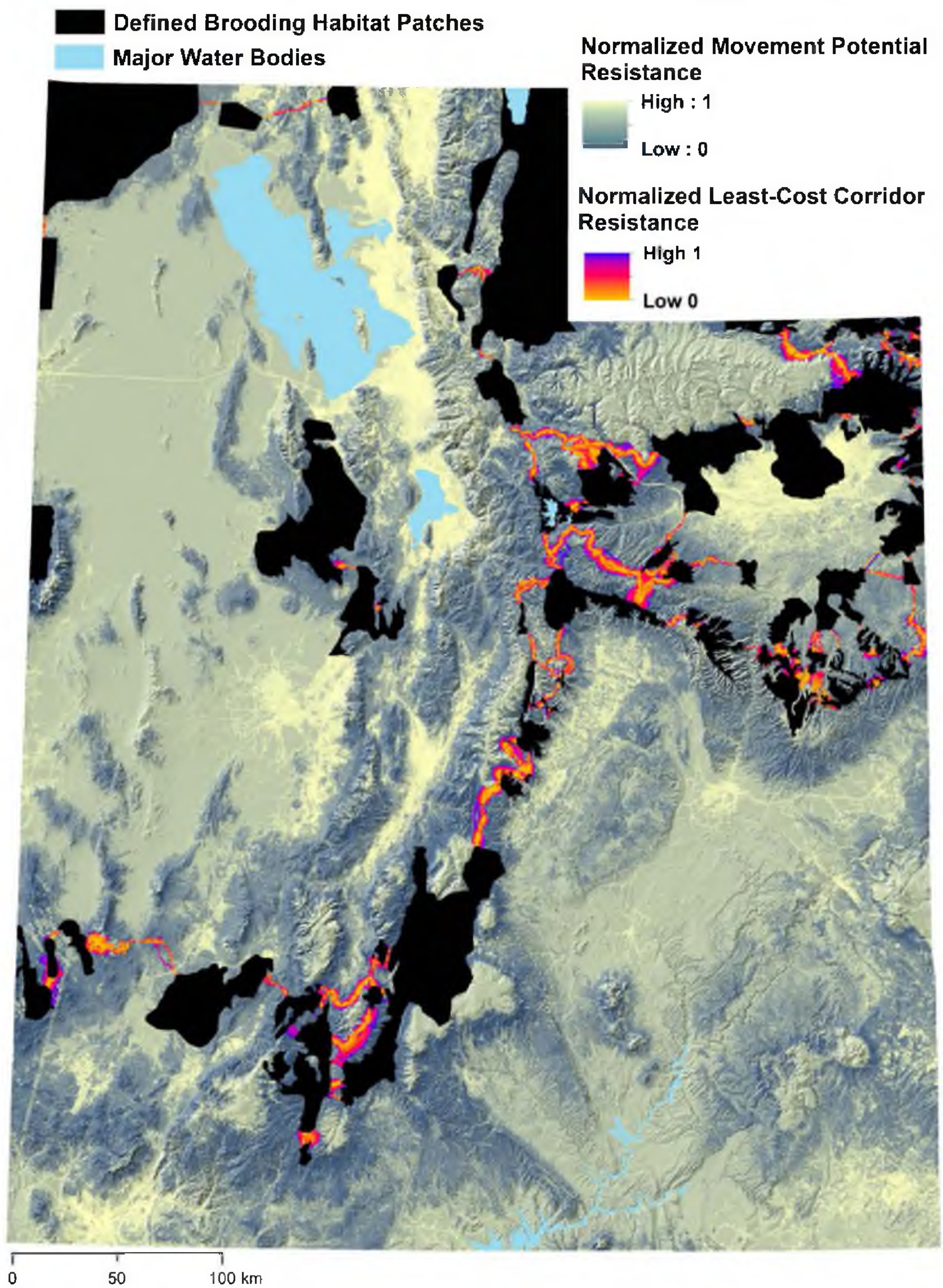


Figure 4.14: State wide movement potential corridors (MPC).

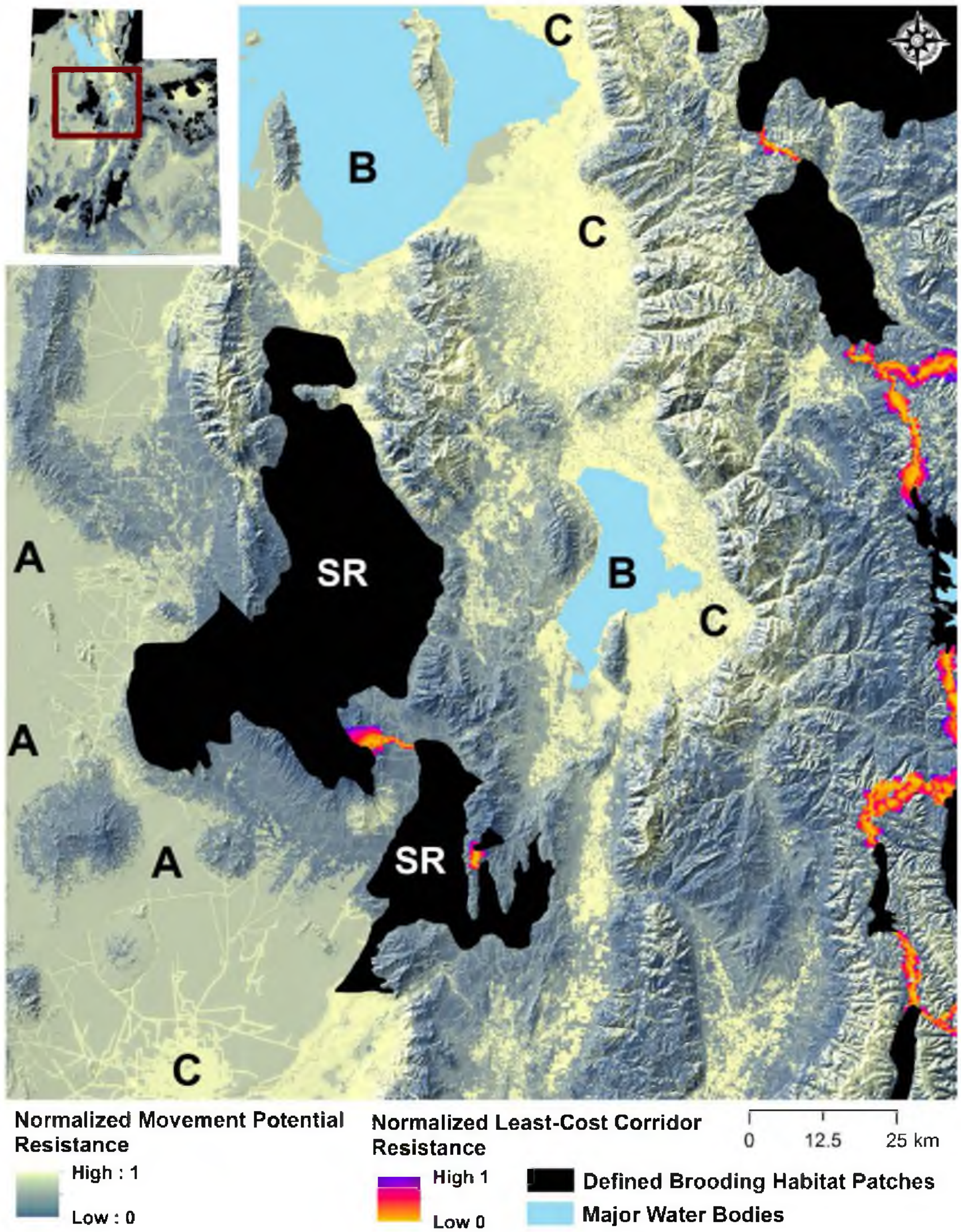


Figure 4.15: SR (Sheep Rock) brooding habitat complex is made up of two interconnected habitat patches otherwise isolated from other patches. The habitat island isolation is due to a combination of natural and anthropogenic barriers. Some examples are shown above as letters. A is a drier basin and is a representation of a natural movement barrier with low human impact and low habitat probability. B represents large water bodies (Utah Lake and the Great Salt Lake) that can be natural movement barriers. C is an extreme example of human impact and settlement with low current probability for habitat and a high human impact.

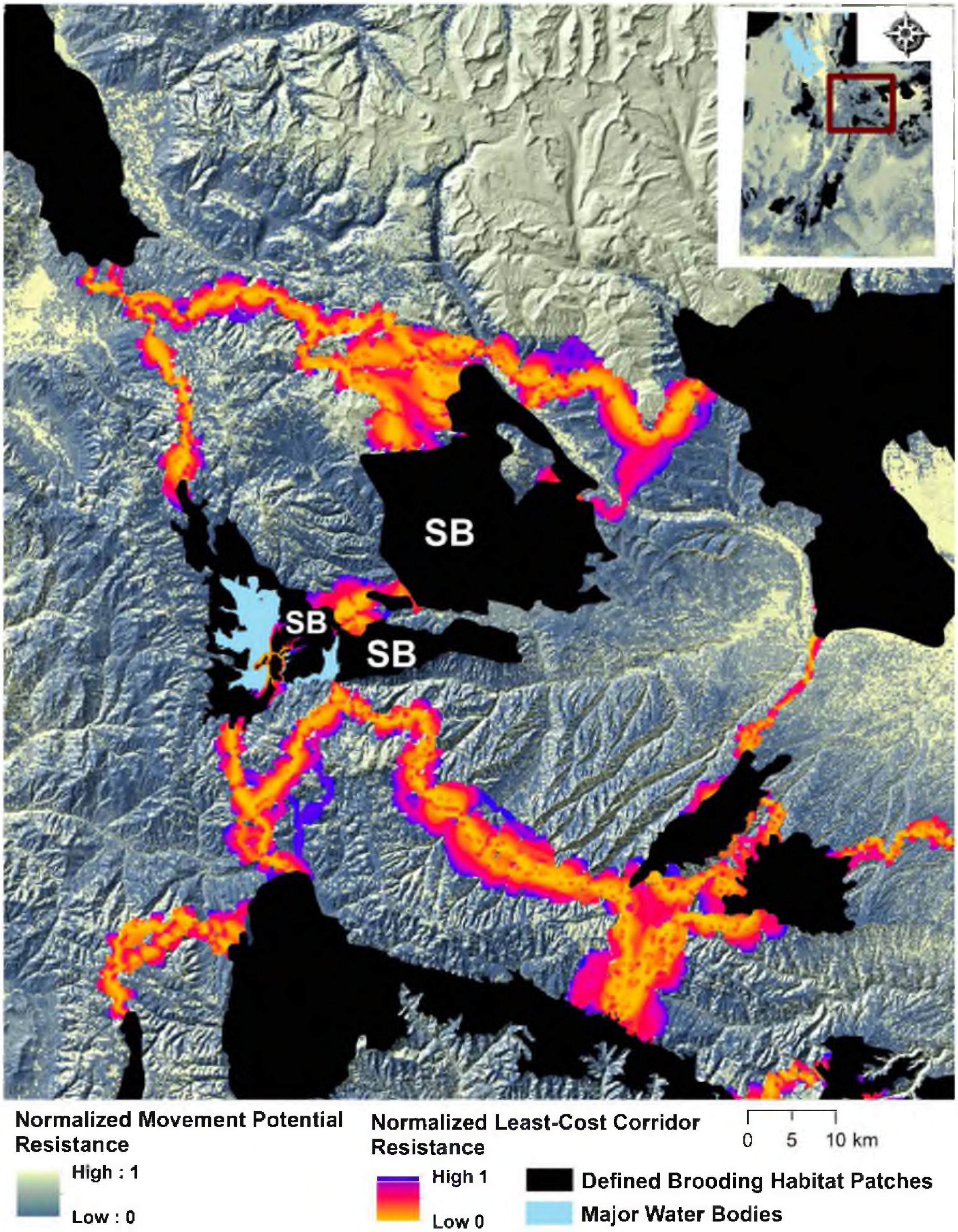


Figure 4.16: Strawberry habitat patch complex. The MPCs help to identify areas of highest probability for movement based on suitable habitat and minimal anthropogenic impacts.

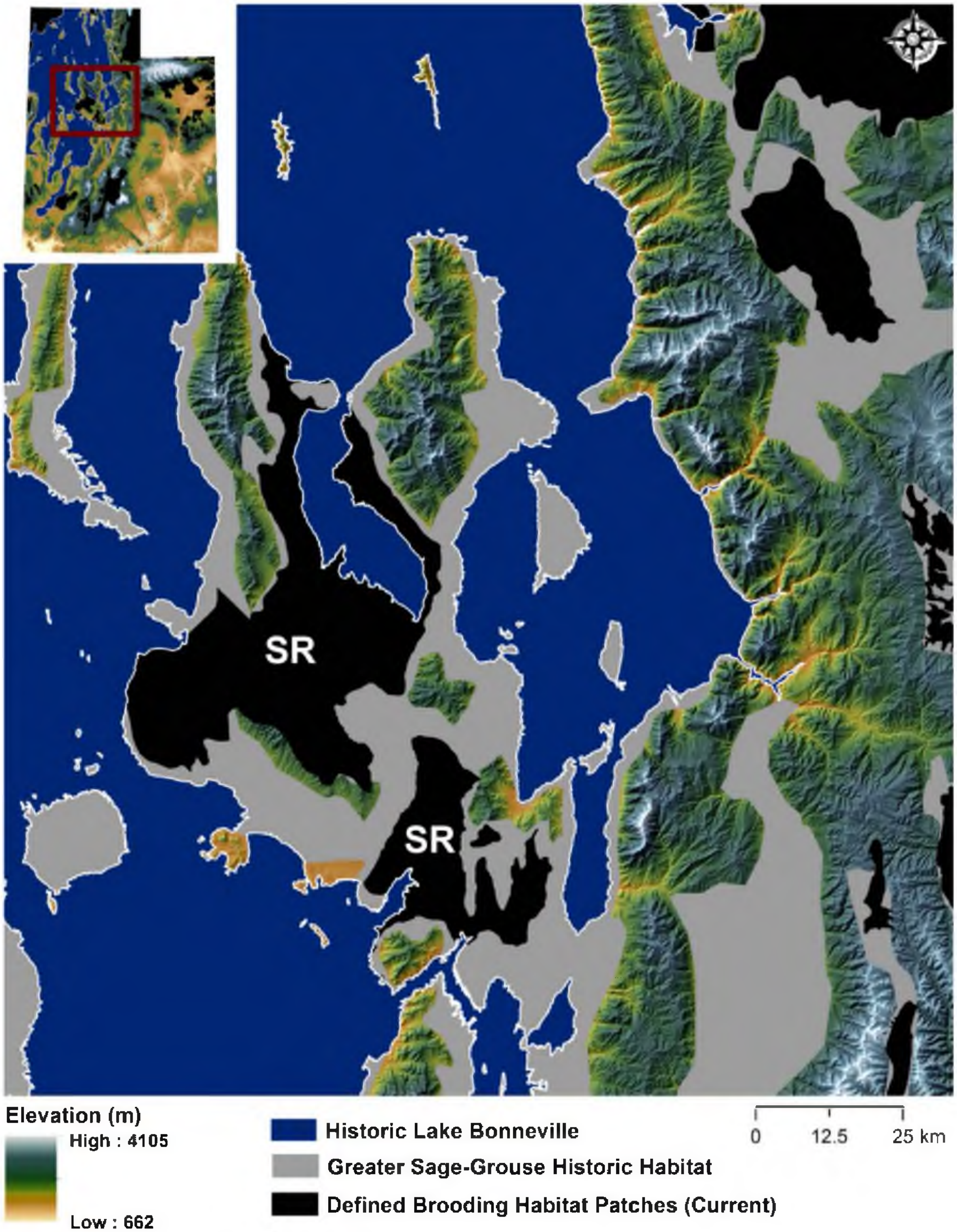


Figure 4.17: Example of potential past temporal natural habitat movement barriers. The area shown is the Sheep Rock habitat patch complex. Compare to current barriers in Figure 4.15.

Table 4.1: DEM derived predictor variables tested in model creation. * Variable found in final model.

Digital Elevation Model Derived (DEM)	
Name	**Description**
Elevation *	Modeled elevation above mean sea level in ms
Slope *	Calculation of the maximum rate of change in elevation between each cell and its eight neighbors
Aspect	The direction of the above listed slope
Curvature	Slope of the slope
Curvature Direction of Slope	Curvature the direction of the maximum slope
Integrated Moisture Index (IMI)	IMI, is a proxy proposed to classify topographically influenced moisture availability (Iverson et al. 1997)
Topographic Position Index (TPI)	TPI is the relative topographic position to surrounding cells (Jenness 2006)
Terrain Ruggedness Index (TRI)	TRI, uses the difference between each cells elevation and the surrounding 8 cells to determine a ruggedness score (Riley 1999)

Table 4.2: This table shows Landsat derived predictor variables. Individual TM bands were tested as well as vegetation indices for model creation. Band numbers designated by the lowercase b in the vegetation indices indicate the TM band used. None of the individual predictors from this table were found in the final sage-grouse habitat model. However, band 4, band 7, MSAVI2 and $NDII_5$ were significant in the sagebrush cover and total vegetation models used in the final model.

Landsat5 Thematic Mapper (TM) Derived	
Name and Reference	**Wavelength or Equation**
Band 1	0.45 - 0.52µm
Band 2	0.52 - 0.60µm
Band 3	0.63 - 0.69µm
Band 4	0.76 - 0.90µm
Band 5	1.55 - 1.75µm
Band 7	2.08 - 2.35µm
Normalized Difference Vegetation Index (NDVI) Rouse et al. (1973)	$\mathrm{NDVI} = \dfrac{(\rho_{b4} - \rho_{b3})}{(\rho_{b4} + \rho_{b3})}$
Normalized Difference Infrared Index ($NDII_5$) Hardiskey et al. (1983) Hunt and Rock (1989)	$\mathrm{NDII}_5 = \dfrac{(\rho_{b4} - \rho_{b5})}{(\rho_{b4} + \rho_{b5})}$
Normalized Difference Infrared Index ($NDII_7$) Hardiskey et al. (1983) Hunt and Rock (1989)	$\mathrm{NDII}_7 = \dfrac{(\rho_{b4} - \rho_{b7})}{(\rho_{b4} + \rho_{b7})}$
Modified Soil-Adjusted Vegetation Index 2 (MSAVI2) Qi et al. (1994)	$\mathrm{MSAVI2} = \dfrac{\left(2 \times \rho_{b4} + 1 - \sqrt{\left((2 \times \rho_{b4} + 1)^2 - 8 \times (\rho_{b4} - \rho_{b3})\right)}\right)}{2}$

Table 4.3: Vegetation cover models created for use in the final model. *Both were found to be important predictors for sage-grouse habitat.

Vegetation Cover Models	
Name	**Description**
Sagebrush presence (>5%) *	Created with nonparametric multiplicative regression. The significant variables for model creation were, in order of importance: elevation, TM band 4, and curvature direction of slope. The overall accuracy of the model was 72%
Total Vegetation Cover *	Created with a generalized additive model. The significant variables for model creation were, in order of importance: MSAVI2 NDII5 TM band 7 and aspect. The RMSE was 6.6%

Table 4.4: TM3732 model creation validation (AUC values) and predictor order. Comparison of the top predictor variables with their order of importance is shown. The rank agreement is percent agreement for each variables importance across all measures.

Model Creation Relative Importance 3732							
Variable	**NPMR**		**Maxent**		**RF**		**Rank Agreement**
	S1/Rank	S2/Rank	PC/Rank	PI/Rank	MDA/ Rank	MDG/ Rank	
Elevation (EL)	0.63/1	0.88/1	59.5/1	65.7/1	230/1	880/1	100%
Sagebrush (SB)	0.43/2	0.6/2	10.3/3	8.3/3	105/4	650/2	50%
Slope (SL)	0.32/3	0.43/3	20/2	18.9/2	170/2	410/3	50%
Total Vegetation (TV)	0.27/4	0.36/4	10.2/4	7.1/4	130/3	390/4	83%
AUC Values	0.80		0.87		0.96		

Table 4.5: TM3732 Accuracy assessment. Percent overall accuracy compared to ground data and predicted area is shown.

3732 Validation		
Model	**Area of predicted habitat (ha)**	**Percent Overall Accuracy (n =45)**
Random Forest (RF)	41,752	89%
Maxent	41,298	89%
NPMR	50,611	84%
ADD	57,390	98%
M2+	40,039	90%
M3	25,874	79%
sADD	65,658	100%
sM2+	38,871	93%
sM3	24,407	83%

Table 4.6: Statewide model validation and predictor order. This table is a comparison of the top predictor variables with their order of importance and model AUC values for the state of Utah. The rank agreement shows how often a variable's order of importance agrees across all importance measures.

Relative Importance State							
Variable	**NPMR**		**Maxent**		**RF**		**Rank Agreement**
	S1/Rank	S2/Rank	PC/Rank	PI/Rank	MDA/ Rank	MDG/ Rank	
Elevation (EL)	1.05/1	1.45/1	65.9/1	59/1	129/1	415/1	100%
Total Vegetation (TV)	.50/2	.76/2	11.0/3	15.2/3	85/3	210/2	50%
Sagebrush (SB)	0.24/3	.36/3	4.3/4	8.6/4	95/2	160/3	50%
Slope (SL)	.03/4	.03/4	18.8/2	17.3/2	64/4	148/4	67%
AUC Values	0.92		0.82		0.95		

Table 4.7: Statewide accuracy assessment. Percent overall accuracy (OA) and total ha modeled by each method is separated out by sage-grouse life stages. Columns labeled "State" represent random samples withheld from the entire state. Columns labeled "DMD" represent the entire Diamond Mountain population withheld from model creation. The numbers after the percent in brackets represent ground validation locations that fell in unmolded areas.

Validation					
Model	**Ha**	**OA% Brood State (n =50)**	**OA% Nest State (n=50)**	**OA% Brood DMD (n=100)**	**OA% Nest DMD (n=49)**
Random Forest	276,959	93% (4)	100% (7)	73% (6)	77% (1)
Maxent	224,218	72% (4)	86% (7)	87% (6)	85% (1)
NPMR	224,290	72% (4)	83% (8)	88% (6)	94% (1)
ADD	315,134	96% (4)	100% (9)	100% (6)	98% (1)
M2+	220,120	74% (4)	95% (9)	85% (6)	90% (1)
M3	95,014	67% (4)	78% (9)	44% (6)	38% (1)
sADD	323,397	92% (2)	100% (3)	100% (1)	98% (0)
sM2+	161,638	77% (2)	87% (3)	87% (1)	92% (0)
sM3	47,077	66% (2)	77% (3)	41% (1)	37% (0)

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CHAPTER 5

SUMMARY AND CONCLUSIONS

Discussion

The use of nested predictive ecological niche models was found to be a powerful tool to better understand and visualize greater sage-grouse and their habitat distribution across a broad spatial extent (Utah). Furthermore, models presented in this work show great promise in improving our understanding concerning spatial and temporal aspects of sagebrush habitat changes and influence on sage-grouse utilization. Additionally, the modeling methods used here could be applied to other species across a variety of spatial extents and topographic gradients. Although all models by nature are flawed, there were a series of results that were reached that supported the above stated conclusions. These findings were separated into three categories consistent with the chapters found in this dissertation: sagebrush distribution models (Chapter 2), total vegetation cover models (Chapter 3) and sage-grouse distribution and connectivity models (Chapter 4).

Based on sage-grouses' dependence on sagebrush, the logical starting point was to first create a sagebrush distribution map. In order to capture all habitats relevant to potential sage-grouse use, sagebrush cover of >5% was the cutoff for sagebrush presence. The target extent was broad (Utah) but the target resolution was fine (30m). In order to be applicable to future land managers, the modeling methods needed to meet the criteria of accurate predictions, low cost and easily updatable. It was found that:

1) A fine scale sagebrush distribution model, projected across a geographically diverse and spatially broad extent, is possible using currently available data and software. This was demonstrated with a statewide predictive map with an overall accuracy of 72%.
2) Using climate envelopes and future climate predictions, sagebrush stands that are more vulnerable to climate change can be identified.

Extensive studies have shown that sage-grouse utilize habitat with differing amounts of vegetation cover, depending on their life phase (nest, brood, winter or others; Connelley et al. 2011). For example, sagebrush cover suggested for optimal nest habitat is between 15-25%, compared to winter habitat that can be as high as 43% (Connelly et al. 2000, 2011, Braun 2005, Schroeder et al. 1999). In efforts to map total vegetation cover, it was found that:

1) Accurate fine scale broad extent percent total vegetation cover models are possible. I was able to produce a model that for the state of Utah with a RMSE of 6.6% cover.
2) The spatial extent of one Landsat 5 TM scene (3732 clipped to Utah) and ground data, obtained from Utah's Big Game Range Trend Studies, could be used (with additional predictor variables) to train a total vegetation cover model applicable to the political boundaries of Utah.
3) The temporal limitation (seasonal and annual) of predicting total vegetation cover can be minimized using multitemporal ground (range trend) and sensors (Landsat TM) data. This was demonstrated by predicting total vegetation cover across multiple years with no loss in overall accuracy.

4) Total vegetation models predicted across multiple time periods can be used to identify if an area's vegetation cover has changed. By identifying areas of change, additional comparisons between vegetation cover change and sage-grouse habitat selection were possible. It was found that most sage-grouse locations were in habitat that had experienced an increase in total vegetation cover over the last two decades.

With acceptable sagebrush and total vegetation cover models in place, nested predictive sage-grouse distribution and connectivity maps were created for sage-grouse. The sage-grouse life stages of interest were nest and brooding. These life stages were targeted due to their similarity and close proximity to each other as well as the availability of the data. A challenge to any ecological model is what method and or software package to use. After exploring many ecological modeling techniques (assessing them for their ability, cost and availability) three methods stood out in the literature. These models were nonparametric multiplicative regression (NPMR), maximum entropy distribution (Maxent) and random forest (RF). All three methods were used to model sage-grouse habitat independently. Additionally, a combined method agreement model was created and validated. The sage-grouse ecological niche agreement model was further combined with a human impact model (Leu et al. 2008) to predict potential habitat corridors. It was found that:

1) Statistically, overall performance of all three model methods used was similar. However, there was variation in areas covered be the predictive models. By creating an agreement model with all three methods, I was able to focus on areas with the highest probability for sage-grouse habitat.

2) Using sage-grouse habitat as a component of habitat patch connectivity, I propose two types of potential species corridors. The first represents the potential for a delineated habitat patch to expansion. The expansion potential corridor (EPC) is based on predicted habitat and its juxtaposition to currently delineated habitat. It is important to consider natural as well as anthropogenic driven habitat expansions, contractions or shifts near currently delineated habitat for long-term species survival. This expansion potential could be used when delineating or re-evaluating areas for sage-grouse conservation. The second corridor is a movement potential corridor (MPC). The movement potential corridor identifies potential links, or lack thereof, between delineated habitat patches and populations. The MPC can help to better understand potential connectivity and genetic flow within and between populations. The methods used to create both these corridors could be applied to other species and habitats with minor adaptations.

Management and Conservation Implications

The Utah sagebrush model predicted just over 2 million ha of potential sagebrush (Chapter 2). However, with the well documented loss of sage-grouse habitat and with their current distribution, it can be assumed that much of the existing areas that support 5% or more sagebrush are not suitable or reachable for sage-grouse. This may be due to the sagebrush's overall cover, health, connectivity or other factors unrelated to the sagebrush. Using the juxtaposition of current sage-grouse habitat patches and the modeled sagebrush, land managers could assess the surrounding sagebrush for potential sage-grouse occupation deterrents, such as anthropogenic features, arthropod diversity, undesirable sagebrush understory or others. In some cases, these deterrents could be mitigated in order to expand the surrounding potential sage-grouse habitat. For example, habitat could be improved by seeding desirable understory plants or removal of anthropogenic features where possible. These improvements would be focused on large intact sagebrush stands identified by the models in close proximity to habitat patches currently in use by sage-grouse. Initial climate models show that some sagebrush stands that are currently utilized by sage-grouse are going to be impacted more negatively by future climate change than others. One sage-grouse habitat patch that will be more influenced by changing climate is the Sheep Rock patch (Chapter 4, Chapter 2). The Sheep Rock patch, in every scenario modeled, showed a drastic reduction in the sagebrush climate envelope. Even the most conservative climate scenarios predict that in that patch there will be almost no suitable climate for sagebrush (and therefore sage-grouse) by 2080 (see Chapter 2, Figure 2.7). It is difficult to know what the best practices are to reduce the potential impact of climate change. However, in areas with predicted higher probability to be outside the current climate envelope for sagebrush, more preventative management could be implemented. For example, anthropogenic impacts could be reduced, fire prevention could be prioritized and other factors that would further put pressure on the sagebrush communities in these areas could be minimized. The total vegetation cover model (Chapter 3) could be used in conjunction with the potential sagebrush model to better understand the heterogeneity of the vegetation cover within predicted sagebrush stands. By tracking the total vegetation cover in sage-grouse habitat (or other sagebrush obligates) land managers may be able to detect changes in the health and vegetation type over a large area with minimal cost. These changes may be used for early detection of sagebrush degradation. For example, in more xeric sagebrush stands, where cheat grass (*Bromus tectorum* L.) and other invasive species are known to invade the interspaces, modeled rapid increases in total vegetation cover may be used as an early warning sign for reduced sage-grouse habitat potential of those sites. Within the nearly 2 million ha of potential sagebrush, the sage-grouse model (SM2, Chapter 4) only predicted roughly 162 thousand ha (less than 1%) as potential sage-grouse habitat in Utah. By narrowing the areas of potential habitat land managers can focus the limited funds and personnel on areas with the highest potential for habitat. When assessing where to invest money for habitat improvement and maintenance, it is important to be able to see the connectivity of the site to be improved, even if the treatment is small. For example, if there were only sufficient funds to improve or protect one habitat patch in a fiscal year, and there were multiple patches proposed for treatment, the models could be used to identify, at the landscape scale, patches that have more influence on the overall connectivity to the population. The modeled corridors could also be used or altered to identify areas within sage-grouse habitat that may be converting to future barriers for genetic flow. For example, habitat areas that have woodland encroachment on the upslope and private agriculture encroachment on the downslope could be identified with the predictive models. Early prevention plans could be implemented. These plans could include tree removal on the upslope and or agreements with the private land owners to maintain suitable habitat (easement) on the downslope. If no proactive measures were possible at the time, higher priority could be given to the existing habitat based on potential connectivity loss.

The work presented here focused on sage-grouse and their habitats at a landscape scale. However, the methods used and the theories applied are universal in their application to a variety of species at multiple scales. As improvements are made in modeling techniques, remote sensing platforms and data sharing continues, so will our ability to improve these models and apply them across more areas. Additionally, ground data for sagebrush will be explored for more spatial and temporal coverage. Furthermore, a management focused tool with a simple interface could be developed, that would create the desired habitat and corridor models presented here.

Future Research

After reviewing the current literature and discussions with land managers and conservation groups, I feel the most pressing future work for sage-grouse conservation (outside of habitat conservation itself) is to better understand the impacts of future climate changes. In the face of hotter and drier climate conditions, many of the known sage-grouse habitat stressors will be exacerbated. My future work will focus on improving climate change predictions for sagebrush by averaging more global climate models and exploring ways to reduce potential error of future predictions. I will seek to better understand and communicate the drivers of uncertainty and variability in future climate predictions for variables such as temperatures and precipitation. I will look to advancing our ability to incorporate more biological interactions and species vitality metrics (e.g., nest success) to more fully capture a species niche. If ecological niche models can be advanced to more reliably predict potential climate change impacts to current habitat patches, they will greatly improve how we manage and study species at the landscape scale.

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