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Estimating wildfire potential on a Mojave Desert landscape using remote sensing and field sampling

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ESTIMATING WILDFIRE POTENTIAL ON A MOJAVE DESERT LANDSCAPE USING REMOTE SENSING AND FIELD SAMPLING

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ABSTRACT

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Wildland fire and fuel characteristics are useful in developing wildfire prediction tools that can be used to allocate wildfire resources and guide land management practices. Wildfire prediction in arid habitats in the southwestern United States is of specific concern because of the negative ecological impacts of fire on desert habitats and the current lack of accurate fire prediction tools for such areas. Wildfires in desert ecosystems threaten endangered wildlife such as the desert tortoise (*Gopherus agassizii*) , damage native plant species through increased seed and plant mortality, and jeopardize unique plant communities through increased likelihood of exotic plant invasions. By measuring fuel loads within various vegetation types of the Mojave Desert and using remote sensing techniques to model those fuel loads, this study examines the ability to model previous fire occurrences and estimate future fire potential using satellite imagery derived Normalized Difference Vegetation Index (NDVI) and Fuel Moisture Content (FMC) along with ignition potential data (lightning strikes and distance to roads), topographical data (elevation and aspect), and climate information (maximum and minimum temperatures). Satellite data were used to create a suite of potential fuel load models that were then evaluated using AIC model selection and narrowed to the two best fit models for describing fuel load estimates derived from on-the-ground fuel load

surveys. Of those two models, Model 2 had a better R^2 (0.35) and AIC (-366.5703) than Model 1 (0.29 and -348.2616 respectively). However, Model 1, which incorporated spring NDVI, elevation, maximum temperature, and aspect, was chosen as the most defensible model in terms of the ecological interactions driving fuel production. Model 1 was then used in conjunction with 2005 remote sensing and fire occurrence data to predict fire potential for that year. Fuel load Model 1 along with spring FMC at maximum temperature, lightning strikes, distance to roads, and perennial vegetation type were modeled and a Receiver Operating Characteristic (ROC) curve was used to evaluate the agreement between model predictions and actual fire occurrence. The ROC evaluation rendered an Area Under the Curve value of 0.90 indicating accurate prediction of fire occurrence for 2005. This study provides evidence that remote sensing techniques can be used in combination with field surveys to accurately predict wildfire potential in desert habitats observed in Gold Butte, Nevada. Additionally, this research provides a baseline by which future wildfire potential estimates can be streamlined for the Gold Butte area with the possibility for improved estimate accuracy with continued research to improve on the techniques described herein. Improving the accuracy of wildfire prediction in the area of Gold Butte can help land managers maximize their efficiency and effectiveness in wildland fire suppression as well as expand on the base of knowledge used towards protecting natural plant communities, restoring endangered species habitat, and managing public access and use in natural areas. This research also has potential applications in other arid and semi-arid ecoregions of the American southwest and perhaps other countries as well.

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CHAPTER 1

INTRODUCTION

The goal of this research was to expand on the current knowledge of modeling wildland fire potential in an area of the Mojave Desert known as Gold Butte, NV. In a broader sense, this study was also meant to improve our understanding of the driving ecological factors influencing wildfire activity in arid and semi-arid environments. Since the 1970s, areas of the southwestern United States have had increased wildfire frequency in conjunction with increased human activity and concomitant invasions of alien annual grasses (Brooks and Esque 2002). In fact, such invasions have been observed to dominate post-fire landscapes in desert regions (Brooks et al. 2004), only complicating the fire potential and land management issues. Research has shown that increased fire frequency, size, and temperature can have major impacts on desert ecosystems. Brooks (2002) found that annual plant biomass and plant diversity was reduced after fire, which he attributed to seed mortality at peak fire temperatures. Desert wildfires have also been shown to threaten native plant communities (Abella et al. 2009) and endangered species (Esque et al. 2003). These negative ecological impacts are further compounded by the lack of knowledge pertaining to fire hazards in North American deserts because, until recently, there has been little research due to historically infrequent fire activity.

In order for land managers to develop fire management and restoration plans, fuels information and fire hazard maps are necessary. With accurate and detailed wildfire hazard estimates, land managers can allocate resources efficiently for the prevention of fire and the restoration of natural systems after fire. Although large-scale efforts have been made to map fuels and estimate fire risks, including the National Fire Danger Rating

System, many researchers and land managers agree that local-scale fuels information and fire hazard mapping is the best way to achieve accurate predictions by which to tailor land management practices (Chuvieco and Congalton 1989, Pala et al. 1990, Maselli et al. 1996). Resource allocation is also a major concern when examining wildfire potential and developing fire hazard tools. For this reason it is important to consider cost effective and time efficient ways to measure fuels and fire risk factors.

This research demonstrates one method to estimate desert wildfire potential. This study used a combination of field surveys to provide accuracy of estimates and remote sensing to maximize the area of land covered while also minimizing costs and time. Combinations of on-the-ground measurements of fuel loads with remotely sensed ecological factors driving wildfire potential were used to model the potential for wildfire in desert environments. This study used previous fire occurrence to verify the model's capability to estimate wildfire potential.

All of the research within this thesis was conducted within the area of Gold Butte, Nevada and amongst various vegetation types and elevation ranges existing there. This area provided a variety of landscapes that typify the broader Mojave Desert, thus imparting potential for extrapolation of this information to the Mojave bioregion. The main objectives for this study were to: (i) measure on-the-ground fuel loads among various vegetation types within the study landscape; (ii) examine the major driving factors that influence desert wildfire potential and how those factors can be expressed through remotely sensed imagery; (iii) develop a model to estimate desert wildfire potential; and (iv) use the model developed to express wildfire potential across the landscape of Gold Butte. These objectives were meant to provide useful tools to guide the

Bureau of Land Management in the allocation of wildfire prevention resources as well as development and restoration practices. This research also provides potential for use and application in other areas of the Mojave Desert with similar wildfire characteristics and management issues.

Literature Cited

Abella SR, EC Engel, CL Lund, and JE Spencer (2009) Early post-fire plant establishment on a Mojave Desert burn. *Madroño* **56**, 137-148.

Brooks ML (2002) Peak fire temperatures and effects on annual plants in the Mojave Desert. *Ecological Applications* **12**(4), 1088-1102.

Brooks ML, TC Esque (2002) Alien plants and fire in Desert Tortoise (*Gopherus agassizii*) habitat on the Mojave and Colorado Deserts. *Chelonian Conservation and Biology* **4**, 330-340.

Brooks ML, D'Antonio CM, Richardson DM, Grace J, Keeley JJ, DiTomaso JM, Hobb R, Pellant M, and Pyke D (2004) Effects of invasive alien plants on fire regime. *BioScience* **54**, 677-688.

Chuvieco E, Congalton RG (1989) Application of remote sensing and geographic information systems to forest fire hazard mapping. *Remote Sensing of the Environment* **29**, 147-159.

Esque TC, Schwalbe CR, DeFalco LA, Duncan RB, Hughes TJ (2003) Effects of wildfire on desert tortoise (*Gopherus agassizii*) and other small vertebrates. *Southwest Naturalist* **48**, 103-111.

Maselli F, Rodolfi A, Bottai L, Conese C (1996) Evaluation of forest fire risk by the analysis of environmental data and TM images. *International Journal of Remote Sensing* **17**(7), 1417-1423

Pala S, Taylor D, Holder G (1990) Integrating satellite-derived forest fuel data into fire management decision support models. Proceedings of the 2nd National GIS conference, Ottawa, 5-8 March 1990.

CHAPTER 2

LITERATURE REVIEW

Introduction

The history of wildfire and human interaction is rich and contains evidence of how human history and culture, as well as the world's landscapes, have all been shaped by fire. Though wildland fire undoubtedly outdates human existence, there is still a long history of human contact with wildfire involving coexistence, suppression, and destruction. In North America, the earliest known examples of such interactions involve the use of fire by Native Americans and European settlers to replenish the land, to clear the land, or in hunting and war activities (Pyne 1995). With the settlement of North America came agriculture and communities that were vulnerable to the natural wildfire cycle. Additionally, human activities such as agriculture and prescribed burning began changing fire regimes in a manner that led to increased wildfire size. The Great Fire of 1910, which burned three million acres across Washington, Idaho, and Montana, killed 78 fire fighters and brought national attention to wildfire issues (Pyne 2001). As wildfire invariably destroyed humans and their resources, the U.S. mindset toward wildfires became that of suppression by the late nineteenth century. This suppression policy resulted in large-scale fuel accumulations in many ecosystems across the U.S. over a period of several decades (Busenburg 2004).

Together with growing national concern for wildfire activity, forest fire research interest also became a focus of the federal goverment. By 1922 the U.S. Forest Service had assigned the first forest fire research scientist, Harry T. Gisborne, to examine fire hazards (Hardy and Hardy 2007). By 1930 Gisborne had published articles describing the

basic influencing factors relative to fire potential and behavior. These influences included weather (Gisborne 1922, 1925, 1927*b*), duff and fuel moisture (Gisborne 1923, 1924), and lightning (Gisborne 1926, 1927*a*). Additionally, by using three factors (fuels, wind, and relative humidity) he described an early form of a fire-danger rating system (Gisborne 1928, 1929). These publications along with the development of instruments for measuring such fire-influencing variables provided a basis for future monitoring, modeling, and management of wildfire potential.

Through the 1930s, 40s, and 50s, fire-danger rating systems and meters developed further and continual adjustments and tests were conducted in an attempt to more accurately determine fire potential for an area. From 1931 to 1954, the original fire-danger meter was developed and underwent seven different variations to incorporate newly acquired knowledge deemed helpful in predicting fire behavior or remove concepts from previous meters that were found excessive (Hardy and Hardy 2007). However, by 1958 the variations in fire-danger meters reflected the variation in fire-danger rating systems across the country. As many as eight fire-danger rating systems were implemented regionally throughout the U.S.

In order to facilitate cooperation between agencies and throughout various regions of the country, as well as to standardize firefighting and fire prevention measures, a truly national fire-danger rating system was sought during the 1958 meeting of the national American Meteorological Society (Hardy 1958). In the time from 1958 to 1964 a committee of fire management and fire research personnel created a fire spread phase rating system for both open and closed canopy fires, testing them in 1961 and 1962 and implementing them in 1964 through the Forest Service Handbook, section "FSH

5109.11” (Deeming et al. 1972). Although this implementation brought a national standard to fire-danger prediction, some fire managers and scientists found these spread phase ratings subjective and analytically problematic.

Additionally, during the 1960s U.S. policy, and public mindset, began to shift away from the idea of fire suppression and toward that of managing, monitoring, and using wildfire to manage natural lands as noted by the passage of the Multiple-use Sustained-Yield Act (1960), the Wilderness Act (1964), and the National Environmental Policy Act (1970) (Donovan and Brown 2005). Along with this shift in fire management policy came a desire for better understanding of wildfire behavior and prediction. Thus, fire prediction and fuel load models began gaining focus as an important area of research. This shift in policy and attitude from that of suppression to management parallels a shift in research on fire potential. Early research had focused on the use of a Burning Index (BI) which indicated the potential required to contain a fire within a particular fuel type, or the potential of fire behavior within a given fuel classification. However, as focus shifted to forecast and management of fire activity, fire researchers began providing further consideration for weather in predictions. The 1964 United States Department of Agriculture (USDA) produced National Fire Danger Rating System focused on the use of a Spread Index (SI) over the BI because it was found to be similar in results to the BI but was more sensitive and more accurately accounted for weather influences such as wind speed (Nelson 1964). The 1964 USDA handbook on the National Fire-Danger System only considered two fuel models, but it also recognized the important role of weather in determining fire potential while also providing a basis for the addition of many future fuel model and fire prediction approaches.

Fuel and Fire Modeling

In response, the USDA Forest Service chartered a National Fire-Danger Rating System (NFDRS) Research Work Unit in Fort Collins, Colorado in 1968. The group adopted much of the work being conducted by Richard Rothermel at the Fire Laboratory in Missoula, Montana to create a stronger national system. Rothermel's work focused on quantitative values for indices that describe the spread rates of surface fires (Rothermel 1972). The application of Rothermel's work as the basis for the fire-danger rating system meant that analyses by the system would focus on the physics of fire behavior. More importantly though, the focus for the development of a revised system was to accommodate future changes in the system, incorporating new research and knowledge as it became available and deemed useful. The result of these revisions was the 1972 NFDRS which used Rothermel's spread component to describe fire behavior in each of nine different fuel load models created for various fuel-type groups (Deeming et al. 1972).

In keeping with the idea of a readily accommodating new knowledge for future revisions of the system, an update was planned for 1978. This manner of trial and error reflected the earlier research done on fire danger meters, which in turn led to the development of the NFDRS itself. New knowledge emerged in the mid-1970s regarding combustion physics, wildland fuel types, and fire occurrence variables which could then be included in an updated system. Some of the changes from the 1972 NFDRS included the addition of a live fuel moisture model, two fire occurrence indexes (lighting caused and human caused), an increase in the number of slope classes from three to five, and most importantly an increase in the number of fuel models from 9 to 20 (Deeming et al.

1977). The NFDRS was amended again in 1988 after fire managers in humid environments overwhelmingly agreed that deficiencies in the system made for inaccurate estimates of fire danger in the eastern and southeastern U.S. The updates addressed included improved response to drought in humid environments, flexibility regarding live fuel moistures, and the adjustment of models to accommodate for better fire danger predictions in humid environments (Burgan 1988). These changes made in 1988 emphasized a growing need in wildfire predictions to account for local differences in fuel type and fire behavior characteristics.

Many of the adjustments made to the NFDRS used information from various fields of fire research. For instance, research conducted on measuring fuel characteristics in the field provided managers with better predictions of fire behaviors and the ability to allocate management resources better. This research performed by Brown (1974) developed a rapid survey technique for inventory of dead and downed woody fuels that were used to create a greater number of fuel load models to give a more accurate range of fire behavior predictions. Likewise, work on mathematical fire behavior models performed by Albini (1976) provided knowledge of inadequacies in previous fire behavior models as well as further constructive feedback to fire managers for the use of improved models as tools in fire management. This continued research with varying types of focus helped to provide new knowledge to be applied in future updates of fire-danger rating systems as well as to develop other means by which to model fire occurrence and behavior.

In 1982 another approach to identifying fuel load models was presented by Anderson. His research aimed to help managers assign fuel load models based on

photographic evidence rather than through measured field experiments. The idea was to provide a more efficient process by which managers could identify fuel load characteristics in order to apply management practices. This report dealt with 13 of the 25 fire behavior models, but rather only thirteen of the models that had already been applied by Rothermel and Albini (Anderson 1982). Although Anderson's guide was not all inclusive, it was indicative of future research in wildfire prediction because it was intended to reduce the time and money spent on field observations, a goal later revisited with the advancement of satellite technologies.

Another technical advance in wildfire behavior and occurrence modeling appeared in 1984 with the creation of the BEHAVE system. BEHAVE is a fire behavior and fuel modeling system that integrated computer technology with wildfire prediction. The BEHAVE method provided interactive computer systems that allowed for site-specific fuel models to be created and also, like the NFDRS, allowed for periodical state-of-the-art updates as new knowledge emerged (Burgan and Rothermel 1984). The BEHAVE system used the same 13 models dealt with by Anderson (1982), but instead of using photographic evidence, BEHAVE included new and simplified techniques for collecting fuel data plus the ability to modify existing fuel load models to provide more reasonable fire prediction for areas not described accurately. Like the NFDRS, BEHAVE also received updates and revisions, first in 1986 with the addition of a fire behavior subsystem, BURN, which included the use of computer programs to predict site-specific fire behaviors (Andrews 1986). This subsystem also received further adjustments in 1989 when a second part of the BURN subsystem was added focusing on improvements in the user interface of the computer program (Andrews and Chase 1989). In all, these

subsystems that make up the BEHAVE system combine two important concepts that continue throughout wildfire modeling research, the use of state-of-the-art technologies and a commitment to continual evaluation and adjustment with the availability of new information.

Remote Sensing

One of the most recent state-of-the-art advances in fire and fuel load modeling research involves the use of remotely sensed imagery collected by satellites. Remote sensing allows for quick and easy development of spatial fuel property layers that are important in guiding fuel and fire management decisions (Sandberg et al. 2001). The idea of using remote sensors to improve fuel mapping goes back as far as the mid-1960s, when researchers first mentioned how such a tool could revolutionize the field of wildfire research (Adams 1965). Since the introduction of remote sensors, several techniques have been developed to improve fuel classifications. These fuel classifications use remote sensing techniques to summarize the fuel characteristics of large groups of vegetation, also known as fuel types (Pyne et al. 1996). A broad range of algorithms and sensors are available that make sensing techniques adaptable to many different scenarios.

One type of fuels mapping that has been explored by many researchers uses medium-resolution multispectral remote sensing. One example of this is Landsat MSS (Multispectral Scanner) or TM (Thematic Mapper; Salas and Chuvieco 1995, Maselli et al. 2000, van Wagtendonk and Root 2003). More recently, higher resolution sensors have also been examined for fuel classification purposes (Arroyo et al. 2005, 2006, Gitas et al. 2006). The major limitation of this type of remote sensing technique is that forest and vegetation canopies cannot be penetrated in order to account for surface fuels underneath

(Keane et al. 2001). This is an obvious disadvantage in terms of identifying surface fuels to estimate wildfire potential and behavior in areas with vegetation canopies. Additionally, with these remote sensors it is difficult to distinguish between surface fuel sizes and category types or vegetation height even when surface fuels are visible, further limiting the ability to accurately model fuel and fire characteristics (Keane et al. 2001, Rollins et al 2004).

Medium to low resolution multispectral remote sensing is another approach to fuels classification and often classifies the vegetation categories of an image first and then assigns fuel characteristics to each vegetation class. Many authors have attempted to classify fuels using variations of this techniques, including Kourtz (1977), who used supervised classification, unsupervised classification, and principal components to identify multiple fuel classes. Cohen (1989) used a tasseled cap transformation approach with Landsat TM multispectral data to classify fuel characteristics in chaparral shrub vegetation in California, and van Wagtendonk and Root (2003) used an unsupervised classification algorithm to define 30 unique classes of Normalized Difference Vegetation Index (NDVI) used to create fuel models for Yosemite National Park, USA. However, the accuracies of these approaches ranged from 65% to 80% (Chuvieco et al. 1999), indicating room for improvement. Still, these studies show the potential convenience of combining multiple sources of information and data techniques for the purpose of accurately mapping fuels.

Even more recently, newer sensors have provided finer scale and higher resolution for use in mapping fuel characteristics. Advanced spaceborne thermal emission and reflection radiometer (ASTER) imagery has been used to map fuels and finer scales

and has shown accuracies greater than 90% (Guang-xiong et al. 2007, Lasaponara and Lanorte, 2007). Other sensors such as QuickBird and IKONOS have provided sub-meter spatial resolutions and have been applied to research on vegetation characteristics (Wang et al. 2004, Mallinis et al. 2008), but these sensors have had limited application in fuel mapping as of yet. The most successful applications of these sensors include Arroyo et al. (2006), where forest fuels of central Spain were mapped with an accuracy of 82% reported, and Giakoumakis et al. (2002) and Gitas et al. (2006) who used IKONOS and QuickBird imagery to map Prometheus system fuel load estimates for which both studies reached overall accuracies of up to 75%. The comparable success of these higher-resolution sensors to those of medium or low resolutions advocates further research.

Hyperspectral remote sensing techniques have also been examined with respect to spatial discrimination of fire-related attributes in vegetation. Airborne visible/infrared imaging spectrometer (AVARIS) imagery is commonly used in combination with Spectral Mixture Analysis (SMA) for hyperspectral analyses. With regard to fuel characterization, Roberts et al. (1998) pioneered this combined approach for mapping chaparral fuels in California. More recently, Jia et al. (2006) used SMA techniques with AVARIS imagery for mapping major forest components in the Colorado Front Range, USA. However, the highest accuracy levels (90%) have been obtained using Multispectral Infrared Visible Imaging Spectrometer (MIVIS) for Prometheus system fuel modeling (Lasaponara and Lanorte 2006). The main disadvantage to these types of remote sensors is the reduced spatial coverage of airborne sensors compared to satellite sensors, which can inhibit the overall coverage of fuels mapping per project.

All of the aforementioned multispectral and hyperspectral sensors are forms of passive sensors. There are also technologies that implement active sensors. One type of active sensor is a Light Detecting and Ranging (LiDAR) sensor. LiDAR can be effective in overcoming some of the limitations of passive sensors. For example, LiDAR technologies have been used to estimate fuel heights and provide information about surface fuels that are covered by forest and vegetation canopies. These and other fuel characteristics can be derived from LiDAR data (Dubyah and Drake 2000). Lefsky et al. (2002) demonstrated how canopy height can be estimated from LiDAR systems, and Raiño et al. (2003, 2004) used LiDAR technology to estimate surface canopy height, surface canopy cover, canopy base height, and crown bulk density in conifer and deciduous forests. Continued research provides growing evidence in support of the use of LiDAR data for forest canopy and subcanopy characterization for the purpose of defining and mapping fuel and fire characteristics (Hyppa et al. 2008).

Another active type of remote sensing involves using microwave sensors to predict forest attributes crucial to define and map fuel types. Research has been conducted to estimate foliar biomass (Harrell et al. 1995, Ranson et al. 1997, Austin et al. 2003), and tree height (Toutin and Amaral 2000, Garestier et al. 2008) by incorporating microwave sensor technologies, though few studies yet describe the use of microwave sensors to directly estimate fuel loads. However, one study by Saatchi et al. (2007) developed techniques to estimate biomass distribution along with three major fuel load parameters (canopy fuel weight, canopy bulk density, and foliage moisture content) for Yellowstone National Park, USA, with accuracy levels ranging from 70% to 85%. This research suggests that active sensor techniques, especially those involving microwave

data, have strong potential to improve on fuel type classification and mapping of passive sensor techniques in cases dealing with canopy obstructed fuel loads of interest. However, the most common element expressed throughout the research on fuel load and fire mapping is the use of combined data collection and analysis techniques in order to produce the most accurate fuel representations (Arroyo et al. 2008).

Literature Cited

Adams JL (1965) *Fuel Classification and Mapping for Forest Fire Control*. University of California, Berkeley.

Albini FA (1976) Estimating Wildfire Behavior and Effects. USDA Forest Service, Intermountain Forest and Range Experiment Station General Technical Report INT-30, Ogden, UT.

Anderson HE (1982) Aids to Determining Fuel Models For Estimating Fire Behavior. USDA Forest Service Intermountain Forest and Range Experiment Station General Technical Report INT-122, Ogden, Utah.

Andrews PL (1986) BEHAVE: Fire Behavior Prediction and Fuel Modeling System – BURN Subsystem, Part 1. USDA Forest Service, Intermountain Research Station General Technical Report INT-194, Ogden, Utah.

Andrews PL, Chase CH (1989) BEHAVE: Fire Behavior Prediction and Fuel Modeling System – BURN Subsystem, Part 2. USDA Forest Service, Intermountain Research Station General Technical Report INT-260, Ogden, Utah.

Arroyo LA, Pascual C, Manzaner JA (2008) Fire models and methods to map fuel types: The role of remote sensing. *Forest Ecology and Management* **256**, 1239-1252.

Arroyo LA, Healy SP, Cohen WB, Cocero D (2006) Using object-oriented classification and high-resolution imagery to map fuel types in a Mediterranean region. *Journal of Geophysical Research* 111, GO4SO4 doi:10.1029/2005JG000120.

Arroyo LA, Cocero D, Manzanera JA, García-Montero LG, Pascual C (2005) El empleo de clasificadores de context para la obtenciónde cartografía en la interfase urbano forestal. *GeoFocus* **5**, 115-128.

Austin JM, Mackey BG, Van Niel KP (2003) Estimating forest biomass using satellite radar: an exploratory study in a temperate Australian Eucalyptus forest. *Forest Ecology and Management* **176**, 575-583.

Brown JK (1974) Handbook for Inventorying Downed Woody Material. USDA Forest Service, Intermountain Forest and Range Experiment Station General Technical Report INT-16, Ogden Utah.

Burgan RE (1988) 1988 Revisions to the 1978 National Fire-Danger Rating System. USDA Forest Service, Southeastern Forest Experiment Station Research Paper SE-273, Asheville, North Carolina.

Burgan RE, Rothermel RC (1984) BEHAVE: Fire Behavior Prediction and Fuel Modeling System – Fuel Subsystem. USDA Forest Service, Intermountain Forest and Range Experiment Station General Technical Report INT-167, Ogden, Utah.

Busenburg G (2004) Wildfire Management in the United States: The Evolution of a Policy Failure. *Review of Policy Research* **21** (2), 145-156.

Cohen WB (1989) Potential utility of the TM tasseled cap multispectral data transformation for crown fire hazard assessment. *In*: ASPRS/ACSM annual convention proceedings: Agenda for the 90s', vol. 3, Baltimore, MD, pp. 118-127.

Chuvieco E, Carvacho L, Rodríguez-Silva F (1999) Integrated fire risk mapping. *In*: Chuvieco, E. (Ed.), *Remote Sensing of Large Wildfires*. Springer, Berlin, pp. 61-84.

Deeming JE, Burgan RE, Cohen JD (1977) The national fire danger rating system-1978. USDA Forest Service, Intermountain Research Station General Technical Report INT-39. (Ogden, UT)

Deeming JE, Lancaster JW, Fosberg MA, Furman RW, Schroeder MJ (1972) The National Fire-Danger Rating System. USDA Forest Service Research Paper RM-184, 165 p. Rocky Mountain Forest and Range Experiment Station, Fort Collins, Colorado.

Donovan GH, Brown TC (2005) Wildfire Management in the U.S. Forest Service: A Brief History. *Natural Hazard Observer* **29** (6), 1-3.

Dubyah RO, Drake JB (2000) LiDAR remote sensing of forestry. *Journal of Forestry* **98**, 44-46.

Garestier F, Dubois-Fernandez PC, Papathanassiou KP (2008) Pine forest height inversion using single-pass X-band PollnSAR data. *IEEE Transactions on Geoscience and Remote Sensing* **46**, 59-68.

Giakoumakis NM, Gitas IZ, San-Miguel J (2002) Object-oriented classification modeling for fuel type mapping in the Mediterranean, using LANDSAT TM IKONOS imagery – preliminary results. *In*: Viegas (Ed.) 'Forest Fires Research & Wildland Fire Safety'. Millpress, Rotterdam.

Gisborne HT (1922) Weather records applied to the fire problem. USDA Forest Service, Northern Rocky Mountain Forest and Range Management Experiment Station Applied Forestry Note 42, Missoula, Montana.

Gisborne HT (1923) Importance of duff moisture content in the forest fire problem. *Journal of Forestry* **21**, 807-809.

Gisborne HT (1924) Moisture content of fuels as an index of fire danger. *Lumber World Review* **45**, 44.

Gisborne HT (1925) The effect of weather on the inflammability of forest fire fuels. USDA Forest Service, Northern Rocky Mountain Forest and Range Experiment Station Applied Forestry Note 58, Missoula, Montana.

Gisborne HT (1926) Lightning and forest fires in the Northern Rocky Mountain region. *Monthly Weather Review* **54**, 281-286.

Gisborne HT (1927*a*) An investigation of lightning storms in the Northern Rocky Mountain region. *Northwest Science* **1**, 72-73.

Gisborne HT (1927*b*) The objectives of forest fire-weather research. *Journal of Forestry* **25**, 452-456.

Gisborne HT (1928) Measuring forest fire danger in Northern Idaho. USDA Miscellaneous Publication 64. Washington, D.C.

Gisborne HT (1929) The complicated controls of fire danger. *Journal of Forestry* **27**, 311-312.

Gitas IZ, Mitri GH, Kazakis G, Ghosn D, Xanthopoulos G (2006) Fuel type mapping in Annapolis, Create by employing Quickbird imagery and object-based classification. *Forest Ecology and Management* 234 (S1), S228 doi:10.1016/j.foreco. 2005.08.055.

Guang-xiong P, Jing L, Yun-hao C, Abdul-patah N (2007) A forestfire risk assessment using ASTER images in peninsular Malaysia. *Journal of China University of Mining &Technology* **17**, 232-237.

Hardy CC, Hardy CE (2007) Fire danger rating in the United States of America: an evolution since 1916. *International Journal of Wildland Fire* **16**, 217-231.

Hardy CE (1958) The proposed national fire danger rating system. *In*: 1958 National Meeting of the American Meteorology Society, Logan, Utah. American Meteorology Society, Washington, D.C.

Harrell P, Bourgeau-Chavez LL, Kasischke ES, French NHF, Christensen NLJ (1995) Sensitivity of ERS-1 and JERS-1 radar data to biomass and stand structure in Alaskan boreal forest. *Remote Sensing of Environment* **54**, 247-260.

Hyppa J, Hyppa H, Leckie D, Gougeon F, Yu X, Maltamo M (2008) Review of methods of small-footprint airborne laser scanning for extracting forest inventory data in boreal forests. *International Journal of Remote Sensing* **29**, 1339-1366.

Jia GJ, Burke IC, Goetz AFH, Kaufmann, MR, Kindel BC (2006) Assessing spatial patterns of forest fuel using AVARIS data. *Remote Sensing of Environment* **102**, 318-327.

Keane RE, Burgan RE, van Wagtendonk J (2001) Mapping wildland fuel for the fire management across multiple scales: Integrating remote sensing, GIS, and biophysical modeling. *International Journal of Wildland Fire* **10**, 301-319.

Kourtz PH (1977) An application of Landsat digital technology to forest fire fuel type mapping. *In*: 11th International Symposium on Remote Sensing of Environment, Ann Arbor, pp. 1111-1115.

Lasaponara R, Lanorte A (2006) Multispectral fuel type characterization based on remote sensing data and Prometheus model. *Forest Ecology and Management* 234S, S226.

Lasaponara R, Lanorte A (2007) Remotely sensed characterization of the forest fuel types by suing satellite ASTER data. *International Journal of Applied Earth Observation and Geoinformation* **9**, 225-234.

Lefsky MA, Cohen WB, Parker GG, Harding DJ (2002) LiDAR Remote Sensing for Ecosystem Studies. *BioScience* **52**.

Mallinis G, Koutsias N, Tsakiri-Strati M, Karteris M (2008) Object-based classification using Quickbird imagery for delineating forest vegetation polygons in a Mediterranean test site. *ISPRS Journal of Photogrammetry and Remote Sensing* **63**, 237-250.

Maselli F, Rodolfi A, Bottai L, Romanelli S, Conese C (2000) Classification of Mediterranean vegetation by TM and ancillary data for the evaluation of fire risk. *International Journal of Remote Sensing* **17**, 3303-3313.

Nelson RM (1964) The National Fire Danger Rating System: Derivation of Spread Index for Eastern and Southern States. USDA Forest Service, Southeastern Forest Experiment Station, Asheville, North Carolina.

Pyne SJ (1995) *World Fire: The Culture of Fire on Earth*. Seattle, WA: University of Washington Press.

Pyne SJ (2001) *Year of the fires: the story of the great fires of 1910*. Viking Press: New York.

Pyne SJ, Andrews PL, Laven RD (1996) Introduction to Wildland Fire, second ed. John Wiley &Sons, Inc., New York, NY.

Ranson KJ, Lang RH, Chauhan NS, Cacciola RJ, Kilic O, Guoqing S (1997) Mapping of boreal forest biomass from spaceborne synthetic aperture radar. *Journal of Geophysical Research* **102**, 29599-29610.

Raiño D, Meier E, Allgöwer B, Chuvieco E, Ustin SL (2003) Modeling airborne laser scanning data for the spatial generation of critical forest parameters in fire behavior modeling. *Remote Sensing of Environments* **86**, 177-186.

Raiño D, Chuvieco E, Condés S, González-Matesanz J, Ustin SL (2004) Generation of crown bulk density for *Pinus sylvestris* L. from LiDAR. *Remote Sensing of Environment* **92**, 345-352.

Roberts DA, Gardner M, Church R, Ustin S, Scheer G, Green RO (1998) Mapping chaparral in the Santa Monica Mountains using multiple endmember spectral mixture models. *Remote Sensing of Environment* **65**, 267-279.

Rollins MG, Keane RE, Parson RA (2004) Mapping fuels and fire regimes using remote sensing, ecosystem simulation, and gradient modeling. *Ecological Applications* **14**, 75-95.

Rothermel RC (1972) A mathematical model for predicting fire spread in wildland fuels. USDA Forest Service, Intermountain Forest and Range Experiment Station Research Paper INT-115, Ogden, Utah.

Saatchi S, Halligan K, Despain DG, Crabtree RL (2007) Estimation of forest fuel load from radar remote sensing. *IEEE Transactions on Geoscience and Remote Sensing* **45**, 1726-1740.

Salas FJ, Chuvieco E (1995) Aplicación de imagines Landsat-TM a la cartografía de modelos de combustible. *Revista de Teledetección* **5,** 18-28.

Sandberg DV, Ottomar RD, Cushon GH (2001) Characterizing Fuels in the 21st Century. *International Journal of Wildland Fire* **10**, 381-387.

Toutin T, Amaral S (2000) Stereo RADARSAT data for canopy height in Brazilian forest. *Canadian Jounral of Remote Sensing* **26**, 189-199.

van Wagtendonk JW, Root RR (2003) The use of multispectral Landsat normalized difference vegetation index (NDVI) data for mapping fuels models in Yosemite National Park, USA. *International Journal of Remote Sensing* **24**, 1639-1651.

Wang L, Sousa WP, Gong P, Biging G (2004) Comparison of IKONOS and Quickbird images for mapping mangrove species on the Caribbean coast of Panama. *Remote Sensing of Environment* **91**, 432-440.

CHAPTER 3

MANUSCRIPT: ESTIMATING WILDFIRE POTENTIAL ON A MOJAVE DESERT LANDSCAPE USING REMOTE SENSING AND FIELD SAMPLING

Abstract

Landscape-level wildfire prediction can be used to allocate wildfire resources and guide land management practices. Wildfire prediction in arid habitats in the southwestern United States is of specific concern because of the negative ecological impacts of fire on desert habitats and the current lack of accurate fire prediction tools applicable to desert habitats. This study examined the ability to model previous fire occurrence and estimate future fire potential using satellite imagery and on-the-ground field survey techniques along with ignition potential data (lightning strikes and distance to roads), topographical data (elevation and aspect), and climate information (maximum and minimum temperatures). The satellite data were used to create a suite of potential fuel load models that were then evaluated for the best fit models using Akaike Information Criterion model selection. The best fit fuel load model was then used in conjunction with 2005 remote sensing and fire occurrence data to model fire potential for that year. The fuel load model along with spring fuel moisture content, lightning strikes, distance to roads, and perennial vegetation type were used to model fire occurrence and Receiver Operating Characteristic (ROC) statistics was used to evaluate the agreement between model predictions and actual fire occurrence. The ROC evaluation yielded an area-under-the-curve value of 0.90 indicating accurate prediction of fire occurrence for 2005. This study provides evidence that remote sensing techniques can be used in combination with field surveys to accurately predict wildfire potential in Mojave Desert habitats.

Introduction

Desert ecosystems are characterized by a lack of perennial vegetation cover, low primary productivity, and limited fuel load, which has caused deserts to be historically less prone to fire than many other ecosystems (Humphrey 1974, Brooks and Matchett 2006). Exotic plant invasions throughout arid and semi-arid lands of the western USA in recent decades have changed ecological processes and altered natural fire regimes by increasing continuous fuel cover (D'Antonio and Vitousek 1992, D'Antonio 2000, Brooks et al. 2004). Consequently, the frequency, size, and intensity of fires in deserts such as the Mojave Desert have increased in concert with fine fuel density increases as a result of invasive grasses (Brooks and Esque 2002, Brooks and Minnich 2006, Esque et al. 2010) and a rise in human-caused ignitions (Brooks and Matchett 2006).

Given the historically infrequent wildfire occurrence in the Mojave Desert, many plants and animals are not well adapted for survival under conditions of increasing fire size, frequency, and intensity (Esque et al. 2003, Defalco et al. 2010). Adverse effects of fires are of particular concern for land managers because fires alter the composition of unique plant communities (Abella et al. 2009) and kill or injure threatened and endangered species such as the desert tortoise (*Gopherus agassizii*; Esque et al. 2003). However, effects of fire on many Mojave Desert species are largely unknown. Research on fire regimes and fuel characteristics can expand the knowledge of where, when, and how desert fires may occur and provide insight for the management of wildland fires.

Invasive annual grasses change the spatial distribution of fuels across desert landscapes and affect fire regimes (D'Antonio and Vitosek 1992). Fine fuel cover is of particular concern because in desert ecosystems fine fuels (e.g., invasive annual grasses)

create a continuous fuel bed needed for fire to spread through naturally large gaps between perennial plants (Brown and Minnich 1986, Brooks 1999). These kinds of interactions between invasive plants and fire regime characteristics create a complex matrix of fire influence variables that are not entirely understood by desert researchers and land managers. This matrix of variables can be used to create a conceptual model describing fuels and fire potential (Figure 1). Although several fuel/fire models exist for a variety of ecosystems, fuel load models and fire hazard maps for the Mojave Desert are lacking (Brooks et al. 2004b).

A fuel model is a "stylized and simplified description of fuel for a mathematical fire behavior model" (Pyne et al. 1996). This simplified description consists of fire environment characteristics used as inputs to estimate fire conditions. Such models commonly include a set of numeric fuel inputs that quantitatively describe fuel properties. Traditionally, fuel modeling input data are collected through field experiments and observations aimed at classifying fuels by rate of spread, with a focus on designating fire suppression response times (Sandberg et al. 2001). These fuel inputs are required for the widely used Rothermel (1972) surface fire spread model and for calculating fuel load, fire danger indices, and fire behavior potential.

Fuel inputs are commonly measured using Deeming's (1977) particle size classes for dead and downed woody material: 0 – 0.6 cm, 0.6 – 2.5 cm, 2.5 – 7.6 cm, and > 7.6 cm. These size classes, also known as fuel time-lag classes, are based on the amount of time required for a fuel particle to respond to 63.2% of the new equilibrium moisture content. In other words, the fuel particle size determines how long it will take for the fuel to become dry enough to ignite. Thus, fuel particles 0.6 cm in size and smaller fall into

the 1 hour time-lag class, while 10 hour, 100 hour, and 1000 hour time-lag classes are associated, respectively, with the remaining increasing particle size classes. The inputs of each time-lag fuel class can be used to express the fuel loads of each size class in terms of biomass (kg/m^2). In order for a fuel load model to be most useful for land managers, researchers, and fire fighters, it must be as accurate as possible and reflect the environmental conditions and fuel loads that are most common to the specific area of interest (Chuvieco and Congalton 1989, Pala et al. 1990, Maselli et al. 1996). For these reasons it is necessary to design a local-scale, site-specific fuel load model in order to achieve the most accurate and reliable fire prediction possible (Andrews 1986).

In recent years many wildland fire researchers have used remote sensing to generate data for fuel characteristics or models (Rabii 1979, Agee and Pickford 1985, Burgan et al. 1998). However, remote sensing capabilities are also limited by issues of scale and land surface obscurities, such as clouds or forest canopy. In arid and semi-arid regions, fuel variability across landscapes with respect to topography and environmental characteristics can be difficult to map due to the complexity (Poulos 2009). In some cases though, these limitations can be avoided by spatially interpolating field data into high-resolution, GIS-based models. This technique was used herein to extrapolate finer scale fuel load measurements across coarser remote sensing imagery to create a fuel load model at the landscape scale.

Some of the most important characteristics for modeling desert fire potential include fuel load, potential ignition sources, and fuel moisture (Figure 1). This study examined fuel characteristics and major fire components of desert systems in order to create a model of fire potential for a landscape in the Mojave Desert. In this study, fire

potential was estimated using a combination of field observations and remote sensing techniques that measure or estimate the factors potentially influencing wildland fires. Field data were collected to estimate fuel loadings and then create a spatial model of fuel throughout the study area using remote sensing data. Estimates were also made for fuel moisture, and potential ignition sources were created using data on historical lightning strikes and the potential for human access via roadways. Models of these contributing factors were used to estimate wildland fire potential to model fire occurrences that were widespread in 2005, and present a fire potential model as a tool to estimate fire potential in any given year.

Methods

Study Area

This study was conducted within the 140,928-ha area known as Gold Butte in the northeastern Mojave Desert of southern Nevada (Figure 2). Located 120 km northeast of Las Vegas, Gold Butte is managed by the Bureau of Land Management (BLM) and borders Lake Mead National Recreation Area to the south and west, the Virgin River to the north, and Grand Canyon – Parashant National Monument in the east.

Gold Butte serves well as a local-scale study area for modeling desert fuels and fire potential because the variety of desert landscapes which comprise the area reflect landscapes across the Mojave as well as neighboring deserts. Gold Butte is currently under consideration for designation as a National Conservation Area (NCA) through the September 2008 Gold Butte Conservation Act proposal. Within the proposed Gold Butte NCA there are many areas of land with special BLM designations including 8 ACECs, 2 Wilderness Areas, 2 Wilderness Study Areas (WSA), a designated Backcountry Byway,

and 7 Traditional Lifeway Areas. Elevation of the area ranges from 2,356 m at Virgin Peak down to lower than 500 m in the valley floor.

The Gold Butte area is diverse with respect to soils, slope, elevation and aspect. Large outcrops of igneous, sedimentary and metamorphic parent materials dominate the peaks and hill slopes of the Virgin Mountains (Luddington 2007). Diverse parent materials result in diverse soil types ranging from fine clays and aeolian sands through sandy loams, talus and bedrock. The diversity of the soils influences the distribution and diversity observed in the vegetation. Dominant vegetation types found within the Gold Butte area include piñon-juniper woodlands, Joshua tree woodlands, blackbrush shrublands, creosotebush scrublands, and saltbush scrublands. Gold Butte occurs in a part of the Mojave Desert that forms a transition zone with three other arid or semi-arid ecoregions: the Great Basin Desert, the Sonoran Desert, and the Colorado Plateau. This unique convergence results in increased biodiversity and provides habitat for several threatened or endangered species such as the desert tortoise (*Gopherus agassizii*) and the Las Vegas bearpoppy (*Arctomecon californica*). However, like much of the Mojave Desert, the Gold Butte area also hosts a variety of invasive annual plants such as red brome (*Bromus maditensis*), cheatgrass (*Bromus tectorum*), and common Mediterranean grass (*Schismus barbatus*), all of which can impact fire regimes by increasing fire spread (Whisenant 1990, Knick and Rotenberry 1997, Brooks and Pyke 2001).

Sampling Procedures

Randomly located field survey plots (n = 300) were generated at Gold Butte to estimate fuel loads beginning in early spring of 2010. Fuel loads were surveyed on 252 of the 300 – 30 m × 30 m (0.09 ha) plots (Figure 3) distributed among 16 different

Southwest Regional Gap Analysis (SWReGAP; Lowry et al. 2007) land cover types and included areas which had been previous burned. Within each plot, four 30-m long transects were measured for live and dead fuel loads using a modification of the planar intersect method (Brown 1974) which reduces the risk of bias for fuels that may be non-randomly oriented in direction (Howard and Ward 1972, Van Wagner 1986). This non-random orientation of fuels is more typical in forest ecosystems, where trees fall in the direction of prevailing winds (Lutes et al. 2006), than in desert environments. Survey protocols from forest assessments (Brown 1974, Lutes 2006) were integrated with those from fuel assessments in more closely related environments like sagebrush steppe (Stableton and Bunting 2009). Brown's planar intersect method used transects radiating outward from plot center point. Here, the modified planar transects use two of four transects centered on the plot, and parallel to one another, with 10 m between them (Figure 4). The second two transects were perpendicular to the first two and also centered on the plot with 10 m between them. At two points along each transect (5 m and 25 m) in 2 m × 2 m quadrats, ocular estimates of live and dead woody cover, live and dead herbaceous cover, live and dead woody species average height, live and dead herbaceous species average height, depth of duff and litter profile (i.e. the layers of vegetative fuel debris on the surface above the mineral soil), and the proportion of litter in profile were determined within a 2 m × 2 m square following Lutes et al. (2006).

Fuels can be categorized by the time required for them to be sufficiently dry to burn, which is related to stem diameter (Pyne et al 1996). For development of the Gold Butte area fuel availability models, this study quantified 1 hr, 10 hr, 100 hr, 1-100 hr, 1000 hr, and 1-1000 hr time-lag fuel loads. Each previously described transect was

divided into 3, 10-m long segments and randomly assigned one of the three lowest fuel classes (i.e. 1 hr, 10 hr, and 100 hr time-lag fuels) for quantification. All 30 meters of each transect (0 m – 30 m) were used to tally 1000 hr time-lag fuels. Additionally, diameter and decay class were recorded for 1000 hr time-lag fuels for use in biomass calculations. The number of planar intersects for each time-lag fuel class was tallied as an index of percent cover along the line and used to estimate biomass (kg/m^2) of each size class.

Fuel Load Estimates

Fuel size-class data were entered into the Fire Effects Monitoring and Inventory Protocol program FIREMON (Lutes et al 2006) to estimate the fuel loadings of each sample plot based on fuel size-class tallies, cover (%) of live and dead fuel types, average height (m) of live and dead fuel types, and duff and litter depths (cm). All fuel loading estimates were adjusted for slope via FIREMON software and based on Brown's (1974) calculations, attributed to each plot using a digital elevation model (DEM; 250 m resolution). The fuel loading estimates at each plot were then used to create a fuel load estimate for the entire study area. To do so, AIC model selection (Burnham and Anderson 1998) was used to select among general linear models constructed to relate the fuel loading estimates with remote sensing data layers likely to indicate vegetation associated with fuel loads. It was determined that fire potential in desert ecosystems should be described using the fuel loads derived from the 1 – 100 hr fuel size classes because they provide the fuel continuity necessary to carry fire among the otherwise spatially isolated heavier fuels of native shrubs and trees. The 252 sites where fuel loadings were measured

were converted to a GIS point file, and the fuel loadings were retained as an attribute for each field in the spatial data layer.

Remote Sensing/GIS Layers

Parameter-elevation Regressions on Independent Slopes Model (PRISM) monthly precipitation estimates (Gibson et al. 2002) for months October through April were summed to produce one layer depicting winter rainfall. Winter rainfall is a strong indicator of ephemeral plant production in the Mojave Desert (Beatley 1974, Turner and Randall 1989). MODerate-Resolution Imaging Spectroradiometer (MODIS; Oak Ridge National Laboratory Distributed Active Archive Center 2010); and Normalized Difference Vegetation Index (NDVI) layers were downloaded for spring and late summer of 2005 and 2010 to estimate live vegetation cover. Additional data layers depicting topology (elevation, slope, and aspect) were calculated from a DEM. Fire history and roads data for the Gold Butte Area were provided by the BLM's Southern Nevada District (Las Vegas, Nevada). Two decades of lighting strike data (1990–2009) for the Gold Butte area were obtained from the Desert Research Institute (Reno, Nevada). Point data depicting lightning were converted to a raster layer of strike density with a resolution of 250 m.

Fuel Load Modeling

Fuel loading points were intersected with 250 m resolution raster layers that could potentially be used to model 1-100 hr fuel loadings. Raster layers included: slope gradient, aspect, elevation, monthly and seasonal maximum and minimum temperature averages (MaxTemp and MinTemp, respectively), winter precipitation (derived from PRISM), and long term precipitation averages (Nussear et al. 2009). Enhanced

Vegetation Index (EVI; Wallace and Thomas 2008), and spring and summer greenness index (SpNDVI and SuNDVI, respectively) were estimated using 250 m × 250 m MODIS satellite imagery. Estimates of the ratio of spring and summer NDVI (NDVIrat) and the difference of spring and summer NDVI estimates for each year were calculated in a manner similar to Wallace and Thomas (2008), but with seasonal vegetation measurements rather than annual measurements. All of the remote sensing variables integrated with the fuel loading estimates corresponded to the timing of the field surveys. These variables were then used to create a suite of models that were evaluated using AIC model selection (Burnham and Anderson 1998) in R (v2.12; R Development Core Team 2010) to identify the best potential models of remote sensing data that predicted the field assessed fuel load estimates.

Fire Risk Model Inputs

Ignition potentials were represented by two sources of data: lightning strike density and distance to roads within the study area. Lightning strike density provides ignition potential for naturally occurring fires while distance to roads represents the potential for human-caused ignition. Most lightning strikes occurred in the area during June and July (Figure 5), and thus a lighting density surface was created that combined lightning for June and July of 2005 (Figure 6; Summer 2005 Lightning), when fires occurred in Gold Butte. The lightning density layers were calculated from point data of individual lightning strike points for the years 1990 through 2009 in ArcGIS (v9.3, ESRI) using the spatial-analyst density tool. A raster layer depicting distance to the nearest road in Gold Butte was created using GRASS GIS (v6.4; GRASS Development Team, 2010; Figure 6; D2Roads).

Four covariates and one factor were included as inputs to the fire risk model as well as interaction terms for several of those elements. Ignition potentials used in the model were represented by (1) lightning strike density, which provides ignition potential for naturally occurring fires, and (2) distance to roads providing the potential for human-caused ignition (described above). Fuel Moisture Content (FMC; Figure 7; FMC Summer 2005) was estimated using an equation adapted from grassland systems (Chuvieco et al. 2004). The grassland model was chosen because the majority of the fuel load in desert ecosystems that carries surface fire is more similar to that of grassland fuel loads than other types that are available. The fuel moisture content estimates considered both maximum (SM) and minimum (Sm) spring surface temperatures to represent the potential temperature extremes in the region. Estimated 1-100 hr Fuel Loading (F; Covariate 4; Figure 7; Fuel Load Model 1) was calculated using Fuel Load Model EQ1 (below). Vegetation Type (V; Factor 1) was determined using the raster layer of vegetation types developed for Gold Butte, Nevada by the United States Geological Survey (USGS). The potential for fire occurrence in 2005 was modeled using a logistic general linear model in R (v2.12 R Development Core Team 2010). Fire occurrence in 2005 was selected to model fire potential in the Gold Butte area because 2005 was an active fire year for the study area, and few fires occurred there prior to that year. Thus the results were expected to be a straightforward validation of the conceptual model (Figure 1). Fire perimeters from all fires occurring in the study area in 2005 (ArcGIS shapefiles) were converted to a binary raster where burned areas and unburned areas were identified separately per raster cell.

Fire Risk Model

The input layers described above (Fuel Moisture content, distance to roads, summer lightning density, fuel load, and vegetation type) were then used to determine the best overall model for modeling fire occurrence in 2005. A suite of potential models portraying fire risk were developed and subjected to model selection using the information theoretic approach (Burnham and Anderson 1998). Because there were ~ 250,000 cells of 250 m × 250 m in the Gold Butte area, smaller random subsets of points (n = 1000) on the landscape were selected for analysis to avoid spurious model over-fitting. This process was iterated 100 times, and competing models were ranked using AIC. The best fitting model was identified for each iteration, and the model with the highest ranking frequency was taken as the best model.

To evaluate performance of the best model, we calculated a Receiver Operating Characteristic (ROC) curve to determine the agreement between model predictions and fire occurrence for 2005 (Elith et al. 2006). The ROC curve, which determines sensitivity of the model by plotting the rate of true positives (i.e. prediction of fire occurrence where fire actually occurred) versus false positives (i.e. prediction of fire occurrence when no fire occurred) for each cell in the model, was calculated by comparing the cells estimated to have high fire potential to those cells with known fire occurrence in 2005. ROC statistics of 0.9 to 1.0 represent sensitive model estimates.

Results and Discussion

Results

Fuel Load Estimates

Fuel loads of the 1-100 hr time-lag fuel classes ranged from 0 to 0.9 kg/m^2 and averaged 0.3 (Figure 8). Based on AIC and R^2, two fuel models (*see* Fuel Load Model EQ1 and Model EQ2 below) correlated well with fuel loadings and were the most defensible with respect to ecological interactions driving fuel production (Table 1). Predicted fuel-loadings were calculated for each 250 m cell in Gold Butte using the equations derived from the modeling process:

Fuel Load Model EQ1: Tf = 24.34 + 0.0001469 × (SpNDVI) – 0.002783 × (Elev) – 0.2216 × (MaxTemp) + 0.0001912 × (Aspect)

Fuel Load Model EQ2: Tf = 1.323 – 0.02133 × (MinTemp) – 0.07138 × (EVI) + 0.001228 × (MinTemp × EVI) + 0.02424 × (EVI × NDVIrat) + 0.000007133 × (EVI × SpNDVI),

where Tf is the estimated fuel load for 1-100 hr fuels, SpNDVI is the spring Normalized Difference Vegetation Index (range of -1 to +1 taken on May 9, 2005); Elev is the elevation (m); MaxTemp and MinTemp are the maximum average air temperature and minimum average air temperature, respectively, from spring to summer in 2005; Aspect is the degrees from true north; EVI is the relative greenness between 2002 and 2005 as described by Wallace and Thomas (2008); and NDVIrat is the ratio of Normalized Difference Vegetation Index from spring 2005 to summer 2005.

Of the two fuel models chosen as the best remote sensing representations of fuel load, Fuel Load Model 2 had a higher R^2 value and a lower AIC value (smaller is better) than Fuel Load Model 1 indicating that the former was a better fit for describing fuel loads via remote sensing techniques (Table 1). Additionally, all variables used in each

model demonstrated highly significant ($P < 0.001$) correlations to fuel load surveys except for the variable of Aspect in Fuel Load Model 1. However, Fuel Load Model 2 included remote sensing imagery that was captured after fires had burned, causing potential biases in the fuel characteristics observed in the satellite imagery and used to model fuel load. Since satellite data were collected to correspond with the months during which on-the-ground fuel load measurements were sampled and those months coincided with peak fire season for 2005, some of the variables in Fuel Load Model 2 were derived from post-fire dated imagery. All variables included in Fuel Load Model 1 were collected before fires occurred, thus Fuel Load Model 1 was the only model chosen for validation with 2005 data.

Fire Risk Model – 2005

Fifteen potential fire risk models were analyzed for predictive ability and ranked based on AIC analyses (Table 2). The most frequent model selected was considered the best model for predicting fire occurrence in Gold Butte for 2005 (see Fire Risk Model EQ1 below), and was the top model in 77 of 100 model runs with an average weight of 70%. Fire risk Model 2 was the top model 23 of 100 times (average weight 30%), but was slightly more complicated, with the added interaction of lightning and vegetation (Table 2).

Fire Risk Model EQ1:

Fire Risk 2005 ~ Distance to Roads + Summer lightning density + Model 1 Fuel + Perennial Vegetation + Spring Fuel Moisture Content using Maximum Temperature * Model 1 Fuel + Spring Fuel Moisture Content using Maximum Temperature * Perennial Vegetation + Model 1 Fuel * Perennial Vegetation

The ROC curve produced an Area Under the Curve (AUC) of 0.90 indicating that for 2005 the Fire Risk Model predicted fire occurrence relatively accurately.

A comparison of the fire risk prediction model for 2005 (Figure 9) with the fuel loading map (Figure 7) and the fuel moisture map (Figure 7) illustrates that areas of low to moderate fuel loading and moderately to high fuel moisture content were predicted to have the highest risk of fire. Furthermore a large proportion of the area predicted to have a high fire risk actually burned (Figure 9). Another smaller area that burned in 2005 was not actually predicted to have a high fire risk (Figure 8). Areas of the greatest fuel loading, at higher elevations on the Virgin Mountains, actually had low fire risk due to the much higher and more continuous fuel moisture in that area.

Discussion

The fuel load and fire risk modeling techniques demonstrated here have shown to be accurate in desert environments where fuel load characteristics are highly variable and present a challenge to predict due to the spatial heterogeneity of the factors driving the system. The fuel load models described ~ 29 – 34 % of the variability in fuel loads, and this study showed that fire risk could still be predicted with relatively high confidence. However, there was still a large amount of unexplained variation in the fuel load models. The lack of high fuel load representation in the fuel models may be attributed to the generally high variability in fuel load characteristics in the desert vegetation that is influenced by climate and topology (Allen 2001). High variability is inherent to the desert system, yet some of the unexplained variation may be due to the variety of fuel types that occur in the Gold Butte area and that were incorporated into modeling. It is also important to note that fuel load models developed by this research are not directly linked to fuel load models commonly used for forest fire research. This project was focused on the Gold Butte area in its entirety; however, if the area of inference was focused only on a

subset of vegetation types such as desert shrublands and eliminated the areas with relatively extreme fuel loads (woodlands and barren rock outcrops), the model could explain more of the variation using the statistical power available. Yet another way to increase the precision of the models is to match the field sampling as closely as possible to the remote sensing units (Miller and Yool 2002) or by examining microsites for fuel load and fire behavior characteristics.

The fire risk potential model incorporated a fire spread model that was successfully used in dense perennial grasslands (e.g. Konza Prairie, Kansas, US - Chuvieco et al. 2004) for procedural efficiency and because the fuels of grasslands most accurately represent the desert shrubland fuel load modified by increased fuel continuity contributed from invasive grasses. However, the fuels found in desert shrublands of the Mojave Desert are qualitatively and quantitatively different from prairie grasslands due to the high spatial variability of fuel loads, fuel geometry, and total fuel loads. For instance, desert shrublands encounter what is called the "fertile island effect" where seeds of annual plants and grasses grow more densely underneath perennial shrubs because those shrubs provide a place for wind-blown seeds to catch and increased soil nutrients (Walker et al. 2001). In addition, prairie grass species are active (green) throughout the summer unlike Mojave grass species which are spring active and dry up (brown) during the summer. Further work with custom fuels modeling dedicated to some of the primary western desert fuel types may benefit fire risk modeling endeavors. Custom fuel models for the Lower bajada and fan Mojavean-Sonoran desert scrub merged with the Mojave upper desert scrub groups (Figure 10) may be of future benefit for predicting fire risks in southwestern desert landscapes.

Both fuel load models can be used with remote sensing data as management tools to depict fire potential for the entire study landscape. These models, or variations on them, also have potential applications in other areas of the Mojave Desert and perhaps other desert ecoregions where invasive grasses have become prevalent (Pucheta et al. *In Press*). For example, this research could be applied in areas of Australia where frequent large desert fires have caused long-term negative impacts to the natural lands and native species alike. Although the models still have a large portion of unexplained error, this work can be used to provide better insight to land managers about fire potential.

Presently the models developed here can be used to predict fire risk across the Gold Butte area. This will require field validation for the target year (e.g. Fire Risk in Gold Butte 2011). Peak precision of the models currently requires that field validation data be collected during peak annual plant production and that occurs during ~April-May of any given year. This provides about one month advance information of fire risk in preparation of the fire season. Clearly, expanding the predictive window on the amount of fire risk would enhance the ability of managers to assemble equipment and other resources in response to the predicted fire risk potential. However, this research provides a better alternative to the current lack of any fuel load and fire potential modeling by land managers in Southwestern arid lands. One way to increase the lead-time on fire risk potential is to develop accurate predictive models of fuel production in advance of plant growth. If possible, this would push back the time frame in addition to the one or two months already available. To do so will likely require accurate availability of fine-scale precipitation data across landscapes (higher resolution than now available) and a better understanding of the relationship between the amount and timing of rainfall and

temperature in relation to fuel development. Developing an antecedent model to predict annual plant density ahead of annual plant growth would provide land managers with more forewarning of high fire potential in areas of concern.

The fuel load models produced in this research successfully demonstrated the potential to use remote sensing data in combination with field surveys for estimating fuel loads across the Gold Butte landscape. This synthesis of techniques presents a cost-saving method for estimating fuel loads across landscapes that have not previously had fuel and fire risk models widely available. Field estimation of fuel loading is costly and logistically difficult (Miller and Yool 2002), and refinement of techniques that can reduce the amount of field sampling necessary while focusing on modeling components may create further cost reduction by improving on the framework presented here.

Literature Cited

Abella SR, Engel EC, Lund CL, Spencer JE (2009) Early post-fire plant establishment on a Mojave Desert burn. *Madroño* **56**, 137-148.

Agee JK, Pickford SG (1985) Vegetation and fuel mapping of North Cascades National Park. Final Report. College of Forest Resources (Seattle, WA) 111 pp.

Allen EB (2001) Temporal and Spatial Organization of Desert Plant Communities. (Chapter 6) *In*: Skujiňş J (Ed.) 'Semiarid Lands and Deserts: Soil Resource and Reclaimation'. Marcel Dekker Inc. (New York, NY) pp. 193-208.

Andrews PL (1986) BEHAVE: Fire Behavior Prediction and Fuel Modeling System - BURN Subsystem, Part 1. USDA Forest Service, General Technical Report INT-194.

Beatley JC (1974) Phenological events and their environmental triggers in Mojave Desert ecosystems. *Ecology* **5**, 856-863

Brooks ML (1999) Alien annual grasses and fire in the Mojave Desert. *Madroño* **46**, 13-19.

Brooks ML, Pyke D (2001) Invasive plants and fire in the deserts of North America. Proceedings of the Invasive Species Workshop: The role of fire in the control and spread of invasive species. Fire Conference 2000: The First National Congress on Fire Ecology, Prevention and Management. Tall Timbers Research Station. (Tallahassee, FL) Misc. Publ. No. 11 pp. 1–14.

Brooks ML, Esque TC (2002) Alien plants and fire in Desert Tortoise (*Gopherus agassizii*) habitat on the Mojave and Colorado Deserts. *Chelonian Conservation and Biology* **4**, 330-340.

Brooks ML, D'Antonio CM, Richardson DM, Grace J, Keeley JJ, DiTomaso JM, Hobbs R, Pellant M, and Pyke D (2004) Effects of invasive alien plants on fire regime. *BioScience* **54**, 677-688.

Brooks ML, Matchett JR, Wallace C, Esque TC (2004b) Fuels mapping and fire hazard assessment in a desert ecosystem. *Arid Lands Newsletter, Fire Ecology II*. No. **55**, May/June 2004.

Brooks ML, Matchett JR (2006) Spatial and temporal patterns of wildfires in the Mojave Desert, 1980-2004. *Journal of Arid Environments* **67**, 148-164.

Brooks ML, Minnich RA (2006) Fire in the Southeastern Desert Bioregion. (Chapter 16) *In*: N. G. Sugihara, J. W. van Wagterndonk, J. Fites-Kaufman, K. E.

Schaffer, A.E. Thode (Eds.), ‘Fire in California Ecosystems’. University of California Press (Berkeley, CA).

Brown JK (1974) Handbook for inventorying downed woody material. USDA Forest Service, General Technical Report INT-16. 24 pp.

Brown DE, Minnich RA (1986) Fire and creosote bush scrub of the western Sonoran Desert. *American Midland Naturalist* **116**, 411-422.

Burgan RE, Klaver RW, Klaver JM (1998) Fuel models and fire potential from satellite and surface observations. *International Journal of Wildland Fire* **8** (3), 159-170.

Burnham KP, Anderson DR (1998) ‘Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach’. Spring Science and Business Media (New York, NY) 497 pp.

Chuvieco E, Congalton RG (1989) Application of remote sensing and geographic information systems to forest fire hazard mapping. *Remote Sensing of the Environment* **29**, 147-159.

Chuvieco E, Cocero D, Riaño D, Martin P, Martinez-Vega J, de la Riva J, Pérez F (2004) Combining NDVI and surface temperature for the estimation of live fuel moisture content in forest fire danger rating. *Remote Sensing of Environment* **92**, 322-331.

D’Antonio CM (2000) Fire, plant invasions, and global change. *In:* Mooney HA, Hobbs RJ (Eds.), ‘Invasive Species in a Changing World’. Island Press (Washington, D. C.) pp. 65-93.

D’Antonio CM, Vitousek PM (1992) Biological Invasions by exotic grasses, the grass/fire cycle, and global change. *Annual Review of Ecology and Systematics* **23**, 63-87.

Deeming JE, Burgan RE, Cohen JD (1977) The national fire danger rating system-1978. USDA Forest Service, Intermountain Research Station General Technical Report INT-39. (Ogden, UT)

Defalco LA, Esque TC, Scoles-Sciulla SJ, Rodgers J (2010) Desert wildfire and severe drought diminish survivorship of the long-lived Joshua Tree (*Yucca brevifolia; Agavaceae*). *American Journal of Botany* **97** (2), 243-250.

Elith J, Graham CH, Anderson RP, Dudik M, Ferrier S, Guisan A, Hijmans RJ, Huettman F, Leathwick JR, Lehmann A, Li J, Lohmann L, Loiselle BA, Manion G, Moritz C, Nakamura M, Nakazawa Y, Overton JM, Peterson AT, Phillips S, Richardson K, Schachetti Pereira R, Schapire RE, Soberón J, Williams SE, Wisz M, Zimmermann NE (2006) Novel methods improve predictions of species’ distributions from occurrence data. *Ecography,* **29**, 129–151.

Esque TC, Schwalbe CR, DeFalco LA, Duncan RB, Hughes TJ (2003) Effects of wildfire on desert tortoise (*Gopherus agassizii*) and other small vertebrates. *Southwest Naturalist* **48**, 103-111.

Esque TC, Young JA, Tracy CR (2010) Short-term effects of experimental fires on a Mojave Desert seed bank. *Journal of Arid Environments* **74**, 1302-1308.

Gibson WP, Daly C, Kittel T, Nychka D, Johns C, Rosenbloom N, McNab A, Taylor G (2002) Development of a 103-year high-resolution climate data set for the conterminous United States. *In*: Proceedings of the 13th AMS Conference on Applied Climatology, American Meteorological Society. May 13-16 (Portland, OR) 181-183. http://www.prism.oregonstate.edu/pub/prism/docs/appclim02103yr_hires_dataset-gibson.pdf

GRASS Development Team (2010) Geographic Resources Analysis Support System (GRASS) Software, Version 6.4.0. Open Source Geospatial Foundation. http://grass.osgeo.org

Howard JO, Ward FR (1972) Measurement of logging residue-alternative applications of the line transect method. USDA Forest Service, Pacific Northwest Resarch Station Resource Note PNW-183. (Portland, OR) 95 pp.

Humphrey RR (1974) Fire in the deserts and desert grassland of North America. *In*: Kozlowski TT, Ahlgren CE (Eds.), ‘Fire and Ecosystems’. Academic Press (New York, NY) pp. 365-400.

Knick ST, Rotenberry JT (1997) Landsacape characteristics of disturbed shrubsteppe habitats in southwestern Idaho. *Landscape Ecology* **12**, 287-297.

Lowry J, Ramsey RD, Thomas K, Schrupp D, Sajwaj T, Kirby J, Waller E, Schrader S, Falzarano S, Langs L, Manis G, Wallace C, Schulz K, Comer P, Pohs K, Reith W, Velasquez C, Wolk B, Kepner W, Boykin K, O’Brien K, Bradford D, Thompson B, Prior-Magee J (2007) Mapping moderate-scale land-cover over very large geographic areas within a collaborative framework: A case study of the Southwest Regional Gap Analysis Project (SWReGAP). *Remote Sensing of Environment* **108**, 59-73.

Luddington S (2007) Mineral resource assessment of selected areas in Clark and Nye counties, Nevada. United States Geological Survey, Scientific Investications Report 2006-5197. http://pubs.usgs.gov/sir/2006/5197/sir2006-5197.pdf

Lutes DC, Keane RE, Caratti JF, Key CH, Benson NC, Sutherland S, Gangi LJ (2006) FIREMON: Fire effects monitoring and inventory system. USDA, Forest Service

Rocky Mountain Research Station General Technical Report RMRS-GTR-164. (Fort Collins, CO)

Maselli F, Rodolfi A, Bottai L, Conese C (1996) Evaluation of forest fire risk by the analysis of environmental data and TM images. *International Journal of Remote Sensing* **17** (7), 1417-1423

Miller JD, Yool SR (2002) Modeling fire in semi-desert grassland/oak woodland: the spatial implications. *Journal of Arid Environments* **153**, 229-245

Nussear KE, Esque TC, Inman RD, Gass L, Thomas KA, Wallace CSA, Blainey JB, Miller DM, Webb RH (2009) Modeling habitat of the desert tortoise (*Gopherus agassizii*) in the Mojave and parts of the Sonoran Deserts of California, Nevada, Utah, and Arizona: U.S. Geological Survey Open-File Report 2009-1102, 18 pp.

Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC) (2010) MODIS subsetted land products, Collection 5. Available on-line [http://daac.ornl.gov/MODIS/modis.html] from ORNL DAAC (Oak Ridge, TN)

Pala S, Taylor D, Holder G (1990) Integrating satellite-derived forest fuel data into fire management decision support models. *In:* Proceedings of the 2nd National GIS conference, Ottawa, 5-8 March 1990.

Poulos HM (2009) Mapping fuels in Chihuahuan Desert boarderlands using remote sensing, geographic information systems, and biophysical modeling. *Canadian Journal of Forest Research* **39** (10), 1917-1927.

Pucheta E, Garcia-Muro VJ, Rolhauser AG, Quevado-Robledo L (*In Press*) Invasive potential of the winter grass *Schismus barbatus* during the winter season of a predominantly summer-rainfall desert in Central-Northern Monte. *Journal of Arid Environments* doi:10.1016/j.jaridenv.2010.11.010.

Pyne SJ, Andrews PL, Lavern RD (1996) 'Introduction to the wildland fire, 2nd Ed.' John Wiley and Sons (New York, NY) 769 pp.

R Development Core Team (2010). R: A language and evnvironment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/.

Rabii HA (1979) An investigation of the utility of Landsat-2 MSS data to the fire-danger rating area, and forest fuel analysis within Crater Lake National Park, Oregon. Ph.D. dissertation, Oregon State University. 410 pp.

Rothermel RC (1972) A mathematical model for predicting fire spread in wildland fuels. USDA Forest Service, Intermountain Forest and Range Experiment Station Resource Paper INT-115. (Ogden, UT) 161 pp.

Sandberg DV, Ottmar RD, Cushon GH (2001) Characterizing fuels in the 21st Century. *International Journal of Wildland Fire* **10**, 381-387.

Stableton A, Bunting S (2009) Guide for quantifying fuels in the sagebrush steppe and juniper woodlands of the Great Basin. Bureau of Land Management, Technical Note 430 (Denver, CO) 81 pp.

Turner FB, Randall DC (1989) Net productivity by shrubs and winter annuals in southern Nevada. Journal of Arid Environments **17**, 23-36.

Van Wagner CE (1986) The line intersect method in forest fuel sampling. *Forest Science* **14**, 20-26.

Walker LR, Thompson DB, Landau FH (2001) Experimental manipulations of fertile islands and nurse plant effects in the Mojave Desert, USA. *Western North American Naturalist* **61** (1), 25-35.

Wallace CSA, Thomas KA. (2008) An annual plant growth proxy in the Mojave Desert using MODIS-EVI Data. *Sensors* **8**, 7792-7808.

Whisenant SG (1990) Changing fire frequencies on Idaho's Snake River plains: ecological and management implications. *In*: 'Proceedings of a symposium on cheatgrass invasion, shrub die-off, and other aspects of shrub biology and management'. (Eds ED McArthur, EM Romney, SD Smith, PT Tueller). USDA Forest Service, Intermountain Research Station General Technical Report INT-276. (Ogden, UT) pp. 4-10.

Table 1 Comparison of AIC and R^2 values as well as estimates and significance of coefficients for two fuel load models portraying fuel loads in the northeast Mojave Desert, USA.

	Model	AIC	R^2
Model 1	SpNDVI, Elev, MaxTemp, Aspect	-348.2616	0.2929
	Coefficients	**Estimate**	**Significance**
	Intercept	2.434e+01	< 0.0001
	SpNDVI	1.469e-04	< 0.0001
	Elev	-2.783e-04	< 0.0001
	MaxTemp	-2.216e-03	< 0.0001
	Aspect	1.912e-04	1
Model 2	MinTemp, EVI, MinTemp*EVI, EVI*NDVIrat, EVI*SpNDVI	-366.5703	0.3477
	Coefficients	**Estimate**	**Significance**
	Intercept	1.323e+00	< 0.0001
	MinTemp	-2.133e-02	< 0.0001
	EVI	-7.138e-02	< 0.0001
	MinTemp*EVI	1.228e-03	< 0.0001
	EVI*NDVIrat	2.424e-02	< 0.0001
	EVI*SpNDVI	7.133e-06	< 0.0001

SpNDVI = spring normalized difference vegetation index (range of -1 to 1 take on May 9, 2005), Elev = elevation (m), MaxTemp = maximum average temperature, MinTemp = minimum average temperature, Aspect = degrees from true north, EVI = relative greenness from 2002 to 2005 (Wallace and Thomas 2008), and NDVIrat = the ratio of normalized difference vegetation index from spring 2005 to summer 2005.

Table 2 Fire Risk Models – AIC rankings of models of 2005 Fire risk prediction.

Model	Average ΔAIC	Average Weight
1. R,L,SM,F,V,F*V,SM*F,SM*V	1.33	0.698
2. R,L,SM,F,V,F*V,SM*F,SM*V,L*V	5.49	0.297
3. R,L,SM,F,V,F*V	24.46	0.004
4. R,SM,F,V,F*V,SM*F,SM*V	27.86	< 0.0001
5. L,SM,F,V,F*V,SM*F,SM*V	46.82	< 0.0001
6. R,L,SM,Sm,F,V	50.23	< 0.0001
7. R,L,SM,F,V	59.41	< 0.0001
8. R,L,Sm,F,V	60.08	< 0.0001
9. L,V	326.10	< 0.0001
10. V	353.00	< 0.0001
11. R	400.00	< 0.0001
12. L	429.00	< 0.0001
13. Sm	429.00	< 0.0001
14. SM	429.10	< 0.0001
15. F	458.60	< 0.0001

*Average ΔAIC (smaller is better), and model weight is given for 100 model runs, of random data sets of 1000 sampled points. R = Distance to roads, L = Summer lightning density, SM = Fuel Moisture Content at Spring Maximum Temperature, Sm = Fuel Moisture Content at Spring Minimum Temperature, V = Vegetation Type, F = Estimated 1-100hr Fuel Loading, and * indicates term entered as an interaction.*

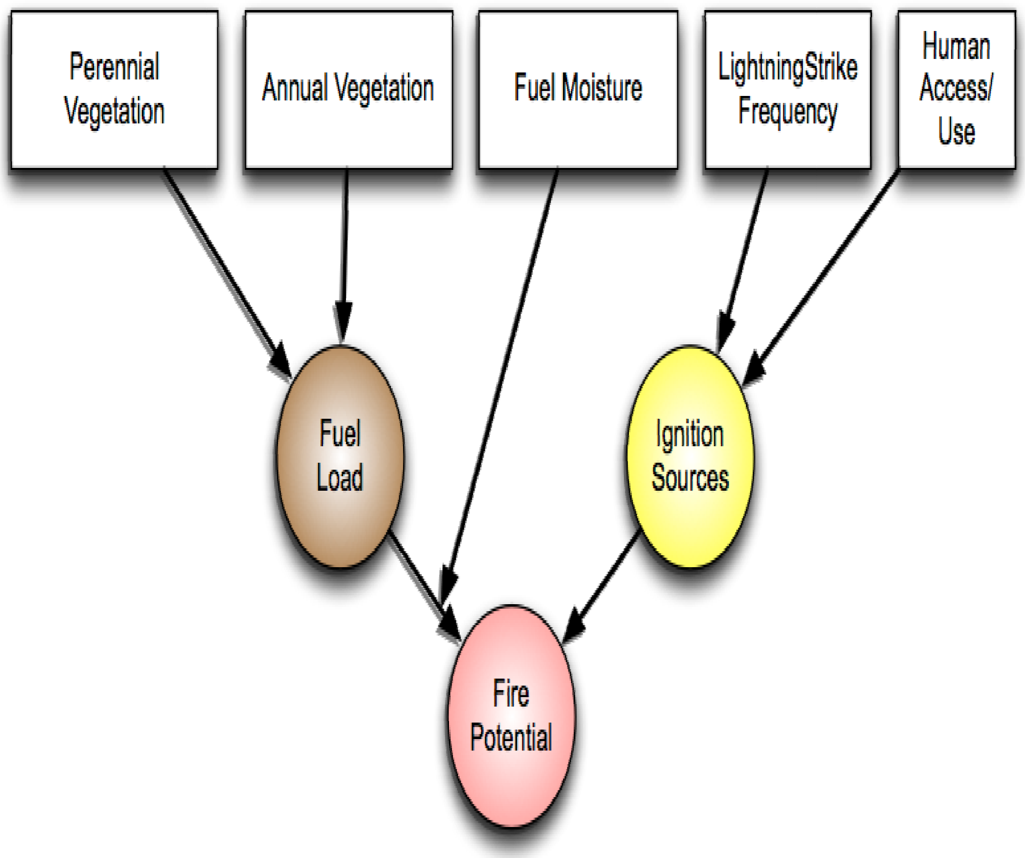

Figure 1 Key constituents likely to be of importance in assessing of fire risk/potential in the Mojave Desert Landscape**.** *Note: fuel moisture interactions differ between annual and perennial vegetation/fuel types.*

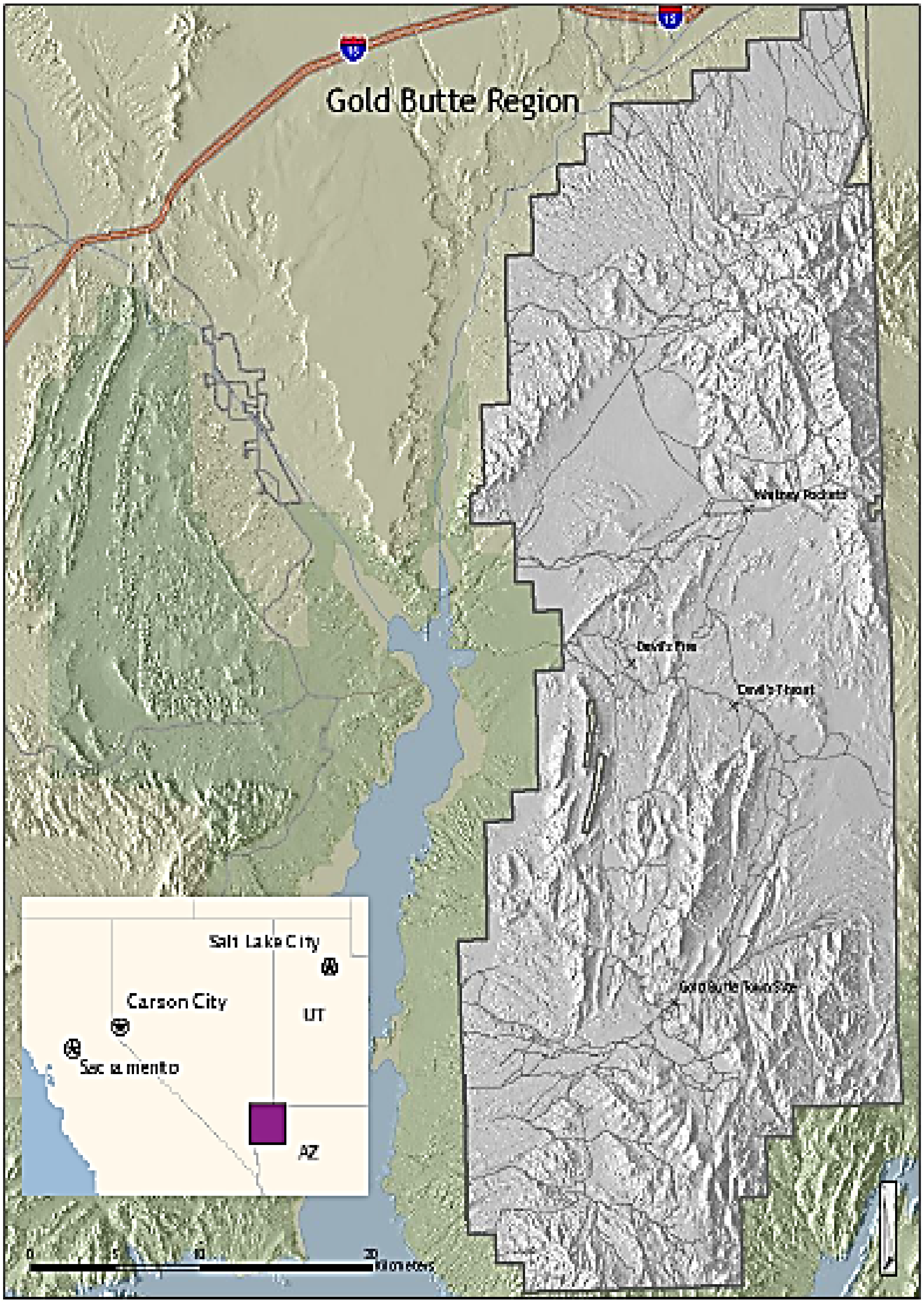

Figure 2 Overview of Gold Butte, Nevada.

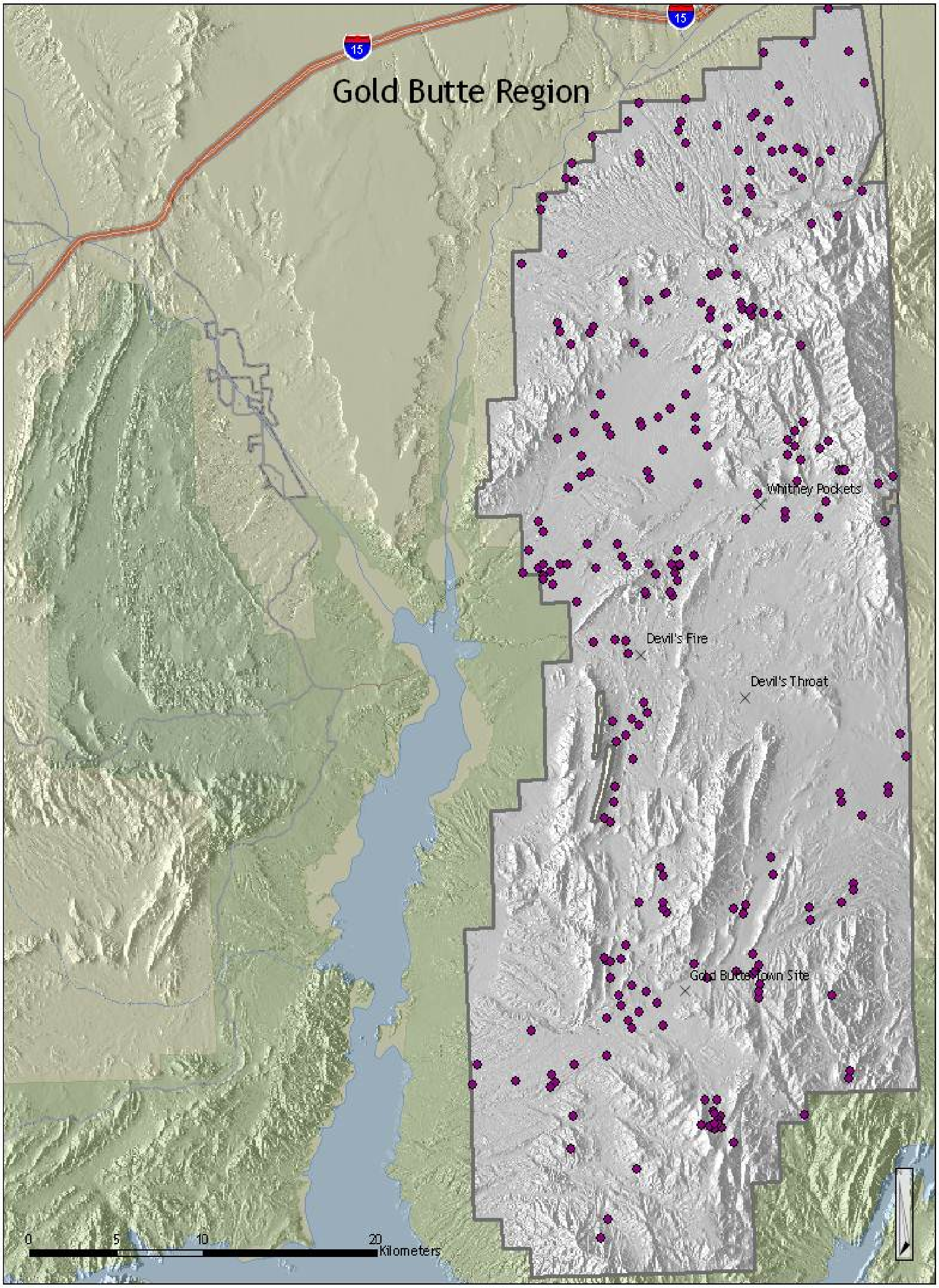

Figure 3 Locations of fuel load assessment plots in Gold Butte, Nevada.

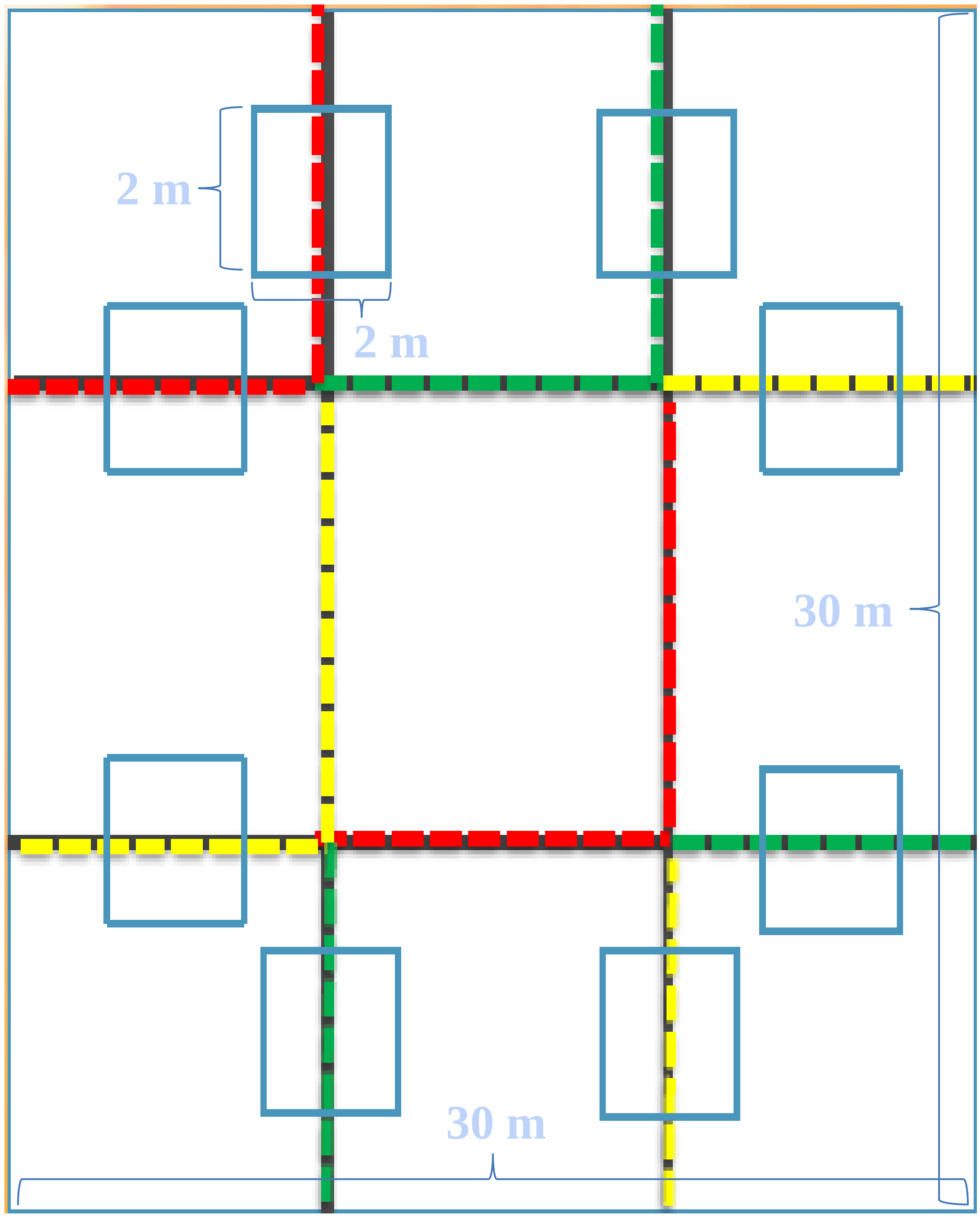

Figure 4 Plot survey design for quantifying fuels. Plot outer boundary is represented by the thin blue line. Red, blue and green dashed lines represent where 1 hr (≤1/4 in), 10 hr (>1/4 in-1 in) and 100 hr (>1 in – 3 in) fuels were randomly sampled, respectively. Solid black transect lines represent the location where 1000 hr (> 3 in) fuels were measured. Open squares represent quadrats where cover, height, litter, and duff estimates were made.

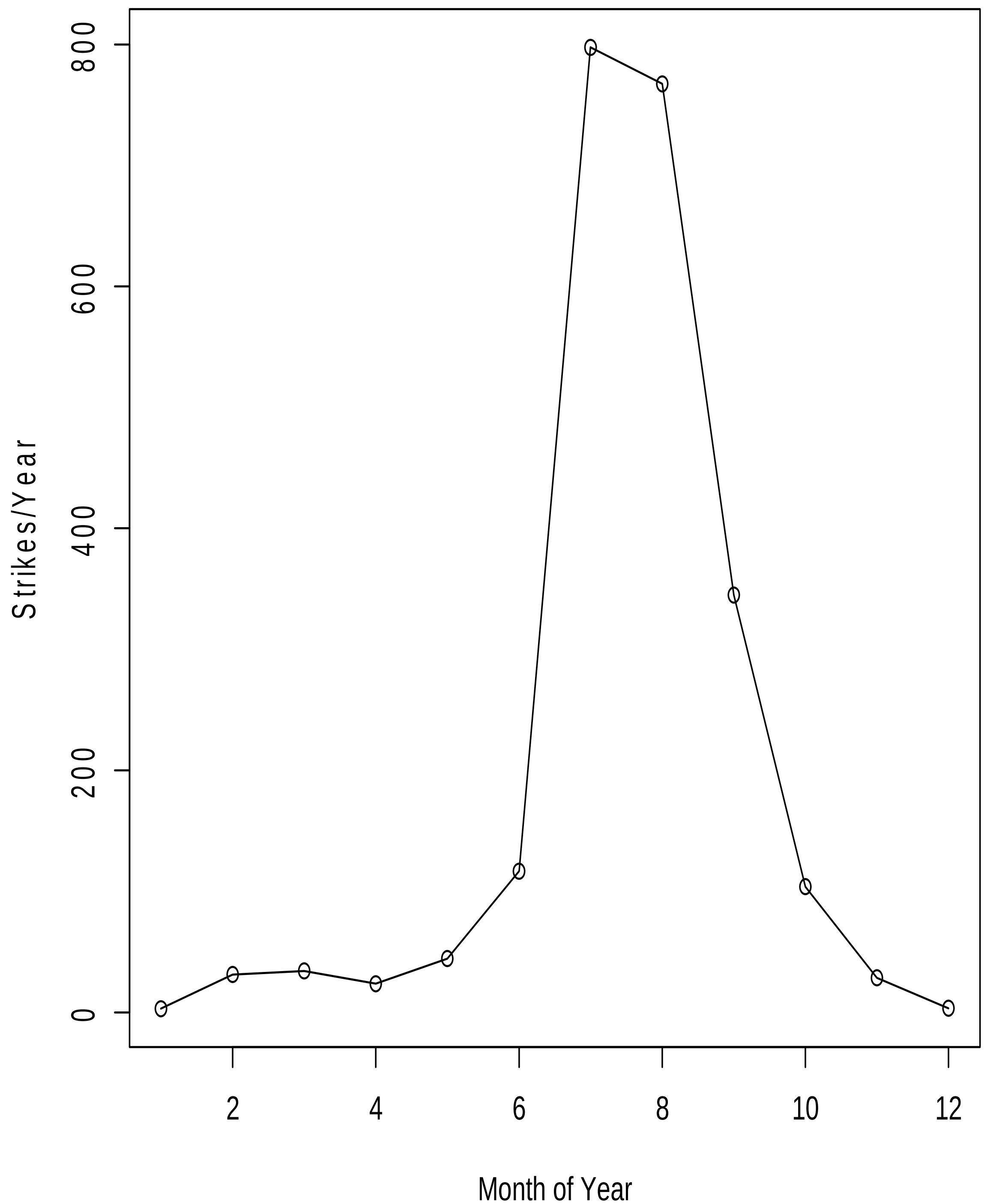

Figure 5 Lightning strikes per year by month in Gold Butte, Nevada from data ranging from 1999 to 2009.

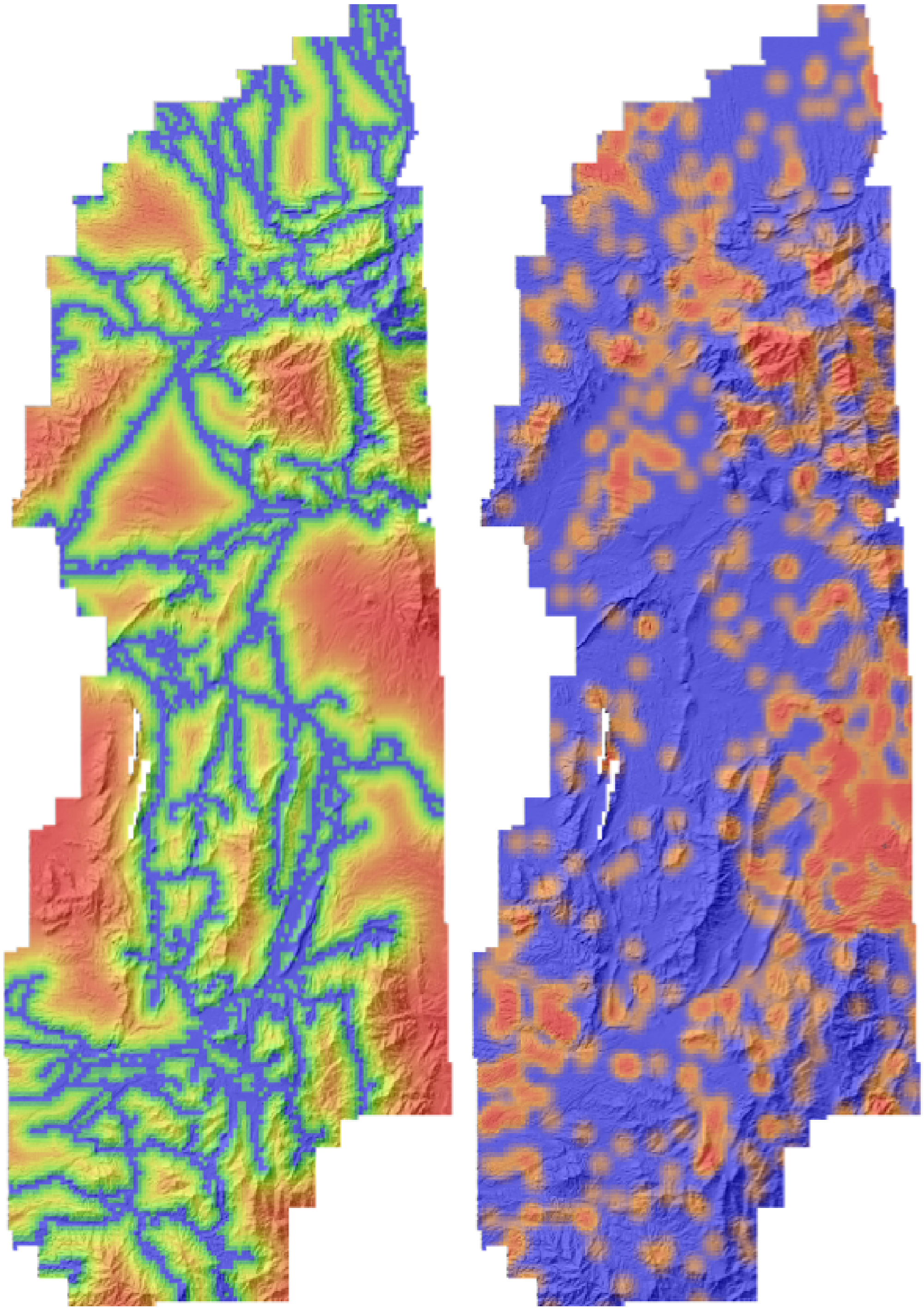

Figure 6 Potential sources of ignition for wildland fires in Gold Butte, Nevada. Roads allow for possible ignition due to human causes and are depicted as and modeled distance to roads (left; dark colors represent high road density). Lightning strikes (number of strikes per 250 m cell) during summer months corresponded with extensive wildfires in 2005 (right; light colors represent high lightning density).

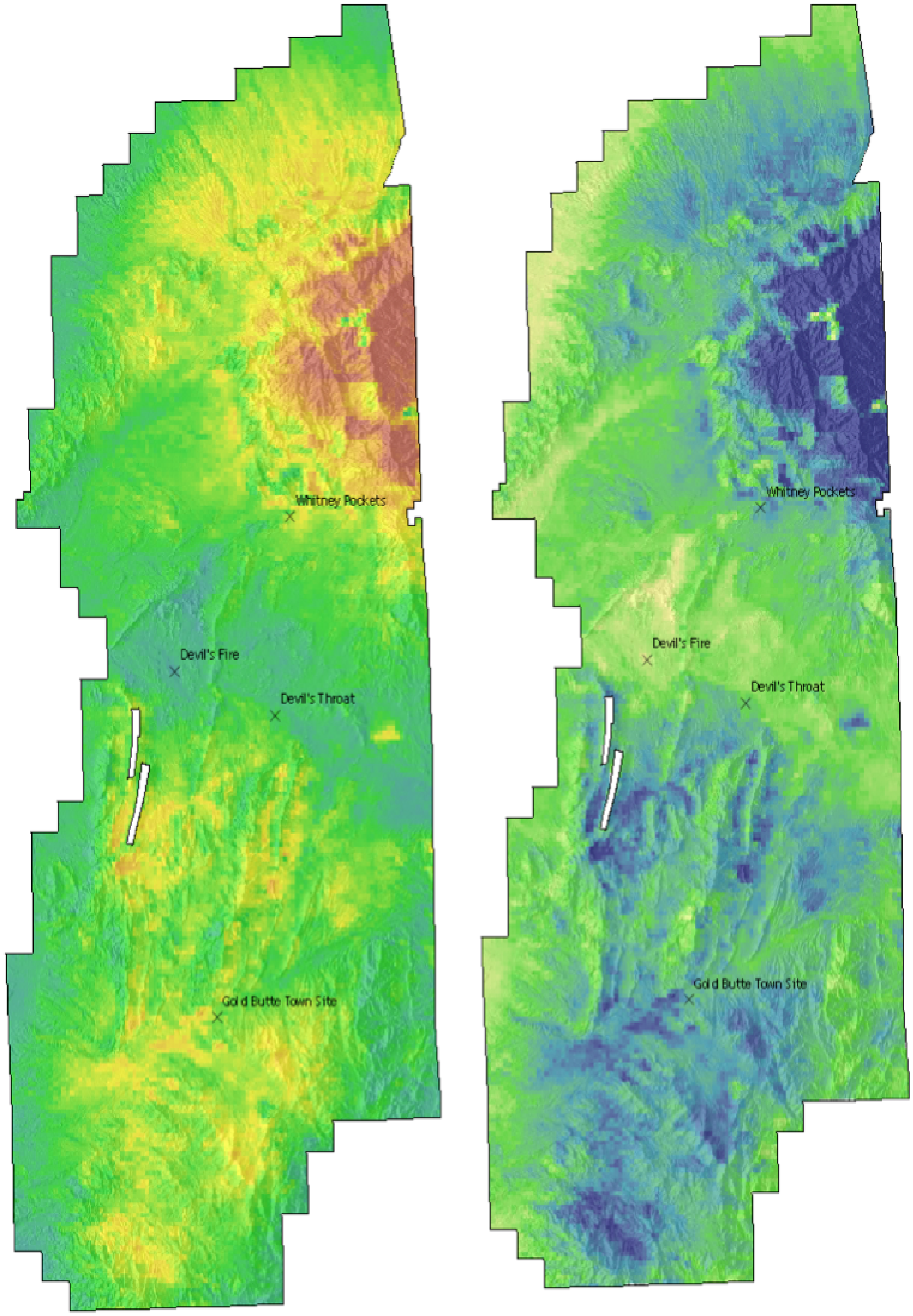

Figure 7 Estimated 1-100 hr fuel loadings (left; lighter colors represent high fuel load), and spring maximum fuel moisture content (right; darker colors represent high fuel moisture) for Gold Butte, Nevada in 2005

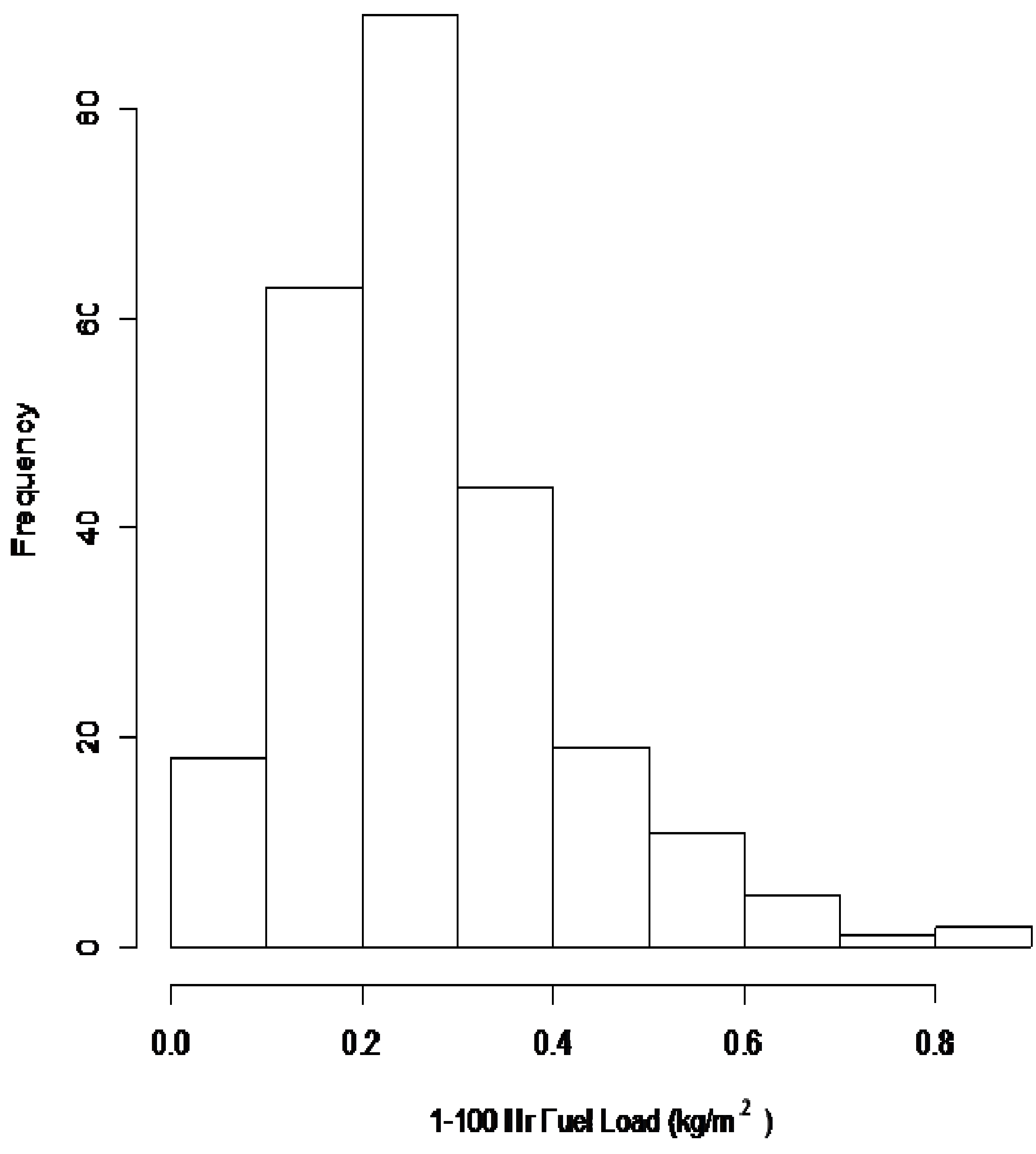

Figure 8 Frequency histogram displaying 1-100 hr fuel load averages per plot (n = 252).

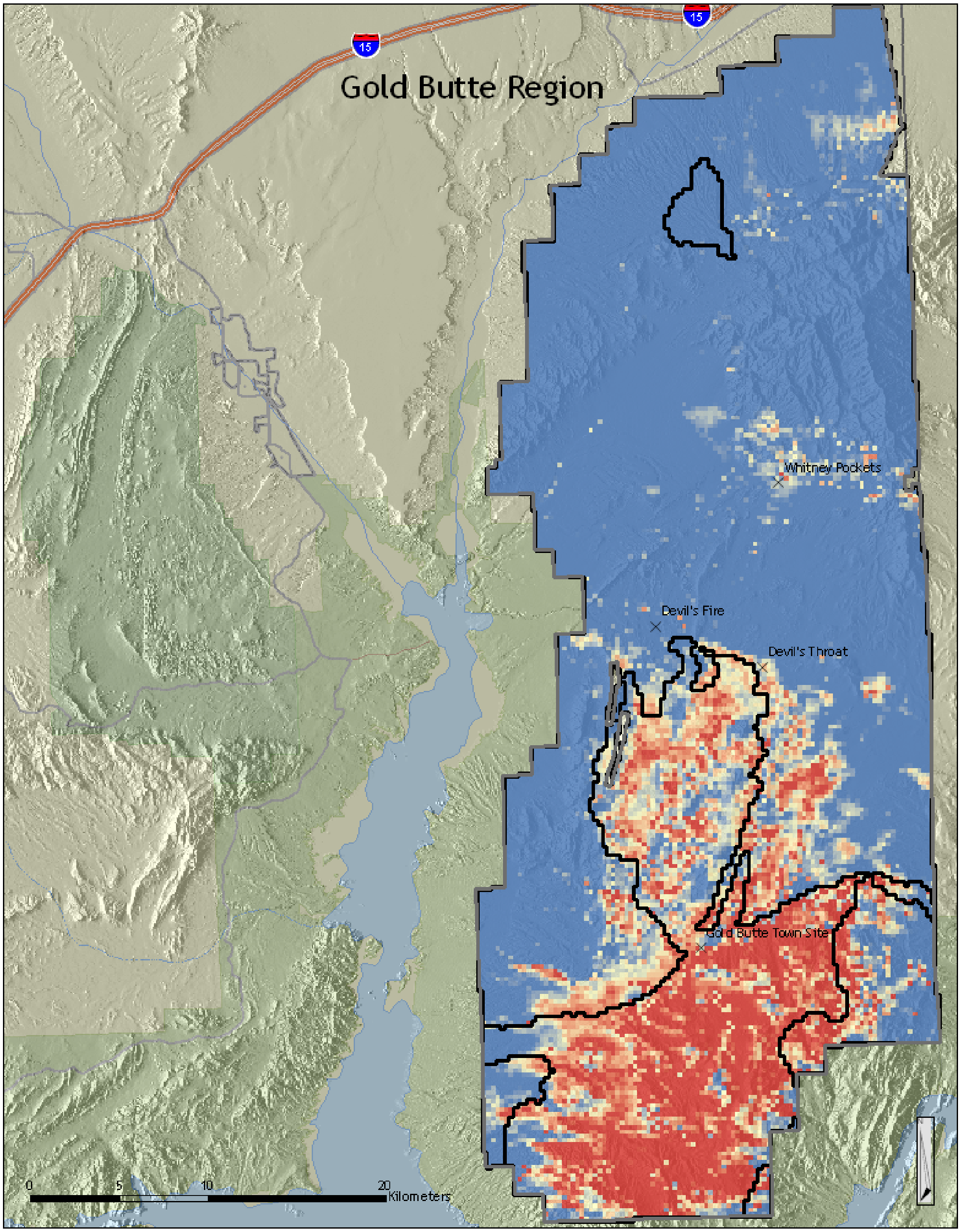

Figure 9 Fire risk prediction model for 2005 and burn perimeters (black polygons) for the same year. Red/lighter colors represent high fire potential and blue/darker colors represent low fire potential.

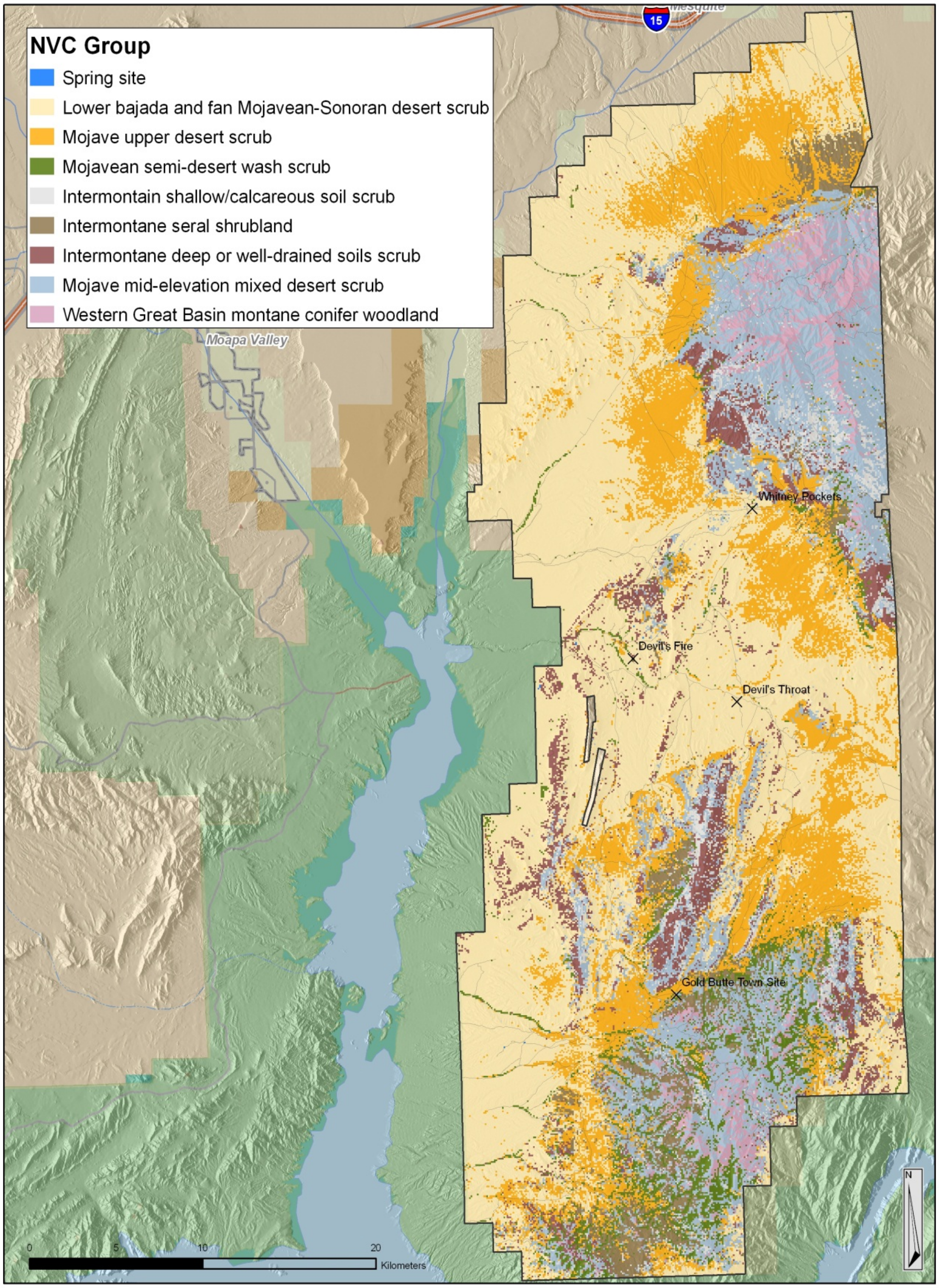

Figure 10 Vegetation map for Gold Butte, Nevada provided by USGS.

CHAPTER 4

CONCLUSION

This study focused on the development of wildfire potential estimates for the area of Gold Butte, Nevada through the use of remote sensing and field survey techniques. The major conclusion from this research is that with the combined use of field survey data and remote sensing data one can obtain reasonable estimates of fire potential for the landscape of Gold Butte. This project found it possible to predict previous fire occurrence with relatively high accuracy using the techniques developed herein. By combining field survey data with remote sensing data, a model was developed that successfully modeled ~90% of the fire occurrence documented in Gold Butte in 2005. The protocol developed in this research provides a reference point from which future wildfire potential estimates can be made and improved upon. Although the models developed for this research are not all-inclusive in terms of the all the ecological variables that may play a role in influencing wildfire potential, the models incorporate significant variables that produce results useful to land managers and resource planners.

Several more conclusions can be drawn from this work as well. First, one of the main challenges facing estimates of wildfire potential in desert ecosystems is the wide variability in fuels continuity that commonly exists in such systems. This research showed that although the fuel load models developed where only able to predict 29-34% of the fuels variability observed from the field surveys, the fuel load models still played a significant role in modeling wildfire potential. This suggests that the variability in fuel loads within desert habitats is in fact difficult to represent when modeling those fuel loads with the field survey and remote sensing data used for this study. Also, capturing all of

the variability that exists in fuel loads of desert ecosystems is not entirely necessary for estimating wildfire potential. Many other factors play significant roles in driving wildfire potential and this investigation demonstrates how the incorporation of those other important factors can help negate the lack represented fuel load variability.

Another important conclusion to draw from this work is that continued research in the estimation of desert wildfire potential is needed to improve on the tools used by land managers to allocate resources for fire suppression and the use of natural lands by the public. In the discussion of this study, several suggestions have been mentioned for improving the results of research like this including narrowing the focus of fuel types being examined to capture stronger fuel load estimates and create more representative fuel load models. By doing so, more information can be gathered to determine which fuel types, if any, are contributing the most to wildfire potential across a landscape with such variable fuels conditions. Also mentioned was the matching of the scale of field survey plots to the spatial resolution of remote sensing data which could help improve the fuel load modeling by strengthening the confidence of fuel load model estimates.

In continuing with the conclusions of this research, it is important to consider the implications for wildland fire resource management that can be drawn from this research. Although the framework presented here only allows for prediction of annual wildfire potential ~ one month in advance of the peak of wildfire activity in the area, further adjustments could be made to expand that window in order to maximize the time and efficiency with which resource planners have to implement fire suppression and management strategies. Land managers could also benefit from conclusions made about the general landscape found to be associated with the areas of higher wildfire potential

assigned by this model. In general, this model estimated that areas of low to moderate fuel loading and moderate to high fuel moisture content had the greatest potential for fire activity. This suggests that land managers would benefit by focusing fire suppression efforts in those areas as opposed to areas in Gold Butte where high fuel load and high fuel moisture co-exist since those areas retain moisture longer throughout the year and thus have less potential for fire activity.

Overall, recommendations to be considered from this research fall into two main foci. The first would consider the focus of future research. Results of this study would suggest that further research is warranted to improve model accuracies, extend the window of prediction before peak fire activity, and streamline the time and monetary costs of such research in order to maximize the usefulness to land managers as well as expand the potential for use in other arid and semi-arid regions. The second focus of the conclusions to be considered here is for resource planners. This research provides a framework that can be used and updated on an annual basis to guide land management practices. One would conclude that resource planners delegate monitoring and fire suppression resources to the areas of higher wildfire potential as predicted by this fire risk model. Also, the conclusions obtained might support recommendations to limit or strategically plan public access to areas in Gold Butte that were estimated to have high wildfire potential in order to minimize ignition sources as well as to protect the public from the threat of wildfires. Beyond these two main foci, considerations should be made for the potential of this framework or similar approaches to be examined across other arid and semi-arid landscapes where similar wildfire and invasive annual grass issues are occurring. By doing so, land managers and researchers in those areas might be able to

better conserve valuable natural resources and protect the general public from fire hazards while also expanding the knowledge and understanding of desert wildfire potential.

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