ASSESSING WILDFIRE RISKS AT MULTILPLE SPATIAL SCALES

BY

JUSTIN FITCH, B.S.

A thesis submitted to the Graduate School

in partial fulfillment of the requirements

for the degree

Master of Science

Major Subject: Wildlife Science

Minor Subject: Geographic Information Systems

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"Assessing wildfire risks at multiple spatial scales," a thesis prepared by Justin Fitch

in partial fulfillment of the requirements for the degree, Master of Science, has been

approved and accepted by the following:

_____

Linda Lacey
Dean of the Graduate School

_____

Mark C. Andersen
Chair of Examining Committee

_____

Date

Committee in Charge:

 Dr. Mark C. Andersen, Chair

 Dr. Kenneth G. Boykin

 Dr. Christopher P. Brown

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# VITA

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|---|---|
| January 15, 1983 | Born in Berlin, Germany |
| 2001 | Graduated from Homestead High School, Fort Wayne, IN |
| 2005 – 2006 | Teaching Assistant, Department of Earth and Atmospheric Sciences Purdue University |
| 2006 | Graduated from Purdue University, Highest Distinction West Lafayette, IN B.S. Environmental Geoscience |
| 2006-2007 | Teaching Assistant, Department of Fishery and Wildlife Science New Mexico State University |
| 2006-2007 | Rocky Mountain Research Station, USDA Forest Service Biological Technician |

## Field of Study

Major Field: Wildlife Science

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ABSTRACT

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In continuation of the efforts to advance wildfire science and develop tools for
wildland fire managers, a spatial wildfire risk assessment was carried out using
Classification and Regression Tree analysis (CART) and Geographic Information
Systems (GIS). The analysis was performed at two scales. The small-scale assessment
covered the entire state of New Mexico, while the large-scale assessment covered
only the Middle Rio Grande ecosystem. The result of this project is a Geographic
Information System (GIS) based predictive model. The model highlights areas of high
wildfire risk, based on the spatial distributions of numerous variables which
contribute to wildfire occurrence. The GIS also provides a simple visualization of the
distribution of risk posed by wildfire to vertebrate communities, based on species

richness data obtained from the Southwest Regional GAP program. At a state-wide

scale, accuracy assessment of the model verifies the usefulness of CART as a wildfire

risk modeling tool. The resulting three-class fire probability model includes areas

classified, relatively, as 11, 37, and 84%. These three land categorizations faced

wildfire frequencies during the test period of 4.55, 10.51, and 32.28 fires per 1000

km$^2$, respectively. Overlaying the wildfire probability maps with species richness data

showed that the largest risks to vertebrate species posed by wildfires are concentrated

along major roads and population centers in the southwestern corner of the state.

Similarly, the highest risks to vertebrate species in the Middle Rio Grande riparian

ecosystem are in and around the cities along the river, such as Albuquerque, Socorro,

and Los Lunas, NM.

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**Introduction:**

Many changes have occurred in the natural systems of New Mexico, particularly within the Middle Rio Grande region, since the beginning of Euro-American settlement. These changes have included fire suppression, reduction in riparian zone, changes in flood regimes, and altered community structure due to the introduction and success of invasive plant species. These changes have resulted in unnaturally high fuel loads, which have led to increased risk of hot, catastrophic wildfires (Merritt and Johnson, 2006).

Similar changes have occurred across the United States, which has led to a recent surge in large, destructive wildfires. Increased fuel loads, resulting from decades of fire suppression, have received much of the blame for this recent outbreak (Busenbuerg, 2004; USDA Forest service, 2006). To combat this situation, the US Forest Service issued the Wildland Fire and Fuels Research and Development Strategic Plan in June 2006 (USDA Forest Service, 2006).

The Strategic Plan set forth three strategic goals:

1) "Advance the biological, physical, social, economic, and ecological sciences" (USDA Forest Service, 2006, 11)

2) "Develop and deliver knowledge and tools to policymakers, wildland fire managers, and communities." (USDA Forest Service, 2006, 11)

3) "Provide Federal leadership for collaborative, coordinated, responsive, and forward-looking wildland fire-related research and

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development for all ownerships, now and in the future." (USDA Forest

Service, 2006, 12)

Various federal agencies and academic researchers have been contributing to

the goals set forth in this document. Currently, the USDA Forest Service's Rocky

Mountain Research Station (Albuquerque Foresety Sciences Lab) has been carrying

out studies including monitoring effects of wildfire, fuels reduction, and exotic plant

removal on vertebrates, invertebrates, vegetation, and water resources of the Middle

Rio Grande riparian system (Merritt, 2005; Finch and Galloway, 2005; Chung-

MacCoubrey and Bateman, 2006). This research has produced knowledge and data

which have helped to meet the first two goals of the Strategic Plan.

In continuation of the efforts to advance wildfire science and develop tools for

wildland fire managers, in accordance with the first two goals of the Strategic Plan, a

spatial wildfire risk assessment was carried out at two scales. The small-scale

assessment covered the entire state of New Mexico, while the large-scale assessment

covered only the Middle Rio Grande ecosystem.

The result of this project is a Geographic Information System (GIS) based

predictive model. The model highlights areas of high wildfire ignition probability,

based on the spatial distributions of numerous natural and anthropic variables which

contribute to wildfire occurrence. The relationships between these variables and

wildfire probability were determined using Classification and Regression Tree

(CART) analysis. The GIS also provides a simple visualization of the distribution of

risk posed by wildfire to vertebrate communities, based on species richness data

obtained from the Southwest Regional Gap Analysis Program (SWReGAP) (Boykin Prior-Magee et al., 2007).

This study hoped to answer the following general questions:

1) Can CART analysis, combined with data on historic wildfire ignition and spatial distributions of natural and anthropic variables be used to successfully predict areas of relatively high or low risk of wildfire occurrence?

2) Is this process able to be carried out quickly and cheaply, with existing datasets?

The study also hoped to answer the following questions, specific to the state of New Mexico and the Middle Rio Grande:

1) What are the important natural and anthropic predictors of wildfire occurrence in New Mexico and the Middle Rio Grande Ecosystem?

2) In which geographic regions of the State of New Mexico and the Middle Rio Grande ecosystem does wildfire pose the greatest risk to vertebrate diversity? That is, which areas should be prioritized for wildfire risk reduction treatments?

**Background**

*Risk Assessment:*

      Risk assessment is the process of estimating the likelihood of a stressor and the magnitude of its adverse effects on an endpoint, or value to be protected (Fairbrother and Turnley, 2005; Landis and Weigers, 1997). Risk assessment began in the insurance industry, being applied to engineering and nuclear science (Fairbrother and Turnley, 2005). Wide-Scale use of risk assessment received its start in 1983, with the publication of *Risk Assessment in the Federal Government: Managing the Process*. This publication was more commonly known as the Red Book (Landis, 2003a). The field of risk assessment slowly worked its way into the realm of the environmental sciences over the next few years. In 1987, the Pellston Conference was held in Breckenridge, CO, with the goal of establishing research priorities for environmental risk assessment (Landis, 2003a). In 1992, the U.S. Environmental Protection Agency (USEPA) published a framework for ecological risk assessment in order to address increased interest in various ecological issues, particularly the means by which humans affect the natural environment (USEPA, 1992).

      Through the mid-1990's, ecological risk assessment was typically based on the USEPA paradigm, which was limited by its design, focusing on the analysis of only a single stressor and a single endpoint. This model also lacked adequate flexibility to incorporate spatial variation of the environment (Landis, 2005). To address these limitations, the Relative Risk Model was proposed by Landis and Wiegers (1997). The relative risk model expanded ecological risk assessment to the

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regional scale, incorporating multiple sources, stressors, and endpoints. Under this framework, ecological risk assessment began to be applied at the watershed level and above. At the time of its development, and in the years immediately following, the primary application area of ecological risk assessment using the Relative Risk Model was the analysis of risks posed to diverse systems by chemical or biological contaminants (Wiegers and Landis, 2005; Luxon and Landis, 2005).

In recent years however, application of the Relative Risk Model has expanded. Landis (2003b) used the relative risk model to evaluate the threats posed by the non-indigenous European green crab off the shores of Cherry Point, Washington. Andersen et al. (2004) used a GIS based relative risk assessment to determine threats to biodiversity posed by military actions on a United States Army base and missile range. Landis (2003a) also mentions the use of ecological risk assessment to evaluate impacts of urbanization, land use change, fishing, and climate change.

Risk assessment as an ecological tool is required by multiple laws. For example, the National Environmental Policy Act (NEPA) requires that federal agencies produce an Environmental Impact Statement (EIS) before taking any action which will significantly affect the human environment. More specifically, NEPA Section 102(2)(A)states that:

"…all agencies of the Federal Government shall…include in every recommendation or report on proposals for legislation and other major

Federal actions significantly affecting the quality of the human

environment, a detailed statement by the responsible official on --

(i) the environmental impact of the proposed action,

(ii) any adverse environmental effects which cannot be avoided should

the proposal be implemented,

(iii) alternatives to the proposed action,

(iv) the relationship between local short-term uses of man's

environment and the maintenance and enhancement of long-term

productivity, and

(v) any irreversible and irretrievable commitments of resources which

would be involved in the proposed action should it be implemented. "

(NEPA, 1969, Sec 102(2))

However, neither NEPA nor any of the other federal laws requiring risk

assessment, such as the Endangered Species Act and the Healthy Forests Restoration

Act, specify how these risk assessments are to be carried out or even the format of the

results (O'laughlin, 2005b).

In 2003, a symposium was held in Portland, Oregon, with the objective of

advancing tools and methods for relative risk assessments, particularly those dealing

with the risks posed by uncharacteristic wildfire (Irwin and Wigley, 2005;

O'Laughlin, 2005a), which had, in recent years, become a burning issue within the

wildland management community.

*Wildfire Science/Risk:*

Wildfire science is another field which has seen drastic changes in recent years. With this change in the scientific outlook on wildfire have come changes in management practices. For approximately 100 years, the U.S. federal government, as well as state and local governments, based their wildfire management decisions on a wildfire suppression policy which was developed between 1905 and 1911, under which all fire outbreaks were suppressed immediately. This policy did not include any means of dealing with heavy accumulations of fuels which resulted from long wildfire-free periods (Busenberg, 2004). As a result, these fuels have accumulated in many of America's forests over the past 100 years, resulting in a recent and drastic increase in number and intensity of wildfires (USDA Forest Service, 2006).

The 2003 Portland symposium on wildfire risk assessment, as well as much of the literature, focuses on the comparative assessment of risks associated with different fire and fuel treatment methods on a single piece of forest. As stated, NEPA requires this type of assessment by federal agencies before they may go forward with any action that will affect the human environment (NEPA, 1969).

The Federal Wildland Fire Management Policy, as updated in 2001, goes so far as to say that sound risk management is a foundation for all fire management activities (O'laughlin, 2005b). In 2003, the United States Congress passed the Healthy Forest Restoration Act. Though a controversial piece of legislation, the Act set the goal of focusing fuels reductions and forest restoration projects on federal

lands on which wildfires pose risks to communities, water supplies, and the environment (O'laughlin, 2005b).

Because it is not explicitly required by law, as is comparative assessment of various fuel reduction or restoration options, much of the literature has ignored the issue of spatial risk distribution. In a nation where 29% of the total land area, 655 million acres, are federally owned, and approximately 190 million acres are at risk of catastrophic wildfire (O'laughlin, 2005b), spatial risk categorizations are essential to prioritize areas for restoration and fuels reduction treatments.

Some researchers have recently used modern technologies to view and analyze both the effects and risks of wildfire from a spatial perspective. Both Remote Sensing and Geographic Information System technologies are being implemented to help advance the field of wildfire risk assessment (Amatulli et al, 2006).

While modern technologies are increasing its ease and potentially its accuracy, prediction of wildfire risk is not a new concept. Short-term risk prediction dates back to the initial publication of the National Fire Danger Rating System (NFDRS) in 1972, revised in 1978. The NFDRS is a set of numerical indices designed to aid in wildfire management and prevention. The primary index is the Burning Index (BI) (Peng et al., 2005). The BI is based on fuel and weather data obtained from Remote Automatic Weather Stations (RAWS). The formula includes two calculated components. The Spread Component inputs wind, slope, and fuel data into a wildfire spread model developed by Rothermel in 1972. The other component, the Energy-Release Component, accounts for the reaction intensity and surface area-

to-volume ratio of the fuel bed. This model is universal, used without modification in all parts of the US (Peng et al., 2005). Peng et al. (2005) analyzed the usefulness of the Burning Index in predicting wildfires in Los Angeles County, CA and concluded that it can be effectively used to predict only a small amount of variation in spatial wildfire risk.

Haight et al. (2004) analyzed the risk of wildfire to human lives and structures in the Wildland-Urban Interface in Michigan. The authors only used two variables to characterize wildfire risk. These were historic fires and current fuel data. Based on historic fire data, they determined what types of fuels were most prone to wildfire. They then built risk maps based on those classifications and up-to-date fuels maps.

Hampton et al.(2003) used a combination of two methods to determine relative spatial fire risk. The first was a measurement of "fire hazard" across the landscape. This was created using a fire modeling program called FlamMap (Missoula Fire Sciences Laboratory, Rocky Mountain Research Station, US Forest Service. 2006. Available http://www.firemodels.org) FlamMap takes spatial vegetation, weather, and fuel moisture data as input, and returns maps showing the potential crown fire intensity and heat per unit area that would be produced by wildfire across the entire study area. Hampton's "fire hazard" layer is a combination of these two FlamMap output variables. The second method was termed "fire risk". This was determined by simply creating a raster layer of number of wildfires/km$^2$ across the study area, based on historic wildfire point locations. Hampton believes

these two layers, fire hazard and fire risk, to be sufficiently accurate to prioritize
restoration treatment locations (Hampton et al., 2003).

The newest version of FlamMap, released in March, 2006, contains a
Treatment Optimization Model. This function determines the optimal locations for
wildfire treatments based on models of fire spread from numerous random locations
throughout a landscape. The treatment areas suggested by the optimization model are
those areas whose treatments will be most beneficial to stopping the spread of
wildfires, not necessarily those areas which are most likely to ignite.

Wildfire risk prediction software, such as FlamMap, responds to a widespread
lack of appropriate statistical analysis techniques in the  field of wildfire risk analysis
(Amatulli et al., 2006). Historically, assessments of risk have been based on
professional opinion. Recently however, trust in this method has deteriorated, as
scientists, policymakers, and the public seek more scientific and reproducible
methods of risk determination (O'laughlin, 2005a).

Academic researchers have also responded to this need. Amatulli et al. (2006)
proposed using Classification and Regression Trees analysis to provide unbiased
statistical models which incorporate spatial relationships between multiple variables
and wildfire risk. Amatulli et al. concluded that the CART method can be very useful
in creating accurate wildfire risk maps. The results of this study, as will be discussed,
support this conclusion, while modifying and simplifying the process.

Beginning in 2006, the Landscape Fire and Resource Management Planning
Tools Project (Landfire) began releasing detailed data layers, derived from Landsat7

imagery and ground data, showing vegetation cover, fuels data, and fire regimes (Landfire, 2007). The project should have continuous coverage available across the United States by 2009. The goal of Landfire is to provide data to contribute to strategic wildfire planning at the national and regional level. The data layers provided by Landfire can be incorporated into predictive programs such as FlamMap, to predict fire behavior and prioritize candidate fuels reduction sites. These data can also be used, as was done in this project, in a CART analysis.

*Classification and Regression Tree (CART) Analysis:*

Fire risk estimations have historically been done using either multiple linear regression or logistic regression, with some work having been done with neural networking (Amatulli et al, 2006). Each method has its benefits and drawbacks.

Logistic regression needs no prior assumptions about the distribution of the input data, which is a plus for modeling fire risk from scratch, given only prior occurrences and spatial distribution of potential causative variables. However, logistic regression is only capable of yes/no output. This means that a model of this type cannot predict probabilities of wildfire, but instead can only classify each area as either at risk or not at risk.

This output problem can be solved using multiple linear regressions. However, this method cannot take categorical variables as input. Categorical variables, such as vegetation type or fuel model, have been shown to be of great importance in modeling of wildfire risk (Amatulli et al., 2006).

The neural networking approach overcomes the drawbacks of both logistic and multiple linear regressions. These models have been shown to produce acceptable results. However, the neural network is somewhat of a "black box", meaning that the modeler has no real explanation for the results obtained from the model. There are no decision rules created and output by the neural network (Amatulli et al., 2006).

The CART model solves the problems of all three of these options. It allows for input of categorical variables, and outputs a set of decision rules, the classification tree, which allows for a continuous classification of fire risk.

Cart is a non-parametric statistical procedure which creates classification or regression trees. Classification trees are those in which the dependent variable is categorical. If the dependent variable is numeric, the output is termed a regression tree (Amatulli et al, 2006).

The process of tree creation involves the repetitive binary splitting of data, based on how well one independent variable acts as a predictor of the value of the dependent variable. Initially, all of the data is split into two categories, based on the value of one predictor variable. Next, each group is subsequently split, based on another (or the same) predictor variable. This process is continued until it is determined that no further splits contribute to the classification of the dependent variable. At this point, the data has typically been split into a large number of classes. The resulting tree is then "pruned" in such a way as to reduce the number of separate classes in the tree while keeping misclassification at a minimum (Salford Systems, 2004).

The result of this recursive process is a classification/regression tree, a flow chart in which each possible combination of predictor variables falls into one, and only one, class. An example of a regression tree is shown in **Figure 1**. Each intermediate node, represented by blue diamonds in Figure 1, represents a decision rule, upon which data is classified. Each rectangle in **Figure 1** is a terminal node, representing one class. Each terminal node is defined by a set of explicit rules, which can be determined by tracing the path downward through the tree from the initial decision rule to a given terminal node.
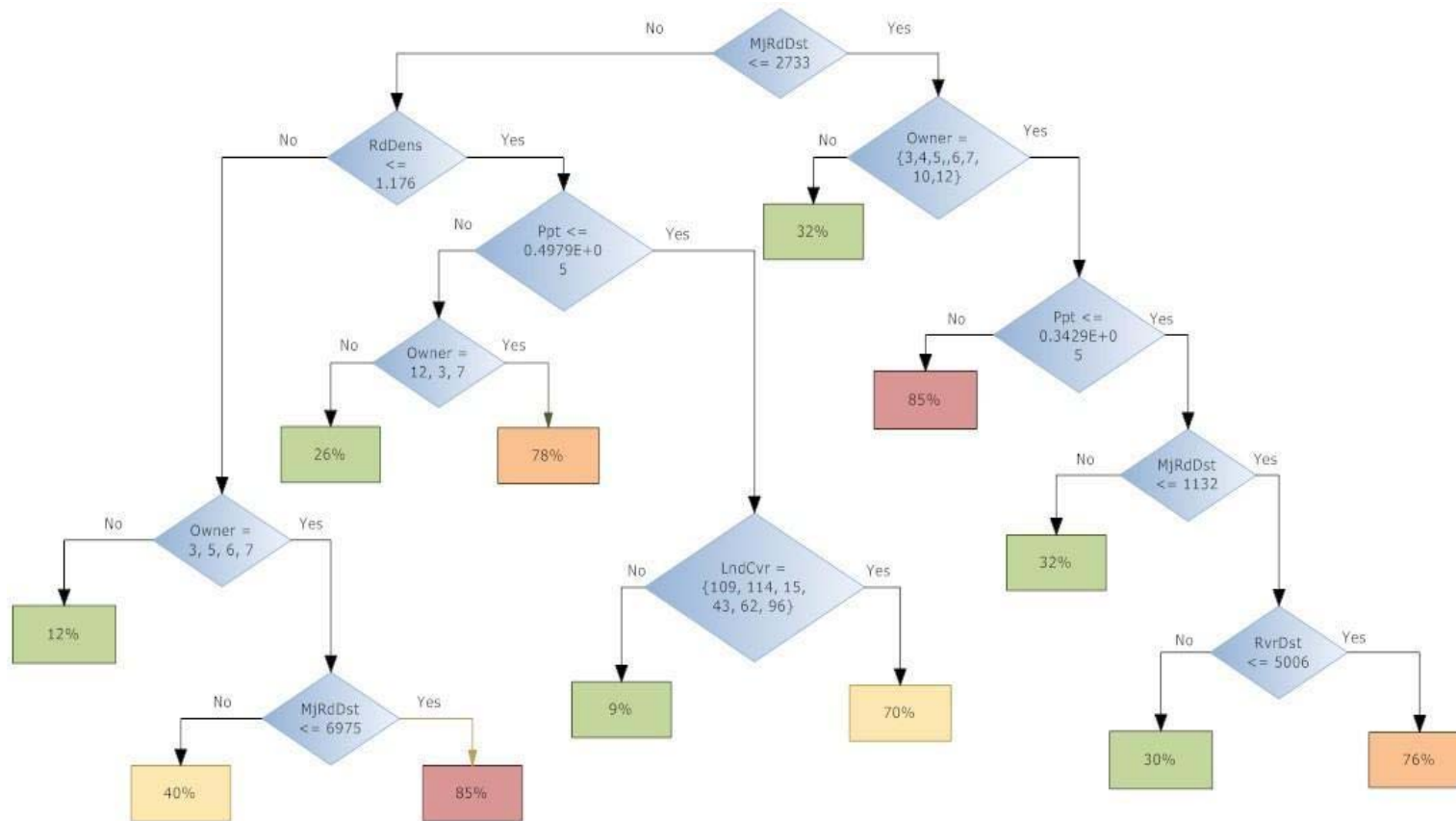
Figure 1: Classification tree resulting from CART analysis of state-wide wildfire probability

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**Study Area**

*New Mexico:*

Measuring approximately 121,666 square miles, New Mexico is the 5th largest state in the United States (NMDGF, 2006). The state experiences a generally dry, warm climate, with an average annual temperature of 54 degrees F. Variation in precipitation is predominantly a function of altitude and latitude (NMDGF, 2006). The high mountains of the southern Rockies receive up to 40 inches of rain per year, while some lower areas receive only eight to ten. There is also a general East/West trend, with slightly higher precipitation levels in the eastern portions of the state (Encyclopædia Britannica, 2008).

New Mexico spans eight Level III ecoregions, as defined by the United States Environmental Protection Agency (USEPA, 2002; **Figure 2**). An ecoregion is "an area of general similarity in ecosystems and in the type, quality, and quantity of environmental resources (USEPA, 2002)." The ecoregions within New Mexico are the Colorado Plateau, Southern Rockies, Arizona/New Mexico Plateau, Arizona/New Mexico Mountains, Chihuahuan Desert, High Plains, Southwestern Tablelands, and the Madrean Archipelago (USEPA, 2002).

The Colorado Plateau ecoregion covers a small potion of the extreme northwestern corner of the state. This is a region of canyons, mountains, mesas and plateaus. Its high elevation yields extensive pinyon-juniper woodlands. Saltbrush-greasewood ecosystems predominate large low lying areas in this ecoregion (USEPA, 2002).
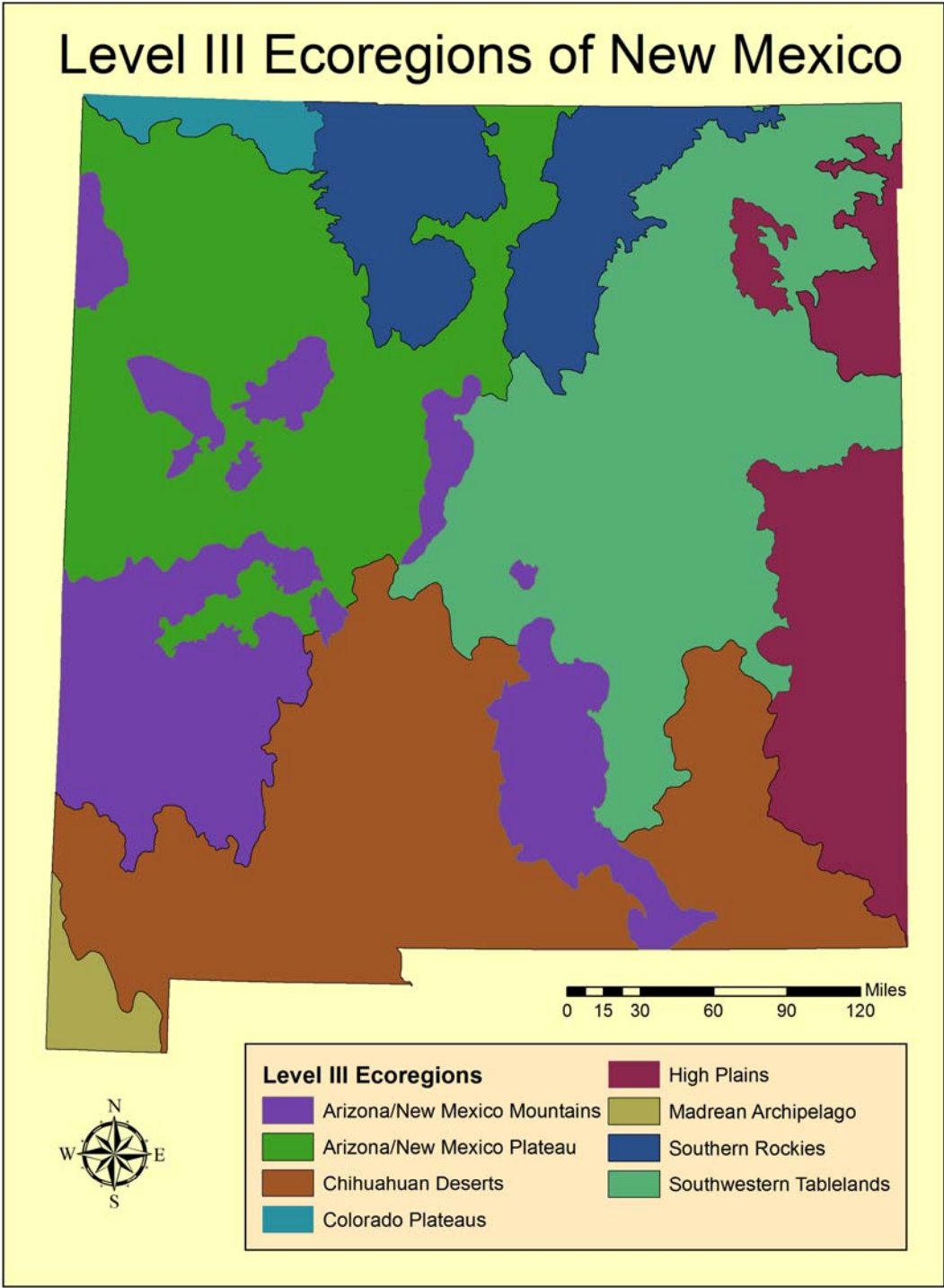
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Figure 2: Level III Ecoregions of New Mexico, as delineated by US EPA

Two lobes of the Southern Rockies ecoregion extend into the state from the North. This region is classified by high steep mountains, and a large elevational gradient. The lower elevations are typically covered by grass and shrub. Middle elevations include Douglas fir, ponderosa pine, aspen, and juniper-oak woodlands. Both the low and middle elevation areas are grazed extensively. The higher elevation areas are predominately coniferous forests, with alpine ecosystems at the highest of these areas (USEPA, 2002).

The Arizona/New Mexico Plateau is a large area comprising most of the northwest quarter of New Mexico, spanning the northern half of the state from the western border with Arizona through the Rio Grande Rift. This region is a transition zone between the low semi-arid grasslands to the south and east and the Colorado Plateau to the North (USEPA, 2002).

The Arizona/New Mexico Mountains are lower in elevation than the surrounding mountains, such as the southern Rockies. Predominant ecosystems in this region include low elevation chaparral, mid elevation pinyon-juniper and oak woodlands, and higher elevation ponderosa pine forests (USEPA, 2002).

The Chihuahuan Desert ecoregion covers most of the southern portion of New Mexico, extending from the Arizona border, north of the Madrean Archipelago to the high plains at the eastern edge of the state. This ecoregion also extends northward along the Rio Grande rift. This area is categorized by wide basins and valleys covered by arid grass and shrubland ecosystems. Oak-Juniper woodlands can be found at higher elevations on mountains in this region (USEPA, 2002).

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The Western High Plains ecoregion extends along nearly the entire eastern margin of New Mexico. This region is differentiated from the great plains of Middle America by increased elevation and reduced precipitation. The predominant natural vegetation in the Western High Plains is saltbrush-greasewood, though large amounts of these areas are now in agricultural production (USEPA, 2002).

The Southwestern Tablelands lie to the west of the high plains and to the north of the Chihuahuan desert. This region is composed of sub-humid and semi-arid grasslands (USEPA, 2002).

Lastly, the Madrean Archipelago ecoregion, better known as the sky islands region, encompasses the southwest corner of New Mexico. This is a basin and range area, with shrubsteppe ecosystems in the basins and oak-juniper woodlands on the mountains. Ponderosa Pine predominates the higher elevation mountains (USEPA, 2002).

The wide variations in elevation and ecosystems make New Mexico one of the more biodiverse states. More than 4,500 plant and animal species have been cataloged in the state (NMDGF, 2006). Included in this count are 504 bird species, 184 mammal species, 105 reptile species, and 26 amphibian species (NMDGF, 2006). Vertebrate species richness is greatest in the southwestern corner of the state, and along the Middle Rio Grande. Species richness is lowest in the eastern high plains (Boykin, K., NMCFWRU, unpublished data).

The wide range of ecosystems in the state allows for a wide range of wildfire risks. Areas of sparse vegetation are at lower risk for catastrophic wildfire than areas

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of dense vegetation. Similarly, regions of drier climate are greater fire risk than wetter areas. Differences in terrain also affect the degree of human infrastructure.

*Middle Rio Grande:*

The middle Rio Grande Study area is completely within the Rio Grande floodplain, but spans across the Arizona/New Mexico Plateau and Chihuahuan Desert level III ecoregions (USEPA, 2002; **Figure 3**). The riparian areas along the Middle Rio Grande historically supported a Cottonwood (*Populus deltoids spp. Wislezeni*)/Willow (*Salix gooddingii*) dominated forest. This forest is the most extensive cottonwood forest remaining in the southwestern United States (Chung-MacCoubrey and Bateman, 2006). These forests were well adapted to frequent flooding and low intensity wildfires. However, flood regimes have been altered and floods have become very infrequent in most areas along the Middle Rio Grande due to damming of the river upstream (Merritt and Johnson, 2006). Because of the near cessation of flooding, human alterations have created a new disturbance regime with wildfire as the most important disturbance (Smith et al., 2006). This altered disturbance regime has contributed to the extensive invasion of Saltcedar (*Tamarix ramoisissima*) and other non-native species in most areas along the river (Merritt and Johnson, 2006).

Saltcedar is a fast growing plant, resulting in an accelerated rate of fuel accumulation, which in turn leads to wildfires of higher intensity. High intensity wildfires often result in the death of the less fire-resistant native trees, such as

cottonwood and willow (Merritt and Johnson, 2006). Following intense wildfires, cottonwoods and other native trees are often replaced by fast growing invasives such as salt cedar and Russian olive (*Elaeagnus angustifolia*) (Finch and Galloway, 2006).
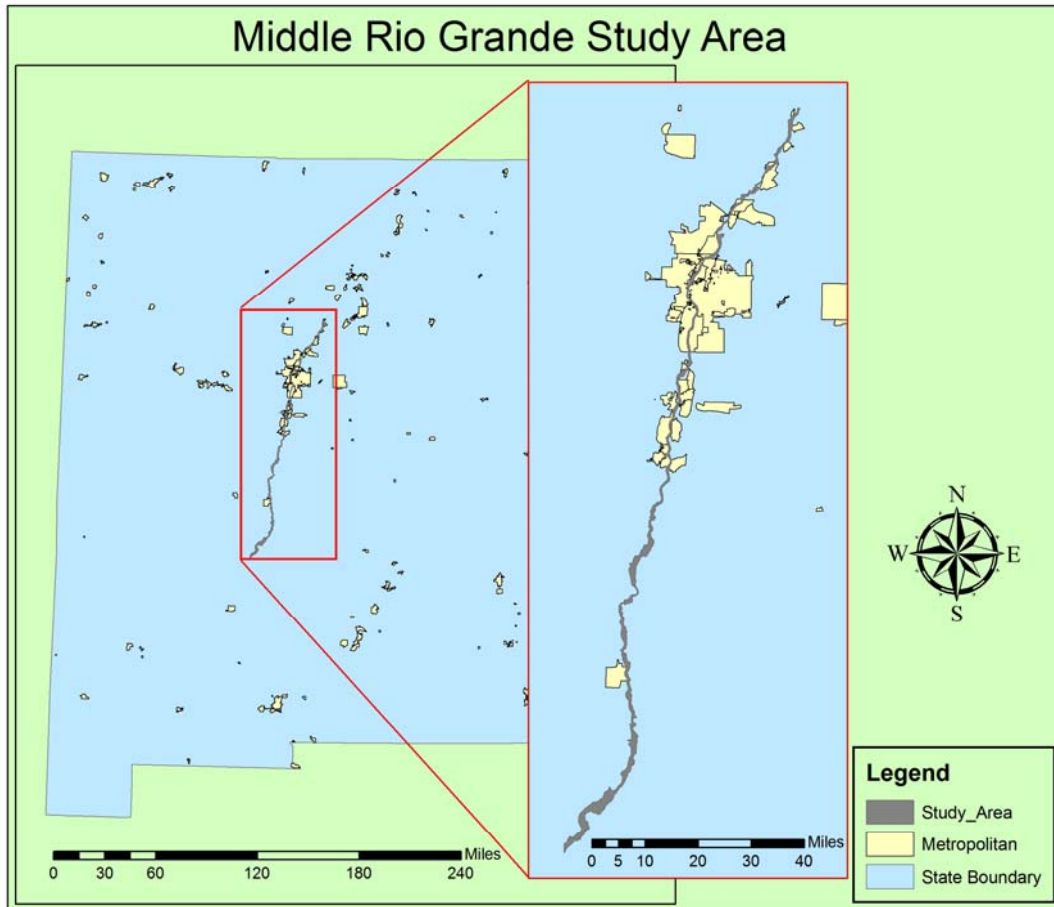


Figure 3: Middle Rio Grande study area

The riparian areas of the Middle Rio Grande support greater numbers of breeding bird species than do the surrounding uplands. Additionally, even given the limited extent of riparian coverage in the desert southwest, these areas support an

even greater number of migrating birds, counted both individually and by species (Ellis, 1995).

Ellis (1995) concluded that bird species richness did not differ between areas dominated by native cottonwood trees and those dominated by the invasive saltcedar. However, more species were found to be unique to cottonwood than to saltcedar. Neotropical migrants, of special concern in the region, showed a slight springtime preference for cottonwoods. Ellis (1995) concluded that while many species may be able to transition into use of saltcedar instead of cottonwood, preservation of native cottonwood forests will be essential to the continued use of the Middle Rio Grande riparian zone by many bird species.

Finch and Galloway (2006) found avian species richness to be slightly greater in post-wildfire sites along the Middle Rio Grande than on unburned sites. Similar to Ellis' findings however, preference between the two types of sites varied by species (Finch and Galloway, 2006).

Studies on bat activity found a negative effect of invasive plants (Chung-MacCoubrey and Bateman, 2006). Monitoring bat activity for two years before and after invasive reduction treatments and on control sites, researchers found a greater increase in bat activity on treatment sites than on control sites for the years following treatments. They also found an uneven North-South distribution, with greater bat activity on the southern sites than on the middle and north sites. 50.2% of this variation was explained by reduced canopy cover on the southern sites (Chung-MacCoubrey and Bateman, 2006).

Existing literature indicates that the Middle Rio Grande riparian habitat is

utilized by at least 50 reptile and amphibian species (Chung-MacCoubrey and

Bateman, 2006). Most species caught in trapping studies tend to be associated with

upland habitats, and were captured in open, sandy areas. A 2000-2005 capture study

found 9 amphibian, 11 lizard, and 13 snake species in the riparian zone. (Chung-

MacCoubrey and Bateman, 2006)

**Methods**

The general methods for the production of each relative vertebrate risk map are outlined by the flowchart in **Figure 4**. In order to analyze the relative levels of risk that wildfire poses to vertebrate resources within the state of New Mexico and the Middle Rio Grande riparian zone, spatial relative wildfire occurrence probabilities were first estimated.
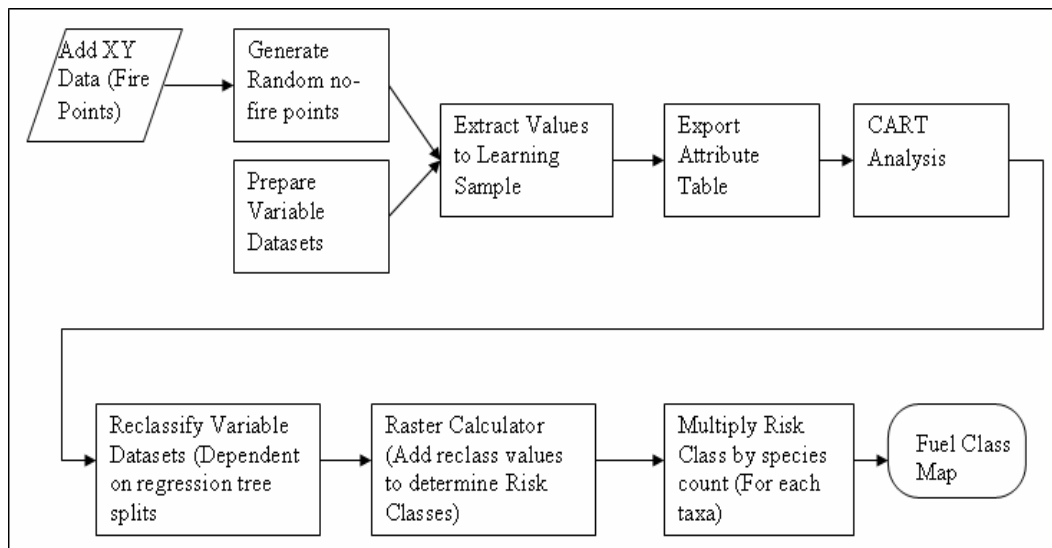


Figure 4: Flowchart showing general steps towards creation of vertebrate risk map

Two separate wildfire probability maps were created, one small-scale map covering the entire state of New Mexico and one larger-scale map covering only the Middle Rio Grande riparian zone. Relative wildfire probabilities were determined by means of a Classification and Regression Tree analysis, incorporating historic wildfire ignition points (Southwest Coordination Center, unpublished data) and various natural and anthropic spatial variables.

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The historic wildfire ignition point dataset contained ignition points (latitude/longitude), burn areas, and ignition causes for all reported wildfires in the state of New Mexico from July 1, 1996 through June 30, 2004, totaling 4,569 data points. For this study, only ignition point locations were used.

*State Wildfire Probability Map:*

The statewide relative wildfire probability map was based on numerous spatial variables. These variables and the data sources are indicated in **Table 1**. The table also shows the notation for the layer used in the CART output, which will be discussed later.

For use in the risk assessment model, some of the datasets had to be converted to more meaningful layers. ESRI's ArcGIS 9.2 was used to convert the Major Roads and Rivers vector layers into raster datasets representing distances to roads and rivers, respectively. This was accomplished using the Straight Line (Euclidian) Distance tool in the ArcGIS Spatial Analyst toolbar. The Detailed Roads layer was used to create a Road Density raster dataset using the Line Density tool. The two distance layers and the road density layer were created as GRID files with spatial resolution of 2.27 km. This spatial resolution was chosen as a compromise between high resolution and low processing time. The ownership polygon file was also converted into a raster dataset with a 2.27 km resolution. The Temperature, Precipitation, and Land-Cover layers were used in their original raster format. Average Maximum July Temperature was used as a surrogate for relative temperature, as the temperature gradient throughout

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**Table 1: Data and sources used in Statewide CART analysis**

| Data Source | Input Data Layer | Figure 1 Notation |
|---|---|---|
| PRISM Group (Oregon Climate Service) | Average Max July Temperature<br>Average Precipitation | Temp<br><br>Ppt |
| Southwest Regional Gap Analysis Project | Major Road Distance<br>Road Density<br>River Distance<br>Land-cover | MjRdDist<br>RdDens<br>RvrDst<br>LndCvr |
| New Mexico Resource Geographic Information System Program (University of New Mexico) | Land Ownership | Owner |

the state is fairly consistent throughout the year. On average, July is one of the

warmest months in the Southwest United States. The Average Precipitation dataset

gives the average annual precipitation for each cell. Each of the two climate variables

are raster datasets with a spatial resolution of .0417 decimal degrees. The Landcover

dataset divides the state into 30 x 30 m cells, each classified into one of 89 distinct

landcover types. Analysis of multiple datasets of various spatial resolutions was

easily and automatically dealt with by ArcGIS.

All fires from July 1, 1996 through June 30, 1997 were isolated. This resulted

in 521 data points. 522 new data points were randomly selected within the state of

New Mexico, all at least 2km from any documented wildfire ignition points, using the

Generate Random Points tool within Hawth's Tools, a free ArcGIS extension package

(Beyer, H. L. 2004. Available: http://www.spatialecology.com/htools). The resulting

1,043 points, wildfire and non-wildfire, were combined into one dataset, with

attributes specifying the location (latitude/longitude) and whether the point represented a fire or no-fire location. The fire/no-fire points were imported into ArcGIS as a shapefile using the Add XY Data tool, and overlaid with the raster layers representing each independent variable. The values of each variable at each fire/no-fire point location were added to the attribute table of the shapefile using the Extract Values to Points Spatial Analyst tool. The attribute table, containing all points and values for each independent value at the point locations was exported. The resulting file was used as input into QUEST 9.1.2 for the CART analysis (Y.S. Shih. 2005. Available: http://www.stat.wisc.edu/~loh/quest.html). This input data, the learning sample, included one full year of wildfire occurrences, thus accounting for fire probabilities both in and out of fire season and during all times of the year.

The CART analysis returned a classification tree with 12 terminal nodes, and 11 intermediate nodes (**Figure 1**). The software classifies each terminal node as 'yes' or 'no' depending on the proportion of wildfire to no-wildfire points placed in each class. If there are more wildfire points than no-fire points, the node will be classified as 'yes'. Alternatively, if there are more no-fire points than fire points, the node will be classified as 'no'. The numbers of points in each category are also output, and were used to calculate a relative risk score, or relative wildfire probability. For instance, if 20 wildfire points and 80 no-wildfire points fall under one terminal node, the relative risk score assigned to that node would be 0.2, or 20%. The 12 terminal nodes represented 10 relative risk classes, as two pairs of nodes were assigned the same risk score.

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The 10 relative risk classes were mapped across the study area based on the series of decision rules leading to each terminal node on the regression tree. This was done using the reclassify tool and the raster calculator within ArcGIS. This could also be accomplished by writing a simple if/then classification script, a method which would be extrememly useful in a case with large numbers of variables and classes.

*Middle Rio Grande Wildfire Probability Map*

Digital Orthophoto Quarter Quadrangles (DOQQs) were used to determine the Middle Rio Grande study area, which includes the entire Middle Rio Grande riparian cottonwood gallery, between Cochiti Dam, NM and Bosque Del Apache NWR, NM. A polygon file, delineating the study area boundaries, was digitized over the DOQQs using ArgGIS 9.2.

As with the statewide fire probability analysis, CART was employed to create the relative wildfire probability map for the Middle Rio Grande study area. Due to the relatively small number of wildfires within the study area over the 9 year period for which data is available (28 wildfires), the CART analysis was based on the full nine years of fire ignition points. As the land-cover and vegetation within the MRG study area are much more uniform than that throughout the entire state, it was useful to include more natural independent variables in the CART analysis for this smaller area. These variables included forest-specific data, such as canopy cover and canopy height. The layers used are listed in **Table 2**, arranged by source.

**Table 2: Data and sources used in Middle Rio Grande CART analysis**

| Data Source | Input Data Layer | Figure 5 Notation |
|---|---|---|
| Landfire Project (www.landfire.gov), USDA Forest Service: | Canopy Bulk Density<br>Canopy Base Height<br>Canopy Height<br>Canopy Cover<br>Scott & Burgan Fire Fuel Models | CBD<br>CBH<br>CHT<br>CCV<br>SB_40 |
| Southwest Regional Gap Analysis Project: | Road Distance<br>Road Density<br>Population Centers Data | Rd_Dens<br>MjRdDist<br>Pop_Dist |
| New Mexico Resource Geographic Information System Project: | Vegetation Classifications (2)<br>DOQQs | Veg1/Veg3 |

A data file, containing fire and no-fire point data, along with associated natural and anthropic variable values, was created using ArcGIS 9.2 in the manner described for the statewide analysis. Again, raster datasets were created from the initial data to represent distances to roads and population centers. A river distance dataset was not used, as the entire study area parallels the Rio Grande River. A road density raster was also created. The vegetation layers were converted to raster datasets. The Landfire data were obtained as raster files with 30 m resolution.

The Landfire data were used in the MRG fire probability assessment, but not in the statewide assessment. This is because many of the Landfire layers, such as canopy cover, canopy height, and canopy base height are specific to forest cover. This made the Landfire datasets more promising for determining variations in fire

probabilities based on small differences in the cottonwood forests of the Middle Rio Grande region.

The CART analysis for the MRG study area was carried out using Salford Systems' CART© software, a proprietary program. CART© was used for this analysis because it was determined to be better at dealing with limited datasets than QUEST. The CART analysis returned the classification tree in **Figure 5**. These results were then converted to a relative wildfire probability map for the Middle Rio Grande region by the process described for the state probability map.

*Species Richness Data:*

Spatial species richness data were obtained from the Southwest Regional Gap Analysis Project (Prior-Magee et al., 2007). These data were compiled over the entire SWReGAP region, including New Mexico, Arizona, Colorado, Utah, and Nevada. The species richness data were based on vertebrate habitat models developed by the SWReGAP. A 65,000 point systematic grid was created, covering the entire region. The number of species occurring at each point was then calculated. This point file was then converted into raster format using a kriging interpolation technique (Boykin,K. Jan 23, 2006. Southwest Regional Gap Analysis Project, personal communication). The GAP data included a total vertebrate species richness raster, as well as a species richness raster for each vertebrate taxon: birds, mammals, reptiles, and amphibians.

Each SWReGAP species richness raster was overlaid with the relative wildfire probability layers in ArcGIS 9.2. Species-wildfire risk maps were created by multiplying the relative wildfire risk score by the species count, using the Raster Caluculator, in each cell for both the statewide fire probability map and the Middle Rio Grande fire probability map. The map values therefore represent a relative weighting of the combination of relative wildfire probability and species richness. Thus, the highest values represent areas with both high wildfire probabilities and high species richness. Similarly, the lowest values represent areas of low species richness which were determined to have a low wildfire probability.
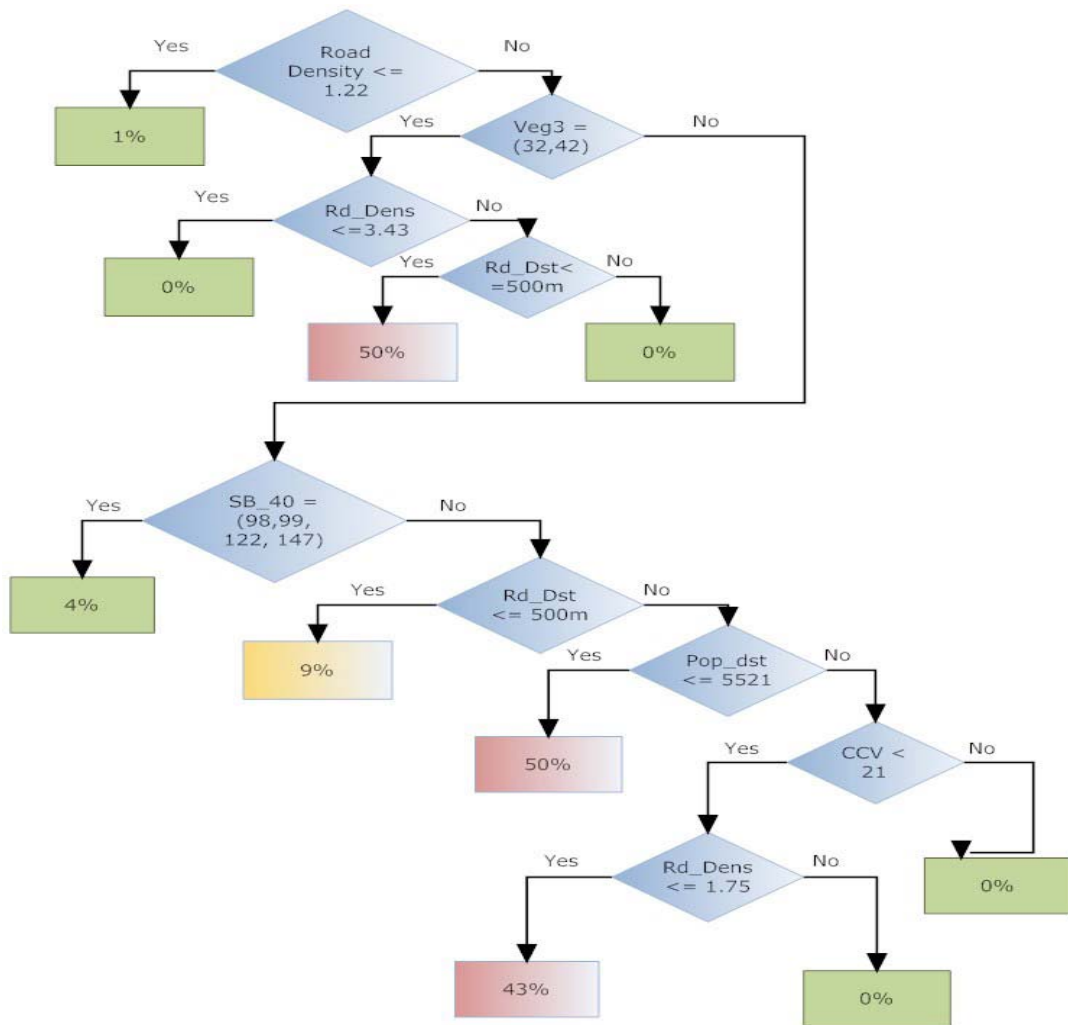
Figure 5: Classification tree resulting from CART analysis of MRG wildfire risk

**Results**

*State Wildfire Probability Map*:

The relative wildfire risk scores yielded by the CART analysis ranged from 9% to 85%. A large proportion of the land area, about 47.5%, fell in the lowest fire probability class (9%). The second largest class, by land area coverage (23.1%), was the highest probability class (85%). The intermediate classes ranged from less than 1% to almost 10% of the total area of the state. The large total coverage of the two extreme fire probability classes seems to be attributed to the large impact that humans have on wildfire frequency/probability. Major roads and developed areas contribute to a high probability of wildfire occurrence. Ownership, precipitation, and land cover also play a role in prediction of wildfire probability. Nonetheless, most areas away from human development are at low probability of wildfire. The highest wildfire probabilities are found along major highways and in or around large population centers.

*Accuracy Assessment:*

The results of the CART analysis yielded the relative risk map shown in Figure 6. Figure 7 shows the relationship between the July 1, 1996 – June 30, 1997 wildfires and the relative risk map. These wildfires were the learning sample, those used by the CART software to establish the risk map. Figure 8 shows the relationship between the July 1, 1997 – June 30, 2004 wildfires and the relative risk map. These wildfire points were the test sample, not used to establish the risk map, but acting as a
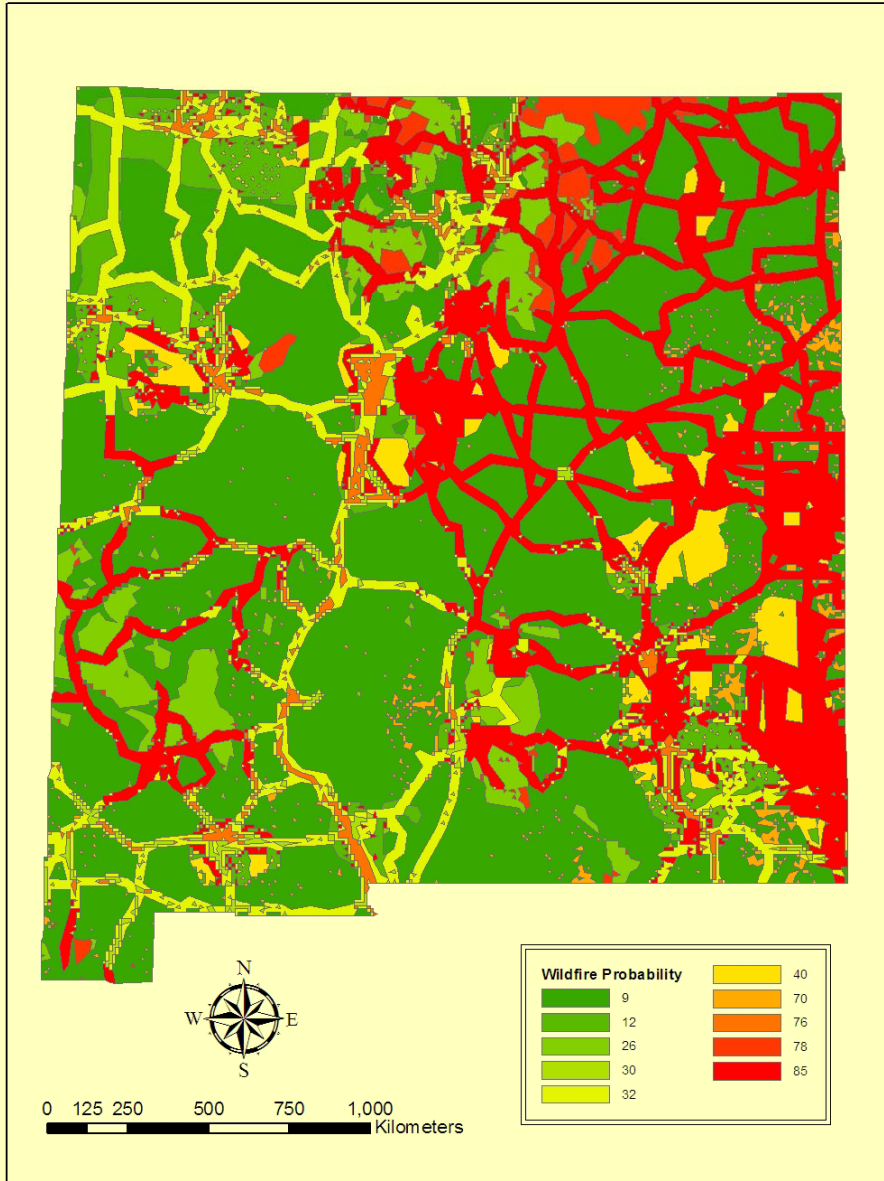
Figure 6: Relative wildfire probability map as
determined by CART analysis

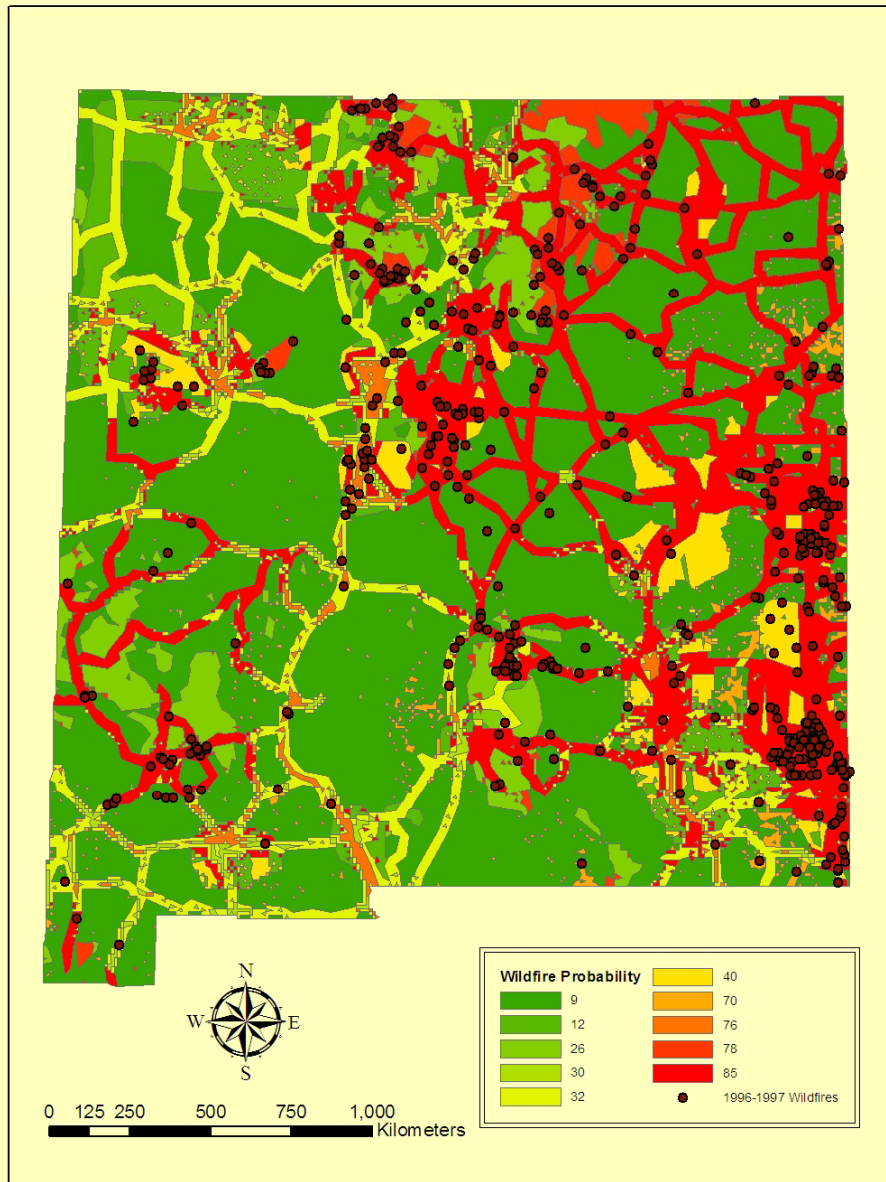# Relative Wildfire Probability With Learning Sample Points



Figure 7: Relative wildfire probability map
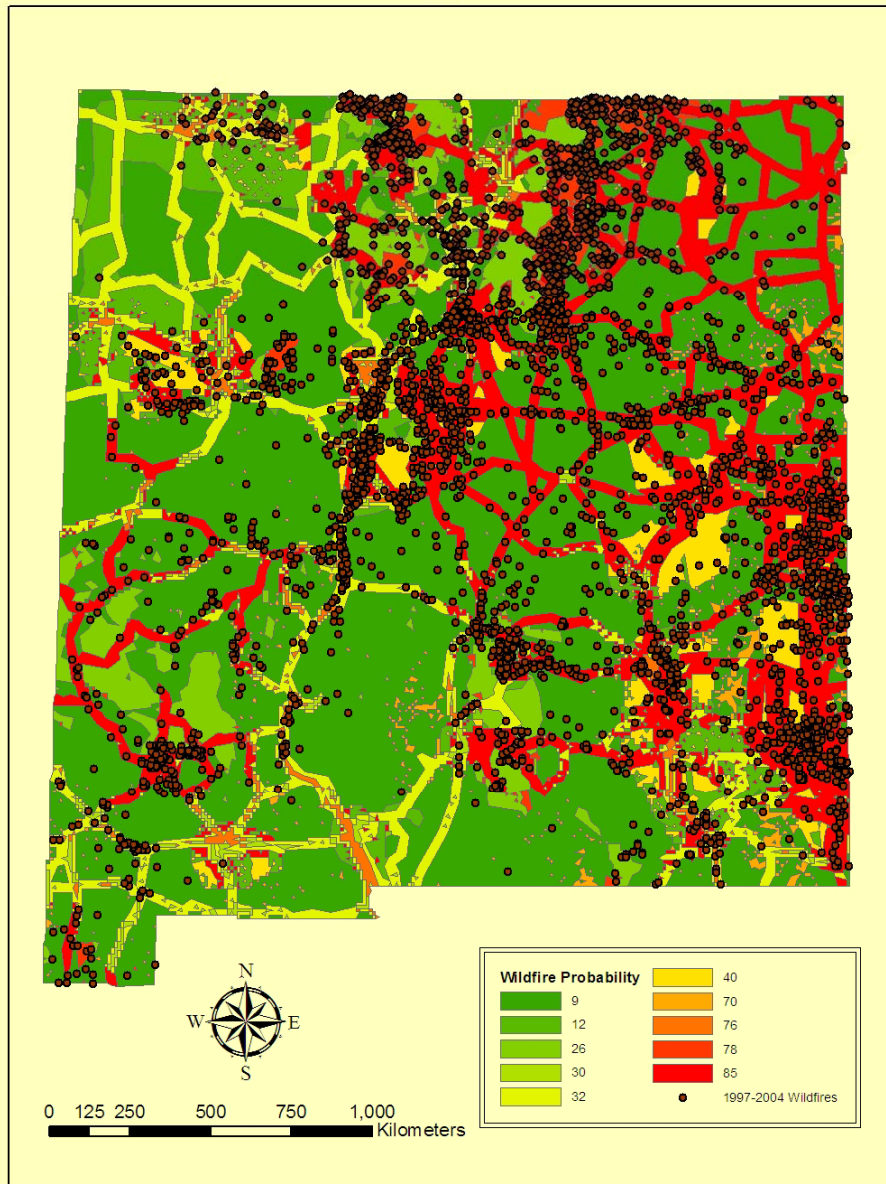overlaid with learning sample points

Figure 8: Relative wildfire probability map
overlaid with test sample points

7-year test of the accuracy of the maps predictions. **Table 3** shows the total amount of

land and number of wildfire points of each period falling into each relative wildfire

probability class.

**Table 3: Areas as totals and percentages of study area and number of wildfire points from each of the original 10 fire probability classes, '96-'97 and '97-'04**

| Risk Score | Area (km$^2$) | Land % | 96-97 pts | 96-97 % | fires/1000 km$^2$ | 97-04 pts | 97-04 % | fires/1000 km$^2$ |
|---|---|---|---|---|---|---|---|---|
| 9 | 14,7000 | 47.10 | 32 | 6.17 | 0.22 | 678 | 16.87 | 4.60 |
| 12 | 16,100 | 5.15 | 3 | 0.58 | 0.19 | 43 | 1.07 | 2.67 |
| 26 | 16,400 | 5.25 | 9 | 1.73 | 0.55 | 95 | 2.36 | 5.79 |
| 30 | 2,800 | 0.90 | 6 | 1.16 | 2.14 | 36 | 0.90 | 12.84 |
| 32 | 31,200 | 9.96 | 26 | 5.01 | 0.83 | 377 | 9.38 | 12.09 |
| 40 | 10,800 | 3.44 | 14 | 2.70 | 1.30 | 84 | 2.09 | 7.79 |
| 70 | 5,480 | 1.75 | 6 | 1.16 | 1.09 | 34 | 0.85 | 6.20 |
| 76 | 5,820 | 1.86 | 20 | 3.85 | 3.44 | 308 | 7.66 | 52.90 |
| 78 | 5,930 | 1.90 | 17 | 3.28 | 2.86 | 268 | 6.67 | 45.16 |
| 85 | 71,100 | 22.70 | 386 | 74.37 | 5.43 | 2096 | 52.15 | 29.50 |

While the total land area of the highest probability class accounts for only

22.7% of the state, 52.15% of the test data wildfires occurred in areas falling under

this classification. Conversely, while the lowest probability classification covered 47.1% of the state, only 16.87% of the test sample wildfires occurred here. Nearly two thirds (66.48%) of the test data wildfires occurred on land in one of the top three probability classes, totaling just 26.46% of the total land area.

The validity of the model is further illustrated by looking at the wildfire frequency within each probability class given in **Table 3** by the number of wildfires per 1000 km$^2$ of ground coverage. While a monotonic increase in fire frequency was not found with increasing fire probability classification, a general trend does emerge. The three lowest wildfire frequencies correspond to the three lowest probability classifications. Similarly, the three highest wildfire frequencies correspond to the three highest probability classes, though the highest of these frequencies, approximately 46 wildfires per 1000 km$^2$, occurred in the second highest probability class, while the highest probability class had a wildfire frequency of only 29 per 1000 km$^2$.

As a result of this non-monotonic match between the ten-class map and the test data, in order to increase the accuracy of the model, the ten probability classes were collapsed into three classes. These classes and their associated land areas and wildfire frequencies are shown in **Table 4**. The relative wildfire risk scores associated with these three classes are 11, 37, and 84%. The 11% classification covers 57.49 percent of the land area and had a '97-'04 wildfire frequency of 4.55 fires/km$^2$. It is composed of the three lowest probability classes of the original model. The 37% probability classification covered 16.05% of the land area and had a '97-'04 wildfire

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frequency of 10.51 fires/km$^2$. It is composed of the middle four classes of the original

model. The 84% classification covers 26.46% of the land area and had a '97-'04

wildfire frequency of 32.28 fires/km$^2$. This fire probability class is composed of the

three highest classes of the original model.

**Table 4: Areas as totals and percentages of study area and number of wildfire points from each of the 3 derived fire probability classes, '96-'97 and '97-'04**

| Risk Score | Area (km$^2$) | Land % | 96-97 pts | 96-97 (%) | fires/1000 km$^2$ | 97-04 (fires) | 97-04 (%) | fires/1000 km$^2$ |
|---|---|---|---|---|---|---|---|---|
| 11 | 179,961 | 57.49 | 45 | 8.67 | 0.25 | 818 | 20.35 | 4.55 |
| 37 | 50,238 | 16.05 | 52 | 10.02 | 1.03 | 528 | 13.14 | 10.51 |
| 84 | 82,807 | 26.46 | 422 | 81.31 | 5.10 | 2673 | 66.51 | 32.28 |

The new, three class relative wildfire probability map is shown in **Figure 9**.

**Figure 10** shows the relationship between the July 1, 1996 – June 30, 1997 wildfires

and the three-class relative probability map. **Figure 11** shows the relationship

between the July 1, 1997 – June 30, 2004 wildfires and the three-class relative

probability map.

*Middle Rio Grande Wildfire Probability Map:*

The MRG classification tree analysis yielded 7 fire risk scores (0, 1, 2, 4, 9,

43, and 50%). These results were mapped over the study area as low (0, 1, & 2%),

medium (4 & 9%) and high (43 & 50%) fire probabilities, resulting in **Figure 12**. The

low probability class covered 77.33% of the MRG study area, while the medium class covered 7.04% and the high class covered 15.63%.

Predictor variables of importance included anthropic variables such as road density, distance, and population distance. Natural variables were also included in the classification tree, such as vegetative cover, Scott and Burgan (2005) fire fuel models, and canopy cover.

A comparison of the results of the MRG risk assessment and the MRG area of the statewide risk assessment shows significant variation. Only approximately 30% of the area within the MRG study area is classified in the same category, low, medium, or high, in the two analyses. Only 20% of the land within the MRG study area classified at high risk in the statewide analysis is similarly classified in the MRG analysis.  Alternately, approximately 40% of the area classified at high risk in the MRG analysis is also classified at high risk in the statewide analysis. Though there was disagreement between the outputs of the two assessments, both analyses found that the areas near and within population centers, such as Albuquerque, Los Lunas, and Socorro, are generally at higher risk of wildfire.
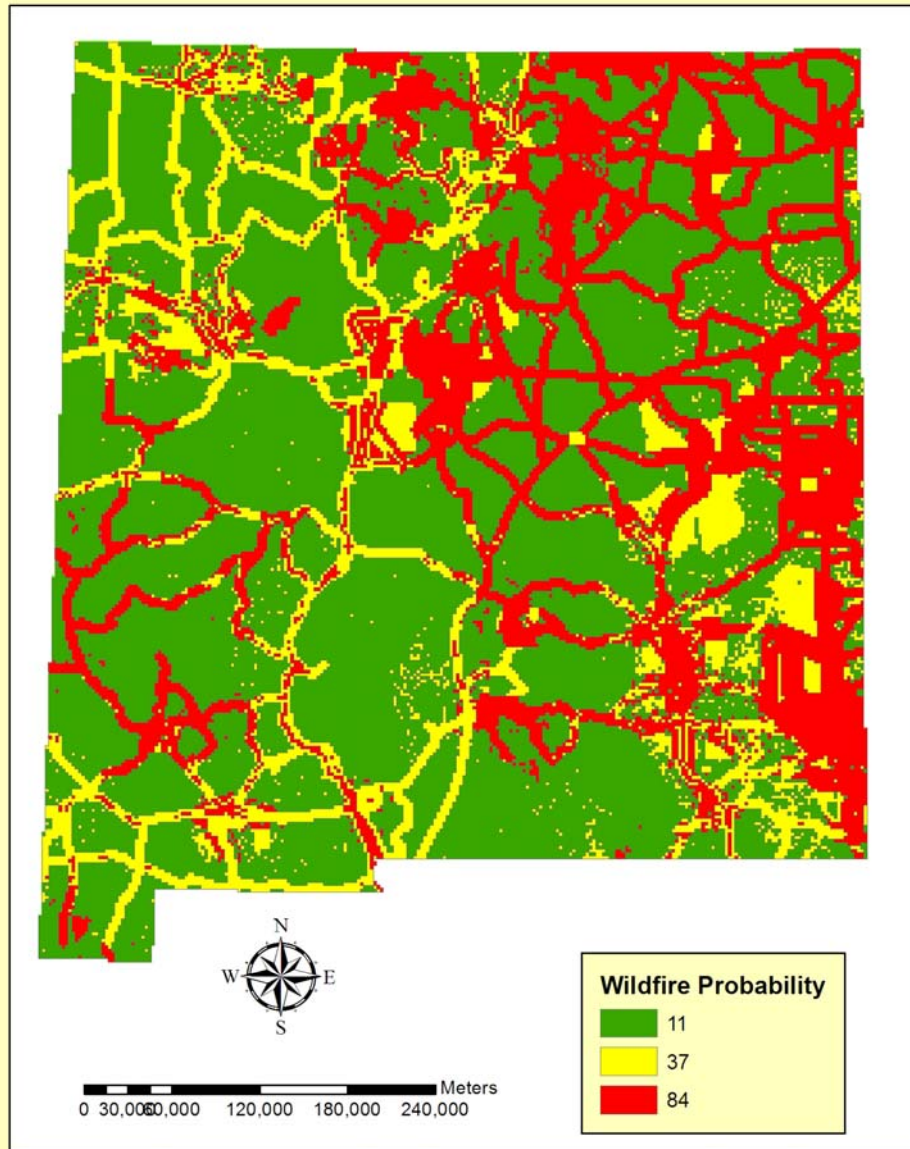
Figure 9: Three class relative wildfire probability map
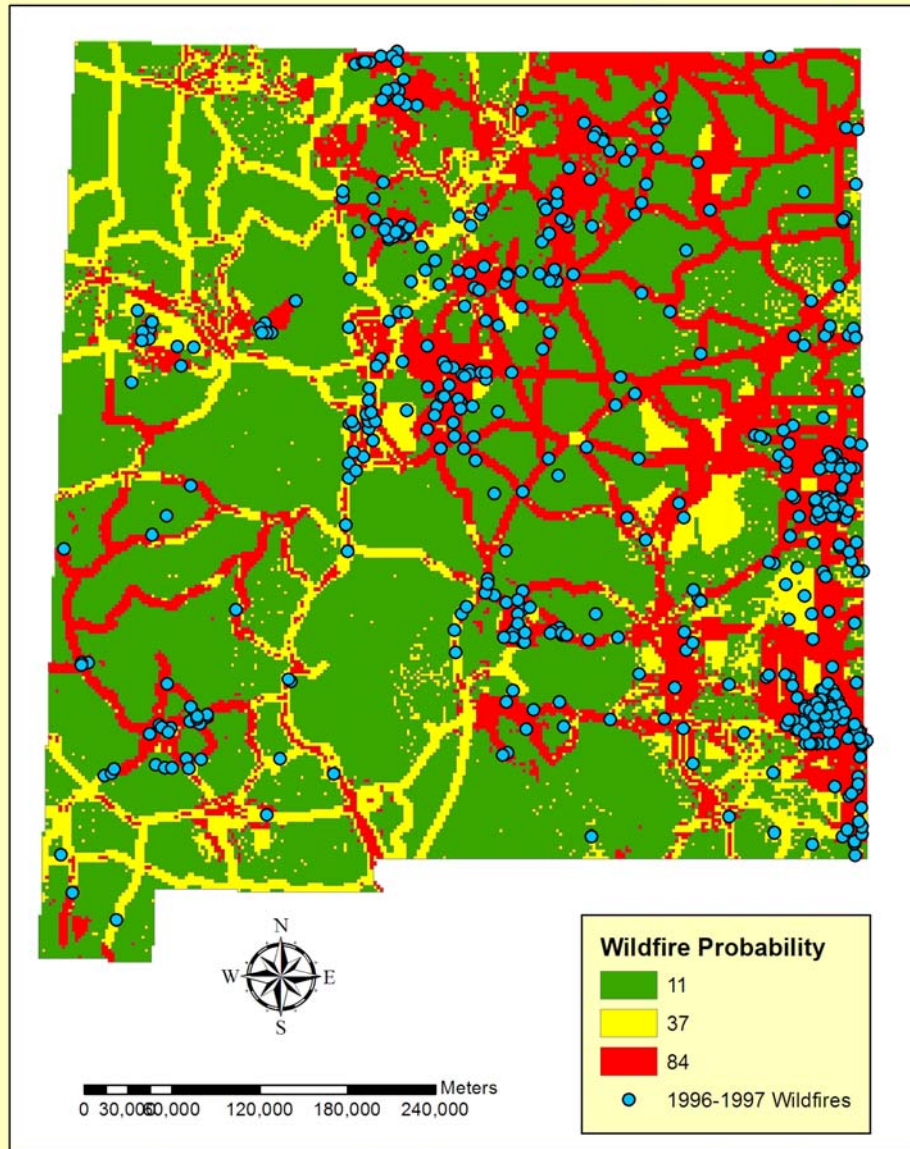
Figure 10: Three class relative wildfire probability map
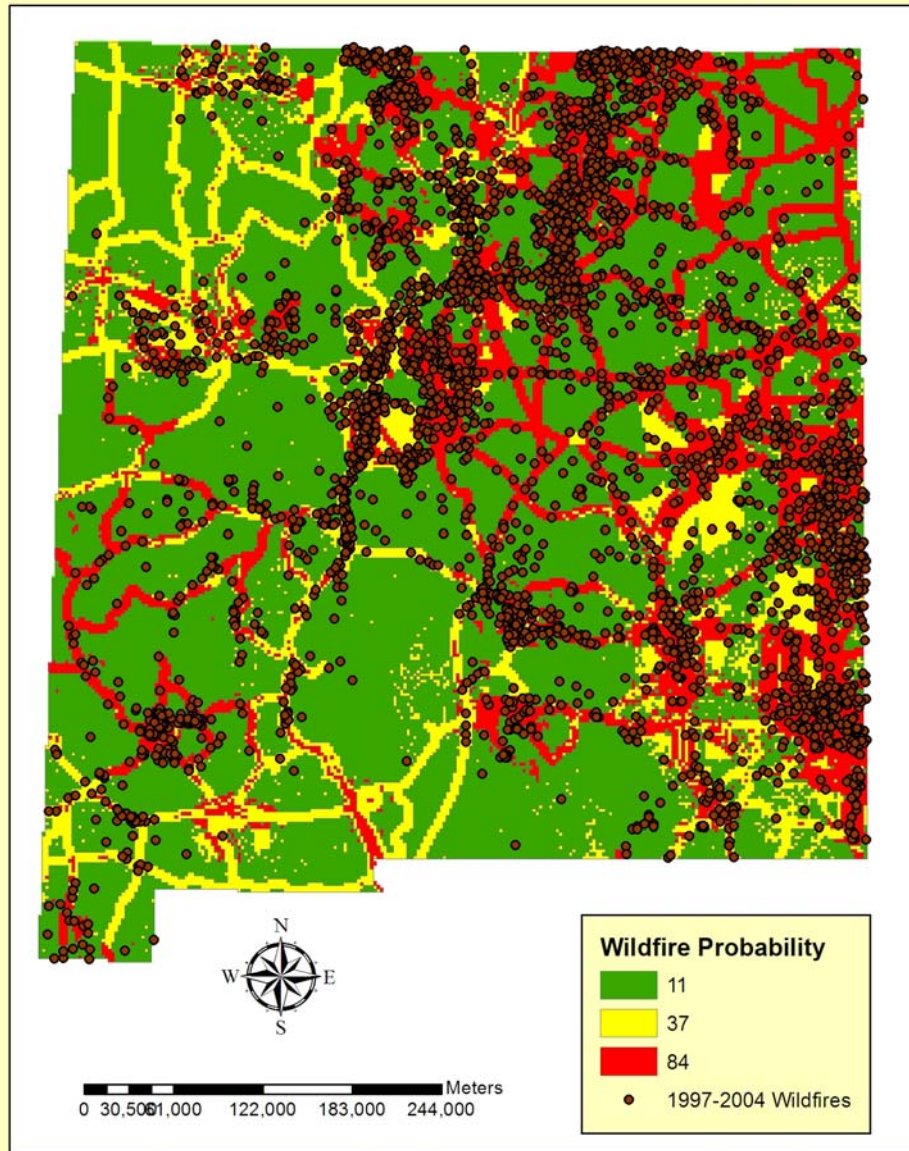overlaid with learning sample

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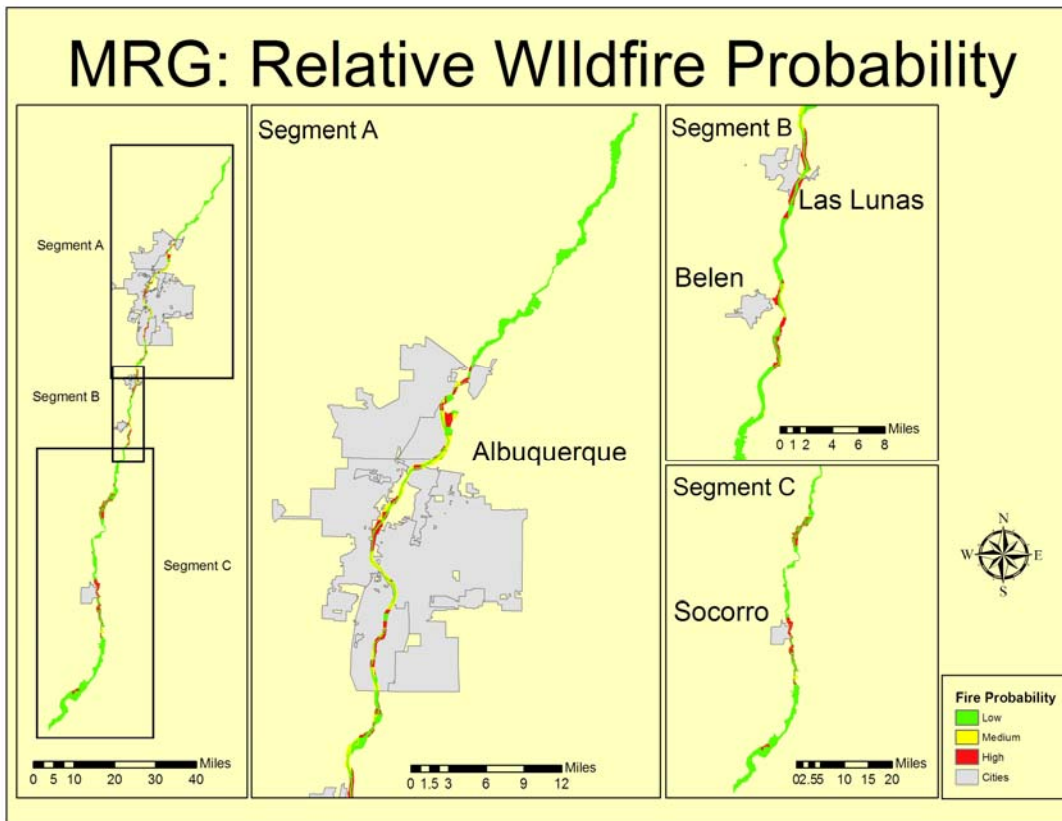Figure 11: Three class relative wildfire probability map
overlaid with test sample

Figure 12: Relative wildfire probability map as determined by CART analysis

*Risk toVertebrate Species*

Maps of relative risk of wildfire to vertebrate communities were created for both the Middle Rio Grande and the entire state of New Mexico. For each study area, a map was created depicting risk to the entire vertebrate community, as well as maps showing risk to each individual vertebrate taxon: mammals, birds, reptiles, and amphibians (**Figures 13 – 22**).

Figure 13: Relative risk of wildfire to all vertebrate species
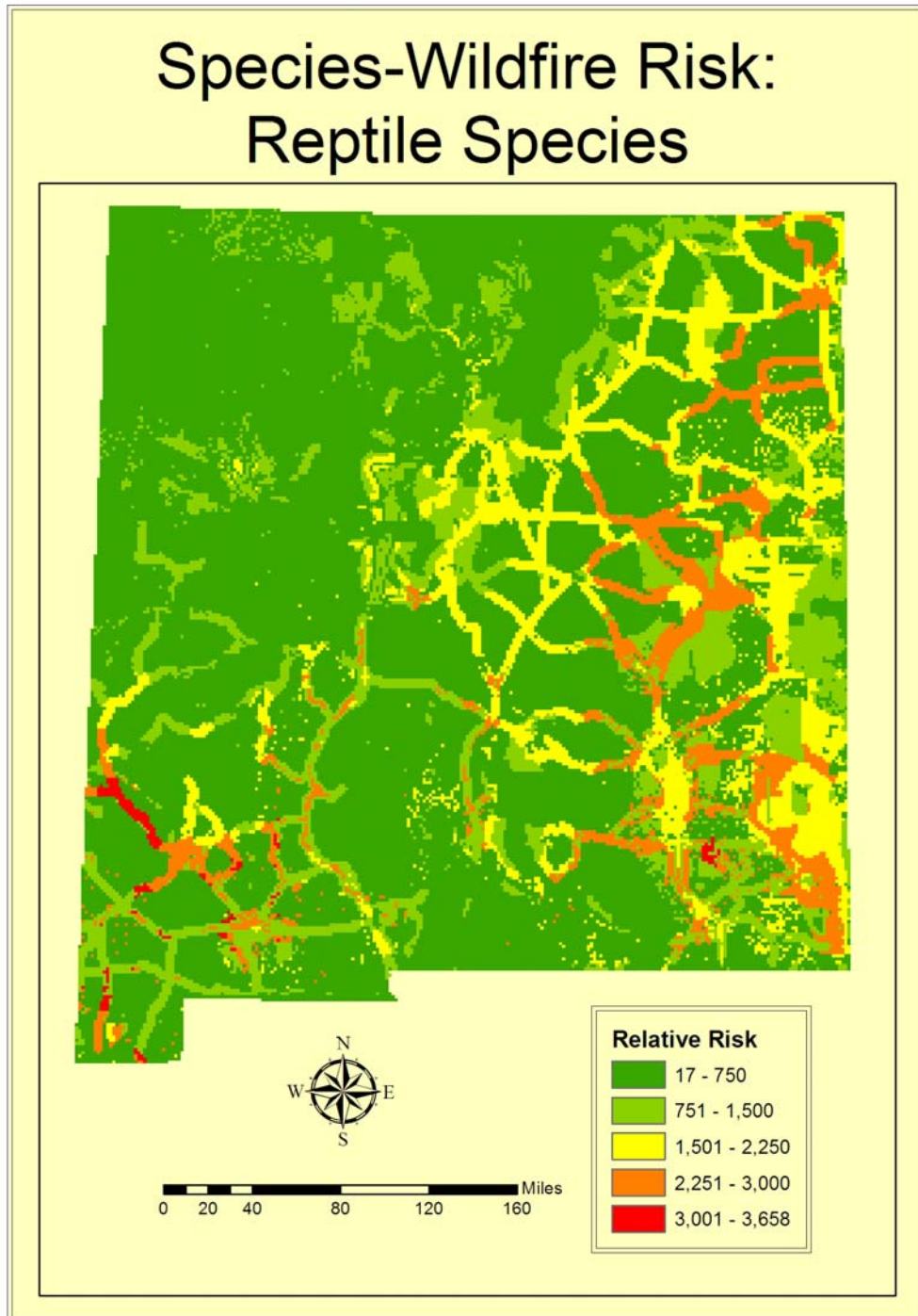
Figure 14: Relative risk of wildfire to reptilian species
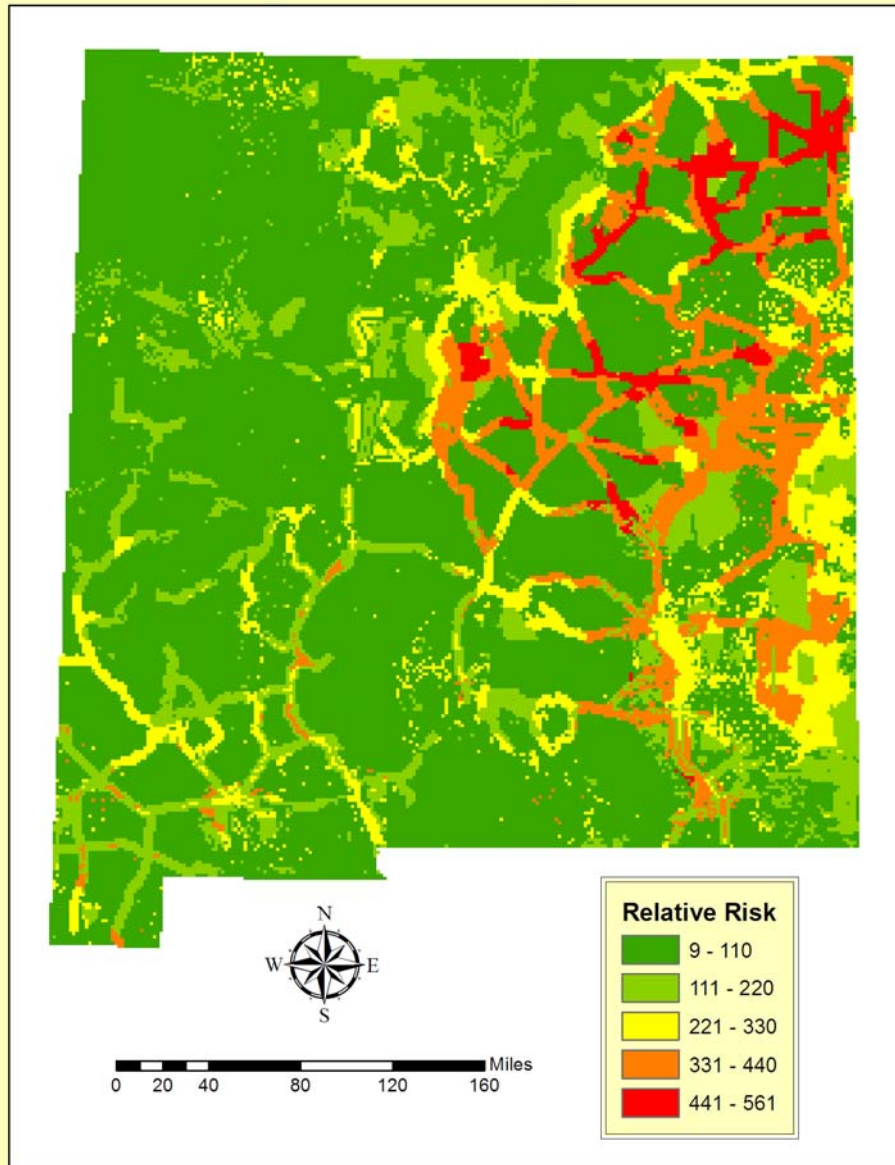
Figure 15: Relative risk of wildfire to amphibian species

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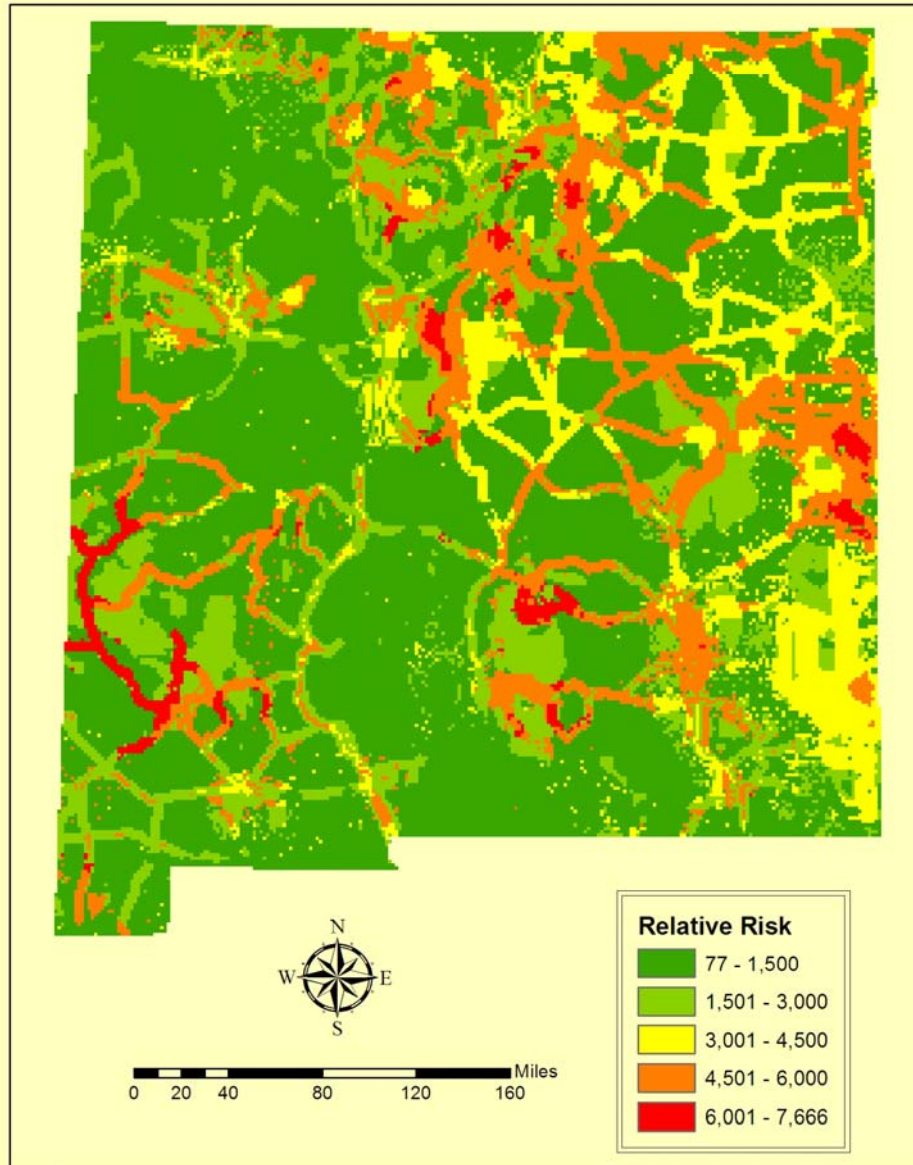
Figure 16: Relative risk of wildfire to avian species
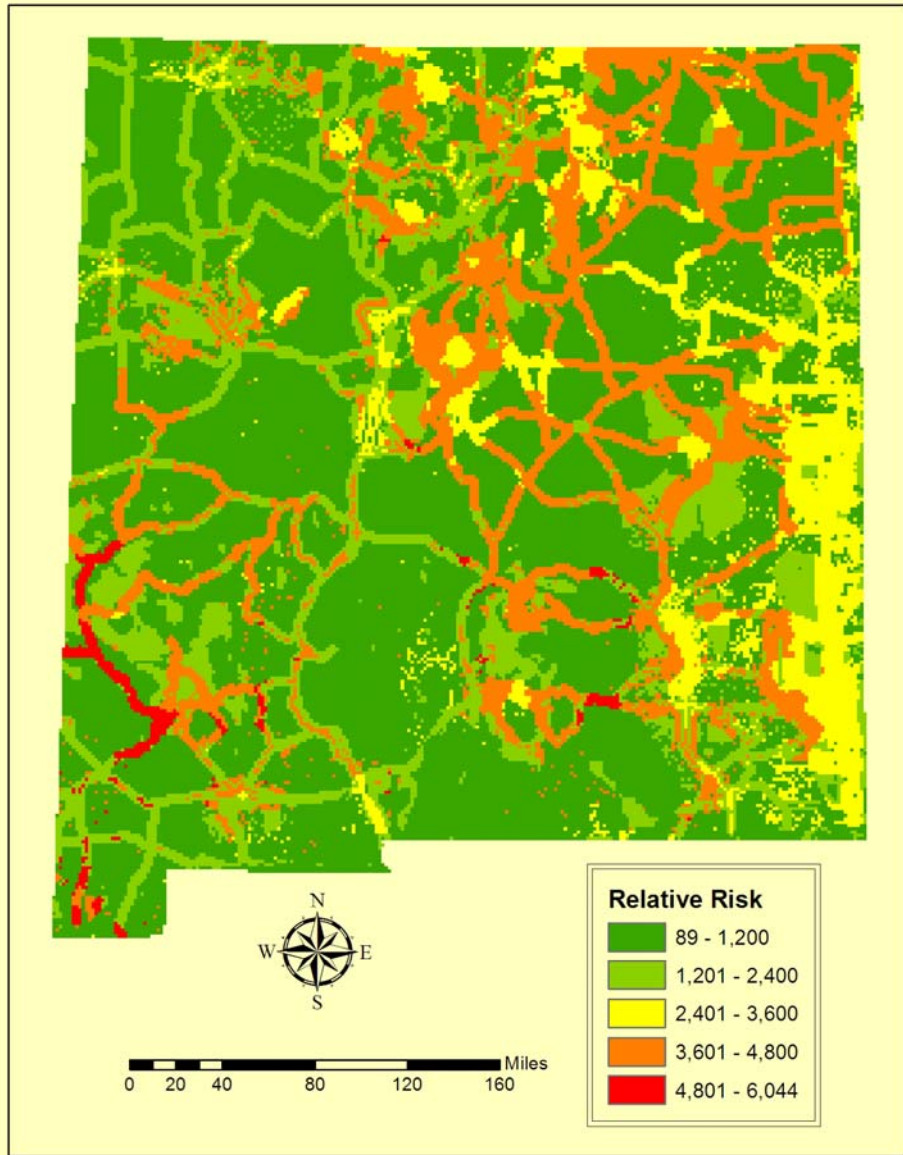
Figure 17: Relative risk of wildfire to mammalian species

Figure 18: Relative risk of wildfire to all vertebrate
species of the Middle Rio Grande

Figure 19: Relative risk of wildfire to reptilian
species of the Middle Rio Grande

Figure 20: Relative risk of wildfire to amphibian
species of the Middle Rio Grande
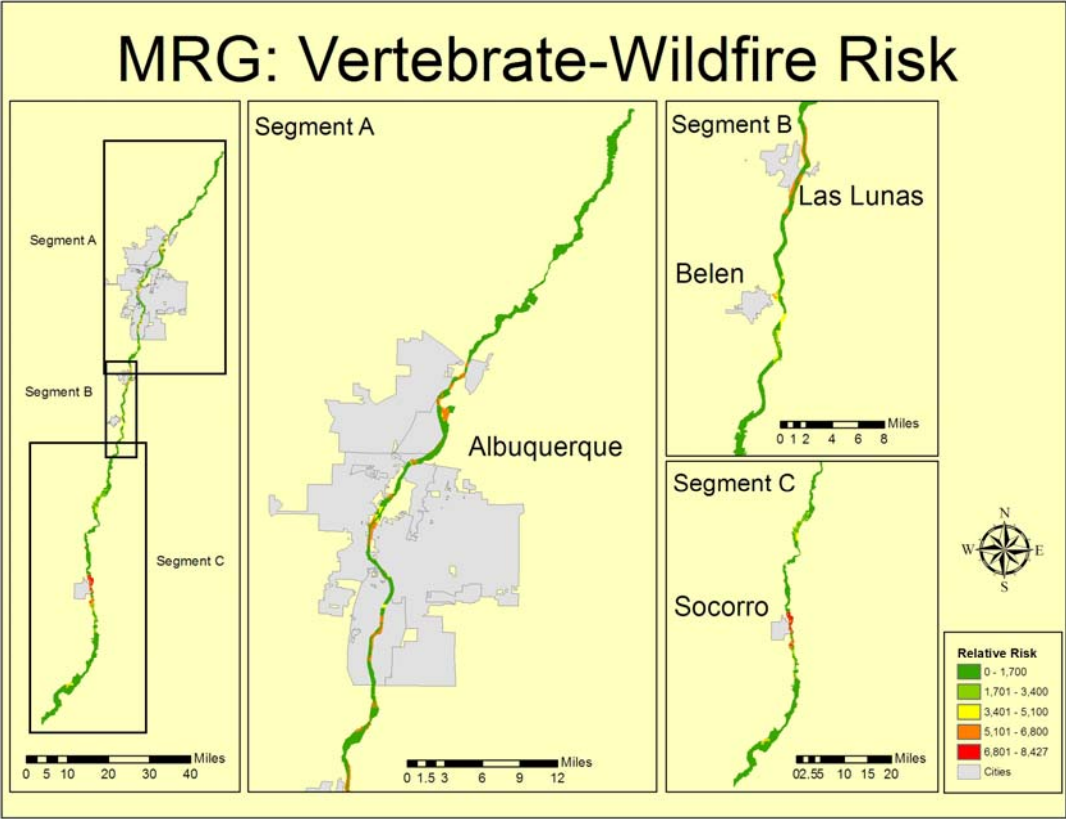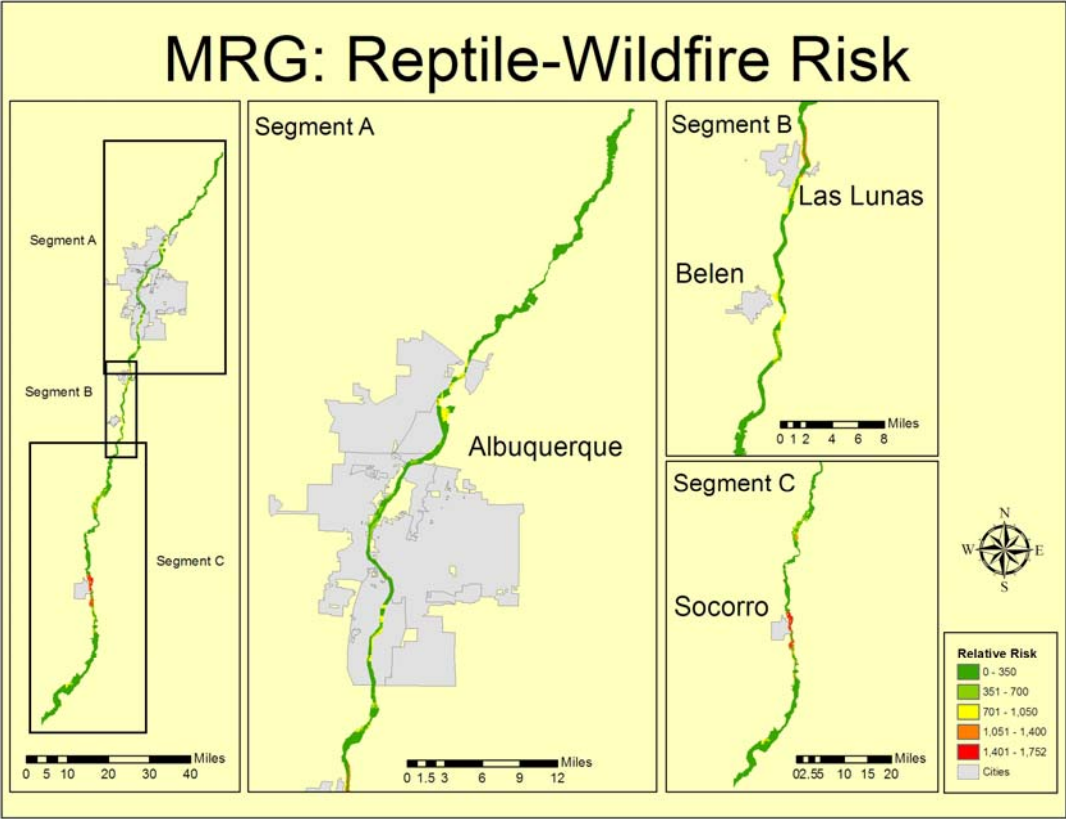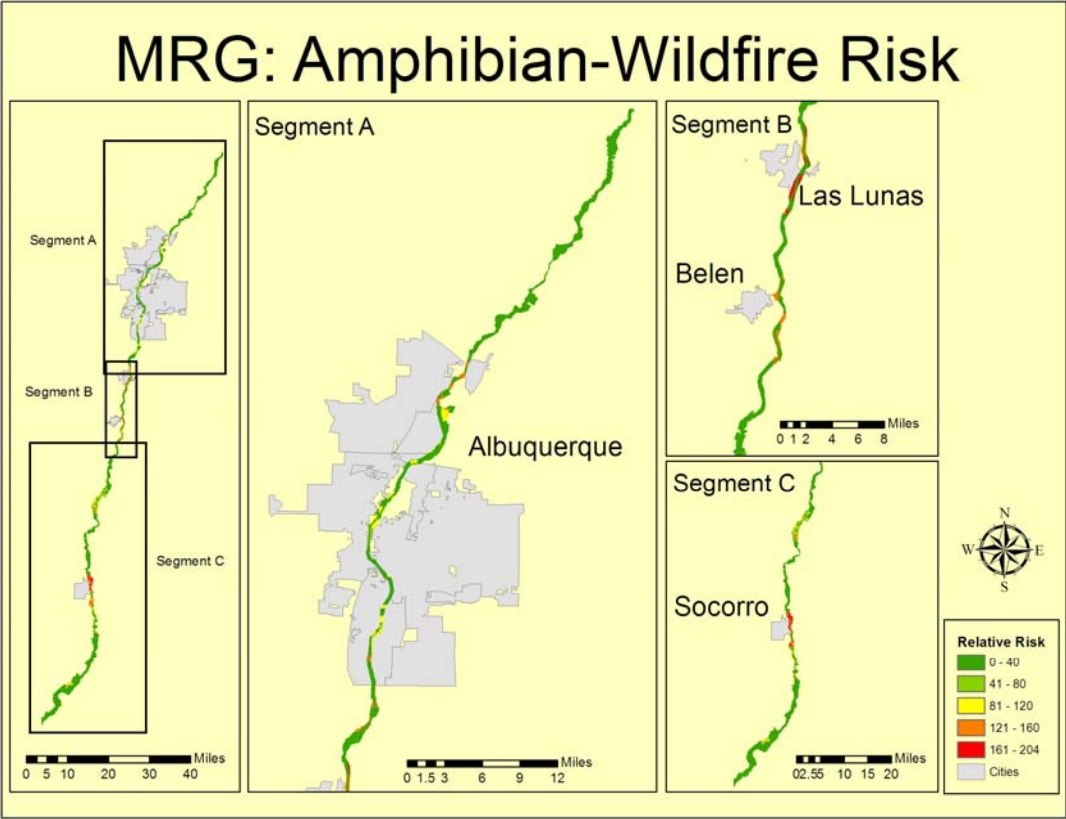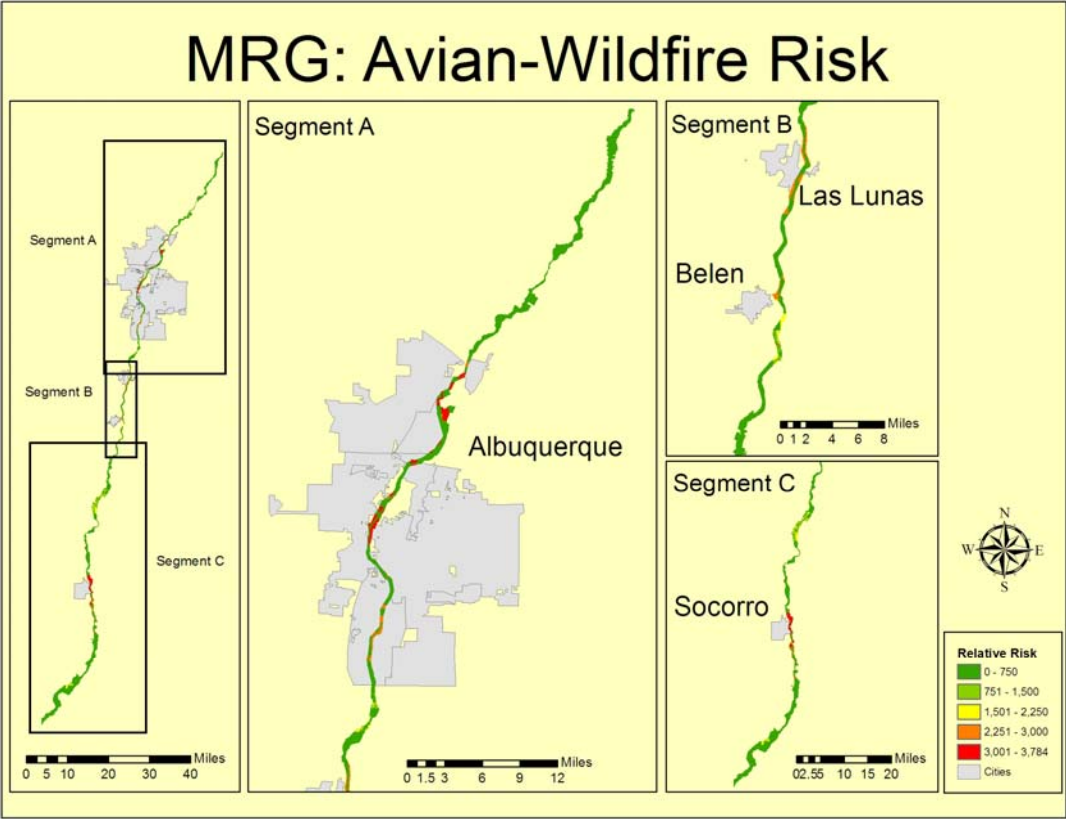
Figure 21: Relative risk of wildfire to avian
species of the Middle Rio Grande
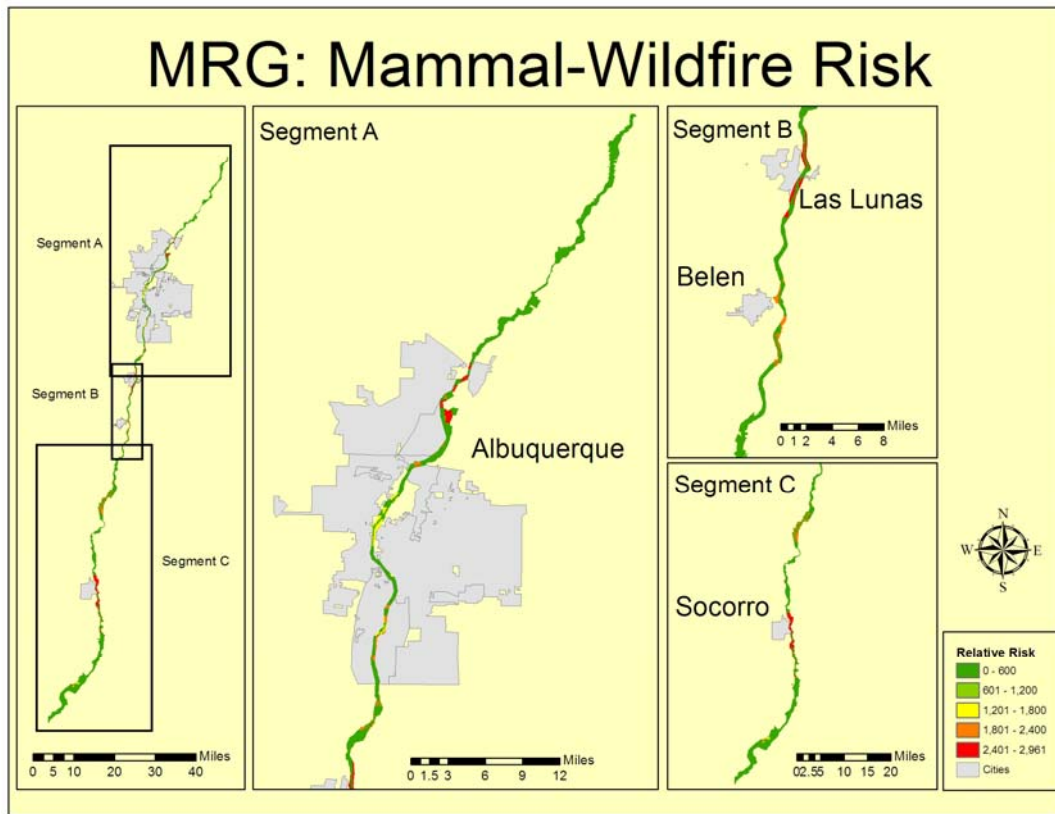
Figure 22: Relative risk of wildfire to mammalian
species of the Middle Rio Grande

**Discussion**

The results of the CART analyses and the resulting maps show that the greatest contributors to fire probability are anthropic variables. For the statewide analysis, Major Road Distance is the most important predictor of wildfire risk, showing up in the classification tree three times. Road Density and Land Ownership were also important predictors. The classification tree for the Middle Rio Grande area includes Road Density three times and Major Road Distance twice. Each tree also includes natural variables, such as Precipitation, Distance To Rivers, Vegetation, and/or Canopy Cover.

The analysis of the test sample, those fires between July 1, 1997 – June 30, 2004, validates the accuracy of the statewide fire probability classification. The three-class fire probability model includes areas classified, relatively, as 11, 37, and 84%. These three land categorizations faced wildfire frequencies during the test period of 4.55, 10.51, and 32.28 fires per 1000 km$^2$, respectively.

Overlaying the two risk maps with the GAP derived species richness data yielded spatial distributions of the relative risk to various vertebrate taxa posed by wildfire. In the data, it can be seen that the high fire probabilities near major roads and population centers caused these areas to be at the highest risk to vertebrate communities (**Figures 13 – 22**). The statewide map of risk to all vertebrate species shows that the highest overall risks are near major roads and populations in the southwestern portion of the state (**Figure 13**).

The pattern of high risk in this portion of the state can be seen in the risk maps for all taxa except for amphibians, which are at highest wildfire risk in the northeastern portions of the state (**Figures 14 – 17**). Based on the Middle Rio Grande risk assessment, the area of highest risk to the most species in this ecosystem is near the city of Socorro. There is also elevated risk around the village of Los Lunas, and through the northern portions of Albuquerque (**Figure 18**).

*Limitations:*

The results of this study are intended as a management tool. Wildfire management is an important and increasingly common tool in the western United States. Land Management agencies can use the risk maps developed here to prioritize areas for fuels reduction or other wildfire management treatments based on the risk of fire to vertebrate communities.

One major limitation of these results can be seen in the conflicting results in the MRG area between the two analyses. As noted, only approximately 30% of this area was placed in the same classification level in the two analyses. There are two possible explanations for this.

The first is a shortage of data in the MRG CART analysis. CART analysis is most successful with large datasets (Amatulli et al., 2006). Because there were only 28 wildfires within the MRG study area during the years in which data was available, the dataset is limited. This could limit the specificity and accuracy of the MRG

assessment, in which case the results of the statewide assessment could be viewed as more accurate.

The second possible cause of the differing classification between the two analyses is the use of different predictor variables. Different predictor variables, naturally, will result in a different classification tree. Because of the relative uniformity of the cottonwood forests of the MRG study area, more forest specific predictor variables, such as canopy cover, were input into the CART analysis. If the input of these layers were responsible for the differences, then it could be argued that the results of the MRG analysis are more accurate. However, of these more specific layers, only one, canopy cover, was determined to be a predictor of wildfire probability, and even it was located in a low level of the regression tree. Most of the intermediate nodes in the tree were populated with anthropic variables, as was the case in the statewide assessment. However, to determine the true culprit behind the differing results, more data is needed for the Middle Rio Grande study area, so that a test sample can be used to determine the accuracy of these results.

While the statewide analysis was validated by the accuracy assessement, there is still a possibility that the classification is biased. The source of this potential bias is the frequency of fire sightings in the areas near and away from human infrastructure. More specifically, it is possible that there is a detection bias in favor of the developed and populated areas, as there are more humans around to see and report small fires. In backcountry areas, small fires could burn without being detected. These fires would not be included in the ignition points dataset. If this is the case, the model resulting

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from the data would predict higher wildfire risk around roads and populated areas, as was seen. Because equal bias would be included in both the learning and test samples, that the accuracy assessment would not detect any inaccuracies in the model.

A major limitation to practical application of the results is that the relative risk categorizations cross jurisdictional boundaries. Since the highest risk areas typically fall close to major roads, and much land along major highways is privately owned, much of the land at highest risk is in private ownership. That which is publicly owned is divided between numerous federal and state agencies. It would be ideal for all of the land management agencies in the state to use these results as a basis of cooperation in combating fire risk state-wide. Even without inter-agency cooperation, because of the universal nature of the GIS model, it would be easy for any given agency to isolate their land in the model and prioritize their lands for wildfire management.

Another limitation of these results stems from the way the land area was classified into fire probability categories. A large portion of the classification tree nodes dealt with anthropic variables, such as Major Road Distance and Road Density. When land is categorized by these variables, the vegetation type and actual amount of available fuels are not accounted for. While the validity of the fire probability map was verified with the test data, the results were simplified from the original tree, which was pruned down from an even larger tree by the software, before being returned. This means that the software reduced over 100 fire probability classes to only 10, which were subsequently combined into the three final classes. Because of

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this, each probability class is a heterogeneous mixture of patches of land of varying

fire probability, which average to the relative probability presented in the model.

Thus, there are smaller areas of varying wildfire probability within the land of each

category. For instance, in the area categorized as the highest fire probability, there are

areas at truly high probability of wildfire, but also some areas with very little chance

of a fire. This could include small rocky outcrops, high alpine areas, or developed

areas with little or no vegetation. Because of this, specific management techniques

cannot be applied across large areas of uniform risk classification.

In addition, the method of multiplying the relative fire probability with the

species richness to determine a relative risk value allows for areas to be categorized at

the same risk, while one might be at a high risk for wildfire but have a low species

richness and the other is at a lower risk of wildfire but has a high species richness. If

this is the case, it is clear that different management techniques would be employed in

the two areas.

Lastly, some areas, while classified at high wildfire risk, may not be amenable

to fuels reductions or other such wildfire treatments. Also, some ecosystem types may

not be as susceptible to long-term damage from wildfires. For instance, much of the

area classified as high risk land along major roads in the southwestern portion of the

state is grassland. While fuels reduction and removal are common practices to reduce

fire risk in forested areas, there is little that can be done to reduce the long-term risk

of grassland fire. The current cattle grazing across the grasslands of New Mexico is

about as much as can be done to reduce this risk. However, following a wildfire,

grasslands are much quicker to return to their former condition than forested lands.

This reduces the impacts of wildfire on some species, particularly those that are

mobile over extensive areas, such as birds and large mammals, and can avoid death in

the wildfire.

*Applications to Wildfire Risk Assessment:*

Researchers have discussed the need of addressing the goals of the National

Fire Plan through advancements and standardization of wildfire risk assessment

(O'laughlin, 2005a). At the 2003 symposium on advancing tools for relative risk

assessment for uncharacteristic wildfires, much discussion focused on using relative

risks to weigh the costs and benefits of wildfire/fuels treatments against the increased

risks posed by wildfires if treatments were not performed (Irwin and Wigley, 2005).

However, publications resulting from this conference overwhelmingly ignore the

spatial aspect of wildfire treatments. The risk assessments discussed in this literature

focus on only the risks associated with different management strategies of a given

piece of forest.

The huge amounts of forested land across the United States and the limited

financial and labor resources of the federal and state governments combine to produce

considerable restrictions to timely wildfire treatments to all areas in need. For this

reason, it is suggested that a spatial distribution of risk be determined during the risk

assessment process. This spatial risk assessment can then be used to determine areas

at higher risk from wildfire. These areas can be prioritized for wildfire prevention

treatments when time and resources are limited. The method of relative spatial risk determination described here provides a quick and efficient means by which to accomplish this task.

*Comparison of Results: Amatulli et al. (2006)*

Amatulli et al. (2006) suggested CART analysis as a reliable method of producing fire risk maps at a regional scale. The results of that study showed that CART can produce a reasonably accurate map of fire risk. The study presented here found similar results.

The two studies varied in their methods. Amatulli et al. (2006) chose a "kernel-density function" approach, in which the CART analysis was based on a fire density estimation, resulting from interpolation of a fire density map. With this method, the dependent variable, fire density, as well as all of the predictor variables, was placed in raster format, and the values for every cell were entered into the CART analysis. The output of this method was a fire density map, predicting the number of fires per unit area per unit time.

Rather than analyzing each raster cell in an entire landscape, and a value determined based on proximity to nearby wildfires, this study used a much smaller set of vector point data, representing isolated points on the landscape where wildfires either did or did not occur. The output of this study was far less quantitative than that of the Amatulli et al. (2006) study. The outputs here were relative fire probabilities. An area with a relative fire probability which is twice that of another area is

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theoretically twice as likely to burn. However, this study makes no quantitative estimation of what those probabilities actually are. Both studies omitted a portion of the historic wildfire record from the CART analysis and used these points as a test sample to successfully verify the accuracy of the resulting risk map.

Amatulli et al. (2006) suggest that their technique can be used to create a national fire risk map, or a fire risk map at any similarly small scale. This can be done efficiently using a cell size of 1-5 kilometers. The state-wide risk assessment performed here used various input cell sizes, resulting in an output cell size of approximately 265 square meters. Due to ever increasing computation speeds and data storage capacities, the spatial resolution of the point-based fire risk estimation method described here, as well as the Amatulli et al kernel-density method, is only limited by the resolution of the input data.

Amatulli et al. (2006) found that human factors had less influence on fire risk throughout their study area, the Garano Penninsula of southwest Italy, than natural factors, particularly Land Cover, but also Temperature and Rainfall. This study found exactly the opposite, with human factors being the most influential on the fire potential throughout the state of New Mexico. This difference of results does not indicate inaccuracy in either method, as each study used a portion of the historic wildfire data as a test sample, verifying the results of the CART analysis. The differences do, however, suggest that no broad generalizations can be made about the relative contributions of natural and anthropic variables to wildfire risk. The relative

weights of these two categories of causative factors vary by location, based on local climates, populations, and other geographic factors.

While both techniques were shown to create reliable and accurate risk maps, the method presented here is simpler and more straightforward. Accuracy assessment for the vector-point based approach can be done by simply tallying test sample points within each category.

The results of the two studies show that wildfire risk assessment based on CART analysis is a reliable technique for estimating relative wildfire probabilities across a landscape. Combining these results with species richness data or any other data on the spatial distribution of ecological or socioeconomic variables is easily performed to create a map of the distribution of ecological/economic risks posed by wildfire across a landscape.

*Conclusions:*

The methods described here are simple, and can typically be performed with existing datasets. Currently, most land management agencies within the United States have some form of GIS capabilities. Most of these agencies, particularly the large ones, such as the US Forest Service or Bureau of Land Management, employ numerous GIS specialists, who will have more than adequate knowledge and skill to use this method to predict spatial variation in wildfire danger, allowing forest managers to prioritize the land under their jurisdiction for wildfire treatments.

As discussed at the 2003 Portland symposium (O'Laughlin, 2005a), the risks of wildfire treatments on ecosystems should also be evaluated. If fuels reduction treatments have a negative impact on a species of special interest, then that effect must be weighted against the reduced risk to the species that would result from the lowered chance of wildfire. However, if the risks associated with intense wildfires are greater than those associated with preventative treatment, it will then become important for managers to determine which areas are most in need of treatment. This study outlined a relatively simple method of making this determination.

This study examined the relative risks posed to vertebrate communities by wildfire across the state of New Mexico and within the Middle Rio Grande ecosystem, but did not analyze the risks associated with wildfire prevention treatments. In order to use this sort of parallel risk estimation to determine the usefulness of wildfire treatments, one would need to do much more quantitative analysis than was performed here. The relative risk values are only meaningful in relation to each other, showing the distribution of the risk posed by wildfire to vertebrate communities across the landscape. These relative risk values are not able to be compared to risks posed by other management activities or natural threats.

One interesting discovery of this study is the heterogeneity of wildfire risk at various scales. In the statewide risk map, large blocks are classified into a single risk category. Intuitively, there might be variation in fire risk within these blocks. The classification tree upon which the state-wide risk classifications were based is a pruned down version of the original tree created by the CART analysis. This original

tree contained over 100 fire probability classes. The pruning was performed automatically by the software, resulting in the 10 probability classes which were later reduced to 3. Thus, areas of homogeneous wildfire probability or risk at the state scale can display heterogeneous risk patterns at a more localized scale. Future study should compare the results of this method of CART-based spatial risk assessment at different scales, using the same variables.

Another implication of this study is the ability to predict wildfire occurrence probabilities without specific data on fuel loading. The Land-Cover layer used for the state-wide fire probability classification divided the state into 89 categories based primarily on satellite imagery. There was no input layer which represented ground fuel loads or biomass. In the past, fuel load data were obtained primarily through field examination. While this continues today (Russell and Weber, 2002), hyperspectral imaging has recently been used to map fuel loads and biomass (Crabtree et al., 2006). However, even satellite based fuel mapping requires *in situ* and ground truth data.

This study shows that a comprehensive map of fuel loads is not essential to creating a map of spatial wildfire risk variability. This allows for increased speed in the prioritization of wildfire treatment areas. As most wildfire treatments revolve around fuels reductions or manipulations, fuel load data will probably be needed before treatments can be started. However, just as the relative risk map allows for prioritization of wildfire treatments, it will similarly allow for prioritization of fuel load mapping sites. Mapping of fuels can begin in areas of high wildfire risk, thus allowing for areas of dangerously high fuel loads in high risk areas to be dealt with in

a quick and efficient manner. In areas where fuel loads have already been mapped, this data can be incorporated in the CART analysis, possibly improving the results.

One federal objective of wildland fire management is the standardization of policies and practices among agencies (O'laughlin, 2005b). The CART assessment method described here has great promise of being a widespread tool for the prioritization of lands for wildfire treatments. While the methods remain constant, each agency can expand the model and add its specific values (e.g. species diversity, endangered species presence, human development, tourist areas, etc) to make the process suit their specific needs. However, land managers have been encouraged to try multiple methods of risk assessment in order to discover which methods prove more successful than others (O'laughlin, 2005b). For this reason, the method of assessing spatial distribution of risk presented here is not final. Not only should other methods be developed, tested, and compared to the CART analysis assessment, but this method itself should continue to be refined and improved.

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