IDENTIFYING THE ENVIRONMENTAL CONTROLS ON WILDLAND FIRE IN THE SOUTH-CENTRAL UNITED STATES

A Thesis

by

CHASE TYLER BROOKE

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Chair of Committee,	Michelle Lawing
Committee Members,	Charles Lafon
	William Rogers
Head of Department,	Kathleen Kavanagh

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ABSTRACT

Fires are responsible for the historical shape, structure, and composition of ecosystems in the South-Central United States. The biophysical settings in which fires readily occur are affected by global processes like climate change, as well as local and regional characteristics like vegetation structure, proximity to human infrastructure, and topography. The increasing number and severity of fires today requires high-resolution and accurate predictions of fire probability. The use of species distribution models (SDM) has allowed researchers to identify predictive environmental characteristics of fire, and depict the probability of fire occurrence. I applied a Maximum Entropy (Maxent) SDM to identify fire predictors and fire risk in Texas; an ideal test case for the South-Central US. To this end, I used 15 years (2001-2016) of remotely-sensed fire occurrence data, along with 13 biophysical variables representing climate, terrain, landcover, and human activity to generate multiple models. Models were generated at the state and regional level to identify the impact of scale on fire predictions. At the state level, annual precipitation was the most important predictor of fire occurrence, with elevation and landcover following. At the regional level, precipitation was consistently a top predictor of fire, though the influence of other predictors varied from region to region. In more arid regions, precipitation was the most significant predictor of fire; while in wetter regions, terrain and landcover had higher predictivity. When comparing the Maxent fire prediction outputs, the regional level analysis had more variance in

prediction, whereas, at the state level, the predictions were less variable. When projecting fire probability in future climate conditions, the degree of fire probability did not drastically change. The central portions of the state had higher probabilities of fire occurrence while the coastal and high plains regions of the state predicted lower probabilities. In the South-Central US, and Texas in particular, the importance of precipitation in driving fire occurrence is significant. Human activity was also a predictor of fire in less populated areas, though a consistent pattern was not apparent. Overall, Maxent allows for useful modeling of fire probabilities and provides new insights into predictors of fire occurrence within this region.

DEDICATION

To Jen, for understanding me and being my calm in the storm of grad school; I would not have made it without your support and love through all of this.

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Part 2, student/collaborator contributions

All work for the thesis was completed by the student, Brooke, under the advisement of Dr. Michelle Lawing of the Department of Ecosystem Science and Management. Brooke conceived the studies in this thesis. Brooke and Lawing designed the studies with the guidance of Rogers and Lafon. Brooke acquired the data, conducted the analyses, and drafted the first versions of all of the chapters. Brooke, Lawing, Rogers, and Lafon contributed to the interpretation of findings and to editing the thesis.

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TABLE OF CONTENTS

LIST OF FIGURES

Page

LIST OF TABLES

CHAPTER I

INTRODUCTION

The recent growth in interdisciplinary approaches in fire science and fire ecology has seen the integration of Species Distribution Models (SDMs) in studying the environmental controls on fire across a variety of landscapes (Parisien and Moritz 2009, Bar Massada et al. 2013). The information that is derived from SDMs about the varying environmental influences on fire occurrences allows us to generate current, past, and future fire distribution predictions (Elith and Leathwick 2009). SDMs additionally allow us to compare fire likelihood predictions to traditional fire hazard and distribution modeling methods (Peters et al. 2013).

SDMs are a statistical method of determining the potential distribution of a species across its realized niche (Austin 2007). Using a variety of methods, these models are able to capture the extent of the species distribution across a geographical region (Elith and Leathwick 2009). Thus, when applying SDMs to modeling fire occurrences, the outputs describe prediction of potential occurrences which can be used to determine relative fire danger across a region (Catry et al. 2010).

When applying fire to SDM, fire can be treated as a species that has physical characteristics favoring particular conditions and areas which define its habitat (Parisien and Moritz 2009). For example, for a fire to burn, it requires fuel, appropriate weather, and an ignition source (Graham et al. 2004). At a large scale, the underlying controls on those factors are broader characteristics such as temperature, water availability, and date of first snowmelt (Westerling et al. 2006, Liu et al. 2014). Thus, by characterizing these suitable environments for fire, we can describe the niche of fire as one would for an organism.

This concept has been executed by multiple studies, which have used a variety of experimental and comparative applications of SDMs. In this introduction, my aim is threefold: 1) I review the applications of SDMs in fire modeling and the major findings and models used, 2) I determine a consistent framework to guide variable selection and distribution data for fire applications, and 3) I propose the use of a Fire Distribution Model to apply the SDM methodology to future studies.

Past applications of SDMs for fire modeling

Species Distribution Models

Since their initial development, a wide variety of modeling techniques have been applied to modeling fire distributions. Within these models, they can be broadly categorized as correlative or mechanistic models (Kearney et al. 2010). Correlative models identify statistical connections between the distribution of occurrences and environmental conditions (Elith and Leathwick 2009). Mechanistic approaches differ in that they use the physiological properties of an organism and its known links to environmental conditions to generate areas of suitable habitat (Kearney and Porter 2009). Of the two, correlative models have been more widely used for species distribution modeling, as their ease of parameterization and application lend them to studying responses to environmental variables (Shabani et al. 2016). In the field of fire science, correlative approaches have traditionally been used to quantify fire probability based on current fuel and weather conditions. For this review, I focused primarily on the applications of correlative SDMs, and the various models which have been applied to fire modeling.

Some of the first statistical fire occurrence probability models were logistic regression (logit) models developed in the mid-20th century, with studies implemented by Crosby (1954), Haines et al. (1970), Martell et al. (1987), and Garcia et al. (1995) who applied these models to try and predict fire occurrences. These studies sought to characterize the probability of a fire occurring on a particular day, given local weather and fuel conditions. These logit models considered the probability of a fire day occurring to be a logistic function of the environmental variables. Many of these initial studies investigating fire distribution and occurrence were limited by the available computation capabilities of the time. In addition, the data and records available at the time were not always considered accurate or representative of ground conditions (Garcia et al. 1995).

Advancing from the earlier logit models, the next series of models were generalized linear models (GLMs). The GLM is an extension of logit models that can process non-Gaussian linear distributions of data (Hastie and Tibshirani 1990), and may use an iterative weighted linear regression to compute the estimated maximum likelihood of the input response variables (Shabani et al. 2016). Bar Massada et al. (2013) compared the predictivity of a GLM with two machine learning SDMs for predicting fire occurrence in the Huron-Manistee National Forest in the American state of Michigan and found that GLMs did not perform as well as machine-learning methods.

Wotton et al. (2010) also used a GLM to characterize fire occurrences in Canada and to predict changes in fire occurrence under different climate scenarios.

Building upon GLMs, General Additive Models (GAM) are models in which the linear relationships are replaced by non-linear smoothers to allow the analysis of more complex response shapes (Hastie and Tibshirani 1990). In application, these models were used to predict fire distributions and fire controls across a variety of regions (Holden and Jolly 2011, Parks et al. 2011, Staver et al. 2011, Fusco et al. 2016). These studies primarily used GAMs to identify relationships between fire distributions and environmental variables, with several generating geographic distribution predictions as well.

The use of GLM and GAM methods are often applied as independent methods of modeling distributions and variable interactions of fire and climate (Fusco et al. 2016), as well as for comparing or validating other machine learning models (Parks et al. 2011, Bar Massada et al. 2013). However, regression based models may not perform as well when compared with machine learning models (Bar Massada et al. 2013), and are limited by the presence-only fire data (Elith and Graham 2009, Ward et al. 2009). Additionally, regression based models typically recommend having greater than 250 occurrences to maximize model accuracy, as GAMs using fewer occurrence were found to have reduced predictivity compared to ones with more occurrence locations (Pearce and Ferrier 2000), which may limit small-scale fire analyses with short temporal spans.

Boosted Regression Trees (BRT) combine the use of regression trees and boosting (a machine learning algorithm used to reduce bias) to create a better performing prediction model (Elith et al. 2008). Parisien and Moritz (2009) used BRT alongside other distribution models to build a fire prediction model across the state of California. They found that BRT performed on-par with other machine-learning distribution models and was well suited to the presence-only fire records used. Parisien et al. (2011) further used BRT to characterize the distribution and controls on fire in Canada.

Random forests (RF) is an ensemble modeling method which uses the average of many classification trees (a method for developing thresholds to separate data into categories), each developed with a subset of the input training data, which describes the known occurrences or variables for the model (Breiman 2001). In application, this allows RF to overcome the limitations of single-tree instability, where the model produces different results with each model run (Dwyer and Holte 2007, Syphard and Franklin 2010) and generates a robust prediction of variable importance and occurrence distribution. Bar Massada et al. (2013) used RF in conjunction with Maxent, and a GLM, and found that it performed as well as other machine-learning distribution methods. Parisien et al. (2014) also compared RF and BRT and found that they performed similarly for modeling fire occurrences.

The Maximum Entropy (Maxent) model developed by Phillips et al. (2006) is one of the more popular machine learning SDMs due to its improved performance relative to other SDMs, and its ease of use (Merow et al. 2013). Maxent contrasts the environmental values associated with the occurrence points to generate a distribution of probability of occurrence for the defined region (Merow et al. 2013). Maxent has been used for studies across the United States (Parisien and Moritz 2009, Parisien et al. 2012, Bar Massada et al. 2013, Peters et al. 2013, Parisien et al. 2016), Mexico (Ibarra-Montoya and Huerta-Martínez 2016), India (Renard et al. 2012), and the globe (Moritz et al. 2012, Batllori et al. 2013).

There is a wide variety of species distribution modeling methods and it is unclear which model is best for modeling fire distribution. When considering the performance of many of these methods, there is little difference in their overall predictions, especially between the use of RF, BRT, and Maxent (Parisien and Moritz 2009, Bar Massada et al. 2013, Parisien et al. 2014). Ultimately, model selection should be based on the goals of the study and data, to ensure sound applications in science and management (Guillera-Arroita et al. 2015). The spatial scale of the study should also determine model choice since the environmental controls on occurrence probability change at different spatial scales and larger scale analyses may not capture finer variations across the region of study (Austin and Van Niel 2011).

Input variables for fire SDM applications

The application of SDMs requires two primary inputs: distribution data and predictor variables (Merow et al. 2013). Distribution data are the known occurrences of the species being analyzed and can be constructed from presence-only, presence-absence, or presence-pseudoabsence records (Elith et al. 2006). Second is the predictor variables, referred to below as environmental data, which describe the biophysical characteristics of the environment.

Distribution Data

Fire records of occurrence and/or absence can be obtained from dendrochronological studies (Swetnam and Betancourt 1990), state and federal fire records (Brown et al. 2002), paleoecological studies (Whitlock and Larsen 2002), remote sensing platforms (Giglio et al. 2009), or other public databases. Although these sources may provide occurrence information for past and present fires, the accuracy and precision of these data vary greatly (Brown et al. 2002). Fire distribution studies have used state and federal databases (Parisien and Moritz 2009, Bar Massada et al. 2013, Peters et al. 2013) and remotely sensed fires (Moritz et al. 2012) to obtain presence data. Within these datasets it is critical that all data are carefully checked for internal consistency, as well as comprehensiveness. Additionally, knowing whether occurrence points are gathered at the center of the burn area, the point of ignition, or some other method is important for building a consistent representation of fires across the study region. After vetting, all the occurrence records should be mapped into a consistent coordinate system to match the environmental data.

Environmental Data

Environmental data for SDM input is generated in the form of a digital grid (raster) that can be derived from remote sensing, interpolations (Hijmans et al. 2005b), field records, or calculated surface metrics. There is no apparent standard for the number or types of variables chosen in any of the studies analyzed, with some studies containing over 20 variables (Parisien and Moritz 2009) and some using as few as four (Peters et al.

2013). Regardless of the number of input variables, the data need to be processed prior to input to create a common cell size, projection, extent, and file format.

It is necessary to test the correlation between predictor variables in order to remove variables that are highly correlated prior to model execution (Anderson et al. 2006). In climate data, measures such as monthly, quarterly, and annual precipitation often result in multi-collinearity, which can inflate the variances of the predicted values between the response variable and the values of the estimated parameters of the predictors (Cruz-Cardenas, 2014). Among existing studies, the correlation threshold for input variables varied with some setting their threshold at 0.6 (Parisien et al. 2012), 0.7 (Parisien et al. 2011), 0.8 (Bar Massada et al. 2013), and even as high as 0.9 (Parisien and Moritz 2009). Some studies have just referenced that they simply sought 'low' correlations (Peters, 2013) and some did not mention any correlation test at all (Ibarra-Montoya and Huerta-Martínez 2016). While there is no defined correlation threshold that is advisable for fire distribution modeling, it is important to check any environmental variables for correlation in order to provide clarity of analysis and interpretation of the model results (Merow et al. 2013).

Model Generation and calibration

Assessing model performance is essential for fire analyses and there are a variety of methods for this assessment (Liu et al. 2009). Principally, model comparison is done through the measure of the area under the curve (AUC) of the receiving operator characteristic (ROC) plot (Hanley and McNeil 1982). This ROC plot represents the relationship between specificity, which is the false positive error rate, and sensitivity, which is the proportion of true positives, for the model. The AUC of the model then represents the probability in any given location that the probability of an occurrence is more likely than that of an absence (Raes and ter Steege 2007). Values for the AUC range from 0.5 (not different from random) to 1 (perfect agreement), with AUC thresholds greater than 0.7 considered as a minimum for good model performance (Fielding and Bell 1997, Pearce and Ferrier 2000). However, fire distribution studies have diverged from that threshold and sometimes consider AUC values greater than 0.6 to be the lower bound for acceptable model performance (Parisien and Moritz 2009). Despite the versatility of using AUC as a cross-model performance metric, AUC is limiting in that the model extents highly influence the value especially when applied at a geographical range greater than that of the occurrence points, which may affect its ability to be used comparatively at multiple scales (Lobo et al. 2008).

Model Projection

One other application of SDMs is projection of future suitability distributions based on future models of environmental data (Fitzpatrick and Hargrove 2009). These projections allow for quantifying the potential degree of shifts in distribution and the importance of predictor variables. However, when planning to use general circulation models (GCMs) to predict fire distributions in future climate conditions, it is critical to properly vet the environmental variables chosen as they can have pronounced effects on the range of suitable areas generated from those data (Porfirio et al. 2014). Additionally, the applications of projections within restricted ranges may also create spurious and unpredictable effects on the tails of the species response curves (Thuiller et al. 2004).

Thus, when predicting fire probability in future climate projections, the environmental variables and spatial extent of the model must be carefully considered prior to generating future predictions of fire suitability.

Fire Occurrence and Variable Selection

From reviewing the literature on fire distribution modeling, there is a surprising lack of consistency in regards to variable selection and results analysis. Of the literature reviewed, every study used a different ensemble of environmental predictors to input into their model (Table 1.1). While this is not unique in regards to fire SDM studies in particular, not having this consistency diminishes our ability to directly compare models and studies (Austin and Van Niel 2011). For example, Parisien et al. (2016) used a total of 33 environmental variables, while Peters et al. (2013) only used four. The study developed by Parisien et al. (2016) was a continental scale analysis looking to define the impact of human activity on fire. Thus, by using large variable selection, they were able to take advantage of the variable rankings output by SDMs (Maxent in their case) and record which anthropogenic characteristics controlled fire at the continental scale. This is contrasted to the study conducted by Peters et al. (2013) which used Maxent to predict fire probabilities across a much smaller scale, only encompassing the American states of Ohio, Pennsylvania, and New Jersey. From this study, they had already identified a smaller suite of predictive variables for the region and were able to generate a fire probability prediction based on those four. While these represent two extremes across the literature, most of the studies tended to use between 12 and 15 variables. Across the studies reviewed, the number of variables was related to their objectives and purpose.

Papers which primarily focused on exploring variable interactions and importance were more likely to have many environmental variables, whereas studies focusing on prediction had fewer.

Table 1.1: Fire species distribution modeling studies reviewed, the models used, the correlation threshold used in variable selection, the number of predictors resulting from the variable selection process, the spatial resolution of the study, the region where the study focused, and the purpose of the study.

Authors	Model	Correlation Threshold	Number of Predictors	Resolution	Region	Purpose
Parisien (2009)	Maxent, BRT	0.9	25	1 km	US, California, CA sub-regions	Analyze environmental effects on fire at 3 scales
Parisien (2012)	Maxent	0.6	17	1 ha, 100 ha, 1,000 ha, 100,000 ha	11 states of the Western U.S.	Modeling wildfire probability
Bar Massada (2013)	Maxent, RF, GLM	0.8	12	30m	Huron-Manistee National Forest, Michigan, US.	Compare predictive models
Parisien (2016)	Maxent	0.7	33	1km	North America	Determine human impact on fire
Peters (2013)	Maxent	< 0.28	4	30m	New Jersey, Ohio, Pennsylvania	Modeling wildfire probability
Ibarra-Montoya et al (2016)	Maxent	-	14	30m	El Área de Protección de Flora y Fauna La Primavera, Guadalajara, Mexico	Modeling wildfire probability
Moritz (2012)	Maxent	0.8	6	0.5°	Global	Modeling wildfire probability
Parisien (2011)	BRT	0.7	14	1km	Canada	Identify controls on fire occurrence

Table 1.1 Continued

Authors	Model	Correlation Threshold	Number of Predictors	Resolution	Region	Purpose
Batllori (2013)	Maxent	-	5	0.5°	Global Mediterranean Ecosystems	Identify controls on fire occurrence

Of concern is that for many of the studies modeling fire distributions, the representation of climate and fuels varies greatly between papers. In reviewing these papers, I analyzed the rationale behind the selected variables and their reason for inclusion. Here, I will use climate as an example of how each variable should be treated when selecting inputs for a SDM. Considering the great influence that temperature and precipitation have on fire (Parisien and Moritz 2009), selecting the best representation of those climatic variables is important for predicting fire occurrence.

Westerling et al. (2006) analyzed the climatic controls on fire in the Western United States, and found that temperature and lengthened warmer seasons provide suitable fire conditions over a longer period. While fire can potentially ignite in any fuel-bearing location, fuel moisture is the determining factor in whether or not fire will ignite (De Luis et al. 2004). Additionally, fuel moisture is tied with soil moisture and precipitation distribution, so that fire occurrence is more likely during droughts (Dennison et al. 2014).

When looking at previous fire distribution studies, there are a variety of ways to quantify climate within the areas of study. Parisien et al. (2011) used three climate measures in their distribution study across Canada, while in a separate study they used

17 to model fire distributions across the westernmost states in the US (Parisien et al.). While the numbers of variables varies, in both studies the authors targeted their climate variables to their regions of study. In the 2011 study, the authors specifically mention the significance of the three climate variables they selected, and the previous body of work which determined the importance of those measures (Parisien et al. 2011). Likewise, in their 2012 study across the western United States, they used a larger suite of climatic variables to explore the variation in climatic predictivity (Parisien et al. 2012).

Variable selection for modeling fire distributions should be done with an eye towards capturing the local climate characteristics, which can determine fire occurrence in the region. When such climatic controls are known, using those variables can simplify the modeling process. If those controls are still not well known, using a larger suite of climatic variables can assist in identifying important climate predictors of fire within the study area (Elith and Leathwick 2009).

Conclusions

Previous applications of SDMs for modeling fire occurrence defined the variables inputs used in SDMs and identified how to select variables for use in different types of models. However, there remains a large gap in fire literature regarding the appropriate selection of variables and analyses for measuring fire probabilities given existing fire records. By providing this context, we can improve future modeling attempts and encourage further analysis of fire distributions across the globe.

CHAPTER II

THE IMPACT OF ANNUAL PRECIPITATION ON FIRE OCCURRENCE ACROSS THE SOUTH-CENTRAL US

Introduction

Temperate forests, grasslands, and deserts cover a large portion of the central and eastern United States and have experienced large shifts in vegetation composition and structure towards forests and shrublands over the past 200 years (Archer 1994, Nowacki and Abrams 2008). The impacts of these ecosystem changes are an increase in wildland fire intensity (Pausas and Paula 2012),which creates a permanent shift in ecosystem state (Scheffer et al. 2001).

Ecological functions and products of temperate forests and grasslands are some of the key components of economies across the world (Sala and Paruelo 1997, Pearce 2001). Thus, human societies in historically fire-dependent areas are greatly affected by changes in fire extent and intensity, which influence plant communities and ecosystems (Lafon 2010). For example, changes in forest structure due to changes in fire regime have severely reduced the extent of the ecologically diverse longleaf pine ecosystem (Frost 1993). The surviving longleaf pine forests are overgrown, such that a fire is likely to kill existing trees; however, fires are necessary for the ecosystem to return to its previous state as a forested savanna (Varner et al. 2005). The shifts that are occurring in fire regimes and the structure of critical ecoregions have profound effects on our ability to manage fire (Dale et al. 2001). Additionally, these changes will have negative effects on our ability to combat fire and on human health and safety due to increased fire intensity and smoke outputs (Barbero et al. 2015).

Fire activity is expected to shift in response to global climate change (Dennison et al. 2014). The degree of climatic influence on fire occurrence is both spatially and temporally variable. The exact manner of these shifts in fire regime will vary according to the physical characteristics of a region (Parisien et al. 2012), as well as the presence of human development and activity (Syphard et al. 2007). For example, there is a wide range of differences in fire activity between the southeast and northeast United States due to differences in vegetation, climate and terrain (Morgan et al. 2001). Understanding the influences that these differences have on fire occurrence will bring new insight on predicting regional wildland fire occurrence and distribution. The spatial variation in fire occurrence across temperate forests, grasslands, and deserts is primarily a function of fuel loading and precipitation distribution (Parisien et al. 2011). In order to best understand the impacts of global climate change on fire occurrences, there is a need for further investigation into the controls on fire distribution and variability.

The use of species distribution models (SDMs) across temperate forests, grasslands, and deserts have established broad connections between fires, climate, fuels, and human activity (Parisien and Moritz 2009, Parisien et al. 2014). Using known fire occurrences and descriptive environmental variables, these models allow for flexible applications across different scales and regions (Parisien et al. 2012). As such, they are able to reveal spatial and temporal trends in fire occurrence and identify potential drivers of occurrence (Ferrarini 2012). Given the spatiotemporal variability inherent in fire occurrence, these models provide a consistent framework from which to analyze and compare fire regimes across varying climates and regions.

Previous applications of SDMs to analyzing fire occurrence have primarily focused on Western North America (Parisien et al. 2012, Parisien et al. 2016), and the northern temperate forests of the United States (Bar Massada et al. 2013, Peters et al. 2013). These studies investigated the various effects of climate (Parisien and Moritz 2009) and fuels (Parisien et al. 2012) in those areas, specifically within the context of the changes in burning season . In contrast, the South Central US has a year-round fire season and is expected to experience climate shifts due over the next fifty years (McKibben 2014). In this context, it is important to analyze region specific influence of climate on fire occurrence and the effects that the changes in climate may have on fire probability in the future.

In this study, I used Maximum Entropy (MaxEnt) SDMs with fifteen years of remotely-sensed fire occurrences across the state of Texas to partition the influence of environmental characteristics in predicting fire occurrences. To identify the drivers of fire occurrence, I modeled the probability of fire occurrence across the state using a suite of descriptive variables, which I categorized as climate, terrain, landcover, and human descriptors, at a 1-km resolution. Fire occurrence predictions based on each category were compared to an inclusive model built using all variables, thereby allowing for the identification of areas where models produce differential expectations in prediction and variable contribution. I expect that precipitation will be a major predictor for fire occurrences throughout Texas due to the importance of precipitation on determining vegetation (or fuel) distribution (Stephenson 1990). Additionally, I predicted that population density and proximity to populated areas are important variables as well due to the anthropogenic cause of most fire ignitions (Syphard et al. 2007). Previous work by Westerling et al. (2006) established a strong link between climate and fire in the western United States. They found that increased global temperatures were lengthening fire seasons and thereby increasing the potential time for fires to occur. As such, I expect that climate, and especially precipitation, will be a predictor of fire across the regions of study. Parisien et al. (2016) found that there are profound anthropogenic effects on fire occurrence in North America where proximity to human habitation and activity is correlated with fire ignitions. Therefore, I expect to see that measures of human development and population have an inhibitory effect on fires. Finally, I expect that the use of SDMs will provide an accurate, high-resolution prediction of fire occurrence probability. I address three questions in this study: 1) How does variation in environmental characteristics influence fire occurrence?, 2) How do environmental variables interact in modeling fire occurrences in the present and near future?, and 3) Will fires become much more probable given future climate conditions?

Methods

Study Area

Across the South-Central United States, I constrained my modeling to the state of Texas as a representative example of the larger region. This was done for two reasons: First, Texas contains a wide diversity of the ecoregions which are present across the

South-Central US. Secondly, Texas also contains a robust set of GIS and remotely sensed data which allow for rapid acquisition and processing of the modeling inputs needed for the study. Texas is ecologically and geographically diverse (McMahan et al. 1984) and has a wide variety of fire dependent ecosystems (Albert 2007). Precipitation across the state ranges from less than 36 cm annually in the west to more than 134 cm per year in the east (Hijmans et al. 2005a) and elevation ranges from sea level to 2667 m (USGS 2008). Texas is home to three of the ten most populous cities in the US and has population densities ranging from 0.03 people per sq. km in Loving County to over 1007 people per sq. km in Harris County Bureau (2010).

Remotely sensed fire occurrence

Fire occurrence data used for this study were collated from the USDA Active Fire Mapping Program (https://data.fs.usda.gov/geodata/maps/active-fire.php) between the years 2001 and 2016, and they represent 135,798 fires (Figure 2.1). The MODIS active fire product detects fire in 1km pixels using middle-infrared and thermal infrared brightness (Giglio et al. 2009).

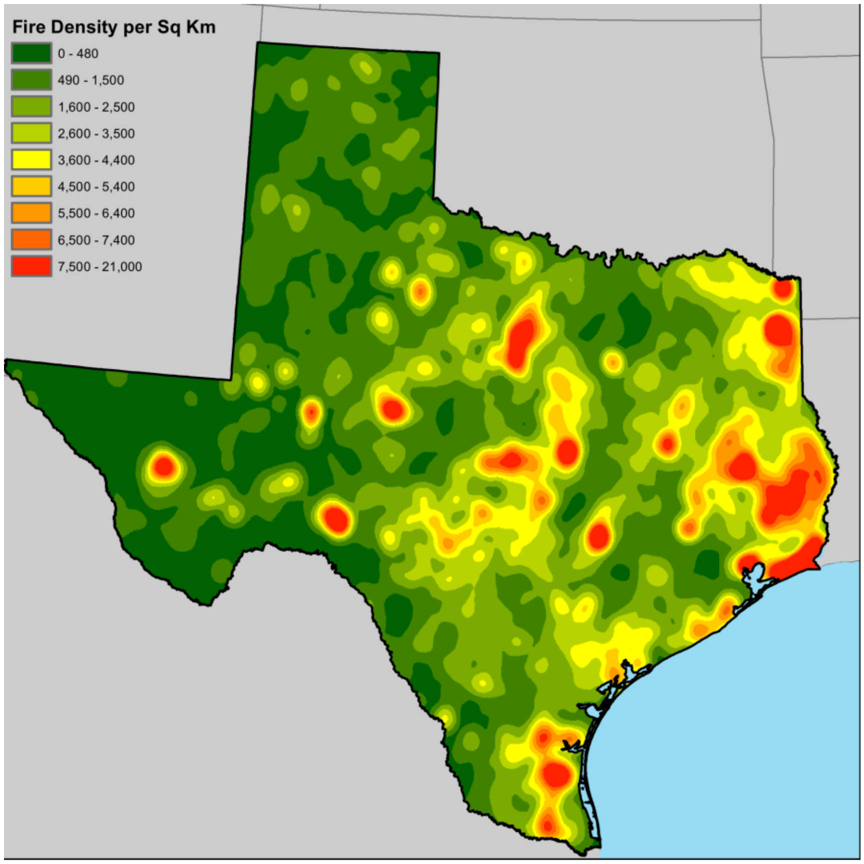

Figure 2.1: Kernel density of the 135,798 fires detected between 2001-2016 by the MODIS Active Fire Monitoring Program. Areas of red indicate higher densities of fire, while green areas indicate regions of lower fire density.

The 1-km spatial resolution of fire data serves as a filter to exclude smaller, non-ecologically significant fires that might occur due to household burns. These occurrence points are annually provided as a national dataset. The data were clipped to retain only the points within the study area and data from multiple years were merged into a single comprehensive dataset for the 15 year time period.

Explanatory variables

The cartographic boundary for the state was defined based on the 2010 Census boundary and served as the clipping and processing extent for all environmental data layers. Environmental data were selected from a suite of climate, terrain, landcover, and human variables chosen for their relation to fire occurrence and spread (Table 2.1). To remove redundancy and improve the model and the interpretation of results, any strongly correlated ($R > 0.7$) variables were reviewed, and the variable with the least applicability to fire prediction was removed (Merow et al. 2013). The remaining 13 variables were grouped into categorical variable sets based on their representation of climate, terrain, landcover, and human influence.

Table 2.1: List of input variables for Maxent representing a suite of climate, terrain, landcover, and human influences on fire occurrence. Each variable was computed or acquired at a 1km resolution.

Category	Variable Name	Definition	Units	Source
Climate	BIO_1	Annual Mean Temperature	C	WorldClim
	BIO_5	Max Temperature of Warmest Month	C	WorldClim
	BIO_8	Mean Temperature of Wettest Quarter	C	WorldClim
	BIO_9	Mean Temperature of Driest Quarter	C	WorldClim
	BIO_12	Annual Precipitation	mm	WorldClim
Terrain	Elv	Elevation	m	USGS
	TRI	Topographic Roughness Index		USGS
	SolRad	Solar Radiation		
	Asp	Aspect	Direction	USGS
Landcover	Lcvr	Vegetation landcover	categorical	USGS
Human	Pop Dens.	Population Density	Pop. per Sq. Km	US Census
	DtC	Distance to nearest municipal boundary	km	USGS
	DtR	Distance to nearest major road	km	USGS

To determine the potential effects of topography on fire occurrence, I used a suite of terrain variables generated from a 1km digital elevation model (DEM) from the US National Elevation Dataset (USGS 2008) including elevation, a topographic roughness index, and aspect. Topographic roughness represents the elevation difference between adjacent pixels (Riley 1999) was calculated by using the difference in elevation between a center cell and its eight neighbors. Then each difference value was squared, the squares were averaged, and the square root of the value taken. Roughness values near zero represent relatively smooth topography while higher values indicate large variations in adjacent elevation. Southern and eastern facing slopes tend to have more intense fires than northern and westerly facing slopes (Beaty and Taylor 2001). Aspect was calculated using the DEM to determine the direction of a slope as a range between 0 and 360 degrees. Solar radiation is a measure of the insolation of a landscape in watt hours per square meter per year and takes into account the latitude of the area and topography to determine areas of greater and lesser sun exposure. This measure reflects the direct sun exposure and therefore drying potential for fine fuels and evapotranspiration.

The bioclim dataset is a suite of 19 climate variables that have been shown to be biologically important (Hijmans et al. 2005a). The bioclim variables are interpolated at approximately one km spatial resolution from 50 year averages of climate station data across the globe (Hijmans et al. 2005a). All the climate data were downloaded at 30 arc-second resolutions and resampled to a 1km spatial resolution. These data are commonly used for SDMs and are particularly well suited for occurrence-based distribution modeling (Booth et al. 2014). Removing highly correlated variables improves interpretation of the MaxEnt models and projection of models into future climate scenarios (Braunisch et al. 2013). After removing the highly correlated variables ($r > 0.7$), our resulting climate variable set included Mean Annual Temperature (C), Maximum Temperature of the Warmest Month (C), Mean Temperature of the Wettest Quarter (C), Mean Temperature of the Driest Quarter (C), and Annual Precipitation (mm).

The influence of landcover type on fire occurrence is tied to the fuels present and the contiguity of fuel for fire spread (Littell and Gwozdz 2011). I used the 2011 National Landcover Database (Homer et al. 2015) to define the primary form of landcover present. This database divides landcover into a variety of classifications including shrublands, coniferous forests, urban, and water, among others. I resampled this layer to 30 arc-seconds and clipped it to the extent of the Texas boundary to match the spatial properties of the other data layers.

I incorporated the influence of human activity and infrastructure on fire occurrence through the use of population density (units), distance to the nearest city boundary (units), and the distance to the nearest interstate (units). I collected data on the population density by downloading the 2010 census block data (Bureau 2010) and extracting population density per pixel for each census block. The locations of each defined municipal boundary were obtained from the 2010 census, which includes any incorporated community within the state as well as unincorporated areas of human habitation that are defined by a local community. The distance to these communities was generated to identify areas with large areas between municipalities, which may be more removed from firefighting capabilities and roads. Additionally, another distance measure was generated for the interstates within the study area. These are also representative of human response times and logistics.

Modeling the probability of fire occurrence

I modeled the probability of fire occurrence using Maxent model (Version 3.3.3k) (Phillips et al. 2006). Maxent is an SDM, which uses environmental values at occurrence points to build algorithms to predict probability of occurrence (Elith et al. 2011). Maxent uses randomly selected background points within the extent of the study area as pseudo absences to calibrate the entropy algorithms. To validate a Maxent model, some of the occurrence data are held back. Maxent uses training data to train the entropy algorithms and then uses the held back data to test the trained algorithm. The model generates response curves that are used to map the relative probability of occurrence within the area of study and outputs a list of the relative contributions of each input variable (Phillips et al. 2006).

I ran a series of models to estimate the probability of fire occurrence in modern and 3 future climate scenarios. The series included one model for each variable suite: climate, topography, landcover, and human impact. By partitioning these variable suites, I was able to identify regions of dissimilar estimation and compare the influence of each variable suite with a model that included all of the variable suites. For each model, response curves and jackknife calculations were performed to identify variable predictive ranges and to calculate variable importance. Variable response curves detail predictivity across the range of values for each environmental variable. Jackknife calculations generate independent Maxent models using only one variable and compares the predictivity of that solo model to the overall model using all of the environmental variables. Additionally I defined 135,000 background points, which provides the Maxent model a random sample of values from within the study extent to compare the environmental data of the occurrence points to the background points for fitting model algorithms (Elith et al. 2011). Finally, I withheld a random sample of 20% of the occurrence points for model validation.

Assessing model performance

After generating the model, Maxent validates model performance using the area under the receiving operator curve (AUC). This curve represents the plot of sensitivity of true positives over the specificity of false positives. AUC values range from 0.5, where the model prediction is no better than random selection of test points, to 1, which represents perfect model prediction accuracy (Phillips et al. 2006). In the context of fire, models with an AUC greater than 0.6 are considered informative (Parisien and Moritz 2009). To identify areas with differing model results, I calculated a series of anomaly maps - the prediction from the inclusive variable set minus the prediction from each variable category. The resulting raster values are zero where there is no difference between predictions, negative where the inclusive model had a lower probability of occurrence than the other models, and positive where the inclusive model had a higher probability of occurrence than the other models.

Modeling future climate predictions

In order to predict changing probabilities of fire occurrence given future climates, I projected our models into various future climate scenarios. I used the NOAA Geophysical Fluid Dynamics Laboratory Climate Model 3 (GFDL-CM3) (Griffies et al. 2011). This model has been successfully used for previous studies in Texas, and is well suited for analyzing precipitation and temperature at the state and regional level within the state (Rainwater 2013). I selected three climate scenarios generated from the model to represent the best case (RCP26), middle case (RCP45), and worst case (RCP85) emission scenarios for 2050. Each of these scenarios was clipped to the boundary of the study area and added as projections in the Maxent model. I calculated anomaly maps between modern and future projections of the probability of fire occurrence to evaluate potential change in fire occurrence.

Results

Model Evaluation

All of the models performed satisfactorily with an AUC of 0.681 for the inclusive state model, 0.670 for the climate variable only model, 0.642 for the terrain model, 0.616 for the landcover model, and 0.581 for the human variable model. The AUC represented here is the test AUC, which represents the prediction generated with the test data, while the training AUC represents the model generated with the withheld training data.

Distribution of Fire Probability

The model predicted higher fire occurrence in the central, eastern, and coastal portions of the state (Figure 2.2).

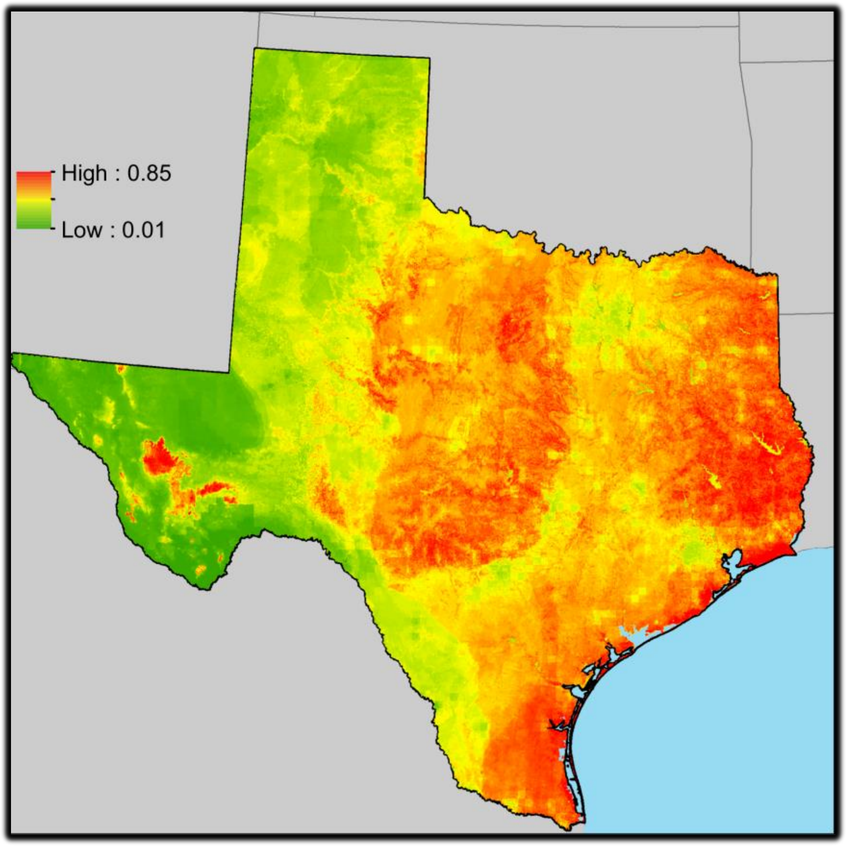

Figure 2.2: Probability of fire occurrence modeled across Texas using Maxent. Red areas indicate a higher probability, while green areas indicate a lessened probability of fire occurrence.

Modeled Drivers of Fire Occurrence

Mean annual precipitation (Bio12) had the highest influence in the overall state model, with mean annual temperature (Bio1) and the maximum temperature of the warmest month (Bio5) having low to moderate influence. Elevation (DEM) had the second-largest influence on fire occurrence, with fire more likely occurring at low and high elevations, and less likely at mid-elevations. Landcover Type (Lcvr) came in third,

Table 2.2: Variable importance for the overall model and the four type models.

Model	AUC	Variable	Percent Contribution	Permutation Importance
Overall	0.681	Annual Precipitation	53.4	55.5
		Elevation	11.1	5.5
		Landcover Type	8.2	11.3
		Max. Temperature of the Warmest Month	5.8	5
		Mean Annual Temperature	5.6	5.1
		Topographic Roughness	5.3	5.7
		Distance to City	4.6	6.4
		Mean Temperature of Driest Quarter	3.4	1.8
		Population Density	1.1	1.3
		Distance to Highway	0.8	0.8
		Mean Temperature of wettest quarter	0.7	1.4
		Solar Radiation Exposure	0.1	0.1
		Aspect	0	0
Climate	0.67	Annual Precipitation	76.1	64.9
		Max. Temperature of the Warmest Month	9.5	13.1
		Mean Temperature of Driest Quarter	7.6	4.3
		Mean Annual Temperature	4.8	13.6
		Mean Temperature of wettest quarter	1.8	4.2
Terrain	0.642	Elevation	92.1	86.5
		Topographic Roughness	7.3	11.9
		Solar Radiation Exposure	0.4	0.7
		Aspect	0.3	0.9
Human	0.581	Distance to City	77.1	62.7
		Distance to Highway	14.5	24.2
		Population Density	8.4	13.1
Landcover	0.616	Landcover Type	100	100

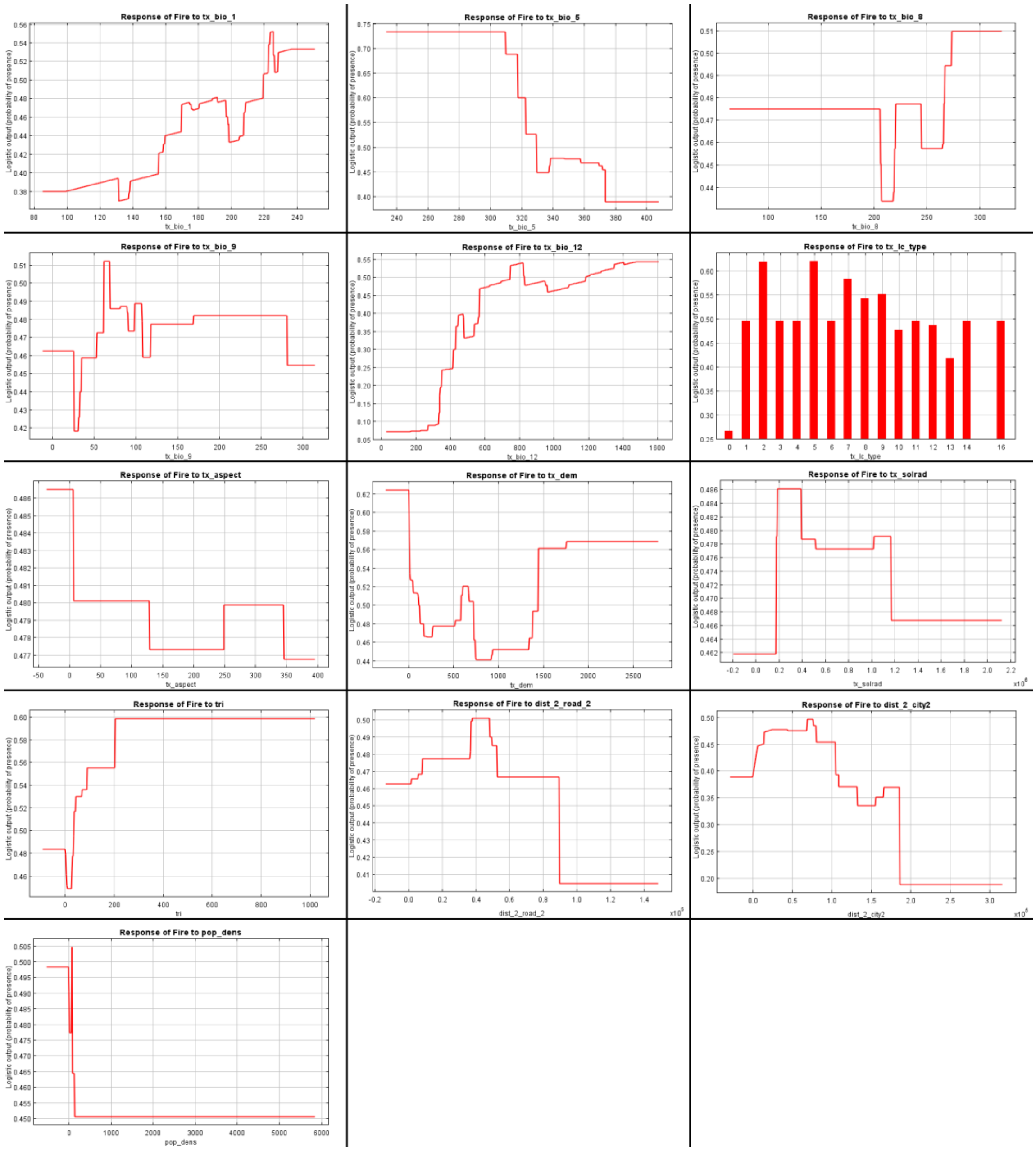

Figure 2.3: Response curves for each of the 13 input variables as determined by the Maxent model. Each curve shows the probability of fire occurring across the range of values or categories for each variable.

with areas classified as coniferous forest, deciduous forest, and shrubland having higher probabilities of fire occurring within those vegetation types. Topographic roughness had a low amount of influence on the models, and the human and other variables having little to no influence overall.

Model Anomalies

When compared to the overall model, the single variable group models underperformed by measured AUC. After calculating the difference in prediction between the inclusive model and each of the sub-models, those with the greatest differences in prediction were the human and landcover only models (Figures 2.3, 2.4). The human prediction map was most different in regions with extremely low population densities, which demonstrates the inclusive model's priority to assigning predictive values to more explanatory variables. In the landcover dataset, the greatest difference in prediction occurred in areas classified as grasslands and shrublands geographically in the Panhandle and Western portions of the state.

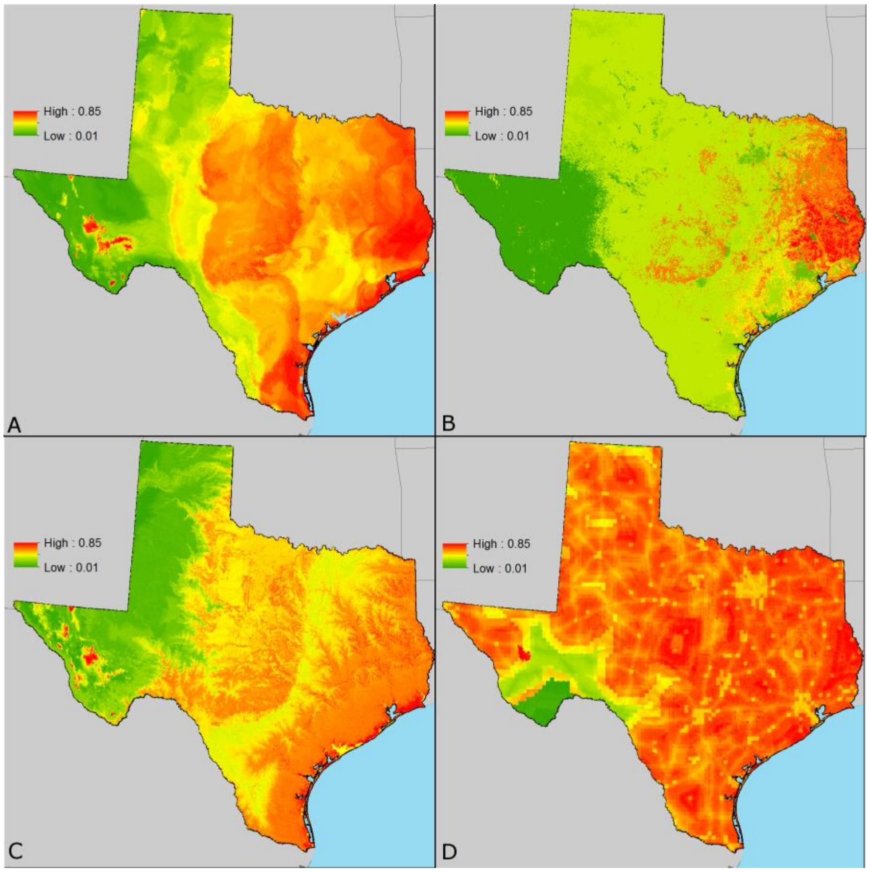

Figure 2.4: Maxent fire probability output using only the A) Climate, B) Landcover, C) Terrain, and D) Human predictors.

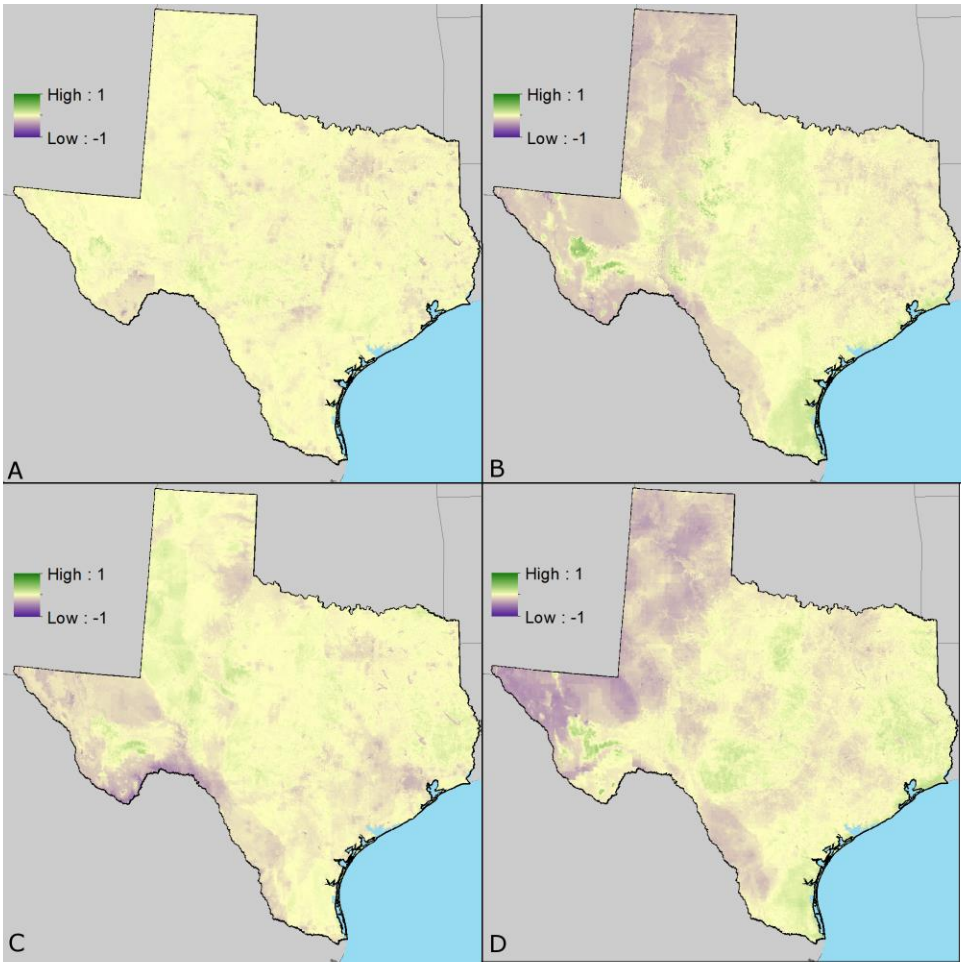

Figure 2.5: Anomaly maps representing the difference in prediction between the Human (A), Topography (B), Landcover (C), and Climate (D) models and the inclusive.

The anomaly maps showed that there was significant divergence from the overall model and a climate-only model in urban areas and in extreme rural areas (Figure 2.4). The climate-only model had an AUC of 0.670 compared to the AUC of 0.681 for the original model, thus leaving a 0.011 difference which indicates the better model performance when including all the environmental variables. Across the prediction map, most of the state had a mean prediction difference of -0.03, slightly favoring the climate-only model prediction. The climate anomaly map reveals that the non-climate variables influence the probability of fire near population centers and urban corridors.

The AUC of 0.642 for the terrain-only model was outperformed by the overall model. In the state prediction map, the mean prediction difference was -0.05 favoring the terrain prediction slightly (Figure 2.5). Western Texas and the Texas Panhandle both had higher predictions of fire occurrence in the terrain-only model. The rest of the state generally was more aligned with the overall model prediction.

Projected changes in future climate and fire occurrence

The projected climates show an increase in mean annual temperature across the state of 0.24 C, 0.28 C, and 0.33 C for the RCP 25, RCP45, and RCP85 scenarios respectively. Annual precipitation is projects to increase by 36.84 mm, 19.58 mm, and 9.37 mm respectively. These climate trends show the state growing warmer and wetter over time, even in the most optimistic of climate scenarios. These changes also corresponded with changes in the predicted fire occurrence across the state. Across all three climate scenarios, there was a drastic reduction in fire suitability, with a few exceptions along the Gulf Coast (Figure 2.6, 2.7).

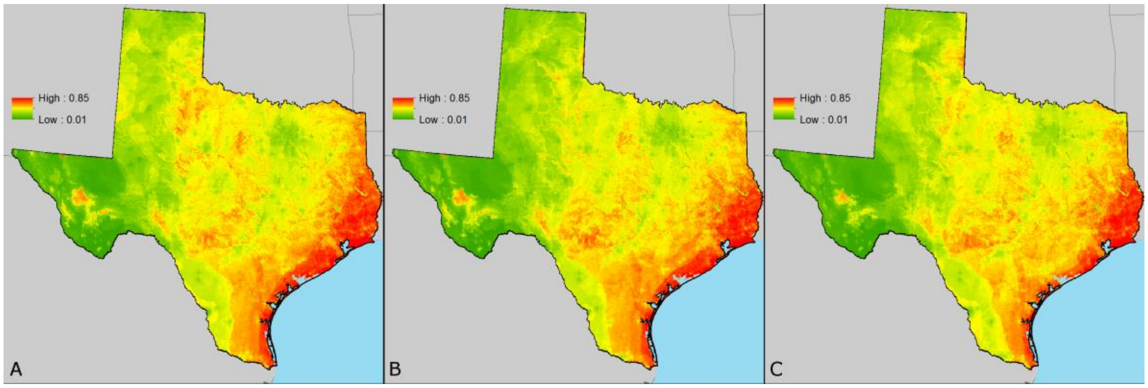

Figure 2.6: Changes in fire suitability for RCP26, RCP45, and RCP 85 scenarios.

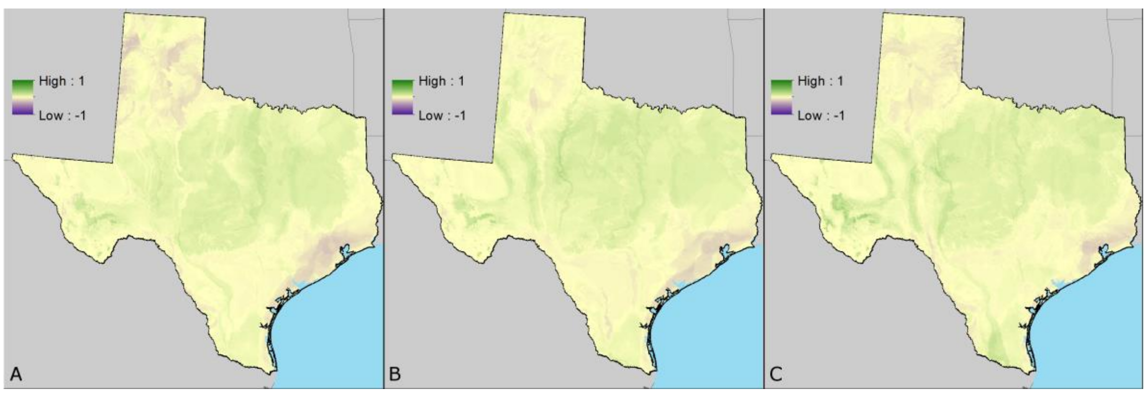

Figure 2.7: Anomaly maps for the A) RCP 26, B) RCP 45, and C) RCP 85 climate scenarios for 2050. Areas in purple indicate areas of higher fire prediction in future climate scenarios while areas in green indicate higher fire probabilities using current climate data.

Discussion

Climate drivers of fire occurrence

The results show that there is a direct connection between fire occurrence and climate. Areas with higher annual precipitation, higher maximum temperatures during the warmest quarter and forest/shrubland vegetation are more likely to have a fire occurrence. This aligns with existing knowledge of ties between fire and precipitation, where increased precipitation allows for the greater growth and accumulation of biomass and fuels (Lenihan et al. 2003).This is often seen in Texas, where the wetter pine forests in the eastern portion of the state are able to accumulate fuels rapidly during the spring/fall growing seasons, while the limited precipitation further west restricts the ability for fuels to grow and provide a continuous fuel bed capable of propagating fire (Archibald et al. 2009).

Particularly of note in Texas is that the state has an effective year-round fire season (Chuvieco et al. 2008). Even during periods of increased precipitation, the time between rainfall events is often long enough to allow for fine (1-hour) and medium (10-hour) fuels to dry enough for there to exist a baseline of fire potential even during wet period (Viegas et al. 1992, Schoennagel et al. 2004). Additionally, fire probability increased with temperature during the warmest month, where higher temperatures decrease fuel drying times as well as decreasing the amount of energy needed to start pyrolysis in the fuels. Therefore, annual precipitation is responsible for creating the fuels for the fire, and the mean annual temperature and the temperature of the driest month both work in conjunction to create the extreme fires that I see within the state.

Predicted Shifts in fire regime due to 21st century climate change

In contrast to many future fire predictions based on predicted climate scenarios, the reduction of fire probability is an interesting result. Most studies which have analyzed climate change effects on fire found that it increased the likelihood of fire occurrence, and increased the fire severity (Westerling et al. 2006). The predicted changes in future occurrence provide some additional insight into the potential for shifts in fire occurrence in the future. Previous work has stated that climate change is likely to increase global fire activity (Flannigan et al. 2009), and my results show that fire trends may be more mixed than anticipated. While some areas may indeed see increased fire activity, there are also regions which may see a decrease in fire activity. Given the importance of precipitation in predicting fire occurrence, the changes in precipitation for projected climate scenarios drive the changes in fire occurrence. While temperature is also important, I can assume that fires in Texas are likely to be more greatly affected by shifts in precipitation rather than temperature.

One note on this prediction is that fire occurrence probability is relative to a 15 year dataset, rather than an absolute occurrence measure (or a fundamental niche of fire). Additionally, this occurrence model is independent from fire intensity or fire spread and does not make any predictions to any changes therein. Existing literature is generally in agreement on the effects of climate change on increasing fire severity (Barbero et al. 2015), so this anomalous prediction is surprising. However, given that Texas is expected to become warmer and wetter, the pattern which I saw in the model projections may not be so anomalous if it is assumed that fire severity will increase regardless of the numbers of fires.

Limitations in predicting current and future fire regimes

While the use of Maxent for predicting potential future fire occurrences is useful for fire research, the use of SDMs for fire has several limitations. The first is that because the Maxent model uses presence and pseudo absence data, any potential bias within the presence data can have a large effect on the output predictions (Phillips et al. 2009). While this study attempted to reduce biases in the presence record with remotely sensed occurrence points, the limited detection of only fires over 250 m in area can bias the results away from smaller fires. Within the state, it is almost certain that many smaller fires occurred and were suppressed before they could reach that threshold. In addition, the probability maps are not representative of the independent probability of a fire occurring. Instead, it defines the range of suitability in which a fire could potentially occur. This means that the maps should be considered as an approximate suitable area rather than a region of known future occurrence.

The use of Maxent to predict change in occurrence probability in future climate projections to determine future distributions of occurrences should be taken with care (Elith et al. 2011). The future fire probability projections only take into account changes in climate, while the other predictors are assumed to be static through time. This is not necessarily representative of the actual future changes in human population, as Texas is predicted to continue to increase in population in the near future (Murdock et al. 2002) which, given the suppressive effect that human populations have on fire (Parisien et al.

2016), may additionally shift fire occurrences further out from cities and population corridors into an expanded wildland-urban interface.

Despite these limitations, the results bring to light the large influence of climate, specifically precipitation, on fire regimes across a large precipitation gradient in the south-central US. While climate change is certainly going to have an effect on fire occurrence, the overall effect is mixed in terms of increased or decreased fire probability. When I consider these trends across the South-Central United States, it is apparent that further study is needed to identify the effects of climate change across the greater region.

CHAPTER III

THE SUPPRESSIVE EFFECT OF HUMAN POPULATION AND INFRASTRUCTURE ON FIRE OCCURRENCE AT LOCAL TO REGIONAL SCALES IN TEXAS

Introduction

Humans shape fire regimes across the globe, which influences ecosystems and communities (Bowman et al. 2011, Parisien et al. 2016). With over 95% of fire ignitions caused by humans or human structures, the growth and location of human communities and infrastructure often drastically change the frequency and spatial pattern of fire occurrences (Gralewicz et al. 2012). In North America, the introduction of fire suppressive policies in the 19^{th} and 20^{th} centuries further altered the role of fire on ecosystems by completely excluding it and causing gradual shifts in ecosystem structure (Lafon 2010). However, despite the proclivity of humans and human systems to generate fires, over the past 100 years the ability to respond to fires and suppress them has caused most fires to be extinguished rapidly before they spread (Arienti et al. 2006, Plucinski et al. 2012). Therefore, human development has this duality of both increasing the number of local fire ignitions, while also suppressing overall fire size and increasing the fire return interval across much of the landscape.

Across many ecosystems, historical wildfires may have been primarily ignited by lightning strikes, though most fires today are anthropogenic in nature (Pechony and Shindell 2010). These fire ignitions are not random, but are distributed spatially and are influenced by variations in climate, topography, human development, and landcover (Krawchuk et al. 2006, Bowman et al. 2011). However, these spatially explicit distributions are not always consistent across landscapes and can vary based on the scale and region of analysis (Parisien and Moritz 2009). By understanding these patterns of occurrence, I seek to better quantify the influence of human population and infrastructure on fire occurrences and predict where fires are potentially more likely to occur.

Despite recent advances in understanding fire behavior and likelihood, there is still a lack of knowledge on the distribution of ignitions and the driving characteristics behind them at a landscape scale. Though the connections between precipitation, temperature, and fuels with fire have been well established (Westerling et al. 2006), they seldom are the sole influence on fire occurrence at the landscape level (Parisien and Moritz 2009). For example, while temperature and precipitation directly affect combustion, they also indirectly affect fuel composition and distribution (Pausas and Paula 2012). Parisien et al. (2012) showed that even though climatic conditions such as the extreme heat and low precipitation would theoretically indicate high fire probability, in regions such as the Sahara desert the true probability of fire is low to nonexistent due to the lack of fuel.

Recently, Species distribution models (SDMs) have been adapted from modeling the distributions of plants and animals (Peterson 2003) to predicting and modeling fire occurrences (Parisien and Moritz 2009). Using SDMs to analyze and model fire occurrences has recently generated insights into fire occurrence at a variety of scales

(Parisien and Moritz 2009, Parisien et al. 2011, Bar Massada et al. 2013). While there has been literature comparing the use of different models, direct application of those models to identify the environmental constraints and drivers of fire occurrences is still unexplored in many fire dependent ecosystems. However, the ability of these models to provide fire occurrence predictions, as well as to give insight into the influence of various environmental descriptors on fire, is of great potential for understanding fire in those regions. By applying SDMs to fire occurrences, I aim to better understand the drivers of fire at different spatial scales and improve variable selection for input into traditional fire models.

The purpose of this study is to quantify the effect of human activity on fires at the regional scale within the state of Texas. I used species distribution models to link fire occurrence from 2001 to 2016 to environmental variables within seven distinct biogeographical regions and across the state. In addition, I compared model performance of a mosaicked regional model to a statewide model. Finally, I looked at the effects of various human population and infrastructure measures compared to climate, terrain, and landcover. In this, I expected that at a regional level, local variations in human population density, vegetation, and topography would drive large variations in which variables would be most predictive of fire. Additionally, I predicted that climate would be important across all regions, due to its importance in determining fuel distributions across the study area.

Methods

Study area

In order to model the probability of fire occurrence in Texas, I conducted my analyses at two scales. The first took place across the entirety of the state of Texas to determine the statewide predictors of fire. Second, I divided the state into seven biogeographical regions representing distinct variations in vegetation type, topography, and human population (Table 3.1). By conducting this study at two scales and multiple regions within the state, I am better able to identify the varying environmental controls on fire (Parisien and Moritz 2009).

Across Texas, there are great variations in topography, with elevation varying from sea level along the Gulf Coast to 2,667 m at the highest peak in the Western parts of the state. Annual precipitation ranges from 1473 mm in the Eastern pine forests to 161 mm in the Western Chihuahuan desert. Maximum summer temperature variations are also large, with annual temperatures reaching a maximum of 39.4 C in the Southwest portions of the state and 24.5 C along the Gulf Coast and Northern Plains. Minimum winter temperatures reach -7.9 C in the north and 10.7 C in the south.

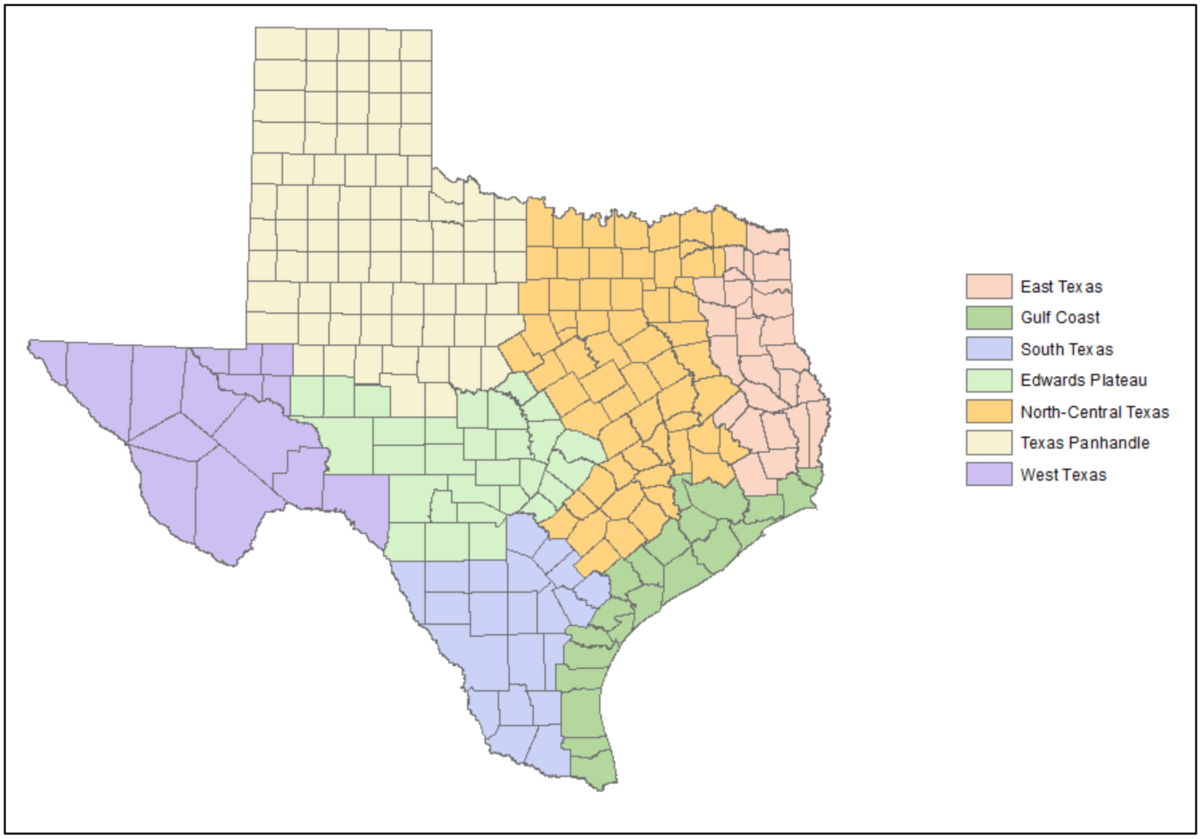

Figure 3.1: Map of the seven regions of study. Each region represents a distinct change in climate, terrain, vegetation, and human settlement.

Table 3.1: Physical descriptions of the seven biogeographical regions used in the study

Region #	Region Name	Precip Max (mm/yr)	Precip Min (mm/yr)	Veg Type
1	Piney Woods	1471	1047	Pine-oak forests
2	Gulf Coast	1476	630	Post oak Savannah
3	South TX Savannahs	912	421	Shrublands
4	Edwards Plateau	892	346	Mixed oak-juniper forest and savannah
5	Cross Timbers	1298	722	Mixed forest
6	Panhandle	789	333	Shortgrass prairie
7	Trans-Pecos Desert	551	157	Desert scrub

The eastern Texas piney woods is primarily a mixed pine forest ecosystem dominated by pine (loblolly, longleaf, shortleaf) and hardwood (oak, sweetgum, elm, among others) species with an understory of grasses, vines, and herbaceous plants' topography is primarily a mixture of low hills and flat terrain. Moving south, the Texas coastline along the Gulf of Mexico is primarily coastal prairies and is characterized by coastal prairies and post oak savannahs, with mesquite occurring across the region. West from the Gulf Coast, the South Texas savannas extend from the US-Mexico border in the south though to Bexar County in the north. Vegetation in this region is primarily shrubs, with mesquite, huisache, and prickly pear dominating many of the areas here. Central to the stat is the Edwards Plateau. Topographically identified by the steep limestone hills and bluffs, mixed oak-juniper forest has largely encroached upon the historical savannas and tallgrass prairies of the region. Moving north is the North-Central Texas cross timbers region, encompassing the blackland prairies, grand plains, and mixed oak hardwood forests of the state. Further west is the Texas Panhandle plains and tallgrass prairies. Vegetation is largely a mix of extensive grasslands, with woody trees and shrubs on slopes and across the plains. Finally, in the far west the arid Trans-Pecos Chihuahuan desert. Following the Rio Grande along the US-Mexico border, this arid region is dominated by desert scrub with sparse grasses and shrubs dotting the landscape. Topography in the area is characterized by dry alkaline soils in the lower basins and forested sky islands in the peaks that dot the area.

Presence Data

To represent the number of fire occurrences in Texas between 2001 and 2015, I downloaded remotely sensed fire occurrence data from the USDA/NASA MODIS Active Fire Monitoring Program (Giglio et al. 2009). In this fifteen year timeframe, the MODIS platform detected 135,798 fires which burned across the state over the fifteen year time period (Figure 3.2). The MODIS fire detection platform functions by detecting the thermal radiance of a fire in the infrared and near-infrared spectra at a 250 m resolution, then uses adjacent pixels for verifying the accuracy of the detection, giving the platform an effective 1km spatial resolution. Additionally, the MODIS platform has

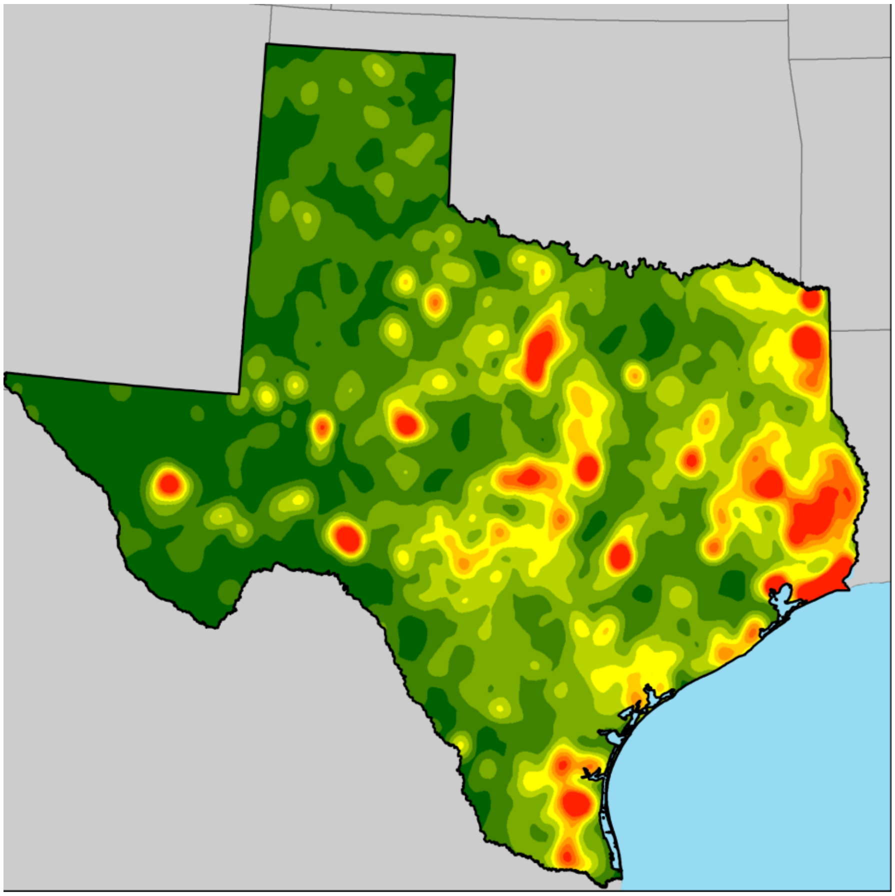

Figure 3.2: Kernel density of the 125,739 fires detected as part of the USDA MODIS Active Fire Monitoring Program between 2001-2016.

a daily temporal resolution, which allows for what is likely the most complete record of fire occurrences within the state for the time period.

Environmental Predictors

I built a suite of 14 environmental predictors for the study areas. Each environmental variable was sampled at a 30 m resolution (Table 3.2). Climate data was gathered from the Bioclim dataset (Hijmans et al. 2005b) and represented Mean Annual Temperature, Maximum Temperature of the warmest month, the mean temperature for the wettest and driest quarters, and annual precipitation. Topographic variables were elevation, aspect, topographic roughness, and solar radiation exposure. Landcover data were acquired from the 2011 National Landcover Database (Homer et al. 2015). Human variables were population density (per the 2010 US Census), distance to the nearest interstate, and distance to the nearest municipal boundary. I calculated the correlation coefficient for all the variables and found that they were all less than 0.75.

Table 3.2: List of input variables for Maxent

Category	Variable Name	Definition	Units	Source
Climate	BIO_1	Annual Mean Temperature	C	WorldClim
	BIO_5	Max Temperature of Warmest Month	C	WorldClim
	BIO_8	Mean Temperature of Wettest Quarter	C	WorldClim
	BIO_9	Mean Temperature of Driest Quarter	C	WorldClim
	BIO_12	Annual Precipitation	mm	WorldClim
Topographic Information	Elv	Elevation	m	USGS
	TRI	Topographic Roughness Index		USGS
	SolRad	Solar Radiation		
	Asp	Aspect	Direction	USGS
Landcover	Lcvr	Vegetation landcover	categorical	USGS
Human	Pop Dens.	Population Density	Pop. per Sq. Km	US Census
	DtC	Distance to nearest municipal boundary	km	USGS
	DtR	Distance to nearest major road	km	USGS

Statistical Models

To model fire occurrence distribution, I used the Maximum Entropy (Maxent) model (Phillips et al. 2006). Maxent is a presence-only species distribution model which predicts the distribution of species based on known occurrence points by comparing predictor variables associated with input coordinate points to a random distribution of points across a defined geographic extent (Elith et al. 2011). Maxent has been used to model fire occurrences in the US (Parisien et al. 2012, Bar Massada et al. 2013), Mexico (Ibarra-Montoya and Huerta-Martínez 2016), and India (Renard et al. 2012).

Model evaluation and comparison

In order to compare the prediction accuracy between each model, I used the area under the curve (AUC) for the receiving operating characteristic (ROC) plot (Elith et al. 2011). The AUC represents the true positive rate against the false positive rate, thereby providing a measure of model accuracy and a means to compare models. With possible values falling between 1 (perfect model prediction) and 0.5 (random data), the closer the AUC reaches 1, the better the prediction. For the purpose of predicting fire, AUC values greater than 0.6 are descriptive, with larger values indicating better model predictions.

Evaluating variable importance

In order to evaluate variable importance for the models, I used the regularized training gain for each variable. Additionally, I used jackknife estimations of variable importance, which compare the model AUC when a given variable is excluded, or the AUC for a model generated using only that variable. Both of these allow for us to quantify and compare the relative influence of each input variable on the overall model's performance.

Comparing prediction maps of ignition probability

As an output of the model, I generated prediction maps for each model as raster datasets. These predictions should not be taken as a measure of probability of occurrence so much as the range of suitability for each pixel for fire occurrence where pixel values range from 0 (being unsuitable) to 1 (perfect suitability). These suitability maps were then visually analyzed for patterns in suitability/unsuitability. Across each region, I also compared the minimum, maximum, and average suitability for each region to compare the overall means and extremes of fire suitability. These regional maps were also compared to the suitability map generated from the model generated at the statewide extent.

Results

Performance of modeling approaches

The predictive performance for all the models varied from average to excellent, with the median AUC (0.705) and mean AUC (0.719) for the regional analyses outperforming the statewide model's AUC (0.681). The worst performing model was that of Region 1 (0.645), and the best performing model was for region 7 (0.890).

Table 3.3: Model AUC for each regional model, the top five variables that contributed to each model, the percent that each contributed to the model (percent contribution), and the importance of that variable if it is left out of the model (permutation importance).

	Model AUC	Percent Contribution	Permutation Importance
Region 1 – Piney Woods	0.645		
Landcover Type		42.3	27.3
Elevation		12.7	5.2
Population Density		11.8	7.5
Distance to nearest city boundary		10.3	12.3
Annual Precipitation		8.1	7.6
Region 2 – Gulf Coast	0.732		
Annual Precipitation		17.9	21.1
Elevation		17.3	16.6
Population Density		17	5.4
Maximum Temperature of the Warmest Month		15.6	13
Distance to nearest city boundary		10.8	6.9
Region 3 – S. TX Savannas	0.688		
Elevation		52.3	55.5
Maximum Temperature of the Warmest Month		14	4.4
Topographic Roughness		9.4	6.1
Distance to the nearest highway		7.3	11
Landcover Type		6.9	3
Region 4 – Edwards Plateau	0.705		
Elevation		26.7	19.6

Table 3.3 Continued

	Model AUC	Percent Contribution	Permutation Importance
Annual Precipitation		23.9	19.5
Maximum Temperature of the Warmest Month		13	11.7
Mean. Temperature of the driest quarter		11.9	19.1
Distance to nearest city boundary		8.1	8.7
Region 5 – Cross Timbers	0.665		
Landcover Type		34.3	29.9
Distance to nearest city boundary		15.6	6.7
Topographic Roughness		11.4	4.7
Annual Precipitation		10.7	16.7
Mean. Temperature of the Dry Quarter		6.8	8.6
Region 6 - Panhandle	0.708		
Annual Precipitation		38.1	37.8
Mean annual temperature		21.8	20
Elevation		11.3	10.3
Topographic roughness		10.7	6.2
Landcover Type		5.3	4.3
Region 7 – Trans-Pecos Desert	0.89		
Annual Precipitation		30.3	47.6

Table 3.3 Continued

	Model AUC	Percent Contribution	Permutation Importance
Mean Temperature of the driest quarter		14.8	7.1
Population Density		13.4	3.4
Distance to nearest city boundary		10.9	19.4
Distance to the nearest highway		10.6	5.9

Variable importance

In all eight models, there was no single consistent predictor of fire occurrence across all the regions. While variables representing climate, landcover, and human measures were all found across the top 5 predictor variables, no single variable was consistently predictive in any of the models (Table 3.3). Regions 1 and 5 had landcover type as a main predictor, with (Class 2, Class 5) landscapes being more predictive in both regions. Regions 2, 6, 7, and the state model had mean annual precipitation as the largest predictor of fire.

Response curves for each region of study contained different levels of productivity across each of the variables (See Appendix). In region 2, fire had a strong positive relationship with annual precipitation. In region 6, annual precipitation had a moderate positive relationship with fire occurrence, and in region 7 fire had an inverse relationship with annual precipitation. Regions 3 and 4 had elevation as the greatest fire predictor. Region 3 had an inverse relationship between fire occurrence and elevation, with the highest probability of fires occurring at very low elevations. Region 4 also had an inverse relationship, with fires being more probable at less than 700 m in elevation.

Six of the seven regions of study had a human variable in the top five contributing variable. Of these, Regions 1, 2, 5 and 7 all had human variable contribution over 10%. Distance to the nearest city boundary was listed the most often, with population density, and then distance to the nearest highway coming in second and third respectively.

Spatial patterns of ignition probabilities

The results from the eight models showed distinct spatial patterns of ignition probability across the state (Figure 3.3). Ignition probabilities tended to be reduced with proximity to urban areas, interstate corridors, and in grasslands compared to forests. The western portion of the state had the least probability of fire ignition, while the central and eastern portions of the state had the greatest probability of ignition.

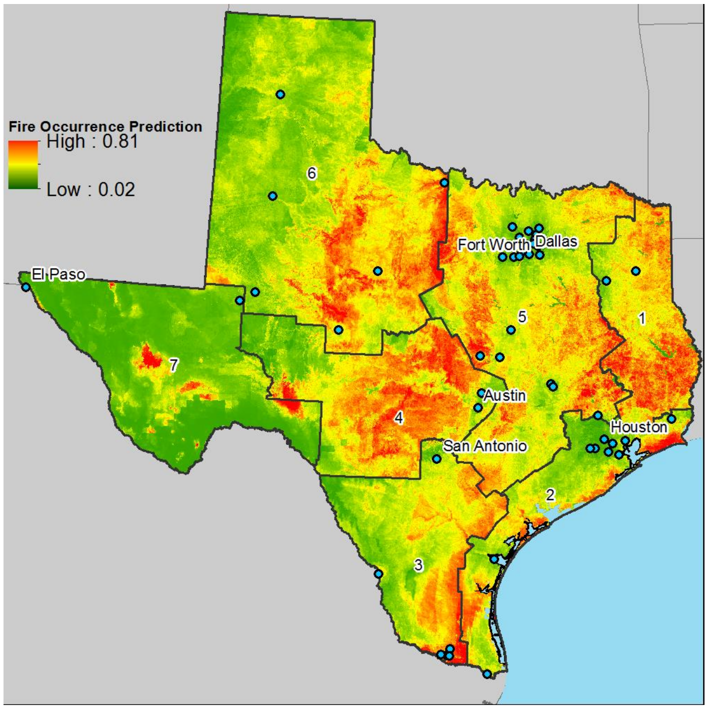

Figure 3.3: Suitability prediction of fire occurrence overlaid with the 50 largest cities in Texas.

Discussion

Comparing the differences in fire suitability across regions and broader spatial extents is important because the scale of fire model and analysis may directly impact the implications and analyses of the model. The regional analysis comparison was in agreement with existing knowledge that regional fire distribution models contain more relative detail than larger extents of analysis. Previous multi-scale studies using SDMs for fire modeling suggest that there are potentially large differences in relative importance of predictor variables at different scales of analysis (Parisien and Moritz 2009).

The suppressive effects of human population centers on fire

Human suppression of fire has been widespread for centuries, and the development of modern firefighting equipment and processes has made fire suppression increasingly effective in modern history. This ability to respond to fire events has been noted in recent literature to change fire regimes and greatly exclude ignitions and fire (Parisien et al. 2016). In the modeling, this pattern of exclusion held true throughout all of the regions analyzed in this study. There was a noticeable decrease in fire suitability in proximity to population centers, and major population corridors such as those along Interstate 35 created a large exclusionary zone covering a wide swath of the state.

The larger metro areas seemed to have a greater extent of suppression in comparison to smaller urban areas. This is likely attributed to the ability of larger cities and metro areas to hire and maintain fulltime firefighters, which are able to respond to fires more rapidly compared to volunteer fire crews (Kloot 2009). Additionally, increased road densities in lands near metropolitan areas allow for faster and more direct navigation to the fire, and for firefighting resources to deploy rapidly on-site (Arienti et al. 2006). This was represented through the distance to city boundary and distance to highway variables, which were most represented in 6 of the 7 regions.

Landcover and Climate effects on fire occurrence

In an area with a diversity of vegetation and climate like Texas, the influence of climate in predicting fire was readily apparent. While climate in the Western United

States has been tied to fire occurrence (Westerling et al. 2006), I found that this held true in Texas as well. The regions where precipitation was most influential were the regions that tended to have drier climates, though precipitation was also predictive to a lesser degree in the wetter regions as well. These dry regions often receive precipitation irregularly, and as a result biomass accumulation in fuels is directly related to water availability (Lenihan et al. 2003). Thus, when precipitation is more plentiful fuels accumulate in the form of additional plant growth. . The influence of temperature varied greatly per region. The Maximum temperature of the warmest month was influential in the south and central Texas regions, while the northernmost regions was more effected by the mean annual temperature. These temperature influences may be attributable to the evapotranspiration potential of the fuels, and therefore fuel moisture. This is similar to what Parisien and Moritz (2009) found in their study of California, wherein areas with higher temperatures and increased precipitation are expected to have more fires occur.

Study Limitations

One of the largest limitations of modeling fire occurrences within the state of Texas is that there is no mandated recording of prescribed burning (TCEQ 2015). As a result, quantifying the number of prescribed fires is difficult. This is evidenced by a section of the coastline between Houston and the Louisiana/Texas border. This region has a large number of wildlife refuges in the area that are frequently burned by the Fish & Wildlife Service and Texas Parks and Wildlife. Additionally, this region is also home to a large number of oil refineries, whose thermal output from gas venting, industrial accidents, and other events may also skew fire detection and prediction towards excess fire occurrence.

Conclusion

I compared the differences in fire prevalence based on variable importance, prediction maps, and performance across seven regions of Texas using Maxent. Across each region, there were variations in model performance and predictive variables for fire. From these results, the influence of climate and human activity on fire is great and provides new insights into fire occurrence within the state of Texas. Most noteworthy was the effect of increased precipitation in Texas corresponding with increased probabilities of fire occurrence, and the inhibitory effect of human roads and population centers reducing the likelihood of fire. Considering the increasing population of many urban parts of Texas and the warming climate globally, future work is needed to further understand the impacts of these changes on future fire occurrences.

CHAPTER IV

CONCLUSIONS

The modeling of fire occurrences in Texas using Maxent has improved our understanding on the controls of fire distributions in an under-studied region of the United States. The scale of modeling is important for determining the types of controls on fire. At the state level, precipitation is the largest predictor of fire distribution across Texas. Additionally, given future climate scenarios of changing temperature and precipitation patterns, the models predicted a slight increase in fire probability in the coastal and plains regions, while a slight decrease in fire probability was modeled for the central and eastern portions of the state. At the regional level, the environmental controls on fire changed, and became distinctly different across each of the seven regions. Human populations had a suppressive effect on fire occurrence throughout Texas, especially in the more fire prone eastern and central portions of the state.

Future work should focus on increasing the scope of the model to the rest of the South-Central and Southeast United States. Given the ecological and historical importance of fire in these regions, enhancing our understanding of fire occurrences is critical to predicting future changes in fire distribution. Additionally, very small-scale models at the ecoregion or county level may further advance predictions of local fire probabilities. As such, this modeling method may lend itself to future fire incident applications.

The importance of fire across the state is apparent in both managing and maintaining natural resources along with mitigating negative fire effects on human lives and structures. With changing climate patterns in Texas bringing warmer and somewhat wetter conditions, the likelihood for more intense wildland fires is a threat even if the overall suitability for fires is decreased. Additionally, given increasing population projections for the state, small fires may become increasingly suppressed near cities, while extreme fires threaten larger areas of human habitation due to expansion of the wildland-urban interface.

REFERENCES

Albert, B. M. 2007. Climate, Fire, and Land-Use History in the Oak-Pine-Hickory Forests of Northeast Texas During the Past 3500 Years. Castanea **72**:82-91.

Anderson, R. P., M. Dudík, S. Ferrier, A. Guisan, R. J Hijmans, F. Huettmann, J. R Leathwick, A. Lehmann, J. Li, and L. G Lohmann. 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography **29**:129-151.

Archer, S. 1994. Woody plant encroachment into southwestern grasslands and savannas: rates, patterns and proximate causes. Ecological implications of livestock herbivory in the West **1**.

Archibald, S., D. P. Roy, V. WILGEN, W. Brian, and R. J. SCHOLES. 2009. What limits fire? An examination of drivers of burnt area in Southern Africa. Global Change Biology **15**:613-630.

Arienti, M. C., S. G. Cumming, and S. Boutin. 2006. Empirical models of forest fire initial attack success probabilities: the effects of fuels, anthropogenic linear features, fire weather, and management. Canadian Journal of Forest Research **36**:3155-3166.

Austin, M. 2007. Species distribution models and ecological theory: a critical assessment and some possible new approaches. Ecological Modelling **200**:1-19.

Austin, M. P., and K. P. Van Niel. 2011. Improving species distribution models for climate change studies: variable selection and scale. Journal of biogeography **38**:1-8.

Bar Massada, A., A. D. Syphard, S. I. Stewart, and V. C. Radeloff. 2013. Wildfire ignition-distribution modelling: a comparative study in the Huron?Manistee National Forest, Michigan, USA. International Journal of Wildland Fire **22**:174.

Barbero, R., J. Abatzoglou, N. Larkin, C. Kolden, and B. Stocks. 2015. Climate change presents increased potential for very large fires in the contiguous United States. International Journal of Wildland Fire **24**:892-899.

Batllori, E., M. A. Parisien, M. A. Krawchuk, and M. A. Moritz. 2013. Climate change-induced shifts in fire for Mediterranean ecosystems. Global Ecology and Biogeography **22**:1118-1129.

Beaty, R. M., and A. H. Taylor. 2001. Spatial and temporal variation of fire regimes in a mixed conifer forest landscape, Southern Cascades, California, USA. Journal of biogeography **28**:955-966.

Booth, T. H., H. A. Nix, J. R. Busby, and M. F. Hutchinson. 2014. BIOCLIM: the first species distribution modelling package, its early applications and relevance to most current MAXENT studies. Diversity and Distributions **20**:1-9.

Bowman, D. M., J. Balch, P. Artaxo, W. J. Bond, M. A. Cochrane, C. M. D'antonio, R. DeFries, F. H. Johnston, J. E. Keeley, and M. A. Krawchuk. 2011. The human dimension of fire regimes on Earth. Journal of biogeography **38**:2223-2236.

Braunisch, V., J. Coppes, R. Arlettaz, R. Suchant, H. Schmid, and K. Bollmann. 2013. Selecting from correlated climate variables: a major source of uncertainty for predicting species distributions under climate change. Ecography **36**:971-983.

Breiman, L. 2001. Random forests. Machine learning **45**:5-32.

Brown, T. J., B. L. Hall, C. R. Mohrle, and H. J. Reinbold. 2002. Coarse assessment of federal wildland fire occurrence data. Report for the National Wildfire Coordinating Group, CEFA Report:02-04.

Bureau, U. C. 2010. Texas Population Census.

Catry, F. X., F. C. Rego, F. L. Bação, and F. Moreira. 2010. Modeling and mapping wildfire ignition risk in Portugal. International Journal of Wildland Fire **18**:921-931.

Chuvieco, E., L. Giglio, and C. Justice. 2008. Global characterization of fire activity: toward defining fire regimes from Earth observation data. Global Change Biology **14**:1488-1502.

Crosby, J. S. 1954. Probability of fire occurrence can be predicted.

Dale, V. H., L. A. Joyce, S. McNulty, R. P. Neilson, M. P. Ayres, M. D. Flannigan, P. J. Hanson, L. C. Irland, A. E. Lugo, and C. J. Peterson. 2001. Climate change and forest disturbances: climate change can affect forests by altering the frequency, intensity, duration, and timing of fire, drought, introduced species, insect and pathogen outbreaks, hurricanes, windstorms, ice storms, or landslides. BioScience **51**:723-734.

De Luis, M., M. J. Baeza, J. Raventós, and J. C. González-Hidalgo. 2004. Fuel characteristics and fire behaviour in mature Mediterranean gorse shrublands. International Journal of Wildland Fire **13**:79-87.

Dennison, P. E., S. C. Brewer, J. D. Arnold, and M. A. Moritz. 2014. Large wildfire trends in the western United States, 1984-2011. Geophysical Research Letters **41**:2928-2933.

Dwyer, K., and R. Holte. 2007. Decision tree instability and active learning. Pages 128-139 *in* European Conference on Machine Learning. Springer.

Elith, J., and C. H. Graham. 2009. Do they? How do they? WHY do they differ? On finding reasons for differing performances of species distribution models. Ecography **32**:66-77.

Elith, J., C. H. Graham*, R. P. Anderson, M. Dudík, S. Ferrier, A. Guisan, R. J. Hijmans, F. Huettmann, J. R. Leathwick, A. Lehmann, J. Li, L. G. Lohmann, B. A. Loiselle, G. Manion, C. Moritz, M. Nakamura, Y. Nakazawa, J. McC. M. Overton, A. Townsend Peterson, S. J. Phillips, K. Richardson, R. Scachetti-Pereira, R. E. Schapire, J. Soberón, S. Williams, M. S. Wisz, and N. E. Zimmermann. 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography **29**:129-151.

Elith, J., and J. R. Leathwick. 2009. Species distribution models: ecological explanation and prediction across space and time. Annual review of ecology, evolution, and systematics **40**:677-697.

Elith, J., J. R. Leathwick, and T. Hastie. 2008. A working guide to boosted regression trees. Journal of Animal Ecology **77**:802-813.

Elith, J., S. J. Phillips, T. Hastie, M. Dudík, Y. E. Chee, and C. J. Yates. 2011. A statistical explanation of MaxEnt for ecologists. Diversity and Distributions **17**:43-57.

Ferrarini, A. 2012. Why not use niche modelling for computing risk of wildfires ignition and spreading? Environmental Skeptics and Critics **1**:56.

Fielding, A. H., and J. F. Bell. 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. Environmental conservation **24**:38-49.

Fitzpatrick, M. C., and W. W. Hargrove. 2009. The projection of species distribution models and the problem of non-analog climate. Biodiversity and Conservation **18**:2255-2261.

Flannigan, M. D., M. A. Krawchuk, W. J. de Groot, B. M. Wotton, and L. M. Gowman. 2009. Implications of changing climate for global wildland fire. International Journal of Wildland Fire **18**:483-507.

Frost, C. C. 1993. Four centuries of changing landscape patterns in the longleaf pine ecosystem. Pages 17-43 *in* Proceedings of the Tall Timbers fire ecology conference.

Fusco, E. J., J. T. Abatzoglou, J. K. Balch, J. T. Finn, and B. A. Bradley. 2016. Quantifying the human influence on fire ignition across the western USA. Ecological Applications **26**:2390-2401.

Garcia, C. V., P. Woodard, S. Titus, W. Adamowicz, and B. Lee. 1995. A logit model for predicting the daily occurrence of human caused forest-fires. International Journal of Wildland Fire **5**:101-111.

Giglio, L., T. Loboda, D. P. Roy, B. Quayle, and C. O. Justice. 2009. An active-fire based burned area mapping algorithm for the MODIS sensor. Remote Sensing of Environment **113**:408-420.

Graham, R. T., S. McCaffrey, and T. B. Jain. 2004. Science basis for changing forest structure to modify wildfire behavior and severity.

Gralewicz, N. J., T. A. Nelson, and M. A. Wulder. 2012. Spatial and temporal patterns of wildfire ignitions in Canada from 1980 to 2006. International Journal of Wildland Fire **21**:230-242.

Griffies, S. M., M. Winton, L. J. Donner, L. W. Horowitz, S. M. Downes, R. Farneti, A. Gnanadesikan, W. J. Hurlin, H.-C. Lee, and Z. Liang. 2011. The GFDL CM3 coupled climate model: characteristics of the ocean and sea ice simulations. Journal of Climate **24**:3520-3544.

Guillera-Arroita, G., J. J. Lahoz-Monfort, J. Elith, A. Gordon, H. Kujala, P. E. Lentini, M. A. McCarthy, R. Tingley, and B. A. Wintle. 2015. Is my species distribution model fit for purpose? Matching data and models to applications. Global Ecology and Biogeography **24**:276-292.

Haines, D. A., W. A. Main, and V. J. Johnson. 1970. Relation between the National Fire Danger spread component and fire activity in the Lake States.

Hanley, J. A., and B. J. McNeil. 1982. The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology **143**:29-36.

Hastie, T. J., and R. J. Tibshirani. 1990. Generalized additive models. CRC press.

Hijmans, R., S. Cameron, J. Parra, P. Jones, A. Jarvis, and K. Richardson. 2005a. WorldClim, version 1.3. University of California, Berkeley.

Hijmans, R. J., S. E. Cameron, J. L. Parra, P. G. Jones, and A. Jarvis. 2005b. Very high resolution interpolated climate surfaces for global land areas. International journal of climatology **25**:1965-1978.

Holden, Z. A., and W. M. Jolly. 2011. Modeling topographic influences on fuel moisture and fire danger in complex terrain to improve wildland fire management decision support. Forest Ecology and Management **262**:2133-2141.

Homer, C. G., J. A. Dewitz, L. Yang, S. Jin, P. Danielson, G. Xian, J. Coulston, N. D. Herold, J. Wickham, and K. Megown. 2015. Completion of the 2011 National Land Cover Database for the conterminous United States-Representing a decade of land cover change information. Photogrammetric Engineering and Remote Sensing **81**:345-354.

Ibarra-Montoya, J. L., and F. M. Huerta-Martínez. 2016. Spatial modeling of fires: a predictive tool for La Primavera Forest, Jalisco Mexico. Revista Ambiente & Água **11**:35-49.

Kearney, M., and W. Porter. 2009. Mechanistic niche modelling: combining physiological and spatial data to predict species' ranges. Ecology letters **12**:334-350.

Kearney, M. R., B. A. Wintle, and W. P. Porter. 2010. Correlative and mechanistic models of species distribution provide congruent forecasts under climate change. Conservation Letters **3**:203-213.

Kloot, L. 2009. Performance measurement and accountability in an Australian fire service. International Journal of Public Sector Management **22**:128-145.

Krawchuk, M., S. Cumming, M. Flannigan, and R. Wein. 2006. Biotic and abiotic regulation of lightning fire initiation in the mixedwood boreal forest. Ecology **87**:458-468.

Lafon, C. W. 2010. Fire in the American South: vegetation impacts, history, and climatic relations. Geography Compass **4**:919-944.

Lenihan, J. M., R. Drapek, D. Bachelet, and R. P. Neilson. 2003. Climate change effects on vegetation distribution, carbon, and fire in California. Ecological Applications **13**:1667-1681.

Littell, J. S., and R. B. Gwozdz. 2011. Climatic water balance and regional fire years in the Pacific Northwest, USA: linking regional climate and fire at landscape scales. Pages 117-139 The landscape ecology of fire. Springer.

Liu, C., M. White, and G. Newell. 2009. Measuring the accuracy of species distribution models: a review. Pages 4241-4247 *in* Proceedings 18th World IMACs/MODSIM Congress. Cairns, Australia.

Liu, Y., S. Goodrick, and W. Heilman. 2014. Wildland fire emissions, carbon, and climate: Wildfire–climate interactions. Forest Ecology and Management **317**:80-96.

Lobo, J. M., A. Jiménez-Valverde, and R. Real. 2008. AUC: a misleading measure of the performance of predictive distribution models. Global Ecology and Biogeography **17**:145-151.

Martell, D. L., S. Otukol, and B. J. Stocks. 1987. A logistic model for predicting daily people-caused forest fire occurrence in Ontario. Canadian Journal of Forest Research **17**:394-401.

McKibben, B. 2014. Climate change impacts in the United States: the third national climate assessment. NEW YORK REVIEW 1755 BROADWAY, 5TH FLOOR, NEW YORK, NY 10019 USA.

McMahan, C. A., R. G. Frye, and K. L. Brown. 1984. The vegetation types of Texas. Texas Parks and Wildlife Department, Austin, Texas, USA.

Merow, C., M. J. Smith, and J. A. Silander. 2013. A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. Ecography **36**:1058-1069.

Morgan, P., C. C. Hardy, T. W. Swetnam, M. G. Rollins, and D. G. Long. 2001. Mapping fire regimes across time and space: understanding coarse and fine-scale fire patterns. International Journal of Wildland Fire **10**:329-342.

Moritz, M. A., M.-A. Parisien, E. Batllori, M. A. Krawchuk, J. Van Dorn, D. J. Ganz, and K. Hayhoe. 2012. Climate change and disruptions to global fire activity. Ecosphere **3**:1-22.

Murdock, S. H., S. White, M. N. Hoque, B. Pecotte, X. You, and J. Balkan. 2002. The Texas challenge in the twenty-first century: Implications of population change for the future of Texas. Department of Rural Sociology, Texas A&M University System Departmental technical report **1**.

Nowacki, G. J., and M. D. Abrams. 2008. The demise of fire and “mesophication” of forests in the eastern United States. BioScience **58**:123-138.

Parisien, M.-A., C. Miller, S. A. Parks, E. R. DeLancey, F.-N. Robinne, and M. D. Flannigan. 2016. The spatially varying influence of humans on fire probability in North America. Environmental Research Letters **11**:075005.

Parisien, M.-A., and M. A. Moritz. 2009. Environmental controls on the distribution of wildfire at multiple spatial scales. Ecological Monographs **79**:127-154.

Parisien, M.-A., S. A. Parks, M. A. Krawchuk, M. D. Flannigan, L. M. Bowman, and M. A. Moritz. 2011. Scale-dependent controls on the area burned in the boreal forest of Canada, 1980–2005. Ecological Applications **21**:789-805.

Parisien, M.-A., S. A. Parks, M. A. Krawchuk, J. M. Little, M. D. Flannigan, L. M. Gowman, and M. A. Moritz. 2014. An analysis of controls on fire activity in boreal Canada: comparing models built with different temporal resolutions. Ecological Applications **24**:1341-1356.

Parisien, M.-A., S. Snetsinger, J. A. Greenberg, C. R. Nelson, T. Schoennagel, S. Z. Dobrowski, and M. A. Moritz. 2012. Spatial variability in wildfire probability across the western United States. International Journal of Wildland Fire **21**:313.

Parks, S. A., M.-A. Parisien, and C. Miller. 2011. Multi-scale evaluation of the environmental controls on burn probability in a southern Sierra Nevada landscape. International Journal of Wildland Fire **20**:815-828.

Pausas, J. G., and S. Paula. 2012. Fuel shapes the fire–climate relationship: evidence from Mediterranean ecosystems. Global Ecology and Biogeography **21**:1074-1082.

Pearce, D. W. 2001. The economic value of forest ecosystems. Ecosystem health **7**:284-296.

Pearce, J., and S. Ferrier. 2000. An evaluation of alternative algorithms for fitting species distribution models using logistic regression. Ecological Modelling **128**:127-147.

Pechony, O., and D. T. Shindell. 2010. Driving forces of global wildfires over the past millennium and the forthcoming century. Proceedings of the National Academy of Sciences **107**:19167-19170.

Peters, M. P., L. R. Iverson, S. N. Matthews, and A. M. Prasad. 2013. Wildfire hazard mapping: exploring site conditions in eastern US wildland–urban interfaces. International Journal of Wildland Fire **22**:567-578.

Peterson, A. T. 2003. Predicting the geography of species' invasions via ecological niche modeling. The quarterly review of biology **78**:419-433.

Phillips, S. J., R. P. Anderson, and R. E. Schapire. 2006. Maximum entropy modeling of species geographic distributions. Ecological Modelling **190**:231-259.

Phillips, S. J., M. Dudík, J. Elith, C. H. Graham, A. Lehmann, J. Leathwick, and S. Ferrier. 2009. Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data. Ecological Applications **19**:181-197.

Plucinski, M., G. McCarthy, J. Hollis, and J. Gould. 2012. The effect of aerial suppression on the containment time of Australian wildfires estimated by fire management personnel. International Journal of Wildland Fire **21**:219-229.

Porfirio, L. L., R. M. Harris, E. C. Lefroy, S. Hugh, S. F. Gould, G. Lee, N. L. Bindoff, and B. Mackey. 2014. Improving the use of species distribution models in conservation planning and management under climate change. PLoS ONE **9**:e113749.

Raes, N., and H. ter Steege. 2007. A null-model for significance testing of presence-only species distribution models. Ecography **30**:727-736.

Rainwater, S. T. D. B. T. K. A. 2013. Assessment of General Circulation Models for Water-Resources Planning Applications. Texas Water Development Board.

Renard, Q., R. Pélissier, B. Ramesh, and N. Kodandapani. 2012. Environmental susceptibility model for predicting forest fire occurrence in the Western Ghats of India. International Journal of Wildland Fire **21**:368-379.

Riley, S. J. 1999. Index That Quantifies Topographic Heterogeneity. intermountain Journal of sciences **5**:23-27.

Sala, O. E., and J. M. Paruelo. 1997. Ecosystem services in grasslands. Nature's services: Societal dependence on natural ecosystems:237-251.

Scheffer, M., S. Carpenter, J. A. Foley, C. Folke, and B. Walker. 2001. Catastrophic shifts in ecosystems. Nature **413**:591-596.

Schoennagel, T., T. T. Veblen, and W. H. Romme. 2004. The interaction of fire, fuels, and climate across Rocky Mountain forests. BioScience **54**:661-676.

Shabani, F., L. Kumar, and M. Ahmadi. 2016. A comparison of absolute performance of different correlative and mechanistic species distribution models in an independent area. Ecology and Evolution **6**:5973-5986.

Staver, A. C., S. Archibald, and S. Levin. 2011. Tree cover in sub-Saharan Africa: Rainfall and fire constrain forest and savanna as alternative stable states. Ecology **92**:1063-1072.

Stephenson, N. L. 1990. Climatic control of vegetation distribution: the role of the water balance. The American Naturalist **135**:649-670.

Swetnam, T. W., and J. L. Betancourt. 1990. Fire-southern oscillation relations in the southwestern United States. Science(Washington) **249**:1017-1020.

Syphard, A. D., and J. Franklin. 2010. Species traits affect the performance of species distribution models for plants in southern California. Journal of Vegetation Science **21**:177-189.

Syphard, A. D., V. C. Radeloff, J. E. Keeley, T. J. Hawbaker, M. K. Clayton, S. I. Stewart, and R. B. Hammer. 2007. Human influence on California fire regimes. Ecological Applications **17**:1388-1402.

TCEQ. 2015. Outdoor Burning in Texas.

Thuiller, W., L. Brotons, M. B. Araújo, and S. Lavorel. 2004. Effects of restricting environmental range of data to project current and future species distributions. Ecography **27**:165-172.

USGS. 2008. Global Land Survey Digital Elevation Model (GLSDEM). Land Cover Facility, University of Maryland.

Varner, J. M., D. R. Gordon, F. E. Putz, and J. K. Hiers. 2005. Restoring Fire to Long-Unburned Pinus palustris Ecosystems: Novel Fire Effects and Consequences for Long-Unburned Ecosystems. Restoration Ecology **13**:536-544.

Viegas, D., M. Viegas, and A. Ferreira. 1992. Moisture content of fine forest fuels and fire occurrence in central Portugal. International Journal of Wildland Fire **2**:69-86.

Ward, G., T. Hastie, S. Barry, J. Elith, and J. R. Leathwick. 2009. Presence-only data and the EM algorithm. Biometrics **65**:554-563.

Westerling, A. L., H. G. Hidalgo, D. R. Cayan, and T. W. Swetnam. 2006. Warming and earlier spring increase western US forest wildfire activity. science **313**:940-943.

Whitlock, C., and C. Larsen. 2002. Charcoal as a fire proxy. Pages 75-97 Tracking environmental change using lake sediments. Springer.

Wotton, B. M., C. A. Nock, and M. D. Flannigan. 2010. Forest fire occurrence and climate change in Canada. International Journal of Wildland Fire **19**:253-271.

APPENDIX

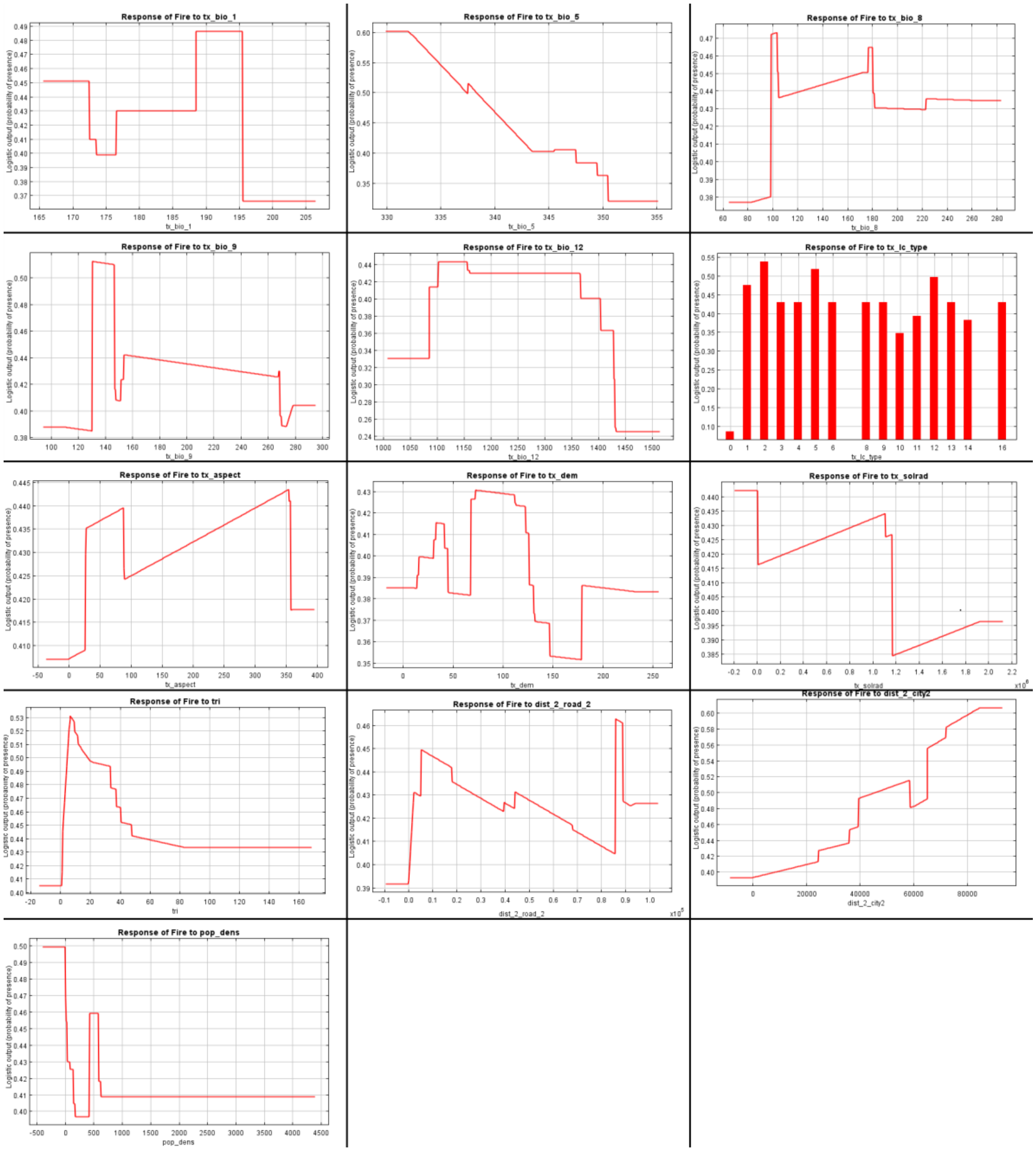

Figure A.1: Variable response curves for the environmental variables modeling fire in the Eastern Texas region. The variation in fire probability is provided across the range of values present for each variable.

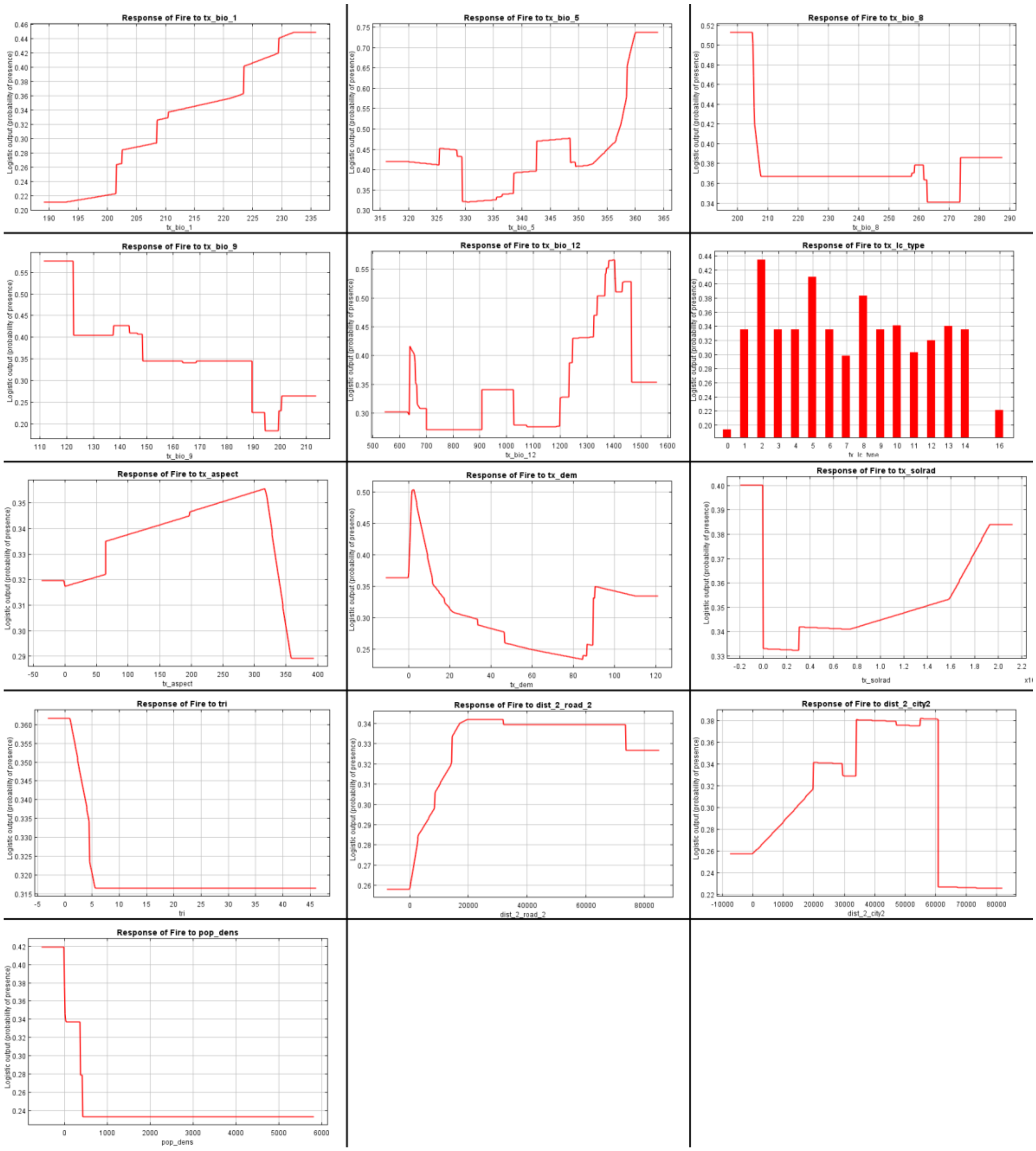

Figure A.2: Variable response curves for the environmental variables modeling fire in the Texas gulf coast. The variation in fire probability is provided across the range of values present for each variable.

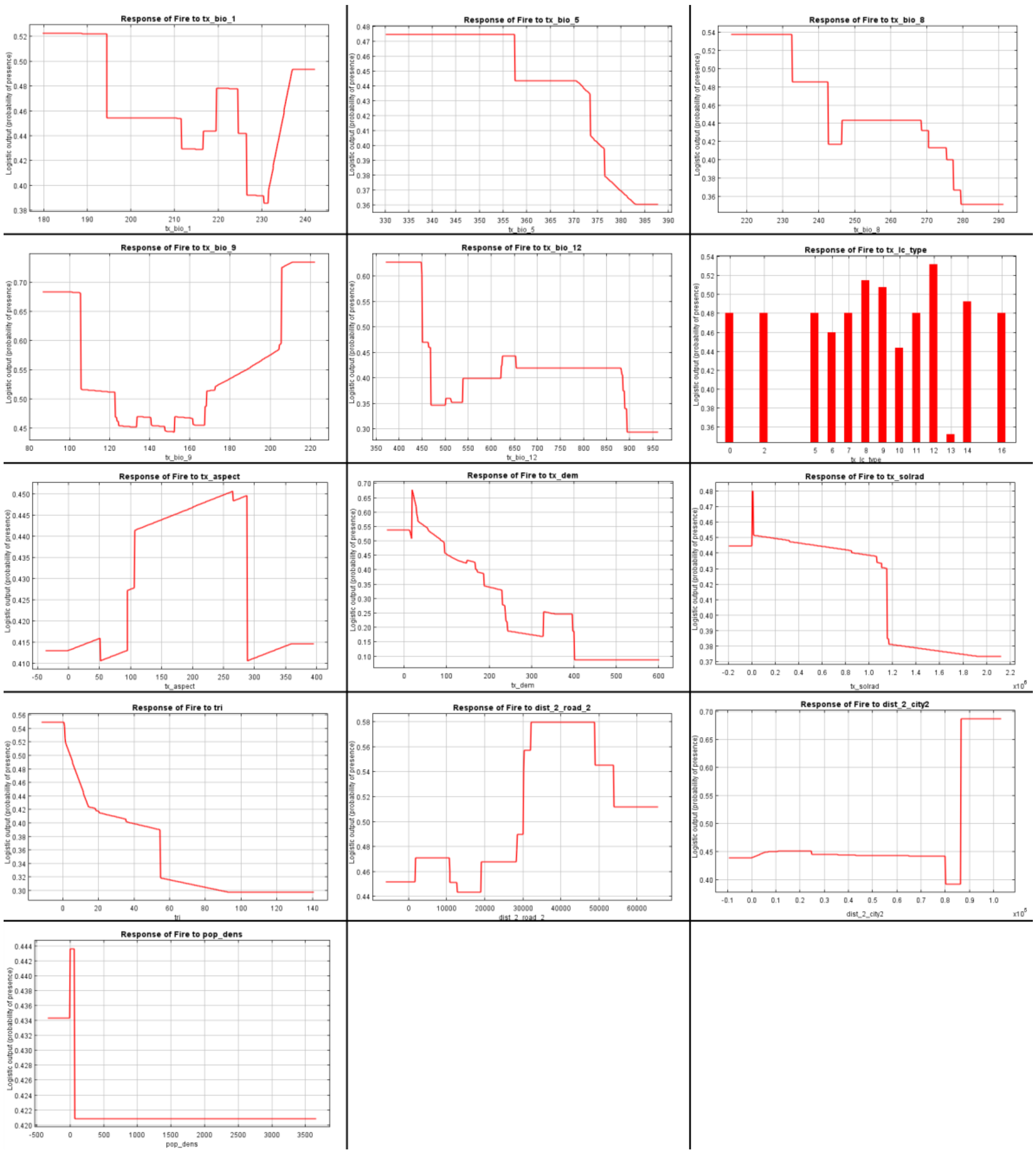

Figure A.3: Variable response curves for the environmental variables modeling fire in southern Texas. The variation in fire probability is provided across the range of values present for each variable.

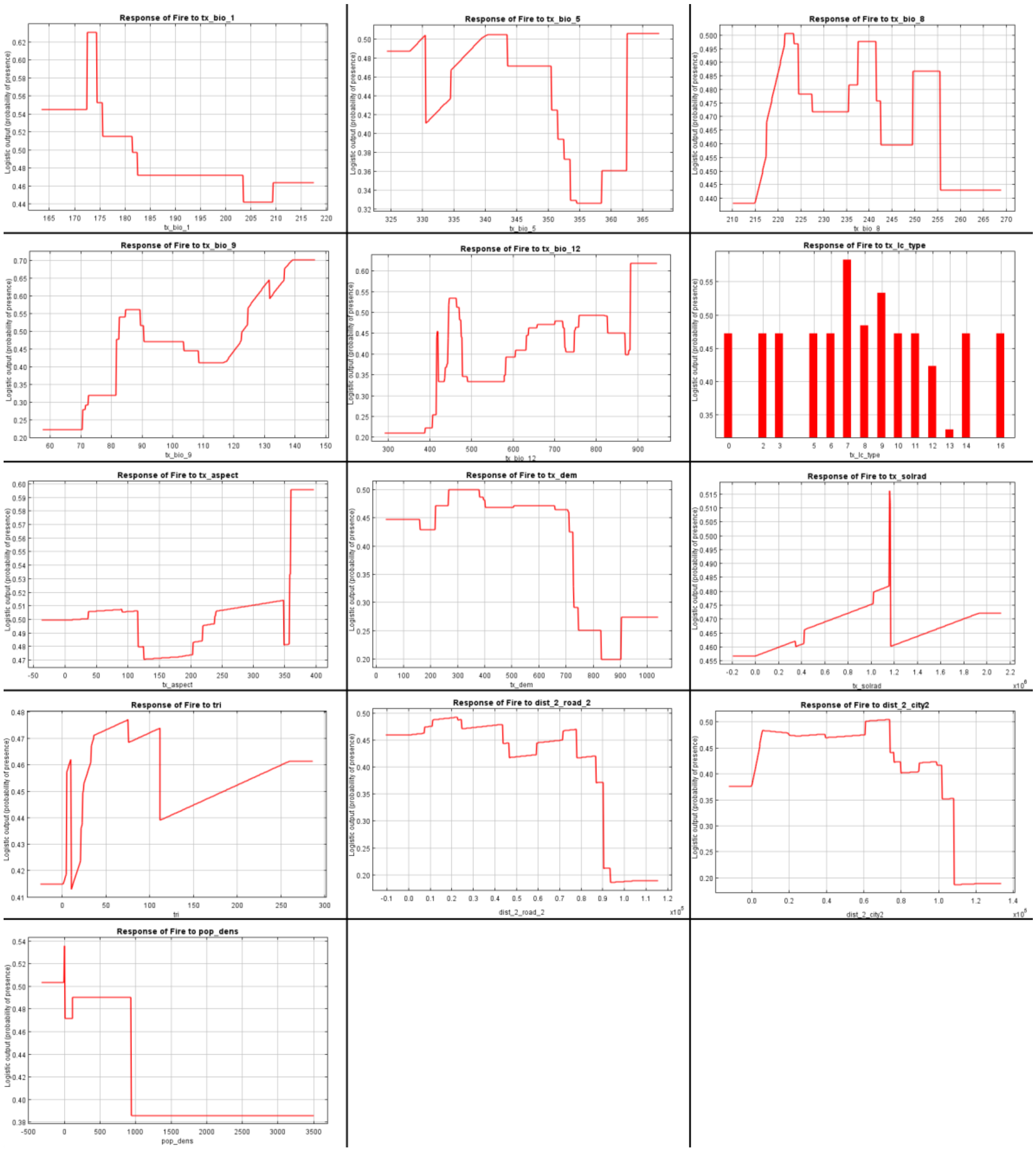

Figure A.4: Variable response curves for the environmental variables modeling fire in the Edwards Plateau of Texas. The variation in fire probability is provided across the range of values present for each variable.

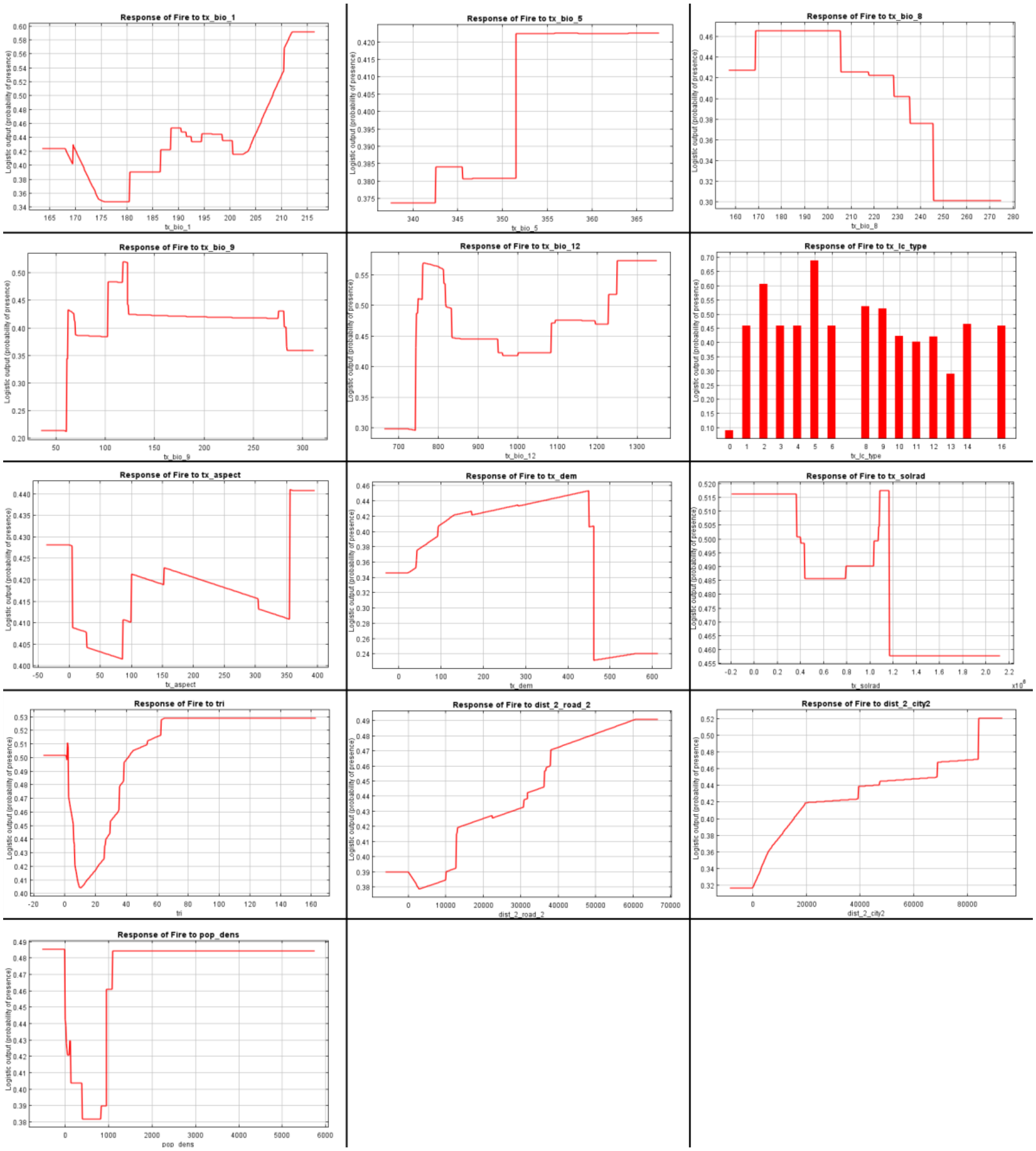

Figure A.5: Variable response curves for the environmental variables modeling fire in the Cross-Timbers of Texas. The variation in fire probability is provided across the range of values present for each variable.

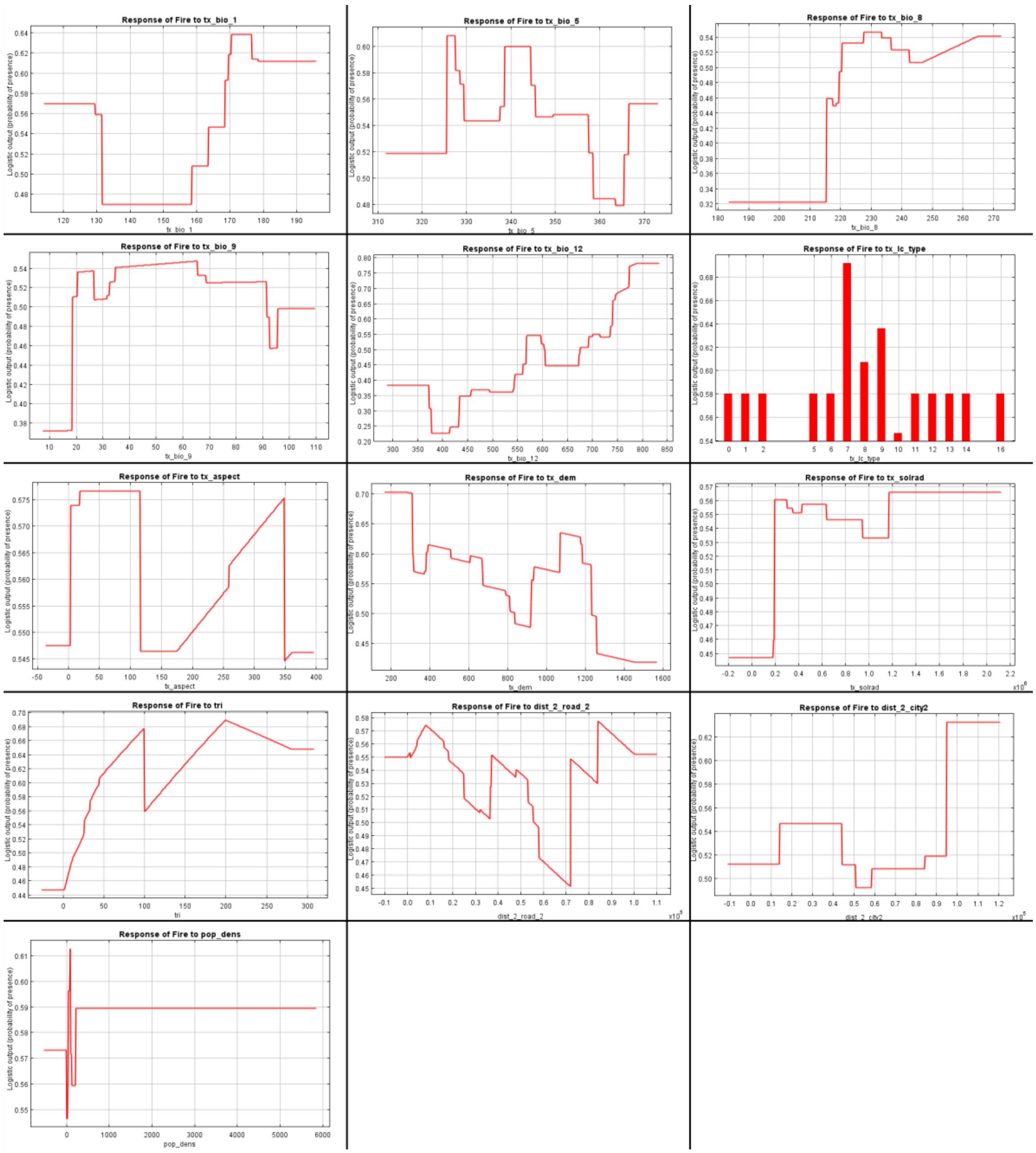

Figure A.6: Variable response curves for the environmental variables modeling fire in the Texas Panhandle. The variation in fire probability is provided across the range of values present for each variable.

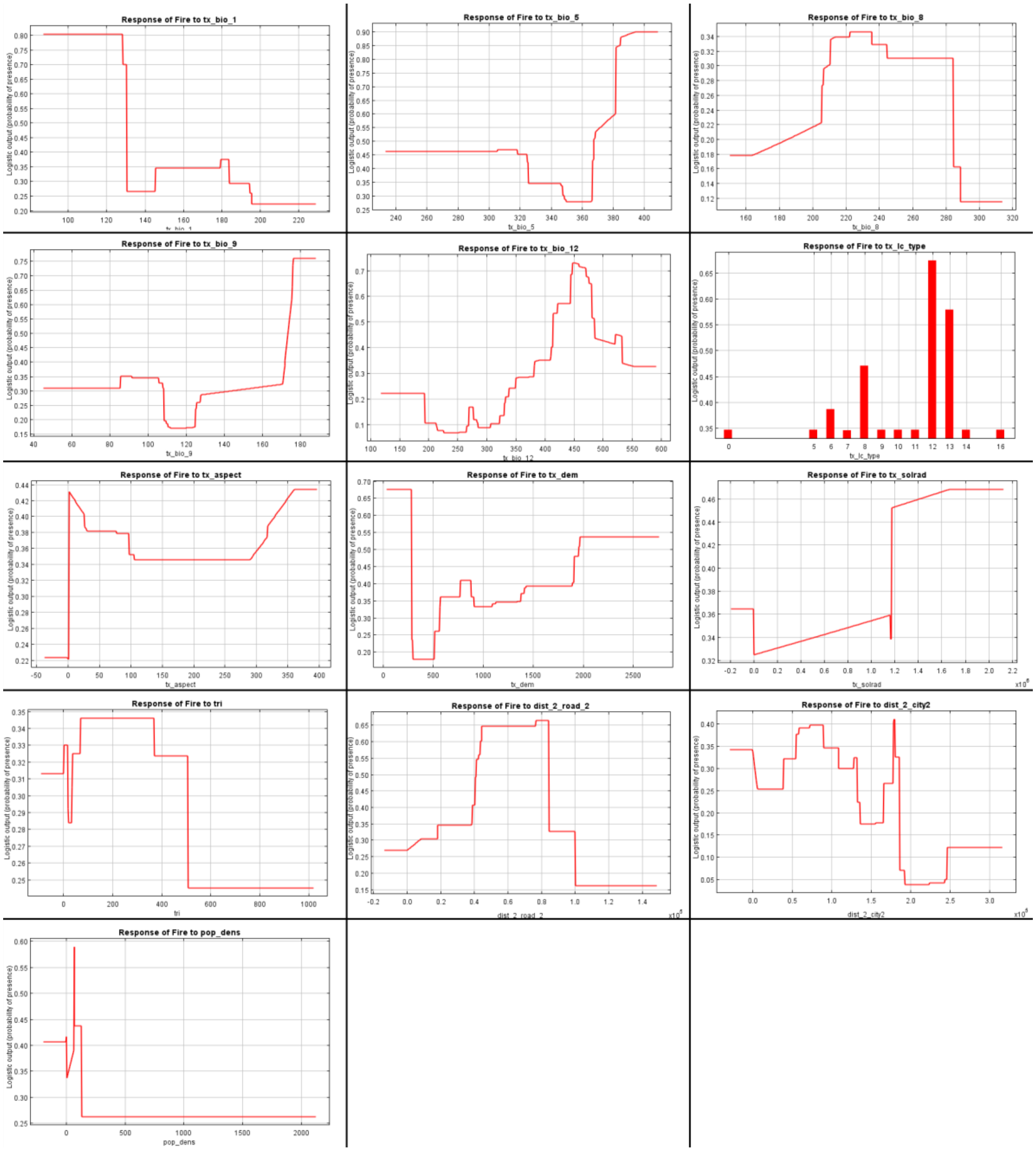

Figure A.7: Variable response curves for the environmental variables modeling fire in the Trans-Pecos region of Texas. The variation in fire probability is provided across the range of values present for each variable.