HOW DOES WILDFIRE RISK DIFFER ACROSS A LANDSCAPE GIVEN HETEROGENEOUS DEVELOPMENT PATTERNS?

A Dissertation

by

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ABSTRACT

This study explores the variation in wildfire risk from different development patterns. The analysis tests how an assortment of variables within the fire risk framework are affected by differing lateral development types. The study area covered Bastrop and Travis counties located in Texas. Two time periods were used in the assessment 2001 and 2012.

Lateral development was categorized into five categories: infill, radial, isolated, clustered, and linear. Within the fire risk framework, fire severity, ignition probability, and burn probability were assessed for the study area. Maximum Entropy was used to spatially predict ignition probability. Burn probability and conditional flame length were simulated using the Minimum Travel Time algorithm.

Ignition probability variation was assessed using a one-way ANOVA and *post hoc* analysis. Burn probability and conditional flame length analyses were more robust. One-way ANOVAs and *post hoc* analyses were used to differentiate variation among lateral development types. Generalized Methods of Moments were used to estimate changes in burn probability and conditional flame length across time. Finally, the simulation's fire perimeters were analyzed for initiation and exposure using social network analysis techniques.

Analyses found that outlying development patterns: isolated, clustered, linear, were at higher wildfire risk than infill and radial development. However, most simulated fires initiated nearest radial development. Being closer to a road increased the likelihood of ignition, but increases in road density decreased burn probability. Changes in fuel loading had a positive correlation with changes in conditional flame length and burn probability. The analysis suggests that increasing populations in the wildland-urban interface are increasing their risk. Policies that reduce the outlying development patterns will reduce risk for the community.

DEDICATION

To my wife, Rachael

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All work for the dissertation was completed by the student, under the advisement of Dr. Highfield and Dr. Brody of the Department of Landscape Architecture and Urban Planning.

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NOMENCLATURE

AUC	Area Under the Curve
BP	Burn Probability
CFL	Conditional Flame Length
CWPP	County Wildland Protection Plan
FLP	Flame Length Probability
HVR	Highly Valued Resources
IP	Ignition Probability
ROC	Receiver Operating Characteristic
SNA	Social Network Analysis
WUI	Wildland-Urban Interface
Δt_1	Development that has occurred between 1992 and 2001
Δt_2	Development that has occurred between 2001 and 2012

Study Time Periods

2001	1999 - 2003
2012	2010 - 2014

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CHAPTER I INTRODUCTION

I.1 Problem Statement

Wildfire risk has progressively worsened due to the enactment of fire suppression policy in the early 1900's. This has come to a head recently, with seven of the most destructive fire seasons occurring in the last 15 years. Four of those fire seasons have burned over 9 million acres (NIFC 2017a). For example, the 2015 fire season was the first fire season on record to eclipse 10 million acres. Federal agencies are spending more each year to stop wildfires (NIFC 2017b). accounting for inflation, suppression expenditures have quadrupled since 1985 (2015 $1.9 billion). Despite increased spending, wildfires burn thousands of structures yearly (NIFC 2017c). These losses are due to the increase in acres burned and an expanding wildland-urban interface (WUI; Martinuzzi et al. 2015).

Within the United States, the creation of the Federal Housing Administration reduced constraints for financing the development of single family homes (Farrell 2002). These actions stimulated the growth of single family development into increasingly suburban and exurban areas, many of which were previously wildlands. Areas of developed lands surrounded by wilderness are the most vulnerable to wildfire (Radeloff *et al.* 2005). Previous research has quantified the interactions between development patterns and fire risk through statistical models. However, due to the complex nature of wildfires, previous research has failed to address the influence of wildfire behavior and how it moves through a community. A more comprehensive wildfire risk assessment is required to assess wildfire behavior. This study explores fire ignition, subsequent movement, and estimates large wildfire probability and severity. Understanding how development patterns influence wildfire risk in the WUI will help planners and policymakers understand the way to develop in a safer manner.

I.2 Research Question and Objectives

This dissertation addresses the overarching question: *What role does development play in shifting wildfire risk on the landscape?* Answering this question was accomplished by assessing changes in development patterns and other mediating variables for Travis and Bastrop counties in Texas between 2000 and 2012. More specifically, I address two complimentary questions: 1) How do changing development patterns affect fire risk? 2) How do the mediating variables of road density and fuel loading influence fire risk?

My research objectives to address these questions include:

I. Quantify development patterns through fragmentation and patch characteristics.

II. Derive ignition location maps through maximum entropy models to predict fire location maps (2000, 2008, & 2010) from development characteristics and socio-economic variables.

III. Create fire risk maps using deterministic fire behavior models for two sets of years (2000 and 2012).

IV. Validate fire risk maps using historic fire data to estimate the models' sensitivity.

V. Quantify the effects that changes in development have on fire risk.

The results of this research challenge the current practice of protecting structures through fine scale fuel reduction. Additionally, results indicate that regional policies that target fuel treatment and land use controls will reduce a community's risk.

I.3 Dissertation Structure

This dissertation consists of seven chapters. Chapter 1 identifies the research problem and objectives and is accompanied by brief background information about their rele-

vance. Chapter 2 reviews the relevant literature for the study. The first body of literature describes the fire risk framework—the backbone of the study, while the second part explores previous research that quantifies development patterns. Finally, Chapter 2 discusses studies that assess both urban patterns and wildfire risk and discusses their findings.

Chapter 3 reviews the preliminary methods used to implement the study, including identifying the study areas and relevant development scales used throughout the study. In addition, Chapter 3 identifies the methods used to categorize development patterns.

Chapters 4 and 5 explore the effects of changes in development on fire risk. Both chapters provide separate literature reviews, methods, and results. In particular, Chapter 4 explores the effects of changes in development patterns on ignition probabilities. This chapter first identifies the statistical methods used in previous research to model a landscape's ignition probability. Chapter 4 then explains the approach used within this study. The third part of the chapter examines the results of the IP model. Chapter 5 adds to the fire risk framework and explores the effects of increased development once a fire has ignited and moves across the landscape. This chapter identifies previous identifies previous wildfire risk studies. Followed by outlining the methods used in this study. Chapter 5 then evaluates the fire risk model for sensitivity and accuracy. These assessments use established evaluation techniques and a novel statistical approach. Finally, Chapter 5 evaluates the interactions between development and fire risk in a series of exploratory and statistical models.

Chapter 6 discusses and synthesizes the results from both Chapters 4 and 5. The chapter identifies the implications of new development on fire risk. Followed by addressing the policy implications of these results. Finally, Chapter 7 concludes the dissertation by describing the key findings, limitations, and directions for future research.

CHAPTER II LITERATURE REVIEW

This chapter identifies and reviews the literature relevant to understanding the interactions between changing development patterns and wildfire risk. This chapter addresses the overarching body of literature relevant for the rest of the dissertation. The chapter has three sections. The first section identifies the fire risk framework literature. The second body of literature focuses on changing development patterns and the WUI. The third body identifies the current understanding of interactions between development and wildfire. Finally, this chapter addresses the gaps and limitations of previous studies.

II.1 Fire Risk Framework

Communities that identify catastrophic risk can adapt and mitigate shocks prior to an occurrence (Beatley 2009). The nature of these shocks varies, whether they are natural (fire, flood, etc.), economic (recession), or technological (i.e. electricity outages). A less resilient community may find a small disturbance becomes a disaster (Paton and Johnston 2006). For example, a small fire may burn an individual tree, and the community gives it little notice. However, given different surrounding fuel composition, weather, and climate conditions, the same small fire might grow and burn thousands of structures. A community can help guide a disturbance towards a more preferred scenario using mitigative actions. In the given example, common practices of total suppression would eliminate the initial fire, but would allow fuel to continue to accumulate, driving the system to a more catastrophic fire in the future (North *et al.* 2015). Another common practice removes the fuel near a structure, which reduces the possibility that the structure will ignite (Dellasala *et al.* 2004). A community can also treat fuels, thus reducing the amount capable of burning and lowering the probability of a fire. By focusing on resilient approaches, a community can address the environmental, economic, and social issues that may help the community cope with a system-level disturbance. However, for a community to adopt resilient approaches,

they must first understand the risks to their region.

Creating a resilient framework requires understanding the probability of a disturbance and which factors shift this probability. Wildland fire research uses a risk framework to understand how fires act. Fire risk assessments occur at various scales, ranging from the home (Mell *et al.* 2010) to the landscape level (Scott 2006). Mell et al. (2010) suggest the key to understanding fire risk is focusing on home ignition and the immediate surroundings. The amount of highly flammable material surrounding a structure dictates the likelihood that a structure will burn (Alexandre *et al.* 2015). Residents can reduce the risk to their homes by following fire adapted codes and recommendations (IIBHS 2015; www.fireadapted.org 2015). Mell et al. (2010) also suggest that community planners should focus on fine scale fire risk. But, by focusing on localized risk, community planners may miss areas of higher risk adjacent to a community or areas of shifting risk. Due to these drawbacks, community planners should also include larger scale (e.g. community or regional level) risk assessments. These assessments can identify high-risk areas for localized planning (BFD 2013).

The fire risk framework is comprised of three components: 1) fire probability, 2) fire behavior, and 3) fire effects (Scott 2006). Understanding fire risk at the community level requires an in depth understanding of the three components. When these components are combined, community planners can better understand the nature of the fire landscape and identify areas with high wildfire risk that should be considered further at a finer resolution (BFD 2013).

II.1.1 Fire Probability

The easiest of the three fire risk components to quantify is fire probability, which quantifies the likelihood that a given location will have a fire (Miller and Ager 2013). Ignition probability (IP) is the likelihood that a fire will ignite; it predicts the possibility that a fire will be initiated at a given location. Burn probability (BP) incorporates fire spread and measures the likelihood of a fire occurring at a specific location. Both BP and IP are usually represented as pixels on a raster. Therefore, BP is a function of IP and fire behavior. This allows BP to be more robust in describing wildfire probability. Details about IP and BP modeling are addressed below.

II.1.1.1 Fire Probability — Ignition

Ignition based models use historic ignition or fire points to gain a better understanding of the spatial nature of wildfire. The point data allows for a variety of methods to understand the nature of the data. For instance, points can be used for a global frequency analysis, which associates ignition rates with larger urban areas across the globe (Syphard *et al.* 2009) or use fires to create an ignition probability raster (Reineking *et al.* 2010). Overall, these analyses allow researchers to understand the fire regime and frequency on the landscape. These models are used to predict deviations from historic patterns across time or space (Bar Massada *et al.* 2013).

One of the major uses of ignition datasets is to create an ignition probability raster. These ignition probability rasters have evolved from species distribution models (Bar Massada *et al.* 2013). Initially, species distribution models predicted the habitat boundaries of a given species (Elith 2000). This was done by creating a contiguous probabilistic raster and then identifying a cutoff probability for the habitat. IP modeling follows the

same process of empirically predicting a contiguous raster where a fire is likely to occur (Scott *et al.* 2012). The IP rasters can be provided in two forms: as a raw dataset or normalized through a log (Elith *et al.* 2011). A normalization is most common due to ease of interpretation (Faivre *et al.* 2014). This follows a logistic normalization:

$$logit(p_i) = \ln\left(\frac{p_i}{1-p_i}\right) \quad [1]$$

This normalization creates a continuous probability between zero and one.

IP models have a variety of uses. Forest managers and land use planners can use to inform County Wildland Protection Plans (CWPP), or to inform initial fire suppression tactics (Syphard and Keeley 2015). IP models can also be used to create a stratified sample for BP models (Bar Massada *et al.* 2011). Using IP models to inform a BP model creates a more realistic simulation model which should enhance sensitivity.

II.1.1.2 Fire Probability — Burn

While IP modeling targets areas for suppression management, the complex drivers of fire on the landscape require a second model to understand the reaches of large fires. BP models use an iterative fire behavior model to estimate the likelihood of a fire occurring at a specific location, traditionally represented by a raster cell. The raster surfaces created by the BP model show the probability of a fire occurring within each cell (Miller and Ager 2013). In its simplest form, BP models can be represented by:

$$BP=F/n \quad [2]$$

Where F is the number of times a fire burned a given pixel and n is the number of fires simulated. IP is generally better for small-scale fires, which may not spread. But, BP modeling helps to understand the nature of large fires (Ager *et al.* 2012).

Understanding the spatial distribution of BP allows planners to target areas at risk

for community outreach (BFD 2013). Identifying high probability areas can help policy makers identify areas that should not develop (Buxton *et al.* 2011). Few plans have recommended avoidance strategies, despite the potential benefits of implementation (Srivastava and Laurian 2006).

II.1.2 Fire Behavior

The location and likelihood of a fire are important aspects of the fire risk framework. But, not all fires burn at the same intensity. Fire behavior includes how a fire reacts based on the landscape and weather conditions (Scott 2006). Fire behavior is closely coupled with fire probability, so BP models are also used to understand fire behavior (Scott 2006).

II.1.3 Fire Effects

Fire effects identify the implications of a fire burning in an area. Understanding fire effects helps assess the vulnerabilities of the landscape (Scott 2006); while many fire effects are considered negative (i.e. structure loss), fires also have positive effects. Many ecosystems are fire adapted, and require fire to remove invasive plants or resprout vegetation (Sugihara 2006). The vulnerable areas of interest on the landscape are considered Highly Valued Resources (HVR). Risk assessments identify these HVR areas and assess the effects that fires will have on them (Calkin *et al.* 2010).

The fire risk framework of fire probability, fire behavior, and fire effects are essential to predicting where losses are likely to occur. The understanding of the fire risk framework will be helpful in drawing conclusions in both chapters 4 and 5.

II.2 Wildland-Urban Interface and Sprawl

For cities, one of the most impactful effects that can occur are structural losses. These losses often occur in the WUI. As discussed below the WUI is a special form of sprawl derived from a city or rural environments. This section discusses the importance of the WUI and sprawl as well as how they have been measured in the past.

II.2.1 Wildland-Urban Interface

In the 1990's suburbanization became such an issue that forest managers began focusing on the protection of the WUI, because these areas are where structures are most at risk (Radeloff *et al.* 2005). Since the importance of the WUI was discovered, research has focused on mapping and understanding the nature (Mell *et al.* 2010) and the best mitigative practices within the WUI (Miller and Ager 2013).

Federal definition categorizes the WUI into two types: intermix and interface. The intermix consists of very low-density structures (>1 structure per 40 acres), while interface areas are higher in density (>3 structures per acre; USDA 2001). These definitions have guided research, yet interpretations vary (Radeloff *et al.* 2005; Bar-Massada *et al.* 2013). When mapping WUI areas, Radeloff et al. (2005) used slightly different definitions: intermix consisted of vegetation (>50%) and low structural density (>1 structure per 40 acres). The interface used the same structural characteristics, but was surrounded by less vegetation (<50%) and located near heavily vegetated areas (>75% within 2.4 km; Radeloff et al. 2005). Other studies have focused on buffers around private lands to identify the WUI (Scott *et al.* 2012; Rodrigues and de la Riva 2014). The varying definitions of the WUI have resulted in varying estimates of the WUI area.

The WUI makes up a significant proportion of land cover in the U.S., approximately 10% in 2010, and an even larger proportion of homes (33.5%, Martinuzzi et al. 2015).

WUI areas are at a higher risk from wildfire since they are adjacent to wildland areas. Syphard et al. (2012) found that lower to intermediate housing densities were more likely to burn than those at higher densities. However, the higher densities referenced in their study were at the urban core, where little fuel exists. Other research suggests that clustering buildings (within 30 meters of each other) within the WUI may increase the chance of those structures burning (Mell *et al.* 2010). While noting the locations of the WUI helps identify areas vulnerable to wildfire, sprawling development patterns vary greatly. One major issue that Mell et al. (2010) identifies with WUI mapping is that it fails to assess vulnerable populations and land covers.

Much of the WUI development occurring near urban areas is due to urban sprawl. Urban sprawl encompasses the majority of the negative characteristics created by urbanization in the 20th century (Knaap and Talen 2005). However, sprawl definitions vary depending on the study and the question addressed (Ewing 1997; Galster *et al.* 2001; Schneider and Woodcock 2008). Research related to sprawl is multi-faceted and may include: the type of development patterns, the degree of population dispersion, the fragmentation of the landscape, the degree of mixed use developments, and the aesthetics of the land along with many other characteristics. The following section will discuss how previous research quantified the development patterns of urban sprawl and the resulting impacts.

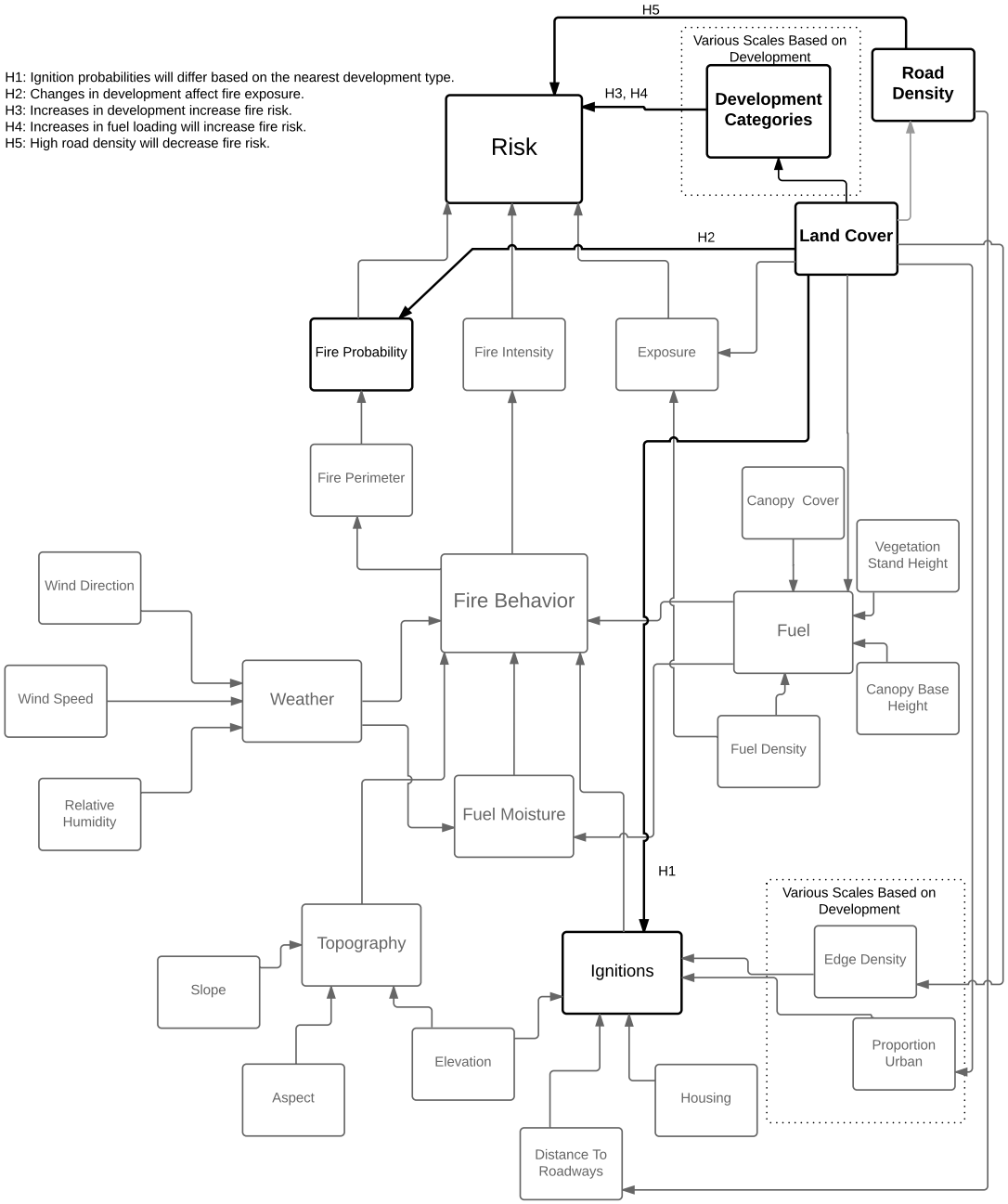
II.2.2 Sprawl and Urban Development Patterns

The term sprawl identifies a systemic issue with recently developed urban environments (Ewing 1997). The advent of the automobile, and federal policies such as the FHA (Farrell 2002), and interstate highway construction, allowed people to move into cheaper lower density housing. Most sprawl develops outwards from the urban core, thus intermixing with wildlands. But, WUI and sprawl research are isolated from one another. The rest of this section addresses the literature that has studied and quantified sprawl.

Sprawl definitions consistently focus on low density development (Ewing 1997; Torrens 2008). Initial urban models imagined cities as monocentric, where the city has one core business area and move outwards from it (Hoyt 1939). However, this model was later challenged, suggesting it failed to account for multi-nodal communities or sector development in the urban environment (Harris and Ullman 1945). Hoyt (1939) suggested three kinds of development patterns: vertical growth, infill growth, and lateral growth. Contemporary sprawl metrics still have some semblance to these initial patterns (Knaap and Talen 2005; Jenerette and Potere 2010). Vertical growth replaces single family homes with higher density larger structures. Infill growth occurs in settled areas where vacant land, either lots or open space, is built upon. Hoyt (1939) suggests that lateral growth occurs in rings moving outward from the central business district. Again, Harris and Ullman (1945) critique the simplicity of Hoyt's model. This simplicity fails to account for multi-nuclearity as well as other developmental characteristics. But, Hoyt's model does show the thought processes in the early stages of urban planning.

More recent research has focused on a landscape's development patterns. Wilson et al. (2003) used metrics focused on a similar approach to Hoyt's (1939) lateral and infill growth. For their research, Wilson et al. (2003) focused on three forms of development patterns: infill growth, expansion, and outlying growth (Figure 1). Based on Wilson et. al. (2003), infill growth occurs when a larger proportion of the surrounding land is developed (>40%), expansion happens when development occurs in an area surrounded by less development (<40%), and outlying growth occurs away from previous development. In addition, outlying growth has three patterns: isolated, linear branch, and new clustered development. Isolated growth consists of small patches of development separate from other development; other research has referred to this as leap frog growth (Ewing 1997;

Figure 1: Conceptual Model. Bold variables identify hypotheses for testing.



Jenerette and Potere 2010; Aguilera *et al.* 2011). Linear branch growth occurs on transportation corridors such as roads and rail lines. One example of linear development is strips of commercial development along a road (Ewing 1997; Schneider and Woodcock 2008). New clustered development consists of multiple structures which are larger than those found in isolated development. For example, clustered developments consist of subdivisions and larger industrial developments.

Lateral growth patterns have also been measured in various ways. For example, Wilson et al. (2003) measured the degree of changes in development between from one year to the next. The authors used the spatial location of new urban development and the threshold of the percentage of surrounding urban (40%) to predict whether an area would be infill or expansion. Other research has used more complex metrics such as contagion (Torrens 2008), fractal dimensions (Lv *et al.* 2012), and interspersion and juxtaposition index to estimate lateral sprawl. Lv et al. (2012) used the fractal dimension to estimate where a city lies on a scale between the states of completely compact and completely dispersed. While Torrens (2008) used contagion to estimate how urban patches were dispersed.

An alternative method to studying development on the landscape uses a regional approach. Research suggests that outlying and infill growth patterns are cyclical. These two patterns grow in a process described as diffusion and coalescence (Dietzel *et al.* 2005b). An urban environment is diffusing when a higher proportion of development is outlying growth. In contrast, an urban environment is coalescing when a higher proportion of urban growth is from infill development (Dietzel *et al.* 2005a). Coalescence of the landscape can occur when multiple smaller urban areas are diffusing towards each other (Li *et al.* 2013). The idea of diffusion and coalescence suggests that today's low density development may become tomorrow's high density development (Torrens 2008).

II.2.2.1 Sprawl — Population Dispersion

Over time, the population density of sprawling urban areas decreases. One explanation for this decrease in density is developmental lateral growth (Schneider and Woodcock 2008). Land use patterns in these sprawling areas are homogenous (Knaap and Talen 2005), consisting of single family housing and strip mall patches (Ewing 1997). Low density sprawling areas maintain their density, leading to decreasing resiliency such as flooding (Brody, Gunn et al. 2011), wildfires (Syphard, Clarke et al. 2007), increased traffic (Ewing, Pendall et al. 2003), or higher infrastructure costs (Carruthers and Ulfarsson 2002).

Population dispersion can be measured in a variety of ways. The most basic method is population density (Jaeger *et al.* 2010). Spatially projected population density used along with development patterns shows population variation by developed lands. Those areas with low populations densities and large amounts of developed lands suggest more sprawl. Another method of understanding sprawl involves the number of housing units instead of population density. Spatially projecting the number of housing units over the landscape explains how buildings and families distribute across the land (Brody *et al.* 2013). Parsing out single family housing (Jaeger *et al.* 2010) and secondary housing density (Romero-Calcerrada *et al.* 2008) creates a finer characterization of sprawl on the landscape. Both measures help to identify areas that use a higher percentage of land than alternative housing practices.

II.2.2.2 Sprawl — Landscape Fragmentation

Urban sprawl fragments wildland areas into smaller patches of vegetation. Fragmentation on the landscape breaks up corridors, reducing the mobility of humans, flora, and fauna (McGarigal 2012). Sprawl from fragmentation is recursive: sprawl creates more

fragmentation, and this increase in fragmentation creates more sprawl (Carruthers and Ulfarsson 2002). Faster growing urban areas tend to be more fragmented, a result of outlying development (Jenerette and Potere 2010). These fragmented areas are dominated by clustered development and isolated growth patterns.

Previous research has used various fragmentation metrics to quantify the landscape. Most of the metrics were simple. For example, patch density measures the number of patches compared with the area of the search window. This metric estimates increases in the number of development patches and how the increases encourage fragmentation (Kong *et al.* 2012). An alternative approach to measuring fragmentation quantifies the degree of development decentralization (Torrens 2008). Alternatively, effective mesh size produces a probability that two locations are within the same patch. Suggesting that as the mesh size decreases, fragmentation increases (Girvetz *et al.* 2008).

II.3 Development and Fire Risk

Few studies have assessed how development of the landscape shifts fire risk. In a cross-sectional study, Chas-Amil et al. (2013) found differences in fire arrangements between a variety of urban patch densities and forest fragmentations. Other research has found a positive correlation between fire frequency and population (Syphard *et al.* 2009). Of the studies focusing on lateral development, evidence suggests that outlying development results in a higher fire frequency than infill (Price and Bradstock 2014).

Another body of research focused on the likelihood of damage to structures. These studies used empirical data and either statistical or machine learning algorithms to estimate structural damage and found that housing density influenced the likelihood of a home burning (Syphard *et al.* 2013; Alexandre *et al.* 2015). Outlying development is the most likely to burn, followed by expansion and infill (Syphard *et al.* 2013). Small, high-den-

sity clusters of development were more at risk for burning than other development types (Alexandre *et al.* 2015). Increasing the number of structures near a fire increases the cost to suppress the fire. These costs vary by development pattern. For instance, areas with individual homes disproportionately increase the suppression costs compared to areas of clustered homes (Clark 2016).

Related studies suggest that a landscape's fuel connectivity and loading will influence structural losses (Alexandre *et al.* 2015). Bar-Massada et al. (2009) suggested that breaks in roadways create unpredictable changes to fire risk. However, the direct effects of spatial composition and fuel load have not been tested. Despite fuel composition around a structure dictating structure loss (Mell *et al.* 2010; Alexandre *et al.* 2015). For flatter areas, such as the plains states, wind speed is considered a more relevant factor for structural loss than topography (Alexandre *et al.* 2016).

II.4 Limitations and Gaps in the Literature

Research has shown that development influences wildfires in many ways. Yet previous studies have struggled to accurately quantify this influence. For instance, Chas Amil et al. (2013) used an ANOVA test to differentiate between the number of fires within different urban patch densities and forest fragmentation. However, without *post hoc* analysis, an ANOVA does not determine which types of development have a higher frequency of fires. Syphard et al. (2009) directly compared fire frequency and population, finding higher population densities was the most important factor in fire frequency. However, this study used a coarse resolution (1 km) and may not completely translate to finer landscape and local scales. Both assessments used a cross-sectional design that failed to consider population changes over time and the impact on fire frequency.

Risk modeling research provides various approaches for studying the distributing

ignitions used in fire models. The two main approaches are a random distribution and a weighted distribution for ignition samples. A random ignition distribution model is commonly used if ignitions on the landscape are lightning based (Ager *et al.* 2014) or assumed to be random distributions (Bowman Consulting Group 2014). In areas dominated by anthropogenic fires, or another understood distribution pattern, a weighted ignition sample is preferred. In this process, ignitions are weighted from an ignition density map (Scott *et al.* 2012) or through the use of an IP model (Bar Massada *et al.* 2011).

Many researchers and planners assume that the WUI is increasing (Rasker 2014; Martinuzzi *et al.* 2015). However, studies from 2005 and 2015 have shown that the total area that meets the requirements for WUI within the U.S. has change relatively little (+0.5%), but the WUI within individual states has shifted in different ways (California -0.5%, North Carolina -0.7%, New Hampshire +2.9%) compared with the national average (Radeloff *et al.* 2005; Martinuzzi *et al.* 2015). These shifting percentages do not suggest that California will continually lose WUI. Instead, applying the concept of Diffusion and Coalescence suggests that while new development is occurring in the wildlands, infill and radial development is occurring around older development. This removes fuel from older areas and shifts the WUI. This was corroborated by a simulation study of Los Angeles that found no net growth of the WUI despite differing types of development patterns (Syphard *et al.* 2007a), suggesting that Diffusion and Coalescence may occur at a range of scales from national to local development—and that while one part of the community is diffusing another portion might be coalescing.

CHAPTER III METHODS

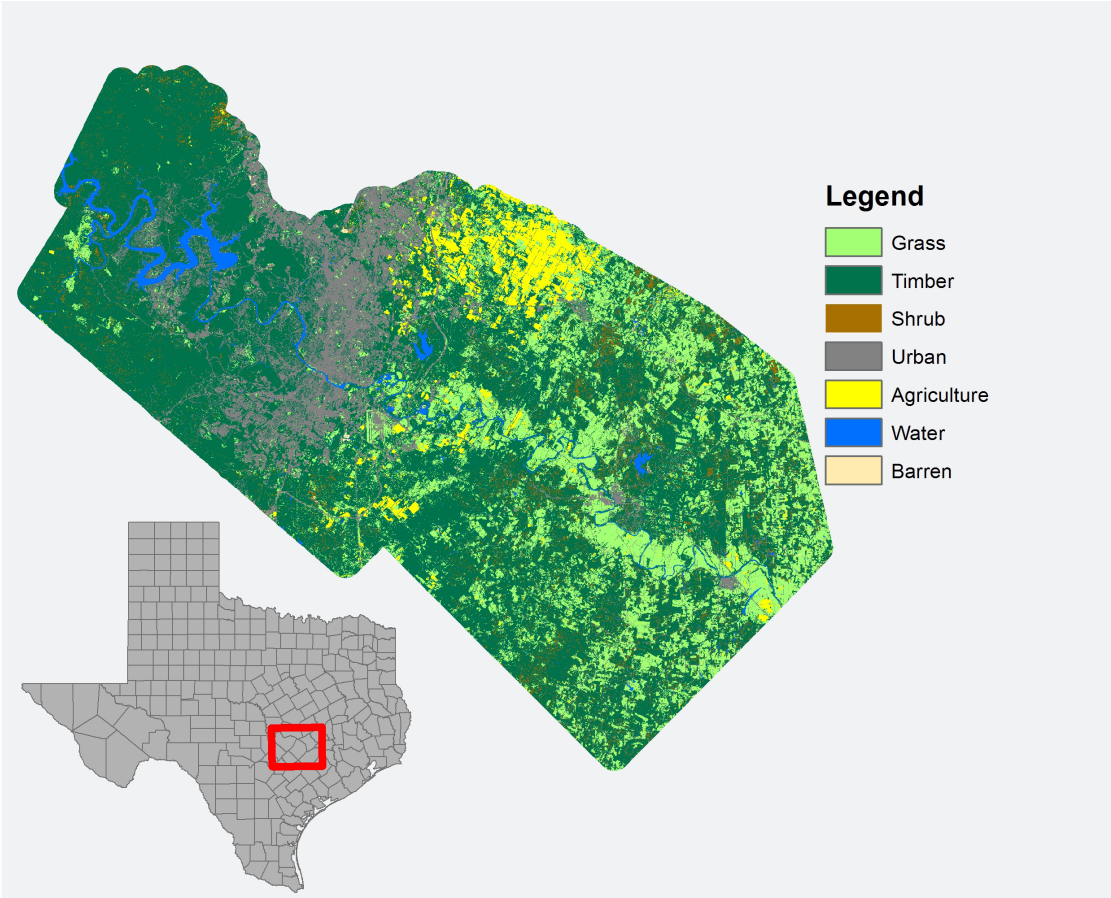
The objective of this study was to create a spatial fire risk model and assess how development influences the fire risk landscape. This objective was addressed through a quasi-experimental simulation approach. Where changes in development were mapped for eleven years and the relationship between development and fire risk was assessed. Risk was calculated by coupling IP and BP models with categorized land cover change (Figure 1) to assess how those changes influence fire risk. This chapter identifies and describes the study area. Followed by discussing the process for quantifying development. These methods include the assessment of relevant scales, the decision process for differentiating between development patterns, and a description of the landscape's development composition.

III.1 Study Area

The area of interest includes Travis and Bastrop counties in central Texas (Figure 2). Travis county consists of 356,000 hectares, while Bastrop is 310,000 hectares. Travis county is a large (1.02 million people in 2010), fast-growing community (26% growth over 10 years; U.S. Census 2010). This growth has led to an increase in development (21,214 Ha 2001-2012). Bastrop county's population is a stark contrast to Travis county. The county has a much smaller population (74,000 in 2010), but Bastrop has still grown quickly over the 10-year study period (28% growth; U.S. Census 2010). Because of the smaller population size, Bastrop has had less development growth (1,343 Ha 2001-2012).

In 2012, much of the vegetation that existed within the study area was grass cover (229,000 Ha), followed by forest (156,389 Ha) and shrub lands (17,174 Ha). Grasslands have increased the most (88,998 Ha since 2001); however, most of these increases are from pasture lands. The biggest changes to the landscape have occurred through fuel ac-

Figure 2: Study area of Bastrop and Travis counties. Fuel types are aggregated to more generalized categories.



cumulation. For instance, tree cover has increased noticeably (42,000 Ha). Much of the forest fuel accumulation is located in Bastrop county. These areas have seen several major fires.

The study area has an active fire regime, with approximately 3,000 ignitions from 1999-2015. While most of the fires are small (77% an acre or smaller), the study area also had eleven fires which burned greater than 1,000 acres. Between 2010 and 2014 most of these fires (>2000) have occurred in Bastrop. The extensive growth of these communities combined with the fires that have occurred in the area, makes these counties an optimal study area to understand the effects of development on the fire landscape.

The time period for the study is centered on two groups of years (1999-2003 & 2010-2014). From this point forward, the 1999-2003 time period will be referred to as the 2001 model and the 2010-2014 time period will be referred to as the 2012 model.

III.2 Quantifying Development Patterns

The primary HVR for this fire risk assessment was urban development. These were categorized into five development patterns. Below I outline the methods used to categorize new development. These include identifying the relevant scale for the analysis, and the decision trees for categorizing development. Following the methods, the results of the development categorization are outlined.

Many of the necessary datasets needed little manipulation for the preparation of the study. Some of the variables, however, required spatial calculations including development categories, edge density, proportion urban, landscape fragmentation, and fuel loading. The first task of the study was understanding the scale at which development occurs in the landscape.

The initial step required identifying development patches. Most fire research focuses on clusters of development, most prominently seen in the definition of the WUI (see WUI section above). One definition of urban cluster consists of using a continuous range to describe the density of building clusters (Syphard *et al.* 2012). Another focuses on four categories of structural clusters: isolated (1 building), dispersed (<7 buildings within 50 meters), clustered (8-155 buildings within 50 meters), and very dense (>155 buildings within 50 meters [Chas Amil et al. 2013]). Focusing on clusters helps explain structural distribution. However, such methods fail to accurately represent lateral growth categories occurring within the landscape.

Landscapes are dynamic. The temporal changes of urban patterns have a hetero-

geneous spatial distribution and state (Wilson *et al.* 2003). Thus, studies focus on lateral growth. A single study within the fire literature has focused on the dynamic shifts of urban patterns. Syphard et al. (2013) focused on three types of lateral development: infill, expansion, and leapfrog (outlying). Within their study, Syphard et al. (2013) used 0.25 acre parcels to identify structures and assumed the following: infill was newly developed land encompassed by developed parcels, expansion was defined as a parcel that had at least one developed parcel adjacent, and leapfrog occurred when a newly developed parcel arose with no adjacent development. By having a baseline estimate of risk and by focusing on the changes to development, Syphard et al. (2013) estimated the structural risk on the landscape. However, this approach assumes that development occurs one structure at a time, which was possible because the study was conducted at a small scale. As previously discussed, lateral development can be defined as leapfrog when it occurs as an isolated development, such as an individual home or farm with few structures clustered nearby. Alternatively, the clustered development patterns occur as subdivisions, where multiple structures are built simultaneously.

III.2.1 Scale

The study's land cover was comprised of two years: 2001 and 2012. Due to the large temporal gap, the search area used for determining a development category needed to be larger than those used in previous research, which used adjacent parcels (Syphard *et al.* 2013). Studies have used several different methods to assess at what scale a process is occurring. Two of the main methods used are Lacunarity and Quadrat Variances. Lacunarity uses a sliding window of gradually larger sizes to assess changes in mean value and variance across the scale of the landscape (Plotnick *et al.* 1993). Quadrat Variance methods are similar to lacunarity in that they also use a sliding window. Quadrat Variance methods are performed along transects on the landscape; a two-dimensional approach that

assesses the patterns across the entire landscape. Unlike Lacunarity, Quadrat Variance uses a two part sliding window (Dale *et al.* 2002) and is best used for reoccurring patterns in the landscape. The study area did not have reoccurring patterns of development, so I chose to use the Lacunarity method to determine which scale was relevant.

III.2.1.1 Lacunarity

Lacunarity measures the variation in scale for a one-dimensional or two-dimensional landscape (Plotnick *et al.* 1993). Lacunarity uses an increasing moving window which calculates the sum within the window and assigns that value to the top left corner pixel. The mean and standard deviation are calculated for the entire landscape based on the sums of each moving window and then graphed based on the equation:

$$1+std^2/mean^2 \qquad [3]$$

High Lacunarity values represent landscapes with large gaps between phenomena, while smaller Lacunarity values represent cells that are more uniform (Romero *et al.* 2009). When graphing across scales, Lacunarity can show the size of the relevant scale for the landscape (Dale 2000). The Lacunarity method has four advantages: 1) implementation is simple, 2) it samples the entire landscape, 3) it is not sensitive to boundaries, and 4) it can be used regardless of the proportion of the landscape covered (Plotnick *et al.* 1993). Using Lacunarity, relevant scales are found at inflection points on the graph. These inflections can be determined by taking the derivative of the Lacunarity graph. Each inflection is noted by a trough or peak within the slope (Butson and King 2006). Subsequently, the second derivative of the Lacunarity graph will show these inflections as the place where the line crosses the y axis.

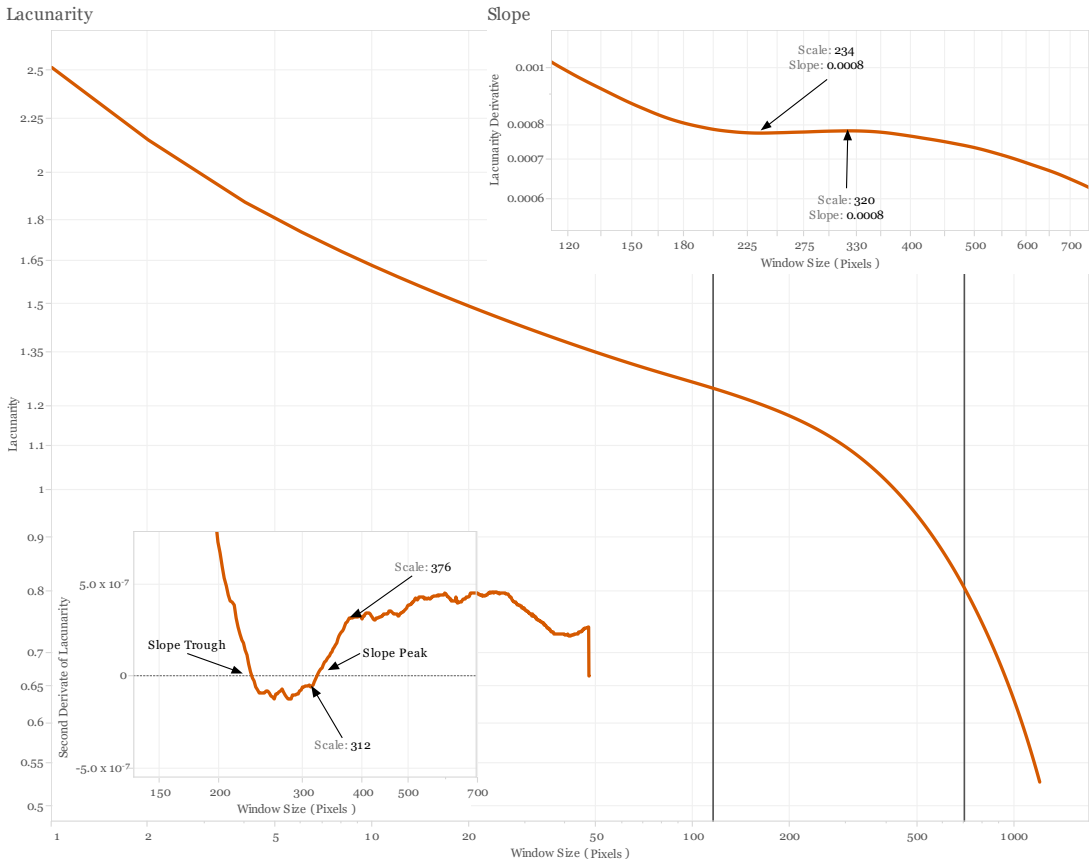
For this study, Lacunarity was calculated for new development within the study area using window sizes between 1 and 1600 pixels. This maximum window size was

large enough to capture the first inflections of the graph. After a qualitative assessment of the graph, the first and second derivatives were used to discover the relevant scales for development on the landscape.

III.2.1.2 Lacunarity Results

Once Lacunarity was calculated for the 2001 landscape, one primary scale was found (1920 m). This value was derived from the trough and peak of the slope derivative of the Lacunarity graph (Butson and King 2006). The scale was located by using the second derivative and locating the first trough and peak before and after where the graph crossed 0 on the y-axis (Figure 3).

Figure 3: Lacunarity graph including the two derivatives. Note slope never crosses the Y-axis, while the second derivative had no true peak and trough.

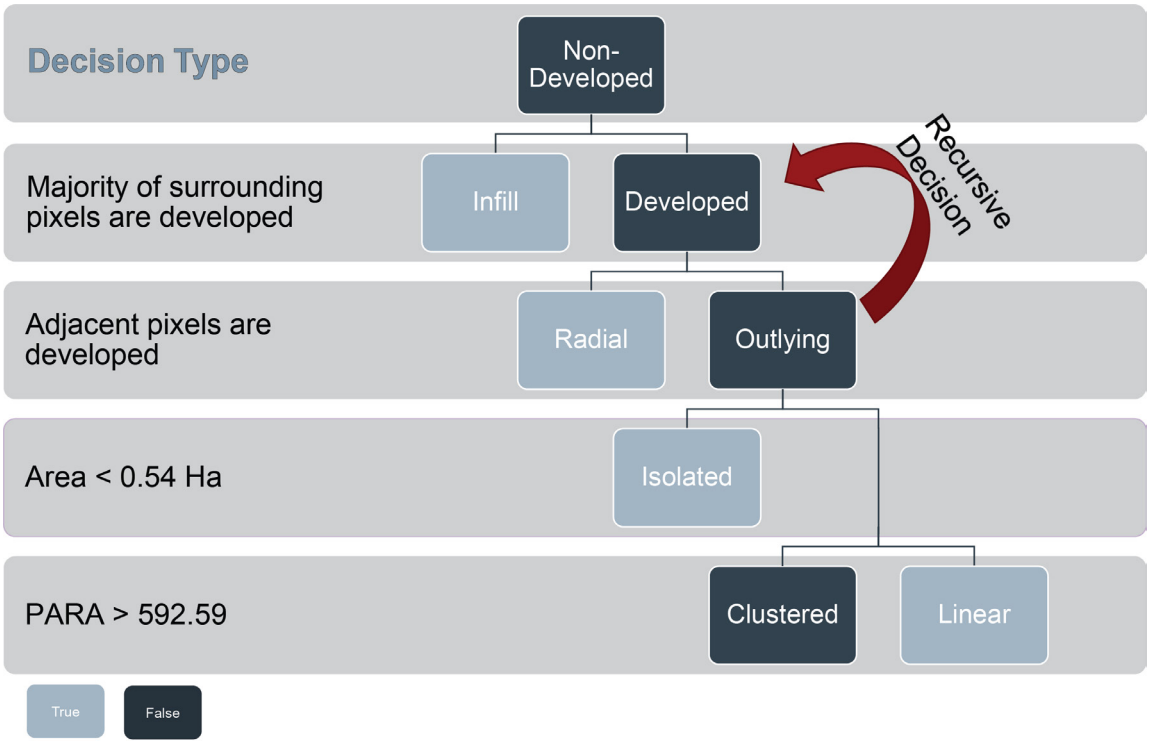


III.2.2 Categorizing Development

Traditionally, fire research has used simplified development categories, while land use research typically uses a more specific set of categories to explain the sprawling landscape. For example, complex metrics such as Contagion (Torrens 2008), Fractal Dimension (Lv *et al.* 2012), and the Interspersion and Juxtaposition Index have been used to estimate lateral sprawl. Lv et al. (2012) used the fractal dimension to estimate where a city lies between the states of completely compact and completely dispersed, while Torrens (2008) used contagion to estimate the degree of fragmentation. Many of these metrics are effective at showing how the landscape shifts and explains the development cycle. For instance, over time a diffusing landscape will have a decreasing contagion metric, while a coalescing landscape will increase (Dietzel *et al.* 2005b). Edge density has the opposite effect: increasing during diffusion and decreasing while coalescing.

A simpler method for categorizing development type focuses on development change. This process categorizes the type of developed land into infill, expansion, or outlying (Wilson *et al.* 2003). These classifications required an initial classification of the non-developed landscape into interior, perforated, and non-developed patches. Interior wildlands are entirely surrounded by non-developed pixels; perforated are primarily surrounded by non-developed (>60%); areas categorized as non-developed patches must be surrounded by less non-developed (<60%) pixels. Using these initial categories allows shifting pixels to be categorized into the correct type of development.

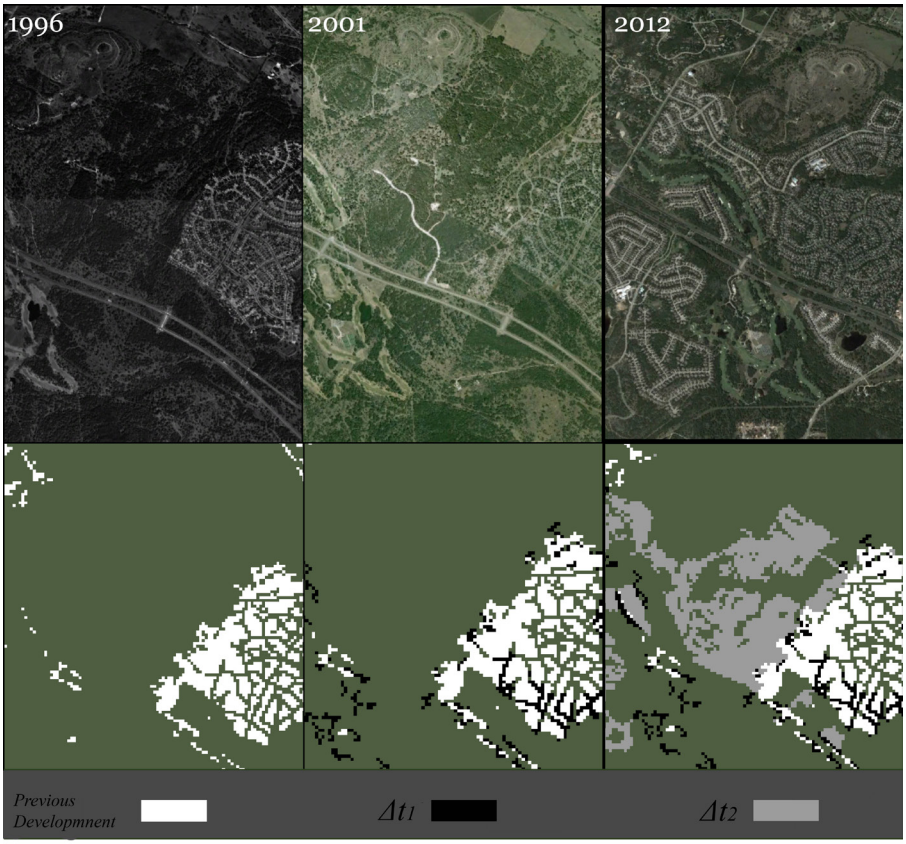
Figure 4: Categorization flowchart for developed lands. This includes rules for how a pixel transitioned from undeveloped to developed. Area values are based on lower quartiles of outlying patches on the landscape while PARA values are based on upper quartiles of non-isolated outlying patches on the landscape.



III.2.2.1 Development Methods

This study categorized development using a decision tree approach (Figure 4). Where each step in the decision tree separated development. This separation started with infill followed by radial and then three outlying development patterns isolated, clustered, and linear. As noted in Chapter 2, isolated growth consists of small patches of development separate from other development. Linear growth occurs on transportation corridors such as roads and rail lines while new clustered development consists of multiple structures. This study's approach was modeled after Wilson et al. (2003), but was not identical. The methods for defining development patterns are described below.

Figure 5: Generations of Development. Note the transitions in development between 1996 - 2001 and 2001-2012.



The study focused on two years where new development occurred (2001 & 2012). Therefore, I used three years of land cover (1992, 2001, and 2012) to define two generations of development (Figure 5). Each generation was defined as development that had not occurred in the previous raster. For example, the Δt_1 occurred on the 2001 landscape but not the 1992 landscape, while the Δt_2 occurred on the 2012 landscape but not the 2001 landscape. The datasets came from two different sources, NLCD and LANDFIRE. Development from 2001 and 2012 were calculated from LANDFIRE, ensuring that the development patterns match with the fire simulations. LANDFIRE does not publish a land cover dataset pre-2001, so I used NLCD's 1992 dataset as a baseline for previous development. I performed an exploratory assessment of NLCD's 2001 dataset with LANDFIRE's 2001

dataset to test for similarity. There was little difference between land covers, suggesting that using the NLCD 1992 did not create inaccuracies in the assessment.

Both land cover datasets provide three classifications for developed area, including high, medium, and low intensity development. These three development intensities were aggregated into a single class (developed), while the vegetation classes were aggregated into a single class (wildland). Once the initial developed and wildland areas were categorized, new development for each year was identified. New developed pixels were categorized as wildland pixels that transitioned to urban between years. For example a wildland pixel in 1992 that transitioned into a developed pixel in 2001. Any development that existed prior to 1992 was classified as previous development.

Categorizing lateral development patterns occurred by year; 2001 new development was categorized first followed by 2012. First, infill was identified as new development that occurred in areas with >=60% developed pixels. This proportion developed was generated using a window size of 1920 m.

After infill was identified, radial development was categorized. Pixels were categorized as radial development if it was adjacent to a previously developed pixel. The radial decision process was iterated until no more pixels were categorized as radial. All new developed pixels that were not categorized as either infill or radial were categorized into outlying development.

Outlying development occurs in three categories isolated, clustered, or linear. Patches of newly developed pixels were used instead of individual pixels to identify the appropriate class. The patch area and Perimeter Area Ratio (PARA) were calculated for each patch. PARA measures the perimeter of the patch over the area (McGarigal 2012):

$$PARA=(p)/a \qquad [4]$$

Where *p* is the perimeter of a patch and *a* is the area of that same patch.

Isolated development was the first to be classified of the three outlying patterns. The isolated development pattern consists of a very small number of buildings in an area. Therefore, I used the distribution of patch areas for new outlying development for categorization. Any new outlying development patch that had an area below the median value (0.54 hectare) was classified as isolated. The median value was used due to a flooring effect of the distribution of patch areas. Those developments that were not classified as isolated were then classified based on their linearity using PARA.

Any new outlying-development patch with a PARA that exceeded median value (592.59 m^{-1}) was designated as linear development, while any patches below that value were designated as clustered development. Using the PARA metric is not without its downside; the PARA metric struggles to differentiate between linear patches and patches with complex edges (McGarigal 2012). However, because I used the PARA metric solely on new clustered development, the edges were not very complex and an inspection of the two classfications showed the threshold to be acceptable.

Once all development types were added, the aggregate median center was calculated for each development category. The median center addresses where both Δt_1 and Δt_2 are primarily developing as compared to the previous development. Development patterns, such as infill, should be developing closer to previous development, while outlying pat-

Table 1: Types and proportions of development occurring between Δt1 and Δt2. Note Radial had the highest growth for both years while isolated had the lowested growth rate

Development Type	Δt1		Δt2	
	Area (ha)	Percentage	Area (ha)	Percentage
Infill	1143	24.89%	1272	15.82%
Radial	3248	70.74%	5997	74.53%
Isolated	11	0.24%	83	1.04%
Clustered	61	1.35%	566	7.03%
Linear	127	2.78%	127	1.58%
Total	4592		8046	

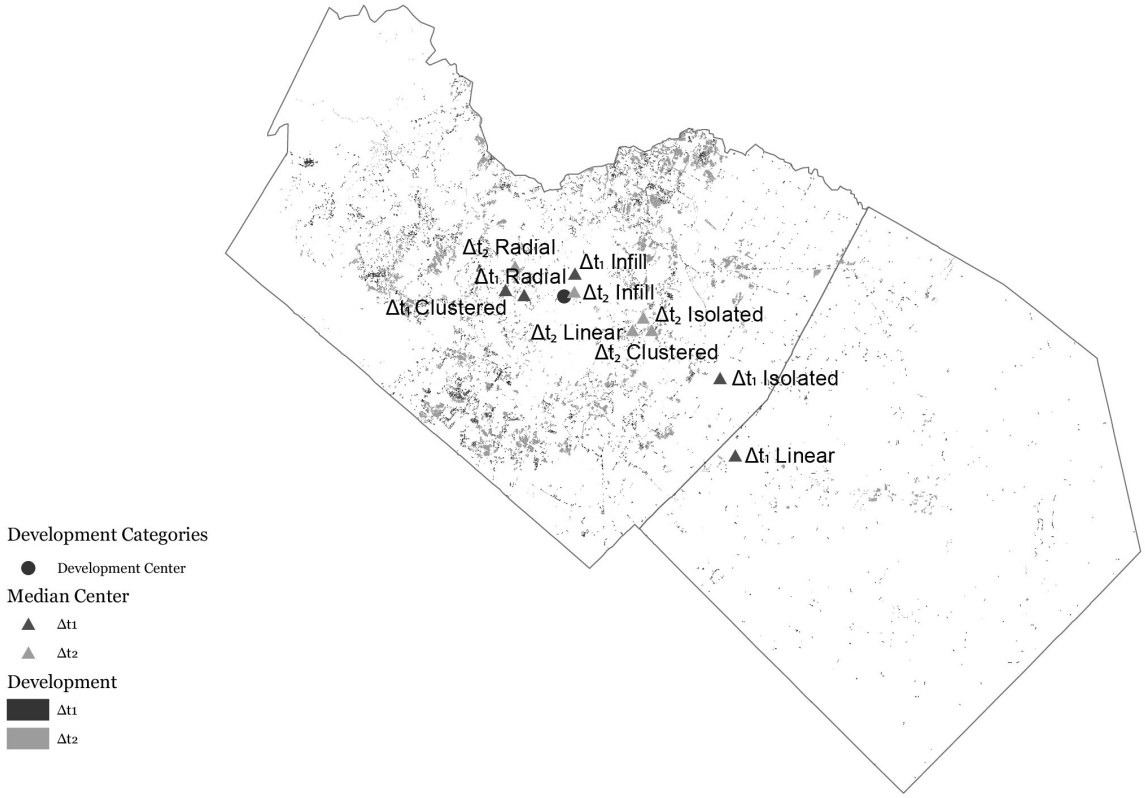
terns should occur further away. This assessment also served as an estimate for whether an area is diffusing or coalescing. If development patterns are further out in the second image (2012) then development is diffusing. However, if similar patterns are closer to the median of previous development then the landscape maybe in a coalescing state.

III.2.2.2 Development Pattern Results

Following the previously prescribed methods for categorization, I created five development categories for both Δt_1 and Δt_2: infill, radial, clustered, linear, and isolated. A qualitative assessment suggests this approach created a reasonable representation of development categories.

Because the cutoffs were different based on the scale used, the category compositions varied. However, the ranking of those compositions did not vary. Across both scales, radial development occurred more often than all other development types combined (Table 1). Clustered and isolated development were the least likely to occur.

Figure 6: Generational Development Centers. Old generations tended to occur further from the urban core than the newer counter parts. This could potentially show evidence of a coalescing landscape.



The spatial median center was calculated for each development pattern. These calculations measure the direction and distance of most of the development types that occur away from the previous development. In addition, the median centers give context for the IP and BP analyses. Results showed that the center of all development occurred, as expected, within the center of Travis county. Radial and infill occurred near this center of development, while the outlying development occurred further from the center. Δt_1 development tended to occur further from the development center than Δt_2 (Figure 6). Clustered development occurred to the western part of the study area, while isolated and linear development occurred further to the east. Within the Δt_2, all three outlying development patterns occurred to the east.

CHAPTER IV IGNITION PROBABILITY PATTERNS

Once development was quantified, the next step was to create a sample of fire ignitions for the two study periods. This chapter assesses fire probability within the fire risk framework. This is done by assessing where a fire ignites in relation to development. By addressing changes in ignition probability, the study can isolate what variation occurs in fire risk before fire behavior is considered. This chapter seeks to answer the first hypothesis:

Hypothesis 1: **Ignition probabilities will differ based on the nearest development type.**

This chapter reviews the processes used by previous studies to understand ignition distributions. Following the literature review, this chapter describes the methods used in this study and discusses the variables necessary for the model. Finally, I discuss the results of ignition patterns across development categories.

IV.1 Literature Review

As noted in Chapter 2, IP models are used to explain where fires are likely to ignite. IP modelling use socio-economic and physical variables to predict ignition locations (Rodrigues and de la Riva 2014). Common variables include distance to roadways, distance to urban areas, elevation, and population (Cardille *et al.* 2001; Badia-Perpinyá and Pallares-Barbera 2006; Scott *et al.* 2012). These four variables identify constraints and access points for the interactions between humans and wildlands. By identifying areas of high ignition probability, land managers can use IP models to improve the allocation of emergency resources, and suppression tactics.

Approaches to estimating IP include a variety of statistical and machine learning models, including logistic regression (Cardille *et al.* 2001; Scott *et al.* 2012; Faivre *et al.*

2014), weight of evidence (Dickson *et al.* 2006; Romero-Calcerrada *et al.* 2008), random forests (Rodrigues and de la Riva 2014), and MaxEnt (Bar Massada *et al.* 2013; Rodrigues and de la Riva 2014). Bar Massada et al. (2013) compared three models: a general linear model, random forest, and MaxEnt, and found that MaxEnt was the most sensitive for predicting ignition locations. This result was corroborated by Rodrigues and de la Riva (2014), who found that machine-learning algorithms were more sensitive than statistical models for predicting ignitions.

Researchers can use IP models as either a predictive model, where the user's end goal is detailing the spatial distribution of ignition probability, or to explain how variables influence the probability of fire on the landscape (Bar Massada *et al.* 2013). Machine learning and statistical models excel at different aspects of these objectives. With machine-learning algorithms, the relationships between the independent and the dependent variables are not easy to interpret. Conversely, traditional parametric multivariate models, such as logistic regression, provide clearer interpretations. For example, a unit change in x will increase the probability of y by the amount provided by the coefficient. Machine learning algorithms show the influence of variables, are regarded as more accurate models (Domingos 2012; Bar Massada *et al.* 2013; Rodrigues and de la Riva 2014).

Bar Massada et al. (2013) assessed the sensitivity of three models: the generalized linear model, a random forest, and MaxEnt. Model sensitivity was evaluated using the Area Under the Curve (AUC) from the Receiver Operating Characteristic (ROC) analysis. The ROC measures each model's sensitivity by assessing true positives and false positives between possible values. The AUC produces a value ranging from 0.5 (predictions are random) to 1 (perfect predictions). In general, values can be categorized as an excellent (>0.9) fit, a good (0.8-0.9) fit, and fair (0.7-0.8) fitting (Swets 1988; Penman *et al.* 2013). In their sensitivity study, Bar Massada et al. (2013) found that MaxEnt was the

most sensitive (0.716) in predicting ignition locations, while GLM was the least sensitive (0.664). A separate study by Rodrigues and de la Riva (2014) assessed the predictive power of logistic regressions, random forests, boosted regression trees, and Support Vector Machines. They found that random forests were the best predictors (0.746), and that the logistic regressions produced the least sensitive model (0.686). However, the models used by Rodrigues and de la Riva (2014) did not use all of the same variables. This dissimilarity of models could have influenced the predictive power of the models and makes them difficult to compare. Most research has found ignition location sensitivity between 0.65 and 0.75 (Catry *et al.* 2010; Scott *et al.* 2012; Bar Massada *et al.* 2013; Faivre *et al.* 2014; Rodrigues and de la Riva 2014). One of the better performing models assessed ignition locations in Australia. This model used only arson-based fires, suggesting that drivers for accidental and arson fires were different (Penman *et al.* 2013). This model had a significantly higher sensitivity (0.95) compared to other studies.

IV.2 Methods

Previous research suggests MaxEnt creates sensitive models without jeopardizing variable interpretation (Bar Massada *et al.* 2013). The MaxEnt model was used for this study. MaxEnt predicts the spatial distribution of a given dependent variable, by approximating the maximum-entropy for a series of spatial independent variables (Phillips *et al.* 2004). MaxEnt uses presence-only data for the distribution model (Elith *et al.* 2011), which is identified through a probabilistic raster. MaxEnt is capable of modeling independent variables which are continuous, categorical, or binomial. MaxEnt also takes into account non-linearities and interactions between variables (Elith *et al.* 2006). The dependent variable, fire events, came from the historic fire datasets (provide by Texas Forest Service & USGS), consisting of all documented wildfires between 1999 and 2014.

Table 2: Ignitions within the study area separated by year

	Ignitions by Year																
Year	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Number of Ignitions	25	40	19	15	24	5	136	440	139	606	391	54	518	191	300	93	31

IV.2.1 Variables

IV.2.1.1 Dependent

The IP model was based on ignition locations gathered from local fire departments, the Texas Forest Service, and federal agencies. This dataset covers fires from 1999-2015 (see Table 2). However, local fire departments did not contribute their records until 2005. I ran a preliminary model which showed that a smaller subset of years (5 years) produces a more sensitive model when compared to a larger subset of years (>=30 years). This is likely because ignition's drivers (e.g. land cover) shift over time, and studies with a larger temporal range cannot take this into account (Faivre *et al.* 2014). Data collection before 2005 was limited; thus, using a sample from a single year limits the model's power. A five-year sample surrounding the date of the land cover data set helped reduce the model's potential for type I errors. Therefore, two subsets were created from the initial dataset for the two study periods (2001 & 2012), which yielded sample sizes of n=123 and n=1156, respectively. These samples sizes are large enough for a sensitive MaxEnt IP model (Barbet-Massin *et al.* 2012). Since each ignition group was centered on specific land cover years, minimal change was assumed in socio-economic and landscape variables.

The earlier ignition sample (2001) is much smaller than the more recent (2012) group. This is because Texas fire departments did not keep records of fire locations prior to 2005. However, sample imbalance is a common form of bias in species distribution

models (Phillips *et al.* 2009). Bias can be estimated by measuring how well the MaxEnt model can discriminate between the target group data (ignitions) and the background. If the sampling distribution is known, then MaxEnt is capable of adjusting for bias (Merow *et al.* 2013). However, because local fire departments are spread throughout the entire two counties, jurisdictional boundaries could not be established, which was required to mitigate the bias (Stolar and Nielsen 2015). Because of the widespread issue, I could not account for the sampling bias.

IV.2.1.2 Independent

Previous research has used various drivers for IP modeling, most variables come from three categories: socio-economic, biophysical, and topographic. Some effects of the variables are well documented (e.g. the closer a pixel is to a road, the more likely an ignition is to occur), while others have been used less (e.g. number of livestock in an area). The following independent variables from the literature were used as drivers of the IP model: distance to roads, housing density, land cover, elevation, and slope. I also used the previously calculated (chapter 3) proportion urban, which measures the percent of surrounding cells that are urban, and urban edge density. This helped measure the amount of exposure each raster cell has from populated areas.

IV.2.2 Statistical Methodology

Ignitions are the initial step for any fire. A limited number of ignitions become large fires, yet each ignition has the potential to grow larger and become destructive. Fire ignitions within the study area are primarily anthropogenic, and their spatial distribution is influenced by the surrounding landscape's development. Therefore, this study assessed whether categories of development had different patterns of ignition probability by analyzing the differences in ignition probability distributions surrounding new development. Differences in the probabilities were tested using an ANOVA, followed by the Tukey *post*

hoc assessment to determine the rankings of development type.

IV.3 Results

The results from the IP model are broken into two sections. The first section addresses the results of the MaxEnt model, which analyzed the spatial ignition distribution. This includes the model's performance and details regarding the influence of independent variables. The second section of results addresses how the IP distributions differ between development patterns. In this section, an ANOVA is used to test for the difference between the distributions.

IV.3.1 Ignition Probability Model

IP models were created for 2001 and 2012. The dependent variables' sample sizes varied between the two groups of years. The most recent group had the larger sample size (n = 916), while the earlier group was significantly smaller (n = 102). Within the study area, most fires ignited within Bastrop county (2001: 100; 2012: 871). The most frequent cause of fires in both Bastrop and Travis counties was burning debris, consisting of nearly half of the ignitions within the study area.

The 2012 IP raster had higher probabilities than the 2001 model (Figure 7). Most of these high ignition likelihood areas occurred in Bastrop county or the northern tip of Travis county. Roads were clearly a major driver of ignitions, as most of the road network is outlined by high IP rates. In both years, the surrounding area of the Austin urban core had low IP rates.

MaxEnt tests for sensitivity given a user-provided test dataset and background pixels using the ROC and accompanying AUC. Due to the limited sample size the 2001 model used a smaller test dataset (n=20) compared with the 2012 model (n=99). The maximum AUC for an IP model is based on the area in which the presence sample covers

Figure 7: Variation in Ignition Probabilities across years. Higher IP's tended to occur in the Bastrop county, with the highest probabilities occurring in 2001.

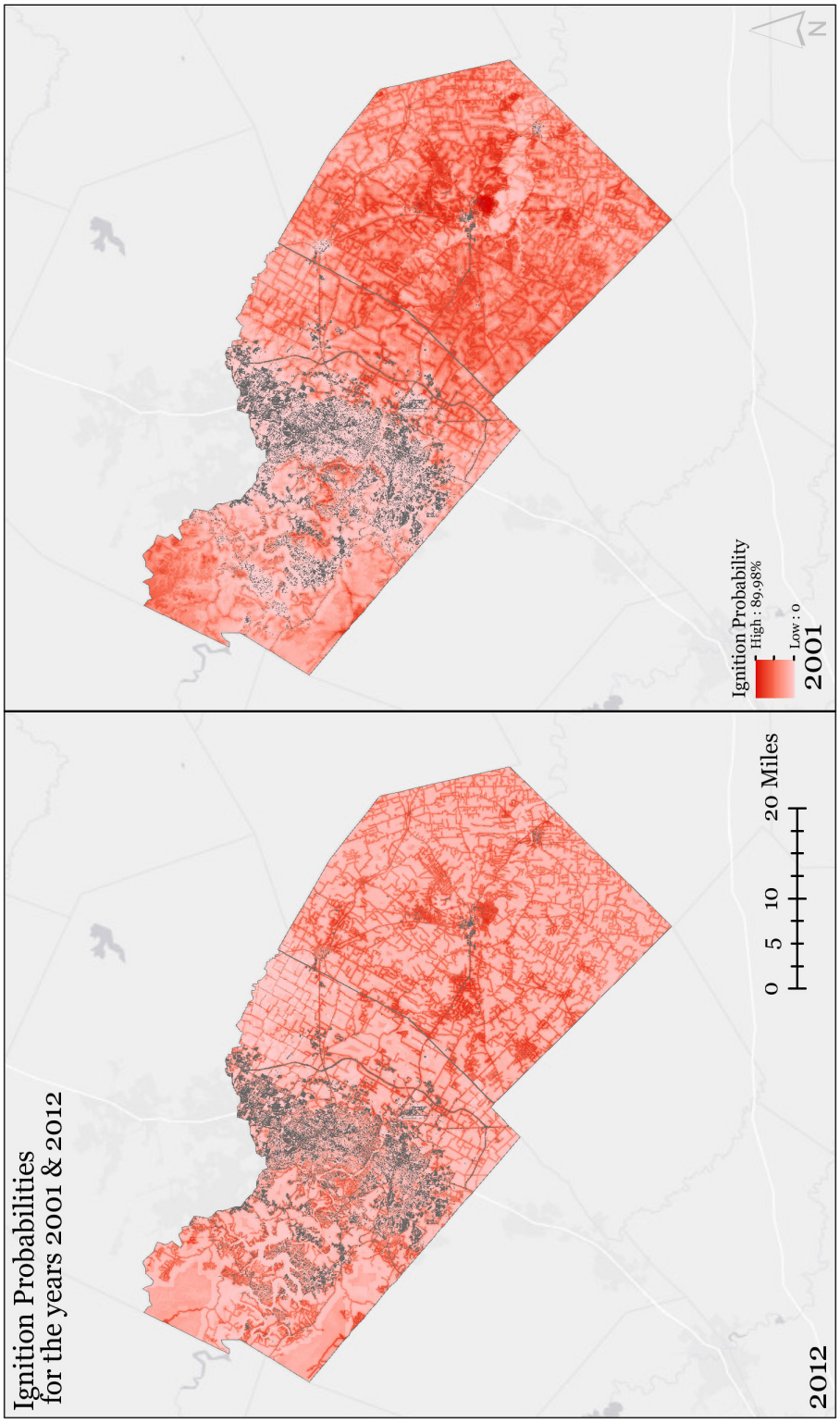


Table 3. IP Sensitivity and Deviation from Model AUC

	AUC		Normal-ized	
	2001	2012	2001	2012
AUC	0.782	0.776	0.998	0.974
Gain	0.647	0.551		
	Without Specified Variable		With Only Specified Variable	
	2001	2012	2001	2012
Distance to Road Way	-0.033	-0.091	-0.115	-0.041
Housing Density	0.009	-0.006	-0.193	-0.155
Elevation	0.004	-0.001	-0.149	-0.209
Land Cover	-0.007	-0.000	-0.218	-0.199
Slope	0.001	0.001	-0.260	-0.270
Proportion Urban	-0.033	0.003	-0.230	-0.160
Edge Density	-0.017	0.004	-0.245	-0.163

as compared to the total study area (Phillips *et al.* 2006). It can be used to standardize the AUC and help determine if the model is maximizing its efficiency (Wiley *et al.* 2003). Additionally, MaxEnt provides the influence of each independent variable on the model's sensitivity.

The 2012 model was slightly more sensitive (AUC: 0.782, Table 3) when compared with its earlier counterpart (AUC: 0.7751). However, when normalized, the older fire model performs better (2001: 0.998; 2012: 0.974). The differences between models are not statistically significant, suggesting that the models should be very similar. The goodness of fit was assessed through gain values (Elith *et al.* 2011). Gain describes how much variation in the model is explained by each variable if all others are held constant. Maximizing the gain value is similar to other optimization measures (e.g. AIC or BIC) and is one way of determining the optimal model (Merow *et al.* 2013). For these sets of models, the 2001 model (0.6469) outperformed the 2012 models (0.5508).

IV.3.1.1 IP 2012 Sensitivity

Removing any single independent variable within the 2012 model altered the sensitivity very little. Distance to roadways had the most positive influence on sensitivity (+0.091 to AUC) while incorporating slope had the most negative influence, slightly reducing sensitivity (-0.001 to AUC). Removing edge density increased the sensitivity compared with the final model (-0.004 to AUC). Incorporating proportion urban decreased the sensitivity of the final model (-0.003 to AUC).

IV.3.1.2 IP 2001 Sensitivity

For the older model, distance to roadways was still the most influential variable affecting the model's sensitivity (+0.033 to AUC), while housing density had the most negative effect (-0.0087 to AUC). Elevation was the only other variable that negatively influenced the model's sensitivity (-0.003 AUC when removed).

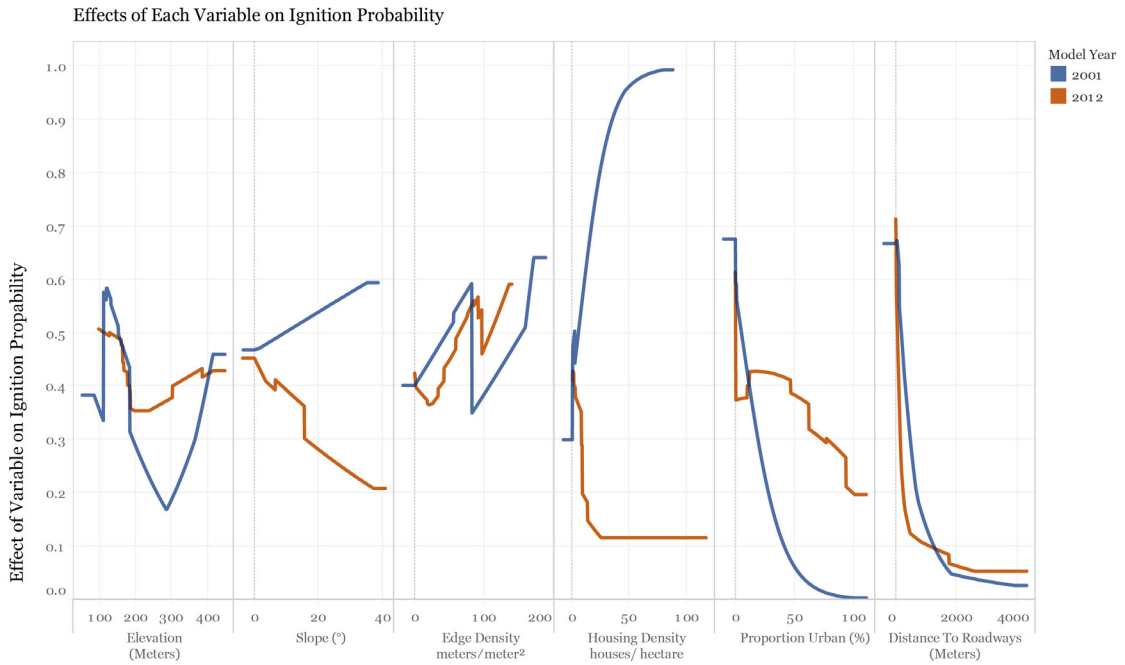
IV.3.1.3 Variable Influence

MaxEnt provides a graph of each independent variable's influence on IP, holding all other variables constant (Figure 8). These graphs are similar to the coefficients from a logit model with the exception that they model non-linearity as well. These graphs show a range of probabilities (0-1) as the values of the independent variables vary. They provide an additional representation of each independent variable's influence on IP across its in-sample values.

IV.3.1.3.1 IP 2012

Holding all other variables constant, each independent variable initially increases the IP, and as the values increase, IP decreases. Edge density is the only exception; IP increases with higher edge densities. Qualitatively, distance to roadways and housing density show exponential decay, while elevation displays by a quadratic function. The

Figure 8: Variable influence on MaxEnt across years. Note the opposite effects of housing density and slope between years.



maximum IP for the variable distance to roadways (*P* (ignition) = 0.71) occurs adjacent to roads. As the distance to the nearest road increases, the ignition probability quickly decreases (*P* (ignition) =0.053 at 2800m). Like distance to roadways, housing density decreases in probability (P (ignition $_{max}$) = 0.429 at 0 houses per ha and P (ignition $_{min}$) = 0.116 at 25 houses per hectare). Edge density maintains a relatively high probability throughout its range (P (ignition $_{min}$) = 0.365 - P (ignition $_{max}$) = 0.591). Overall, as edge density increases so does probability; however, there is a decrease in probability near the maximum edge density (91 – 97 m/ha). Proportion urban peaks at relatively low urban percentages (P (ignition $_{max}$) = 0.428 when urban is at 26%).

IV.3.1.3.2 IP 2001

Qualitatively, the response curves for the earlier model had several differences compared with the latter model. The model still had two exponential decay variables. While distance to road ways (P (ignition $_{max}$) = 0.674 & P (ignition $_{min}$) =0.0265) was still one of those variables, the second changed to proportion urban (P (ignition $_{max}$) = 0.595 & P (ignition $_{min}$) =0.003). Additionally, instead of just one variable that continually increased ignition probability in the 2012 results, the 2001 model had three variables. Housing density switched to a logarithmic form (P (ignition $_{min}$) =0.4035 and P (ignition $_{max}$) = 0.993). Slope and edge density had positive influences on IP. Slope's influence was linear, while edge density had two major linear sections. The initial section of edge density had a higher probability and maxes out when edge density reaches 82 m/ha (P (ignition) =0.5926). This peak decreases immediately once edge density is >82 m/ha IP (P (ignition $_{min}$) =0.350) and then increases gradually until edge density reaches 159 m/ha where the slope steeply increases until 171 m/ha and levels off (P (ignition $_{max}$) =0.641). The elevation variable's graph is also unique and appears to be a single sinusoid oscillation (P (ignition $_{max}$) = 0.584 & P (ignition $_{min}$) = 0.169).

IV.3.2 Statistical Results

Development patterns were also split into two generations: one for areas newly developed in 2001, and one generation for areas with new development in 2012. As note in chapter 3, if development occurred on the 2001 image but not the 1992 image, it was classified as Δt_1 development. If development occurred on the 2012 image but not the 2001 image, it was classified as Δt_2 development. Each generation of development included five categories: infill, radial, isolated, clustered, and linear development. Splitting development categories into two generations allows comparison within development types as well as temporally across generations.

Table 4: ANOVAs for the 2001 and 2012 IP and Development Patterns. The lines under the chart show which development patterns were not statistically different using Post hoc analysis. This suggests IP's for those development patterns cluster together.

2001

Number of obs = 53634 Root MSE = .200948

df	F	Prob > F
10	595.39	0.0000

Development Type	Δt1 Infill	Δt2 Infill	Core	Δt2 Clustered	Δt1 Radial	Δt2 Radial	Δt1 Clustered	Δt2 Linear	Δt2 Isolated	Δt1 Linear	Δt1 Isolated
Mean	0.015	0.028	0.141	0.209	0.231	0.237	0.258	0.282	0.334	0.416	0.425

2012

Number of obs = 53639 Root MSE = .185671

df	F	Prob > F
10	560.51	0.0000

Development Type	Δt1 Infill	Δt2 Infill	Δt2 Clustered	Core	Δt1 Radial	Δt2 Linear	Δt1 Clustered	Δt2 Radial	Δt1 Isolated	Δt2 Isolated	Δt1 Linear
Mean	0.165	0.182	0.311	0.319	0.367	0.400	0.404	0.408	0.415	0.435	0.495

The One-way ANOVA for the 2001 and 2012 model (Table 4) demonstrated significant differences development types ($p<0.0001$). *Post hoc* analyses were conducted using the Tukey-Kramer HSD to identify the differences in mean IP across development types. Each had the same sample size (n=53,639) for the eleven development categories. Both models were significant ($p<0.0001$), suggesting that more variation occurs between development types than within each development type.

Post hoc analyses were conducted using the Tukey-Kramer HSD. Most tests using the Tukey Kramer HSD showed a significance of at least $p<0.1$, causing several clusters

of development types to stand out. For the 2001 model, the lowest ignition probabilities occurred within the Δt_1 and Δt_2 infill, while both Δt_1 and Δt_2 (clustered and radial development) could not be statistically differentiated. The Δt_2 linear and isolated fell within two clusters each, and the Δt_1 linear and isolated were the most likely have a fire started near them. The 2012 model had more clusters of development patterns. Both Δt_1 and Δt_2 infill still clustered together. The rest of the development patterns clustered into several groups each.

The order of several development types change between 2001 and 2012. Some of the development types that changed places were not significant, suggesting little variation exists between these development categories. Specifically, Δt_2 linear and radial or Δt_1 clustered could not be differentiated. However, the change in sequence for Δt_1 and Δt_2 for isolated developments was significant, suggesting older isolated development would potentially have new development surrounding it. Additionally, an increase in IP of newer isolated development in the 2012 model likely occurred because these areas transitioned from wildlands to WUI.

IV.4 Conclusion

This chapter, using historic fires and maximum entropy modeling, provides evidence to support variation in ignitions based on development patterns. The results suggest that both spatial composition and location influence wildfire ignition. Probability results suggest that fire probabilities fall along a development gradient. Those areas nearest previous urban development have lower probabilities while outlying development patterns in the wildlands have higher probabilities. These findings support the first hypothesis: ignition probabilities will differ based on the nearest development type.

CHAPTER V BURN PROBABILITY PATTERNS

Chapter 5 incorporates wildfire behavior to better explain fire probability and severity. Wildfires move on the landscape based on topography and weather conditions. Flame intensity varies due to both fuel load and fuel type, as well as weather conditions. This chapter expands on the results from Chapter 4 by creating ignition samples for the BP model. Through simulation models, this chapter answers four hypotheses.

Hypothesis 2: **Changes in development affect fire exposure.**

Hypothesis 3: **Increases in development increase fire risk.**

Hypothesis 4: **Increases in fuel loading will increase fire risk.**

Hypothesis 5: **High road density will decrease fire risk.**

V.1 Literature Review

As noted in chapter 2, BP rasters model how a fire moves on the landscape once they have started. The output raster measures: given a fire starts on the landscape, what the probability that it will burn a cell. BP models iterate a deterministic fire behavior model thousands of times, producing the statistical likelihood of a fire occurring in a particular raster cell (Miller and Ager 2013). Several models have been produced to quantify risk through BP modeling, each of which uses a different approach. The algorithms behind FARSITE and FlamMap are considered by some to be the most accurate (Papadopoulos and Pavlidou 2011). FARSITE is an older software which calculates fire growth at specific time frames (Finney and Andrews 1999). FlamMap and similar software such as Randig and FSIM, use the Minimum Travel Time (MTT) algorithm, a faster and less computation-

ally intensive algorithm compared to FARSITE (Finney 2002). The MTT algorithm uses homogenous weather patterns to generate the necessary variables for the entire landscape instead of at each time period (Finney 2002). The level of accuracy is similar for FARSITE and FlamMap, but determining accuracy for either model is subjective (Finney 2000, 2002). For example, Finney (2000) compared the FARSITE model to actual fires under the same weather patterns. Visually the fires were similar with minor variations, which were accounted for by suppression activities and micro-scale weather variations. Finney (2002) also found that FARSITE and the minimum travel time methods used in FlamMap produced identical outputs. FSIM is another fire simulation model, used by the U.S. Forest Service, and employs the same algorithm as FlamMap (Finney *et al.* 2011; Ager *et al.* 2013). FSIM allows the user to create risk models from thousands of fire seasons instead of fire ignitions. However, the FSIM model has limited availability and documentation.

The next two sections address how studies have organized input variables for BP models. Specifically, they focus on how previous studies have addressed weather conditions and simulation times. While BP models require other input variables, these two have the most variability, and can drastically influence what the BP model looks like.

V.1.1 Weather

Weather conditions are a major driver of fire behavior and severity. Weather variables include temperature, relative humidity, wind speed, and wind direction (Salis *et al.* 2014). Weather is a critical aspect of fire risk modeling because it influences the size of fires. Previous BP research focused on weather and fire risk, finding that extreme weather conditions (high winds, low relative humidity, etc.) significantly increase fire risk (Bar Massada *et al.* 2011). This finding is important because most of the acres burned in a given year are due to larger fires (Ager *et al.* 2013). Most research, therefore, focuses on extreme weather conditions to understand the risk of large wildfires.

Methods for selecting weather samples varied, but include: selecting one extreme fire event (Bar Massada *et al.* 2011), 20 years of fire weather for simulations (Scott *et al.* 2012), or using 95th percentile weather events (Bar Massada *et al.* 2009). Bar Massada et al. (2011) used only two weather scenarios while controlling for weather variations across the landscape. Using limited weather scenarios allows for total control of the effects from weather, yet it does not create a scenario that mimics a natural fire regime. Alternatively, Scott et al. (2012) used weather patterns for 20 years of fire seasons and the software FSIM. This analogue approach to weather sampling (Moss *et al.* 2010) includes a broad spectrum of weather patterns, ensuring ample coverage. However, FSIM is not currently publicly available, and this approach is not readily transferred to other software.

The last group of methods use a sample of weather patterns, either by focusing on 95-97th percentile fuel moistures (Ager *et al.* 2010a; Ager *et al.* 2010b; Ager *et al.* 2012; Alcasena *et al.* 2015) or on fire metrics such as Energy Release Component (ERC) to create weather samples (Scott 2006). While the sampling is similar for ERC (95-97th percentile), the use of ERC helps estimate the amount of energy released due to fire in the flaming zone (Andrews and Rothermel 1982). This is because ERC is primarily a function of fuel moisture and fuel packing (Cohen and Deeming 1985). Other research used winds based on peak fire seasons, with the number of scenarios ranging from five (Ager *et al.* 2012) to sixty-six scenarios (Bar Massada *et al.* 2009).

V.1.2 Simulation Times

If a fire ignites on a landscape, the amount of time that it continues to burn is unknown. It can be suppressed quickly, or with optimal weather conditions can burn for days or months. Real fire burn times are dependent on several variables. Depending on the fire's proximity to structures, a fire may be more actively suppressed. A combination of high winds and flashy fuels might make initial suppression impossible. Like empirical

fires, simulated fires burn times vary. Ager et al. (2007) used 24 hr. burn times to emulate a historic fire, while other research used shorter simulation times (e.g. 12 hr.; Bar Massada et al. 2011). Both studies used weather conditions based on previous large fires and simulated accordingly. When using the Minimum Travel Time algorithm, one main limitation of long simulation times is that MTT requires homogenous weather conditions. But, in reality, weather conditions are heterogeneous. Because of this, Bar Massada et al. (2009) used lower simulation times (12 hr.) and had more variation in weather samples.

Another assumption that current BP models make concerns fire suppression. Fire simulation software cannot easily account for suppression measures on large fires (Bar Massada *et al.* 2011). Bar Massada et al. (2011) suggest that suppression may be higher in areas near communities. Because the FlamMap software cannot account for suppression, BP may be over predicted within developed areas.

V.1.3 Behavior and Effects

BP simulation models produce fire severity maps, in addition to BP maps. When assessing the influence of fire behavior, flame length is usually a proxy for final estimates of fire behavior (Ager *et al.* 2014). Flame length is defined as the average length of flames at the head of a fire (Albini 1976) and is an output of BP models used to estimate fire intensity (Finney and Andrews 1999). FlamMap produces conditional flame length (CFL) as a fire severity output. CFL is the estimate of mean flame length for the times that a pixel cell was burned (Scott *et al.* 2013). Flame length is also important for understanding resource loss due to wildfire. Early studies assumed total loss of a given resource (Finney 2005), however recent research has quantified the probability of loss by using flame length. For example, recent studies have started using flame lengths that exceed 2.4 meters as the value for losses within the WUI (Ager *et al.* 2013).

While simulation software has been used to generate synthetic fire severity maps, other research has taken an empirical approach by using machine learning (random forest algorithms) to assess how topography, climate, and weather influence burn severity. Dillon et al. (2011) found that topography had the highest influence on burn severity in the western United States. Within the study, burn severity was estimated by the difference in vegetation pre- and post-wildfire. However, the approach of analyzing fire severity using observed data and regression trees is of limited usefulness for understanding extreme fire effects, due to regional variations and the possibility that fires will not occur during the most extreme weather conditions.

Studies simulating seasonal wild fire risk have found that many landscapes have yet to see their largest possible fires (Finney *et al.* 2011). This could be due to fire suppression or simply a lack of ignitions during extreme weather and fuel conditions. However, the increasing numbers of acres burned yearly (NIFC 2017a) and regional fire deficits (Parks *et al.* 2015) suggest that predicting future fire scenarios may be difficult based on previous fires. In comparison, simulations may be better at estimating fire potential since they allow the use of existing fuel loading and a broader spectrum of weather patterns to drive fire behavior, while manipulating the inputs allow for predictions of future fire potential.

While fire behavior and probability are quantitative in nature, many of the effects of fire are more difficult quantify. Researchers can use preliminary observational studies to estimate at what flame length loss occurs. For instance, Ager et al. (2007) used an exceedance value of 2.5 m flame lengths to estimate loss of crown habitat for the spotted owl. While loss estimates can be procured through extensive field research, an alternative approach is to gather input from experts and stakeholders (Calkin *et al.* 2010). Quantifying the effects of fire on developed lands is more straightforward. Because fire consumes a

structure, total loss of a structure is assumed when simulated fires interact with developed lands on the landscape (Bar Massada *et al.* 2009).

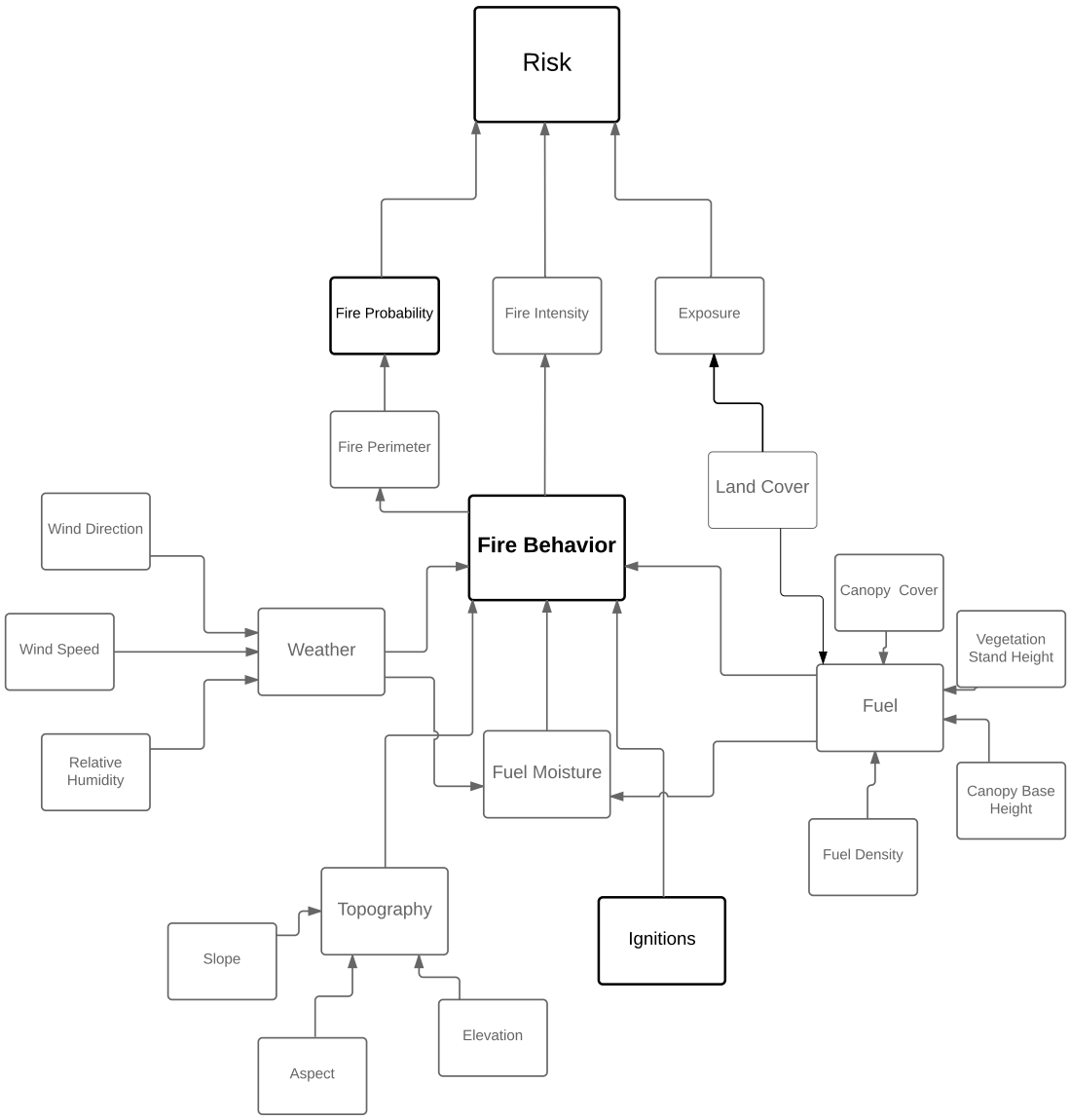
V.1.4 SNA

Large fire movement has also been analyzed using Social Network Analysis (SNA) methods to identify fire movement patterns across land ownership (Ager *et al.* 2015). Planning research has also used SNA's to identify an array of networks, including transportation patterns (Batty 2004) and localized urban forms (Park 2015). SNA's identify how a phenomenon of interests moves between nodes, which can be used to identify the nodes most often in the center of that travel (Corten 2010). In this case, an SNA can be used to measure how a fire igniting near one development moves through the landscape to expose another. SNA's were used to test hypotheses two and three.

V.2 Methods

Burn probability models simulate fire behavior on the landscape; they require a wide variety of input datasets to accurately represent the probability of fire occurrence (Figure 9). The required variables include: weather conditions, topographic conditions, fuel coverage/conditions, and ignitions. Topography and weather conditions were static across both models, while fuel and ignitions varied by year group.

Figure 9: Conceptual model for fire risk. Like the previous IP conceptual model this model has been simplified to the direct inputs to create fire risk. Fire behavior is the central driver of fire risk, with weather conditions, topography, fuel, and igintions the latent variables that drive behavior. The Flammap software outputs fire probability and intensity datasets. These two datasets are two thirds of the risk framework, while exposure is derived from development categories.



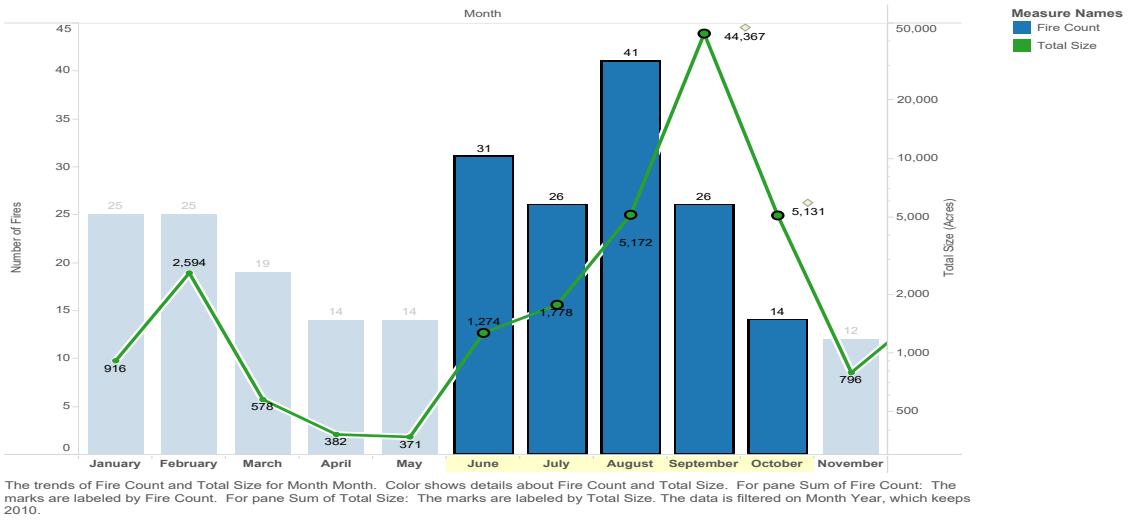
V.2.1 BP Inputs

V.2.1.1 Weather

Weather conditions were collected from the most recent five-year period (2010-2014). The sample used ERC (95th percentile) to estimate the most volatile fire days during the time period. Thirty-nine days had an ERC above the 95th percentile. These scenarios were used for both sets of years, allowing control of climatic variability. While the 20+ years of data used by Scott et al. (2012) ensured the most extreme weather was used for the scenarios this study used five years, 2008-2012, of data. The smaller temporal range ensured that the study emulated fire risk around the latter study period. Using data during the study period ensured the large fires that burned during this time are represented. Weather conditions were collected from the RAWS program (http://www.raws.dri.edu/), which generates daily fire weather. This dataset provides maximum temperature, RH, winds speeds, and wind direction (Team 2005). Data came from a weather station located in Bastrop county which is the only location with a complete dataset for the time of interest.

This study used data collected from only one weather station, however weather conditions are heterogeneous across the landscape. Wind patterns vary based on the prominent wind direction and with terrain (Werth 2011). Since wind data was only available from one location within the study area, the WindNinja software was used to create wind vectors for the entire study area. This software has been used by other studies for risk analysis (Alcasena *et al.* 2015). Additionally, RAWS winds are based on 10-minute average wind speeds. The U.S. Forest Service recommends transforming these wind speeds into 1-minute wind speeds (Crosby and Chandler 2004). While winds were heterogeneous across the landscape, FlamMap does not allow other weather conditions to have the same variability.

Figure 10: Monthly Wildfire count and acres burnded. The acres burned in September is off the chart due to the Bastrop complex fire. The acres burned in September is off the chart due to the Bastrop complex fire. The five months June, July, August, September, and October are the months of focus within the study.



During the study period, many bigger fires (>10 acres) occurred in the months of July, August, September, and October (Figure 10). Interestingly, February does not have many fires, yet the quantity of acres burned is significantly higher than in the surrounding months. The number of acres burned in February is primarily driven by one power line fire (1,500 acres burned) and seems to be an anomaly in the dataset. Thus, the study focused on the five most volatile months (June, July, August, September, and October). Daily ERC values were used to find days above the 95th percentile and used these dates for the fire scenarios. The 95th percentile ERC was used instead of the 97th because of the limited temporal size of the weather conditions, and this threshold added several more weather scenarios to the study, providing a broader spectrum of extreme weather scenarios (Appendix A). By using this analogue of burning days, weather conditions were realistic; winds, humidity, temperatures were aligned as compared to synthesizing from the 95th percentile of each weather variable.

V.2.1.2 Topography

Fire simulators require topographical inputs to identify fire spread rates and direction (Finney and Andrews 1999). These spatial datasets include elevation, slope, and aspect. Spatial heterogeneity within the landscape can influence fire risk since ridges and valley bottoms can create fire breaks (Finney *et al.* 2011). For this study, the topographic datasets were collected from the LANDFIRE website (www.LANDFIRE.gov) and are part of the National Elevation Dataset (NED). The NED has a 900 m^2 grain size and 1 meter vertical resolution. Other datasets offer a higher resolution or grain size; however, NED has the same grain size as the land cover and other inputs, eliminating the need to upscale and resample. Elevation in the study area varies (79 to 433 meters); the highest points are in Travis county while the lowest are in Bastrop.

V.2.1.3 Fuel

Information about canopy cover, stand height, crown base height, and canopy bulk density is also required for fire simulators (Finney and Andrews 1999) such as FlamMap. These datasets are available from the LANDFIRE website (www.LANDFIRE.gov). The fuel characteristics were collected for both study years (2001 and 2012).

V.2.1.4 Ignitions

MaxEnt was used to estimate the spatial distribution of fires (Bar Massada *et al.* 2013), as previously described. A large sample (78,000 points per study year[1]) of ignitions from the IP rasters was used as inputs for the BP models. The ignition samples are a random sample which are weighted by the IP rasters created in chapter 4 using the Geospatial Modeling Environment (http://www.spatialecology.com/gme/). The BP ignition sample

1: Initially the ignition sample size was lower (39,000 ignitions), however a small portion of Travis county would not burn. Even with the larger ignition size, that area remained mostly unburned. This likely due to low ignition probability and an area that is not conducive to burning. Little would have been gained in this area by adding more ignitions, and so simulations were stopped.

size is limited by computational power. Early BP research was limited to 6-10,000 ignitions (Bar Massada *et al.* 2009; Bar Massada *et al.* 2011), but increases in computational power and software efficiency allowed sampling to significantly increase. FlamMap is capable of running more than 50,000 ignitions over two million hectares (Ager *et al.* 2010b) in a single run. Proper sample size is difficult to determine because fires sizes vary based on fuel, weather, and topography. These regional variations mean differing landscapes require different ignition densities. Unlike a static statistical sample that allows researchers to estimate the power of the sample, type I and type II errors, no such rules exist for calculating ignition sample sizes. However, an ignition density ratio for the study area can help estimate proper sampling size. For example, recent studies have used a wide variety of ratios (2-13 ha/ignition) for their sampling size (Ager *et al.* 2010a; Ager *et al.* 2012). The proposed sample size creates a ratio (8.5 Ha/ignition), well within the range of previous research.

V.2.1.5 Simulation Times

This study used 12-hour simulation times and 95th percentile ERC in weather conditions to minimize the impact of homogenous temporal weather conditions. In addition, a 12-hour simulation can also attempt to emulate suppression. A maximum of 12 hours for burn time assumes the fire was effectively put out or suppressed by that 12th hour.

V.2.2 Simulation Outputs

Fire simulation software outputs include: fire perimeters, burn probabilities (BP), fire sizes lists, and flame length probability (FLP). These outputs are used to understand two of the three aspects of risk: probability and behavior. Probability is characterized by BP, while behavior is characterized by the fire perimeters, fire size list, and FLP. These can be combined to show differing aspects of fire behavior. More specifically:

- BP: The primary output from the FlamMap Software is the BP raster. This raster consists of the probability that a cell burns if an ignition occurs on the landscape.
- Fire Perimeters: This output is a polygon of each fire perimeter that was burned on the landscape.
- Fire Size Lists: The fire size is output as a text file list with each unique ignition number and the size of the fire that burned.
- Conditional Flame Length (CFL): CFL estimates the mean flame length of each fire that burned on a given raster pixel (Scott *et al.* 2013). CFL was calculated using the ArcFuels add-in within ArcMap. The single output makes this more conducive to directly measure changes in fireline intensity.

V.2.3 Model Validation

Once the simulated models were created, the outputs were validated to ensure each model represents wildfire potential on the landscape. The models' validity was assessed using historic large fires that have occurred on the landscape. Historic fire perimeters are measured to ensure that inputs for BP models are accurately represented (Jahdi *et al.* 2015). This method uses the ignition location from a historic fire and simulates the fire

using weather from that event. Ideally, if fuel moisture, wind speed, and direction are correct, then the simulated model should represent a similar fire boundary as the historic fire. However, some discrepancies are expected due to suppression tactics, or micro-climatic changes (Dillon *et al.* 2011). Although qualitative, optimizing inputs ensures that the fire burns similarly to the historic fire and gives a reasonable estimate as to how well the model performs before the BP simulation is created.

The initial validity assessment explains how well the FlamMap software emulated fire behavior on the landscape, yet BP models simulate statistical distributions of fires. Not all fires have occurred, but they all have the potential to occur. Ensuring that the model is representative of a landscapes fire behavior is a difficult task. Studies can explain many characteristics using one or two weather scenarios but they may not be representative of what could happen on the landscape. Research using the software FSIM assessed fires on days with similar weather conditions as those on which large fires burned, demonstrating that similar fire shapes have (or have not) occurred (Finney *et al.* 2011). Validating a BP landscape is necessary to ensure that fire managers and planners have access to reliable estimates; it is considered one of the primary research objectives for BP modeling (Miller and Ager 2013).

This study used a different method for understanding BP model fit. A BP map creates a continuous raster of probabilities in which a fire may occur on the landscape. IP models use the AUC derived from the ROC to test how well a model fits historic ignitions. The ROC analysis compares the number of true positive fractions with false positive fractions across a spectrum (0.50 - 1), providing an AUC that measures the sensitivity of a model (Metz 1978). A low AUC score (.50) shows that the model performs no better than random while a high ROC score (.90) shows an excellent fitting model (Swets 1988). However, using this method with BP models is difficult because the AUC graph is biased

towards models with a broader probability distribution between 0-1 (Peterson *et al.* 2008) and does not identify the spatial location of the model's error (Lobo *et al.* 2008). Lobo et al. (2008) suggested that a qualitative assessment of the AUC graph can help to differentiate when a smaller probability distribution is expected. Another alternative is to normalize the data. This can be done by dividing the probabilities by the maximum probability on the landscape if the probabilities are skewed to the left or by the minimum value if they are skewed to the right (Peterson *et al.* 2008). This transformation ensures that true positives and negatives will occur throughout the probabilities, allowing a more appropriate ROC analysis.

The sample for the ROC analysis of BP was comprised of historic large fires from the second study time period (2012). Like IP modeling, a fire could potentially occur at any given location. Instead of true absences, spatially random pseudo-absences measured the sensitivity of the model (Barbet-Massin *et al.* 2012). Random points were generated across the study area (n=20,000), of which a subsample fell within the historic fire perimeters (n=711). By using a random sample across the study area, the sample was a close approximation of the amount of area burned versus non-burned. With the fire presence and absences dataset created, the ROC analysis was used to test how well the models fit historic wildfires. Since this method tests the sensitivity of true positive and false positive fractions, this AUC is capable of being compared across different landscapes.

V.2.4 ANOVA

One-way ANOVA's were used to test differences between both Δt_1 and Δt_2 development categories. Each BP and CFL model ANOVA had the same sample size (n=56,634) for the eleven development categories.

V.2.5 SNA

The last two sections have assessed broad scale initiation and exposure from a wildfire. However, if a fire abuts a development, it likely does so for more than one pixel. In addition, a limited amount is understood about where the fire originated. This next section uses a social network analysis to understand ignition and exposure, and how those two characteristics move across the landscape.

SNA's have two parts: edges and nodes. (Wasserman and Faust 1994). Edges are the connection that occurs between the two nodes. In a directed SNA, sources are defined as "where the event occurs," while the target receives the event. In this application, developments located near the fire ignition location were defined as the source while all development intersecting a fire perimeter became a target. Source nodes only occurred if a fire was within 500m of the ignition location. This cutoff distance was based on the influence of the distance to roadways variable; after 500m, the probability of a development near a roadway is low. For example, if an ignition occurred near a radial development patch and moved to an isolated development patch, the radial development patch would be classified as the source and the isolated development would become the target. Nodes can be aggregated into degrees, which count the number of times a node either is the source (out-degree) or the target (in-degree). Here, degrees explain the influence of exposure (Ager *et al.* 2014) and degree types identify the developments that are initiating and exposing the riskiest fires.

While in-degree and out-degree help to explain which specific developments have the highest interactions with synthetic fires, measuring centrality and prestige aggregate those measures to a development category (Wasserman and Faust 1994). Centrality aggregates out-degree, while prestige aggregates in-degree. These measures are used to order

developments and create a ranking of the riskiest developments. In this study, degree centrality was used to measure the centrality of the system. The directional networks centrality metric is calculated as follows (Everett and Borgatti 2005):

$$\text{normalized group degree centrality} = N(C) / V - C \qquad [5]$$

Where N(C) is the number of unique adjacent vertices not within the grouped development type. V is the total number of vertices in the network, and C is the number of vertices within the group. Degree prestige was calculated similarly but using the in-degree nodes instead of out-degree.

The final aspect quantified in the section is how the fires flow. Fire flow identifies how fires are directed and where the fires move on the landscape. For example, do isolated fires typically move towards radial development, towards more outlying development? Since the study consists of two generations of development patterns, it also quantifies how exposure shifted when the Δt_2 was added to the landscape.

V.2.6 Fire Risk Regressions

Two regression models were used to measure how landscape changes influence BPΔ (model 1) and CFLΔ (model 2). While the previous analyses focused on variations in risk by development patterns, the primary focus of this analysis is understanding the influence of confounding and mediating variables on BP and CFL. Specifically, this study addressed how the changes in surrounding fuel loading and road density influence local BP and CFL. This section uses statistical models to test hypotheses three and four.

V.2.6.1 Concept Measurement

The dependent variables were BPΔ and CFLΔ, which were sampled from the difference between the 2001 and 2012 models. BPΔ measures change in percent likelihood that a fire will reach a given location if a fire starts on the landscape. CFLΔ measures the change in conditional flame length (feet). Independent variables were derived from the 13 fire behavior fuel models (FBFM 13) which was provided by LandFire, and the U.S. Census Tiger files (Table 5).

V.2.6.1.1. Independent Variables

The objective of this analysis is to measure independent variables that may influence fire risk. Two of the main variables of influence are road density and surrounding fuel loading.

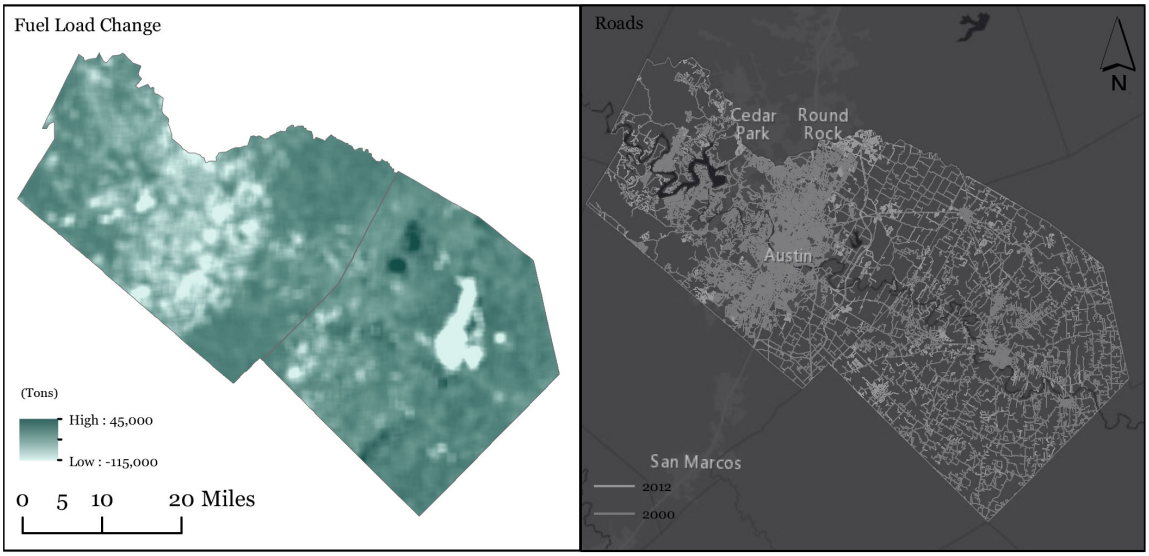
V.2.6.1.1.1 Road Density

Roads are a primary driver of ignition location and frequency (Syphard *et al.* 2007b; Bar Massada *et al.* 2013; Faivre *et al.* 2014). However, roads can act as a fire break from ground fires as well (Bar Massada *et al.* 2011). For this study, road density was calculated as the sum (kilometers) of roads surrounding a pixel. The window size used to measure road density was on the same spatial scale as the rest of the study (1.92 km). The change in road density between the two study periods (Figure 11 right) was then determined.

Table 5. Varible names, definitions, descriptive statistics

Variable	Definition	Mean	Std. Dev.	Range	
	Dependent Variables				
BPΔ	Difference in burn probability between 2012 and 2001 models (%)	0.201	0.287	-0.776	1.560
CFLΔ	Difference in conditional flame length between 2012 and 2001 models (ft)	0.770	1.167	-6.542	8.280
	Variables of Interest				
Fuel LoadΔ	Estimated burnable fuel with in a 1920 m radius (tons)	-12.447	13.282	-113.475	44.675
Log Road DensityΔ	Difference in Road density surrouning a sample. Those samples with a value>0 were log transformed. (Km of Roads/Km^2)	3.818	2.727	-4.581	8.742
	Land Cover Transitions				
Grass to Shrub	Transition States of a Sample	0.004	0.059	0	1
Grass to Timber	Transition States of a Sample	0.007	0.084	0	1
Grass to Urban	Transition States of a Sample	0.020	0.141	0	1
Shrub to Grass	Transition States of a Sample	0.007	0.083	0	1
Shrub to Timber	Transition States of a Sample	0.006	0.075	0	1
Shrub to Urban	Transition States of a Sample	0.001	0.034	0	1
Timber to Grass	Transition States of a Sample	0.149	0.356	0	1
Timber to Shrub	Transition States of a Sample	0.000	0.014	0	1
Timber to Urban	Transition States of a Sample	0.022	0.148	0	1
	Development Transition Type				
Infill	Samples adjacent or within the Δt2 Infill	0.006	0.078	0	1
Radial	Samples adjacent or within the Δt2 Radial	0.025	0.155	0	1
Isolated	Samples adjacent or within the Δt2 Isolated	0.001	0.025	0	1
Cluster	Samples adjacent or within the Δt2 Clustered	0.002	0.047	0	1
Linear	Samples adjacent or within the Δt2 Linear	0.001	0.028	0	1
	Variables for BP model only				
IPΔ	Difference in ignition probability between 2012 and 2001 model (%)	0.003%	0.015%	-0.884%	0.100%

Figure 11: New roads (right) and fuel load changes (left)



V.2.6.1.1.2 Fuel Loading

LANDFIRE provides datasets that include the 13 fuel models for fire behavior (Albini 1976). These 13 fuel models estimate the fuel loading of a pixel (Anderson 1982). Tables provided by Anderson (1982) helped calculate the fuel surrounding a pixel. Then, the difference in fuel loading between the study periods (Figure 11 left) was calculated.

V.2.6.1.1.3 Land Cover Change

Many of the variables within the regression models identified the type of land cover transition that occurred at a given sample location. Four general categories of land cover were used based on the fuel type: grass, shrub, timber, and urban (Anderson 1982). In addition to these transitions, dummy variables were created for samples that occurred within or adjacent to the different Δt_2development. If overlap occurred (e.g. a sample was adjacent to both infill and radial), they were removed to keep the samples independent of each other.

V.2.6.1.1.4 Ignition and Burn Probability

The two models also had one unique independent variable each. IP was added to the regression model explaining change in BP, and BP was added to the regression model explaining CFL. Within the regression models fuel load does not change based on previous ignitions; therefore, a high proportion of ignitions will drive high burn probability areas. However, IP will not directly drive CFL as this is a function of the behavior once that fire begins moving, BP is a better explanation of that fire propagation. Because of this, the CFL model controls for BPΔ but not IPΔ.

V.2.6.2 Statistical Models

The study used two generalized method of moments (GMM) regression models using the PYSAL library for Python (Rey and Anselin 2007). Since the study area rasters have a large number of pixels (>7 Million), the regression models used a random sample (n=100,000) of pixels on the landscape. The sample size allows for a large enough sample (>100) for each sub-group of land cover change. Those samples with overlapping new development types were removed to keep the samples independent (model n = 99,967).

An initial OLS regression was run for each dependent variable, diagnostics for both models suggested they had high spatial autocorrelation ($p<0.0001$). The models used a Queen Contiguity weights matrix to control for spatial autocorrelation. Two-stage least squares lag models were run for each dependent variable. After a spatial lag was introduced, the Anselin-Kelejian (Anselin and Kelejian 1997) test suggested that both models still had spatial autocorrelation issues ($p<.001$). Therefore, the models were estimated to control for spatial lags and corrected for spatial error (Kelejian and Prucha 1998). After controlling for spatial autocorrelation, the CFL model showed signs of heteroscedasticity, so a robust standard errors model was used (Anselin 2011).

V.3. Results

V.3.1 Burn Probability Maps

Simulated fire sizes varied from very small (<0.01 ha) to enormous (20,000+ ha). Fires were more likely to burn larger in the 2012 model than the 2001 model (Figure 12). The maximum BP in 2012 (p_{BP}= 0.01625) was nearly twice as high as 2001 (p_{BP}=0.00830). The high burn probabilities were due to larger fires on the 2012 landscape, while the 2001 landscape produced dramatically smaller fires (max: 7,965 ha). High probability areas for both years occurred in western Bastrop county. Within the 2012 model, a high probability area occurred in northern Bastrop as well. The lowest probabilities occurred near the Austin metro area within Travis county. Some burnable areas near the metro never caught because fire sizes were so small.

V.3.2 Conditional Flame Lengths

Fires burn at different intensities given variations in fuel moisture, fuel amount, wind speed, and other factors. Additionally, different fire intensities will ignite a structure which is dependent on the distance of the fire from a home (Cohen 2000). The two simulation models produced CFL maps (Figure 13) which show the likely fire intensity for a given cell. Those cells with higher CFL's are at a higher risk of total loss within the cell. Overall, the 2012 model produced higher CFL's across the entire study area compared with the 2001 model. Peak CFL was higher in the 2012 model (11.58 ft.) than the 2001 model (10.64 ft.).

Figure 12: Variation in BP for the 2012 and 2001 models. Higher BP occurred on the western part of Bastrop county, notably in the 2012 model. The dark gray indicates urban development within the study area.

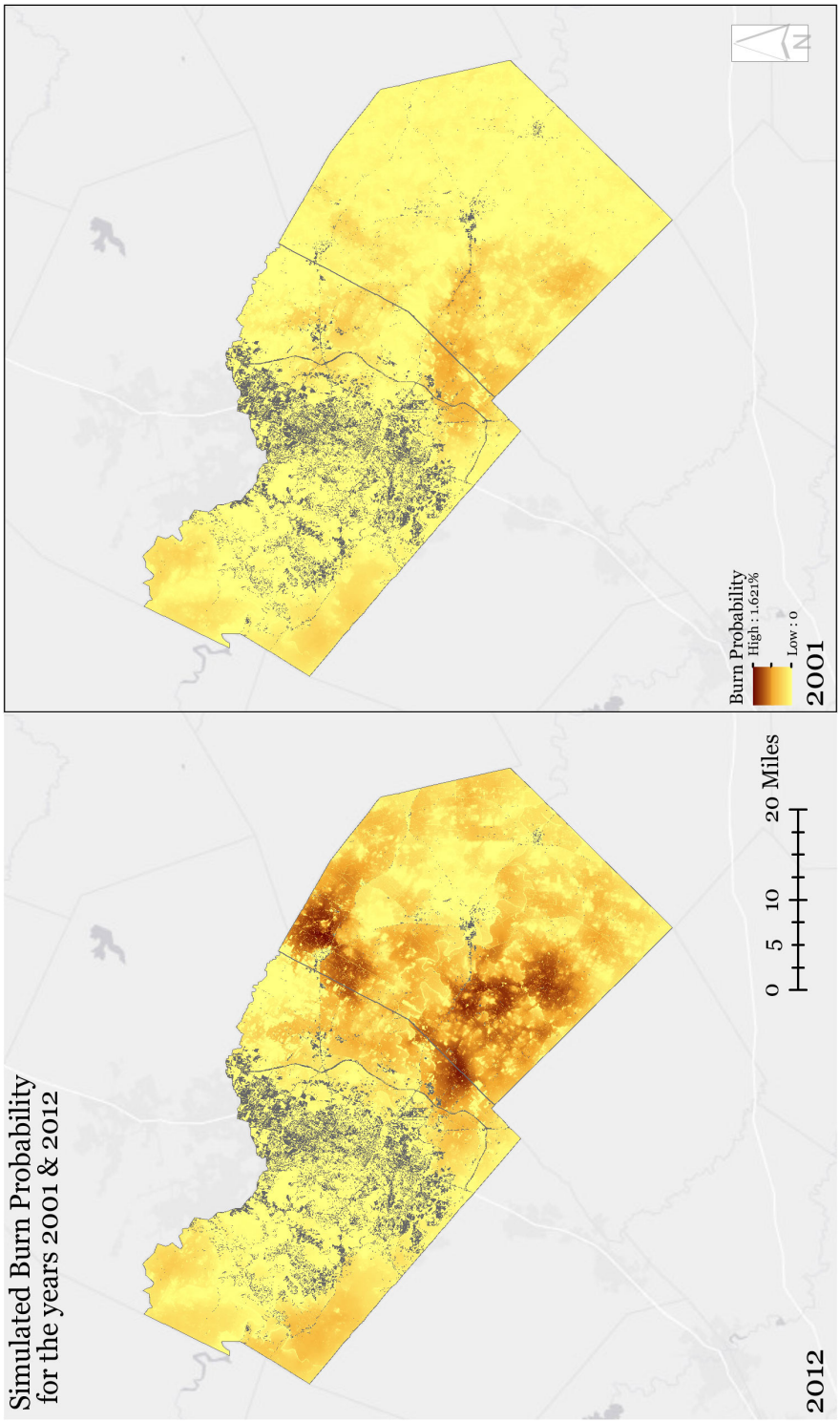
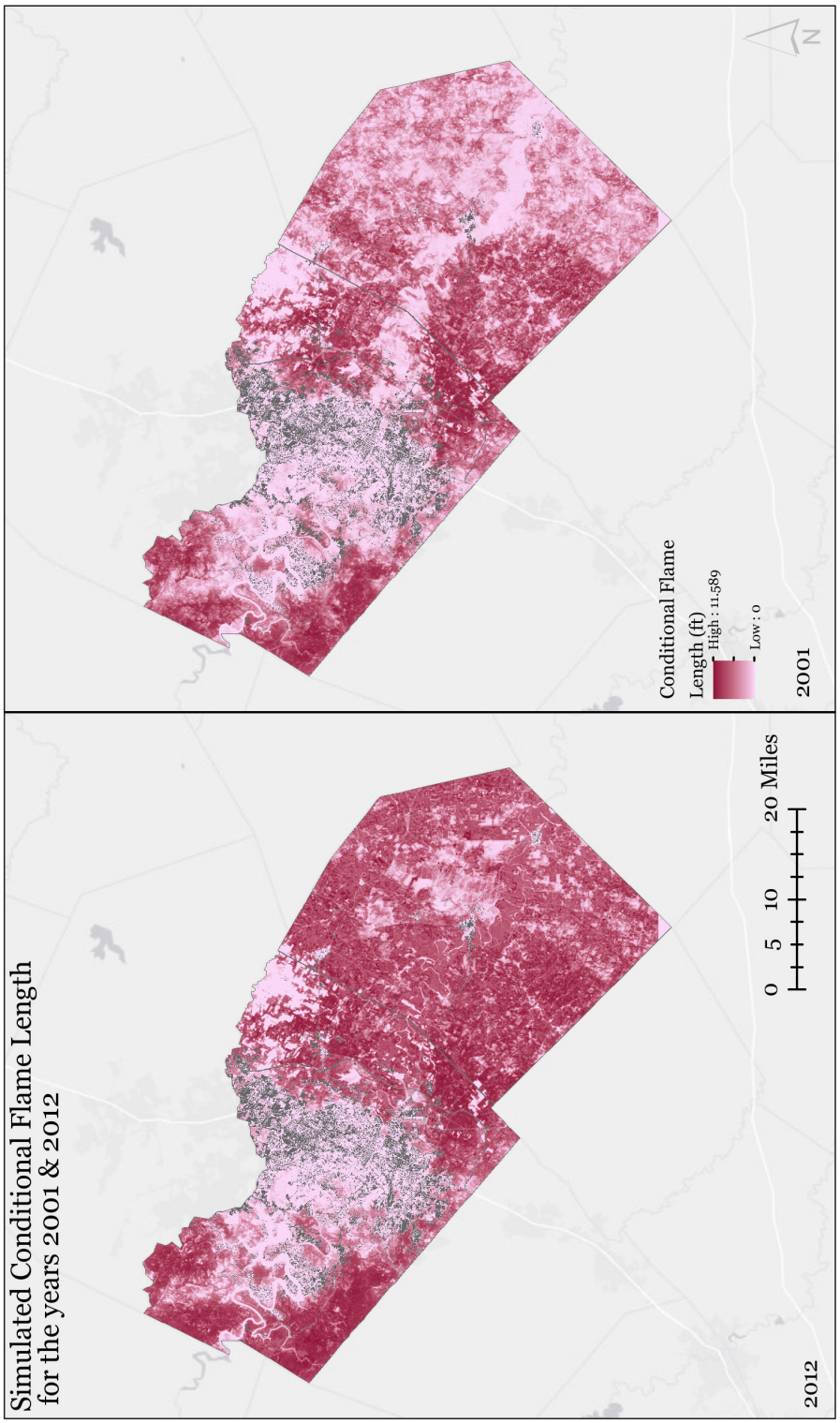


Figure 13: Variation in CFL for the 2012 and 2001 model. Note the increases in CFL across the landscape. The dark gray indicates urban development within the study area.



V.3.3 Model Validation

This study used the EPW fire (Figure 14) as a test fire. The EPW fire burned over 800 acres on Aug 5, 2011. Because the EPW burned a relatively large area within one day, this fire was an ideal test for input variables. Simulating the EPW fire shows a similar burn pattern to the historic fire. The simulation was stopped by the road to the north which shows why the fire did not move further northward. While the maximum fire sizes of the more recent landscape were high, many of the fires resembled historic fire patterns (Figure 14).

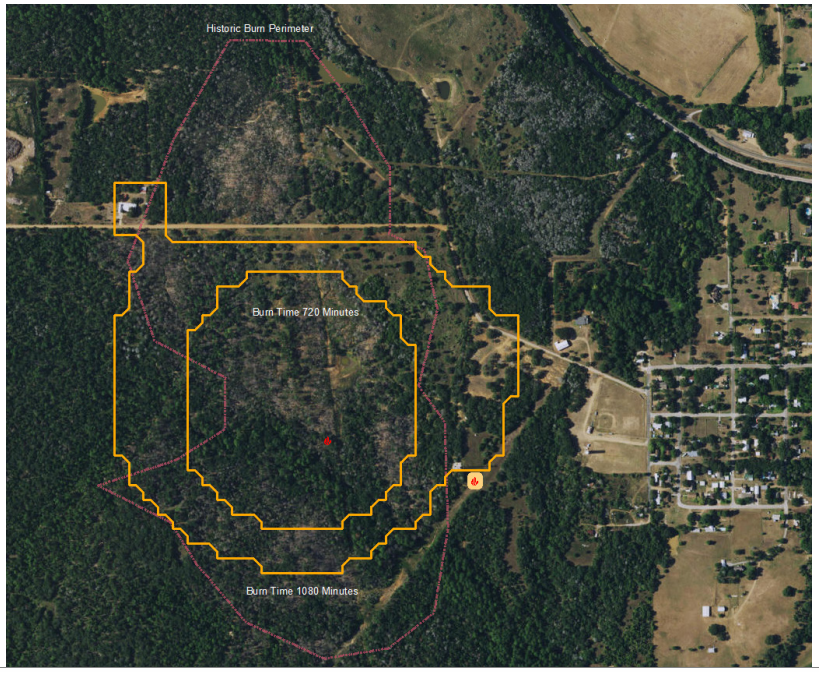
V.3.3.1 Sensitivity

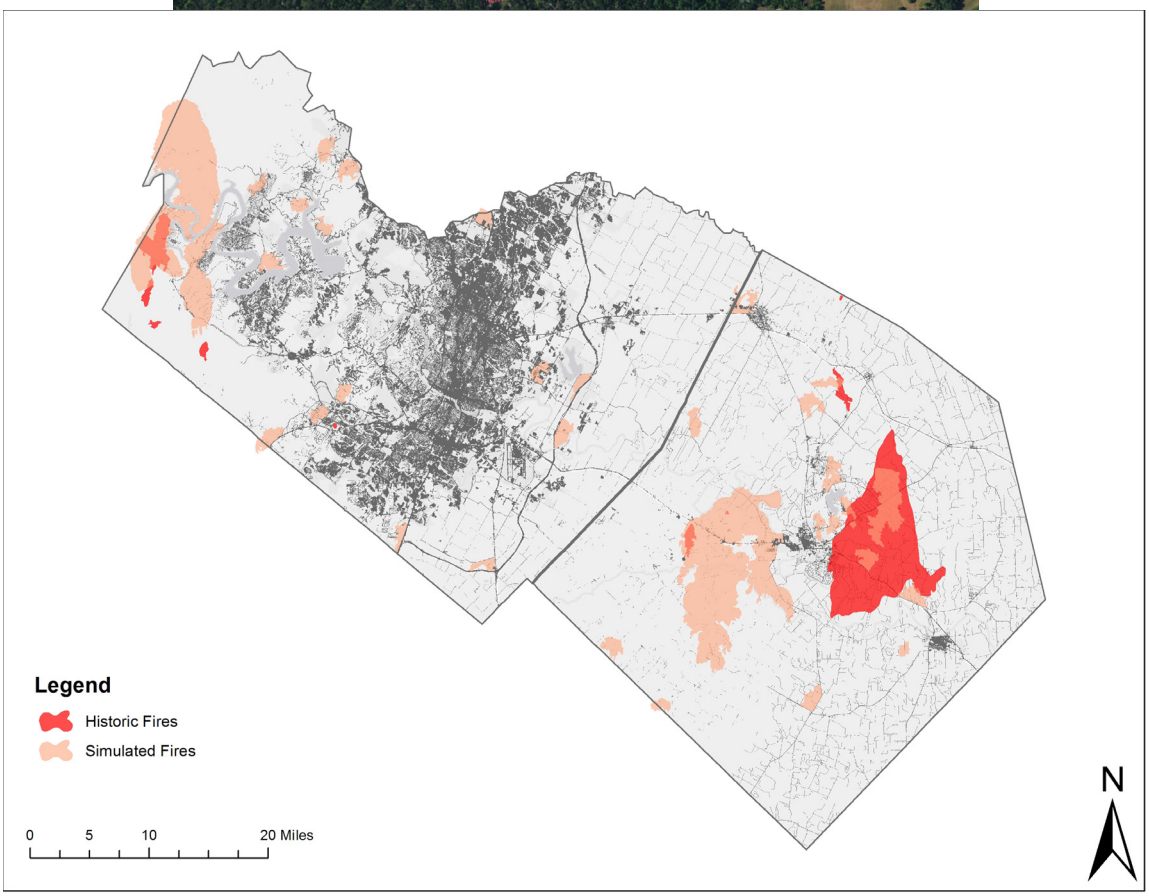
Initial sensitivity tests measured how well the BP model predicted large fires on the landscape. Sensitivity was quantified by measuring the more recent BP model (2012), using the ROC, and measuring the AUC as well as by using historic fire perimeters as presence values and random pseudo absences (Bar Massada *et al.* 2013). Nine historic fire perimeters were used for the presence data. Each of these fires occurred in 2011 and ranged from 7 ha to 19,000. The Bastrop complex was the largest fire within this dataset. Using the fire perimeters, the BP model performed worse than random (Table 6, AUC: 0.475). Most of the errors occurred in Bastrop county, while Travis county performed very

Table 6: Area Under the curve values, based on different parameters.

	Area Under the Curve		
BP	Overall	Without Bastrop Complex	Addition of 2012 Ignitions
Both Counties	0.475	0.68	0.631
Austin	0.87	n/a	0.756
Bastrop	0.253	0.469	0.744

Figure 14: EPW Fire and Simulated Fire Comparison. Top: The outline of the EPW fire (red) and nearby development. Bottom:Historic and simulated wildfires on the landscape. Fires tended to have similar shapes and sizes compared with the historic fires.





well individually. Many of the errors in Bastrop county likely came from the model's inability to correctly simulate the Bastrop Complex. This is likely because the model struggles to emulate the kind of heterogeneous weather conditions which were vital in causing the size and severity of the Bastrop Complex (Rissel and Ridenour 2013). If the Bastrop Fire is removed from the presence data, the model's performance improves.

Most of the area that caused poor sensitivity occurred in the west and north sections of Bastrop county. These areas are better explained by many small fires. If all ignitions (2012) were included, the model predicted fire occurrence more accurately (AUC: 0.631). The model performed even better by removing the Bastrop complex. Additionally, the model was a better fit for Bastrop county alone with no Bastrop Complex. While the fit for Bastrop county seemed to benefit from the smaller fires, the model suffered in Travis county with small fires included (AUC: 0.756). This is most likely due to the number of small fires that occurred near or previously developed areas.

Table 7: ANOVA and post hoc analysis for the 2001 BP model and development patterns. The lines under the chart show which development patterns were not statistically different using Post hoc analysis. This suggests BP's for those development patterns cluster together.

Number of obs = 56634
Root MSE = .080455

df	F	Prob > F
10	887.29	0.0000

Dev Type	Δt2 Infill	Δt1 Infill	Core	Δt2 Radial	Δt1 Radial	Δt2 Clus-tered	Δt1 Clus-tered	Δt2 Linear	Δt2 Iso-lated	Δt1 Linear	Δt1 Iso-lated
Mean	0.003%	0.004%	0.016%	0.059%	0.066%	0.099%	0.142%	0.143%	0.157%	0.212%	0.222%

V.3.4 Statistical Analysis

V.3.4.1 BP

The One-way ANOVA for the 2001 model (Table 7) demonstrated significant differences between development types ($p<0.0001$). *Post hoc* analyses were conducted using the Tukey-Kramer HSD to identify the differences in mean BP across development types. The clear majority of tests using the Tukey Kramer HSD showed significance of at most $p<0.1$. The order of development type probabilities sorted from low to high varied based on the year of the model. The *Post hoc* analysis reveals three main clusters. The lowest risk cluster contains Δt_1 and Δt_2 infill and previously urban development. The next cluster consists of Δt_1 and Δt_2 radial. The highest risk areas make up the last cluster, which contains all outlying development patterns except for the Δt_2 clustered. In addition, a smaller cluster resides within the outlying development patterns. This smaller cluster consists of new linear and isolated as well as old cluster.

Table 8: ANOVA and post hoc analysis for the 2012 BP model and development patterns. The lines under the chart show which development patterns were not statistically different using Post hoc analysis. This suggests BP's for those development patterns cluster together.

Number of obs = 62215 Root MSE = .130901

df	F	Prob > F
11	1151.08	0.0000

Devolpment type Type	Δt2 Infill	Δt1 Infill	Core	Δt2 Radial	Δt1 Radial	Δt2 Clustered	Δt2 Isolated	Δt2 Linear	Δt1 Clustered	Δt1 Isolated	Δt1 Linear
Mean	0.002%	0.005%	0.024%	0.068%	0.125%	0.154%	0.197%	0.216%	0.241%	0.484%	0.512%

The One-way ANOVA for the 2012 model (Table 8) demonstrated significant differences between development types ($p<0.0001$). *Post hoc* analyses were conducted using the Tukey-Kramer HSD. The clear majority of tests using the Tukey Kramer HSD showed significance of at least $p<0.1$. The order of development type probabilities that sorted low-high varied based on the year of the model. The 2012 BP model had three distinct groups. Both Δt_1 and Δt_2 infill and previous urban development make up the lowest risk areas, while Δt_1 isolated and linear make up the highest BP areas. Outlying development ranked according to generation, with Δt_2 categories lower than Δt_1. Both Δt_1 and Δt_2 categories followed the BP order of clustered, isolated, and linear.

Table 9: ANOVA and post hoc analysis for the 2001 CFL model and development patterns. The lines under the chart show which development patterns were not statistically different using Post hoc analysis. This suggests CFL's for those development patterns cluster together.

Number of observations = 56767 Root MSE = .914176 Adj

df	F	Prob > F
10	1591.95	0.0000

Development Type	Δt2 Infill	Δt1 Infill	Core	Δt2 Radial	Δt1 Radial	Δt2 Clustered	Δt2 Linear	Δt1 Clustered	Δt2 Isolated	Δt1 Isolated	Δt1 Linear
Mean	0.152	0.163	0.392	1.157	1.338	1.692	1.927	2.142	2.196	2.347	2.484

V.3.4.2 Severity

The One-way ANOVA of the 2001 model (Table 9) demonstrated significant differences between development types ($p<0.0001$). *Post hoc* analyses were conducted using the Tukey-Kramer HSD. While many tests using the Tukey-Kramer HSD showed significance (45 of 55) when determining the mean difference between development types, four groups of development types clustered together, Δt_1 and Δt_2 infill development, Δt_1 and Δt_2 radial development, and Δt_2 clustered and linear. The fourth cluster was much larger and contained most of the outlying development patterns.

Table 10: ANOVA and post hoc analysis for the 2012 CFL model and development patterns. The lines under the chart show which development patterns were not statistically different using Post hoc analysis. This suggests CFL's for those development patterns cluster together.

Number of obs = 56767 Root MSE = .887079

df	F	Prob > F
10	1949.90	0.0000

Dev Type	Δt2 Infill	Δt1 Infill	Core	Δt2 Radial	Δt1 Radial	Δt2 Clustered	Δt2 Isolated	Δt2 Linear	Δt1 Clustered	Δt1 Isolated	Δt1 Linear
Mean	0.090	0.141	0.384	0.916	1.447	1.729	1.989	2.011	2.233	3.140	3.177

The one-way ANOVA of the 2012 model (Table 10) demonstrated significant differences between development types ($p<0.0001$). *Post hoc* analyses were conducted using the Tukey-Kramer HSD. While many tests using the Tukey-Kramer HSD showed a significance of at least $p<0.1$ (49 of 55), when determining the mean rank between development types, adjacent means were not significant. Unlike the 2001 model, two clusters arise in *Post hoc* assessment. These groups consist of Δt_1 and Δt_2 infill developments and the second was Δt_1 isolated, and Δt_2 linear, and Δt_1 clustered.

V.3.5 SNA

The results are split into three sections (Table 11). The first section identifies trends that occurred within the 2001 model. The second section focuses on trends within the 2012 model. The final section identifies variations that occurred between the two simulation models.

Table 11: Variation in Centrality and Prestige for Development Types

2012 Model								
Degree Centrality					Degree Prestige			
Summarize	Centrality	Rank	Centrality / ha	Rank	Degree Prestige	Rank	Prestige / ha	Rank
Previously Developed	0.4519792003	1	0.0000152517	9	0.3581137082	1	0.0000120842	9
Δt1 Radial	0.3060283764	2	0.0000941837	6	0.3398797145	2	0.0001046019	6
Δt2 Radial	0.1259223964	3	0.0000176092	8	0.1510366096	3	0.0000211212	8
Δt1 Linear	0.039709999	4	0.0003109388	3	0.0515855537	4	0.0004039273	2
Δt2 Isolated	0.0305414913	5	0.0003256717	2	0.0292243869	5	0.0003116271	3
Δt2Clustered	0.0245348457	6	0.000040871	7	0.0172056102	7	0.0000286617	7
Δt2 Linear	0.0178911917	7	0.0001287507	4	0.0195680242	6	0.0001408177	4
Δt1 Clustered	0.007761789	8	0.0001253519	5	0.0071275651	8	0.0001151093	5
Δt1 Ioslated	0.0048307545	9	0.0004328633	1	0.0051679277	10	0.000463076	1
Δt1 Infill	0.0043733883	10	0.0000038262	10	0.005461198	9	0.000004778	10
Δt2 Infill	0.0028109682	11	0.0000022082	11	0.0014045664	11	0.0000011034	11

2012 Model no Δt1								
Degree Centrality					Degree Prestige			
By Exposed	Degree Prestige	Rank	Centrality / ha	Rank	Degree Prestige	Rank	Prestige / ha	Rank
Clustered	0.5352678671	5	0.0086445069	2	0.1259987159	4	0.002034863	2
Previously Developed	9.7834496031	1	0.0003301344	5	4.3080007954	1	0.0001453699	4
Infill	0.0417048962	6	0.0000364872	6	0.0158499446	6	0.000013867	6
Isolated	0.9386457511	3	0.0841080422	1	0.1593714516	3	0.014280596	1
Linear	0.5953816354	4	0.0046619813	3	0.0993293343	5	0.0007777726	3
Radial	4.9667451362	2	0.0015285726	4	0.2911841172	2	0.0000896152	5

2001 Model no Δt2								
Degree Centrality					Degree Prestige			
Summarize	Centrality	Rank	Centrality / ha	Rank	Degree Prestige	Rank	Prestige / Ha	Rank
Clustered	0.0096862777	4	0.0001564321	3	0.0097271866	5	0.0001570928	3
Previously Developed	0.4753897098	1	0.0000160416	5	0.498661511	1	0.0000168269	5
Infill	0.0086049875	5	0.0000075284	6	0.0011228341	6	0.0000009824	6
Isolated	0.0060442418	6	0.0005415987	1	0.0103978702	4	0.0009317088	1
Linear	0.0532566796	3	0.0004170126	2	0.0562398475	3	0.0004403715	2
Radial	0.4396945828	2	0.000135321	4	0.4165332467	2	0.0001281929	4

V.3.5.1 2001 Model

V.3.5.1.1 Ignition

Out-degree varied by individual patches as well as development patterns. The patches with the highest out-degree occurred within the radial (917 fires initiated). Within the top 5% of out-degree patches, most patches were radial development (93.3%) or linear (6.6%).

While out-degree identifies the individual patches that initiated many fires, degree centrality identifies the development type. Radial had the highest degree centrality while infill initiated the fewest number of fires. Isolated and clustered had very similar amounts of fire ignition. Despite the similar centrality, the quantity of degrees for these development patterns is interesting because isolated makes up a significantly smaller amount of the landscape.

By controlling the total amount of each development type's area, degree centrality can approximate the impact of each new hectare of land. Once the degree centrality is normalized, isolated development initiates the most nodes per hectare, while infill is the lowest.

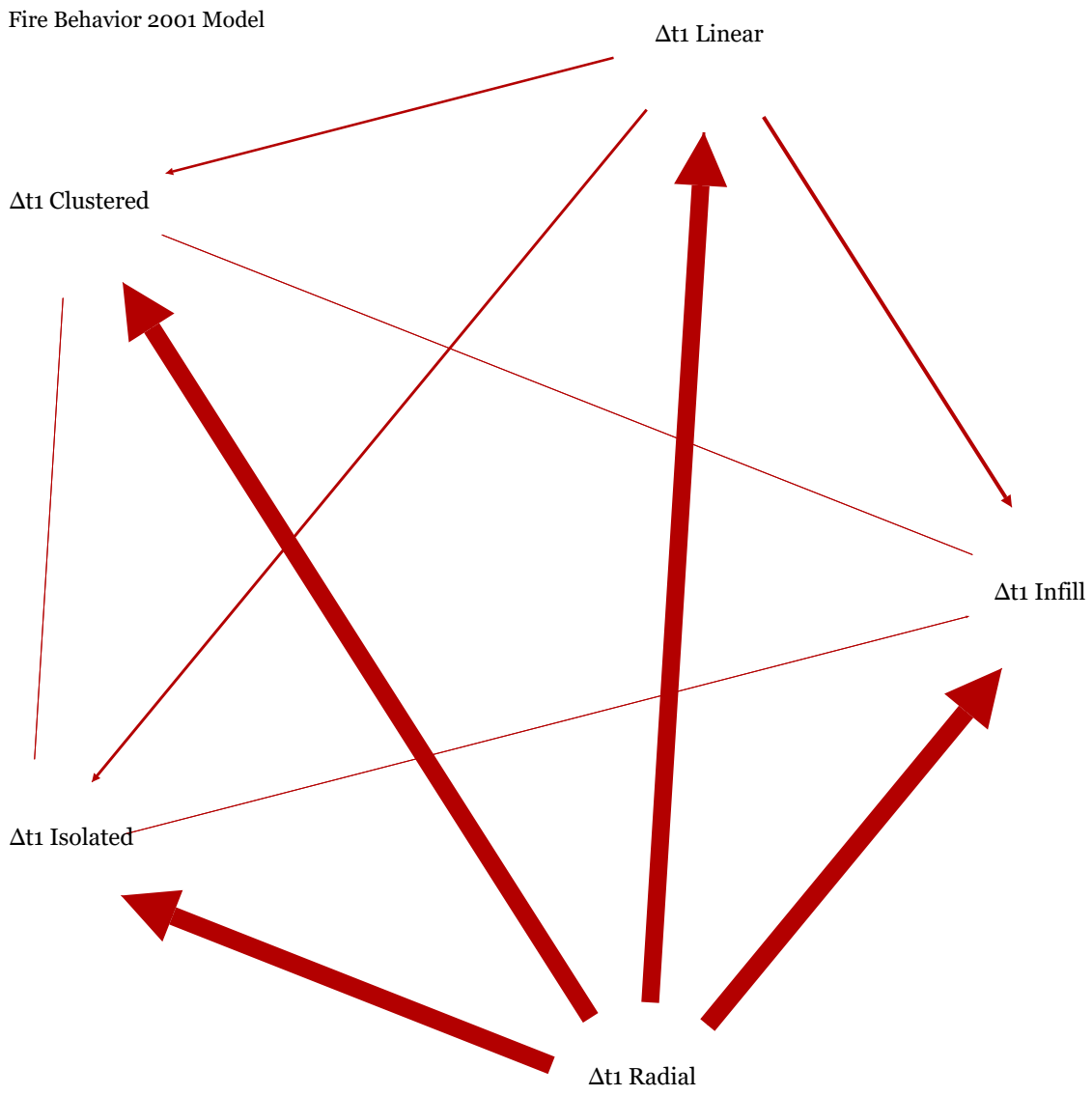
V.3.5.1.2 Exposure

In-degree was similar to out-degree; most patches in the top 5% were categorized radial (97.2%). Clustered (1.5%) and isolated (2.8%) made up the rest of the patches. The order of ranks for prestige centrality was similar when compared with degree centrality. Clustered and isolated had the lowest in-degrees respectively.

V.3.5.1.3 Fire Behavior

Only Δt_1 development was analyzed for the 2001 model since new development was not built at the time (Figure 15). Most development patches initiating and exposed

Figure 15: Network analysis of 2001 fires from BP simulations. The end of the arrows represent those exposed most commonly by fires. The non arrow ends represent those that commonly initiated fires. Thickness of the arrows represents number of exposures.



to fire came from radial development. Most fires initiated by radial development remain a threat to the radial development. Outside of those fires that ignite and threaten radial development, the most common fire transition is between linear and radial development. When initiated near a linear development, most fires threatened radial development (83%), more linear development (11.4%), or infill (1.98%) as compared with the other outlying developments. Fires initiated near infill rarely move towards outlying development. Fires initiated near clustered or isolated development commonly threatened radial development or their outlying counterpart, such as other clustered or isolated development.

V.3.5.2 2012 Model

V.3.5.2.1 Ignition

Like the 2001 model, out-degree varied within the 2012 model. An urban patch developed prior to 1996 had the largest number of ignitions near the patch (3,634 ignitions). The primary development patterns within the top 5% of high out-degree patches were the Δt_1 radial (53.3%), followed by Δt_2 radial (14.1%). Three other patterns occurred within the top 5% of Δt_2s of clustered (3.61%) and isolated (10.9%) as well as the Δt_1 linear (18.7%). The Δt_2 each development type had a higher out-degree than the respective Δt_1 development type. When assessing out-degree for all patches, more fires ignite near Δt_1. The exception is isolated, where new isolated development had the higher out-degree.

When degree centrality was normalized by a category's total area developed, the outlying development patterns rank higher. The Δt_1 isolated had the highest degree of centrality, followed by the Δt_2 isolated. Clustered and radial developments shifted within the rankings as well.

V.3.5.2.2 Exposure

Patterns of exposure varied little when compared with the ignition model. The order for development patches within the top 5% remains the same, with the exception that Δt_2 clustered (5.6%) and isolated (3.43%) switch. In addition, the Δt_2 linear development and the Δt_1 isolated occur in the top 5%. The patterns also remain the same for centrality.

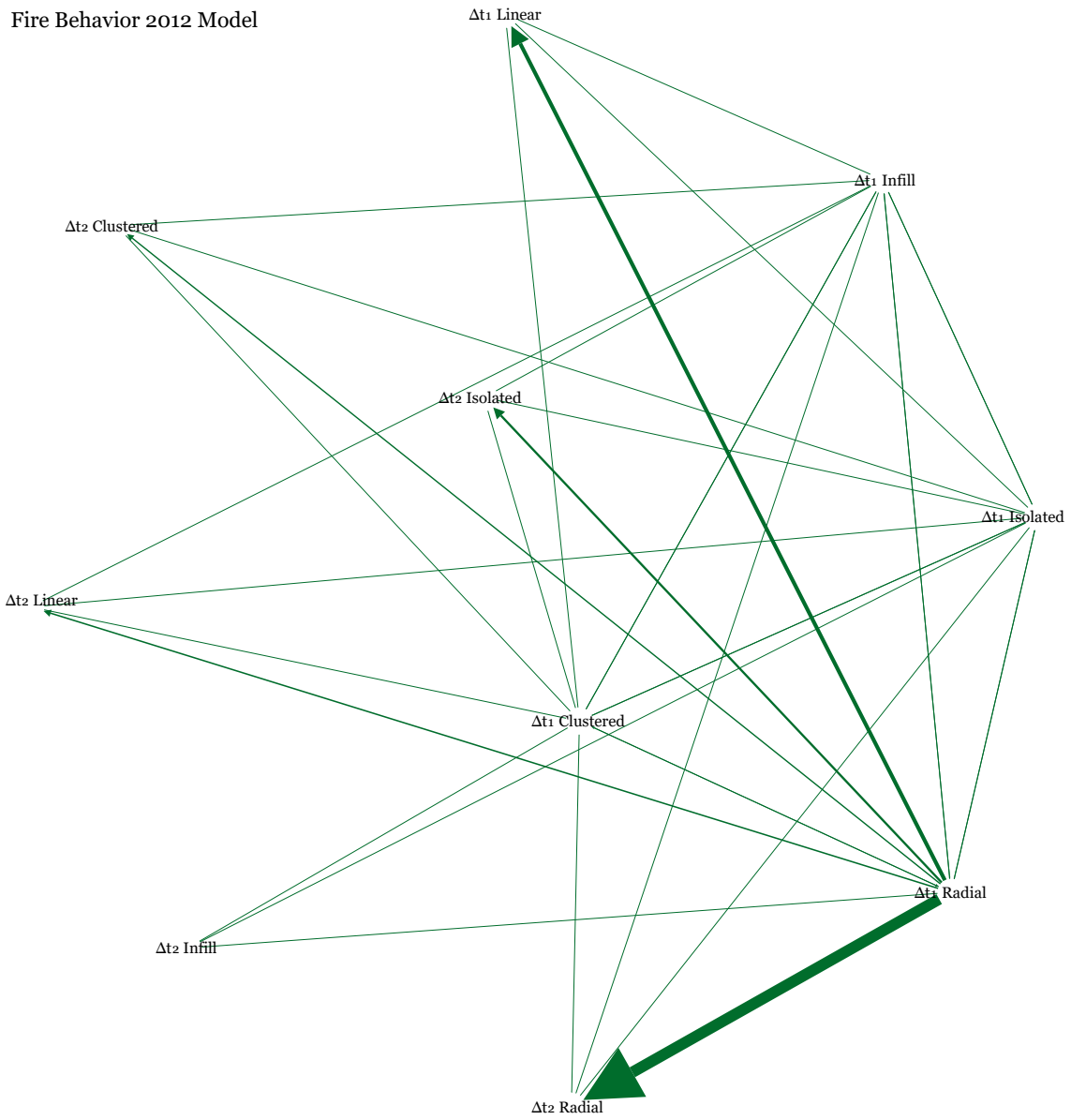
V.3.5.2.3 Fire Behavior

Both development in Δt_1 and Δt_2 were used for assessing fire behavior for the 2012 model (Figure 16). Like the 2001 model, radial developments initiated and were exposed at the highest rates. Most fires were either self-targeted within Δt_1 radial or moved between Δt_1 and Δt_2 radial development. After accounting for fires occurring solely within the radial developments, fires initiated within Δt_1 radial often exposed Δt_1 linear. Δt_1 isolated was exposed relatively rarely in comparison to the Δt_2. Many of the fires exposing isolated development came from areas near Δt_1 and Δt_2 radial, or Δt_1 and Δt_2 linear development, or initiated near the Δt_2 isolated development. The fewest number of fires initiated occurred near infill. Most of these fires threatened radial development and rarely threatened outlying development.

V.3.5.3 Fire Risk Regressions

The following section describes the results for both models. Results from the GMM regressions identify which variables are increasing and decreasing the changes in both BP and CFL. These results are divided by the dependent variable of interest.

Figure 16: Network analysis of 2012 fires from BP simulations. The end of the arrows represent those exposed most commonly by fires. The non arrow ends represent those that commonly initiated fires. Thickness of the arrows represents number of exposures.



V.3.5.3.1 Model 1: Burn Probability

Results from the regression suggest that new urban development is the primary factor in decreasing BP (Table 12). All other variables increased BP to some degree ($p < 0.05$). Because all variables outside of infill showed statistical significance, the results section focuses on the β-coefficients. Since several of the variables were continuous and units for each variable differed, a standard deviation increase within the β-coefficient was used to represent a standardized effect.

Increases in road density and fuel loading, increased BP. Of the two variables, increases in road density (stand dev. increase: 0.009%) added more to BP than increases in fuel loading (stand dev. increase: 0.004%). Changes in IP negatively influence changes in BP (stand dev. increase: -0.0036%).

Pixels that transitioned from timber to grass had the highest increase in BP (0.104%). Pixels that transitioned from timber to shrub had the second highest increase (0.059%). Transitions from "shrub to timber" fuel types increased BP, but by the lowest amounts (0.0127%). This was followed by transitions that were originally grass ("grass to shrub" 0.0218%; "grass to timber" 0.0293%). A transition from "grass to urban" had the largest negative impact (-0.0838%) of the transition variables.

A pixel within or around a new clustered or isolated development had the highest decrease (-0.0871% for both) in BP. New development near previously developed areas had little effect on BP change. Infill development had the least effect (0.00746%), followed by Δt2 radial development (-0.0292%).

Table 12: Spatial Regression output for BP model

Change in Burn Probability Model				
Variable	Coefficient		Std.Error	Standardized Coefficient
Fuel Load Difference	0.000	***	0.000	0.004
Log Road Density Difference	0.003	***	0.000	0.009
IP Difference	-0.237	***	0.025	-0.004
Grass to Shrub	0.022	***	0.006	
Grass to Timber	0.029	***	0.004	
Grass to Urban	-0.084	***	0.003	
Shrub to Grass	0.050	***	0.004	
Shrub to Timber	0.013	**	0.005	
Shrub to Urban	-0.047	***	0.011	
Timber to Grass	0.104	***	0.001	
Timber to Shrub	0.059	*	0.026	
Timber to Urban	-0.028	***	0.003	
Infill	0.007		0.005	
Radial	-0.029	***	0.003	
Isolated	-0.087	***	0.014	
Cluster	-0.087	***	0.008	
Linear	-0.066	***	0.012	
Constant	0.013	***	0.001	
W	0.823	***	0.003	
λ	0.115			
Note *** p-value<0.0001, ** p-value<0.01, * p-value<0.05				
Pseudo R-Squared:	0.859			
Spatial Psuedo R-Squared:	0.383			

V.3.5.3.2 Model 2: Conditional Flame Length

As in the first model, a given pixel transitioning to urban will decrease CFL (Table 13). However, unlike Model 1, many of the fuel transitions decreased CFL as well. Most variables were significant ($p<0.001$) but two variables were not statistically significant: the transitions "shrub to grass" and "grass to shrub". Like the previous regression results, this section focuses on the β-coefficients or a standard deviation increase within the β-coefficient to represent the effect each variable had on CFL.

Unlike BP, where the variables of interest correlate similarly with BP change, the two variables of interest have opposite signs for CFL. Increases in fuel loading increase CFL (0.00912 ft. per standard deviation increase). Conversely, increases in road density decrease CFL (-0.0396 ft. per standard deviation increase). Changes in BP have a greater positive influence (0.292 ft. per standard deviation increase).

CFLΔ varies widely by landscape transition type. As expected, pixels that transition to urban decrease in CFL. The highest change in CFL for those types is "grass to urban" (-0.502 ft.). While "timber to urban" has the least effect (-0.104 ft.). Transitioning from timber to another fuel type has the largest positive effect on CFL ("timber to shrub": 1.21 ft.; "timber to grass" 0.678 ft.). Little variation was found between "grass to shrub" and "shrub to grass" transition states.

Like BPΔ, the biggest changes in CFL that occurred based on development type occurred in clustered (-0.699 ft.) and isolated (-0.539 ft.). New radial development also had a large effect on CFLΔ (-0.484 ft.). Infill had limited effect on CFLΔ (-0.04 ft.).

Table 13: Spatial Regression output for CFL model

Change in Conditional Flame Length Model				
Variable	Coefficient		Std.Error	Standardized Coefficient
Fuel Load Difference	0.001	**	0.000	0.009
Log Road Density Difference	-0.015	***	0.001	-0.040
BP Difference	1.018	***	0.018	0.293
Grass to Shrub	0.037		0.027	
Grass to Timber	-0.141	***	0.018	
Grass to Urban	-0.503	***	0.017	
Shrub to Grass	0.024		0.022	
Shrub to Timber	-0.207	***	0.021	
Shrub to Urban	-0.434	***	0.072	
Timber to Grass	0.678	***	0.008	
Timber to Shrub	1.209	***	0.193	
Timber to Urban	-0.104	***	0.009	
Infill	-0.040	**	0.014	
Radial	-0.484	***	0.017	
Isolated	-0.539	***	0.099	
Cluster	-0.699	***	0.079	
Linear	-0.177	*	0.086	
Constant	0.139	***	0.008	
W	0.544	***	0.007	
λ	0.862	***	0.862	

Note *** p-value<0.0001; **p-value<0.01; * p-value<0.05

Pseudo R-Squared:	0.742
Spatial Psuedo R-Squared:	0.468

V.4 Conclusion

This chapter, through simulation modeling and statistical analysis, provides evidence to support that wildfire risk varies by development patterns. The results suggest that both spatial composition and location influence exposure to wildfire.

Probability results suggest that fire probabilities fall along a development gradient. Those areas nearest the urban core have lower probabilities while outlying development patterns in the wildlands have higher probabilities. This trend occurs for BP models while CFL's show similar but not identical results. These findings support the second and third hypotheses, suggesting that changes in development affect fire exposure. Additionally, new development increases fire risk.

SNA results suggest that many fires originate near radial development and move towards outlying development types. While fuel load and road density variables play an important role in fire risk. Fuel loading increased BP as well as CFL's. Inversely, removing fuel from the surrounding area should reduce fire risk locally. This evidence supports the fourth hypothesis, suggesting that increases in fuel loading increase fire risk. On the other hand, road density has mixed results. Increasing road density reduced CFL's; however, it increased BPs. Increasing BPs and decreasing CFL's reduces risk, which supports the fifth hypothesis, suggesting that increases in road densities will decrease fire risk. However, because changes in road density do not decrease BPs, this does not represent a complete decrease in fire risk.

The study found that AUC tied with historic fires provides reasonable validation of BP models. However, due to suppression policies not all areas on the landscape have large wildfires. A sample for the sensitivity analysis should include both suppressed fires as well as historic large fires.

CHAPTER VI DISCUSSION

The purpose of this study was to simulate fire risk and assess how fire risk varied by development patterns. Chapter 2 found that development patterns in Δt_2 were closer to previously developed urban areas than Δt_1. In other words, newer development shifted closer to the urban core. Chapter 3 found that development influences IP locations, while chapter 4 identified how development, road networks, and fuel load affect fire behavior and intensity. These results from both the IP and BP modeling merit further discussion. This chapter examines and expands on those results. These results discussions are followed by a discussion of policy implications.

VI.1 Development Patterns

The trends in development patterns help explain the risk on the landscape. The two primary development types that occur on the landscape are radial and infill. A significantly smaller proportion occur as outlying development. These trends suggest that most development is occurring at a higher density and in the relatively lower risk areas near Austin's urban core. This trend of a large proportion of development occurring near the previously developed urban patches is further seen in Δt_2 outlying development. Outlying development in the Δt_2 was much closer to the previously developed areas. This suggests that during the second stage of the study, this area was undergoing a coalescing process. Diffusion and coalescence would not be unique to this study area, since the process has been seen in other cities within Texas (Dietzel *et al.* 2005b). However, because it was not in the scope of the study to assess diffusion and coalescence, further research is needed to confirm this process is occurring.

VI.2 Fire Risk Sensitivity

One of the primary purposes of this study was to create a sensitive BP model for the year 2012. The model had some predictive ability but failed to solely represent large fires on the landscape. However, the addition of historic ignitions to the test sample improved the sensitivity significantly. The model was further improved when focusing on Travis county (AUC: 0.870).

Previously, Travis county created a wildfire risk model for their County Wildfire Protection Plan (CWPP; see https://data.austintexas.gov/browse?q=CWPP). The CWPP risk assessment used a random set of ignitions and more homogenous weather conditions (Bowman Consulting Group 2014) and serves as a good comparative assessment of the dissertation's BP sensitivity. Using the same sample from the dissertation's sensitivity analysis, the CWPP sensitivity is lower (AUC: 0.376). The higher AUC for this study suggests that sensitivity is improved using an IP model for ignition sample and historic weather conditions.

Interestingly, the sensitivity for Bastrop and Travis counties differed. The BP model better represented large fires in Travis better than Bastrop. Some of this is likely due to the flashy fuels in western Bastrop county, which were not as prominent in Travis. The fuels such as grasses are easier to ignite, and suppress. In addition to fuel variation, suppression policies by department varies. Travis county resources are available for collaborative suppression in western Bastrop. While the distance to the eastern side of the Bastrop county, reduces the effectiveness of these resources.

VI.3 Discussion of Probability Shifts

Results of the probability models for both IP and BP show some interesting findings. First, both ignition and burn probabilities fall within clusters of lateral development infill, radial, and outlying. Two major clusters occur at the extremes of the development spectrum: infill and isolated development. Depending on the type of probability (IP or BP), the remaining development categories are less definite. Development categories tend to shift in order between years, these shifts primarily occur with the Δt_1 and Δt_2 radial and clustered development. Second, the large amount of radial development increases potential exposure to wildfire. However, acre-for-acre, the outlying development patterns are at a higher risk of loss.

As expected, infill had low wildfire risk. Throughout the analysis the probability of any form of fire near infill development is low. Regarding IP, newer infill is more likely to ignite than older, but remains improbable. For the BP analysis, Δt_1 and Δt_2 shift, newer infill has less exposure than older infill. Δt_1 and Δt_2 infill development are indistinguishable from the previously developed urban areas. Throughout the fire simulations, Δt_1 and Δt_2 of infill showed the fewest fires originating near infill and were exposed the fewest number of times. These outcomes make sense because infill development is shielded from wildfire by previously developed areas.

On the other extreme of wildfire probability, the small patches of lateral development show the highest probability of fires occurrence. In terms of ignition, the addition of lateral development creates new locations for human interaction with the wildlands. This was shown by the Δt_2 isolated development's increase in IP. Adding lateral development reduced BP's for wildland areas. However, these former wildland areas remained high in probability.

The most interesting changes occur between wildland and urban areas. This center of the development gradient is where much of the variation between development patterns occurs. The largest amount of variation occurs between radial and clustered development. In the initial IP model, there is no statistical difference between radial and clustered development. But this shifts in the 2012 model, with the Δt_2 radial and the Δt_1 clustered dramatically increasing IP. These two development types might be correlated because an old subdivision may continue to grow (i.e. radially). However, these trends do not transition to increases in BP. With respect to BP, the Δt_2 clustered development and the Δt_1 radial development are not statistically different, while their counterparts, Δt_2 radial and Δt_1 clustered, are different.

Most new development occurring during the study period occurs as radial development (70% of new development for Δt_1; 77% of new development for Δt_2). The large amount of development drove the high number of initiated fires near radial development as well as the large amount of the total exposure on the landscape. Normally fires near urban areas are suppressed at a higher and faster rate (Haight *et al.* 2004).

The regression models showed differing results for changes in BP, as the change from wildland to any type of development decreases the BP. This is likely due to the decrease in fuel load that coincides with new development. In this model, cluster and isolated development reduce BP by the largest amount, while infill and radial reduce it the least. The small changes in BP from infill and radial agree with the previous studies, because the initial BP surrounding these areas is low.

Interestingly, all fuel transitions increase BP with the exception of urban transitions. However, the degree of increase follows along the lines of successional species. While transitioning to grass had the highest increase in BP, transitioning to timber had the lowest increase in BP.

VI.4 Discussion of Severity Shifts

Some of the findings regarding CFL's also merit further discussion. CFL shifts followed a dispersion pattern similar to BP: infill maintained lower mean CFL's while the outlying development patterns had higher CFL's. Another interesting finding is that, within the second model, Δt_1 outlying development had higher average CFL's compared with their newer counterparts. This suggests that those outlying development patterns are at higher risk from wildfire.

Like BPs, infill development across the study period was not statistically different in regards to CFL but infill CFL's were the lowest across all development patterns. While the overall trend showed increasing CFL's across the landscape, infill development still decreased overall. The lower CFL's and decreasing trend in infill development is likely explained by decreasing fuel availability. As the landscape transitions from urban to wildlands, CFL's increase. Unlike BPs, where the middle development patterns were clustered depending on the model, CFL's have a distinct order with respect to development type. New radial development has lower CFL's than its older counterpart. Within the 2001 model, Δt_1 and Δt_2 radial development patterns were not statistically different from each other. However, in the 2012 model, these two radial development patterns have statistically distinct CFL's. CFL's near outlying development are the largest compared to other development patterns. Holistically, these trends show a gradient of fire risk from urban to wildland areas; developing further from other developed areas increases fire risk.

Another interesting trend within the CFL models is the clear distinction between Δt_1 and Δt_2 development. Each of the Δt_2 development patterns has a lower CFL than the Δt_1 counterparts. This may be due to the location of the development pattern instead of the development category. This distinction between generations furthers the idea of a gradient from the urban core to wildland areas.

VI.5 Policy Implications

Risk modeling can be used to avoid developing in high risk areas. For instance, areas within a regulatory floodplain (high risk) require specific codes to protect structures. Communities may require elevated buildings or (in some areas where risk is exceptionally high) may prevent structures from being built (Beatley 2009). Communities surrounded by high wildfire risk may have structural codes to reduce their risk. But, historically they have been less inclined to regulate development or use incentives to reduce development (Schwab *et al.* 2005). Through careful planning and regulation, communities should be able to reduce fire risk (Buxton *et al.* 2011). But in the absence of development policy, people will continue moving into wildland areas (Syphard 2007) placing themselves and others at higher risk.

The results of this study provide several recommendations for policies within the specific regional area but they can be generalized to other regions. Many wildfire mitigative actions focus on education of residents (Sturtevant and Myer 2013) or fuel reduction surrounding the homes (Absher and Vaske 2011). Because these practices are shown to have a degree of effectiveness and have been discussed thoroughly in the literature (Mell *et al.* 2010), the recommendations of this dissertation will focus on potential regional land use policies as an alternative tool to reducing fire risk. Overall, results suggest that when assessing fire risk there are two important factors with respect to development patterns: development location and category.

VI.5.1 Policy Window

Shifting development locations suggest that the landscape could potentially be coalescing towards the urban core. As developers are increasingly developing inward near Austin, a potential policy window opens. A shift to coalescence is effectively a transition

state within the panarchic cycle. Because development is moving towards the urban core, areas within the wildlands should have less resistance to risk reduction practices. During this coalescence phase, policies could be implemented to protect wild areas and reduce fire risk. An example of a policy that could be implemented during this time is land acquisition. When development is occurring near the previously developed urban patches there is a potential for less of a market in the wildlands. This leaves an opening for non-profits or communities to buy open land before it is planned for development (Beatley 2009). Alternatively, state and regional subsidies could protect lands through tax incentives. These governmental incentives could subsidize agricultural lands and deter new development without policy, therefore reducing the risk to the overall population.

However, adaptation of the diffusion and coalescence theory is still relatively new, and little research has addressed the concept (Dietzel *et al.* 2005b). Future research should try to understand the temporal range of this phenomenon as well as identify variables that influence the transition shift.

VI.5.2 Land Use Regulations

Community planners can look to flood risk management for best practices to guide development. Flood risk reduction practices include a variety of measures ranging from regional land use to development codes (Schwab 2016). These measures can be used to address different issues found within this study.

Areas near the previously developed urban patches consistently had lower wildfire risk compared with those further into the wildlands. Development should be incentivized to continue growing near these previously developed urban patches. Practices could include parcel densities bonuses near the near these urban patches, increased floor-to-area ratio (F.A.R), or land acquisition. Allowing for an increased parcel density, or increased

F.A.R., would incentivize developers by increasing their potential profits (Burby *et al.* 2000). Acquiring lands can ensure those lands are not developed and remain wild. This can occur either through private organizations or through governmental agencies (Burby *et al.* 2000). While buying properties to reduce risk is not always a cost effective approach, evidence suggests that it can effectively reduce hazard risk (Tate *et al.* 2016).

Land use regulations can also guide development location but, this is only part of the issue since there are differences in risk based on development category and size. Communities should try to guide development type into less risky development categories. Subdivision review is an effective way of moderating the size of clustered development (Schwab 2016). Increasing the size of the subdivision development allows for concentrated suppression efforts—which should reduce overall costs (Clark 2016).

The most relevant area for reducing development occurs in the eastern portion of Travis county. Tx-130 Tollway creates a boundary for BP and CFL. Areas to the east of the toll way are greater than 1 in 500 odds of a fire occurring on a pixel. While much of the area inside the tollway are significantly lower. Incentivizing development to occur east of the Tx-130 Tollway, or along I-35 or Tx-71, new development will be built in less riskier areas.

VI.5.3 Fuel Treatments

Development that occurs within the interior of the wildlands tends to have higher risk than near more urbanized areas. As such, most development should be guided closer to these urbanized areas. However, not everyone wants to live in an urban area, and many isolated structures already exist on the landscape. Structures in the interior wildland are expensive to protect, so specific practices should be in place to reduce their risk. These areas should be especially controlled for vegetation and landscaping surrounding the build-

ings as well as for specific building codes. By reducing the vegetation height around a building (along with other practices such as fire resistant roofs), structures will be more likely to survive (www.fireadapted.org 2015).

In addition to placing fire mitigation responsibility on the resident, communities can also target fuel treatments in areas with isolated development. Targeted fuel treatments can reduce risk, which should also reduce the governmental costs for suppression (Ager *et al.* 2010b). Similar to BP, CFL's could likely be reduced in Travis county by targeting fuel treatments near the Tx-130 Tollway. Much of the ΔT_2 radial development is occurring in this area west of Tx-130. Fuel treatments in this area will likely reduce flame lengths for the development that occurs in the WUI.

Quantifying the influence of fuel treatments can be performed through simulation modeling (Miller *et al.* 2008) and can be used to efficiently reduce the risk of fire (Ager *et al.* 2011), making fuel treatments a reasonable practice in terms of cost versus benefit.

CHAPTER VII CONCLUSIONS

This study, through statistical analysis and simulation modeling, provides evidence to support a regional land use policy that reduces wildfire risk. The results suggest that both spatial composition and location influence exposure to wildfire.

The study followed a series of methods to create a wildfire risk assessment. Probability results suggest that fire probabilities fall along a development gradient. Those areas nearest the urbanized patches have lower probabilities while outlying development patterns in the wildlands have higher probabilities. This trend occurs in both IP and BP models while CFL's show similar but not identical results. These findings support hypotheses 1-3. Conversely, most of the fires exposing development originate in those areas where larger amounts of development abut the wildlands.

Δt_1 and Δt_2 development varied in probability across all models. When new developments were added to the landscape by 2012, they tended to be closer to previously developed urban patches than Δt_1. In addition, those developments were associated with lower probabilities and CFL's.

Fuel load and road density variables play an important role in fire risk. Fuel loading increased BP as well as CFL's. Inversely, removing fuel from the surrounding area should reduce fire risk locally. This evidence supports hypothesis four. On the other hand, road density has mixed results. Increasing road density reduced CFL's; however, it increased BPs. Increasing BPs and decreasing CFL's reduces risk, which supports hypothesis five. However, because changes in road density do not decrease BPs, this does not represent a complete decrease in fire risk.

The policy recommendations aim to reduce fire risk for developed areas. The study has also identified a potential policy window during a coalescence phase of development where regulations and acquisition of land may have less opposition. Additionally, the research suggests that land use guidelines should help funnel development towards the urban core and away from high risk areas. Finally, for those areas where development occurred in the high-risk wildlands, communities should practice treating fuel between the high-risk areas and areas that have a high potential of igniting fires.

VII.1 Limitations

This study provides insight into the interactions between development patterns and fire risk. While this study gives support to the ideas that spatial and compositional components are relevant factors influencing fire risk, the limitations of this study require more research to better understand the issue.

As with all models, the simulation model is a representation of reality. This representation has room for improvement. This study quantified how the model performed; however, that performance was a moderate fit at best. Emulating suppression within the simulation software remains an issue, and future research should attempt to better represent the practice. In addition to suppression tactics, another limitation to the simulation model comes from representing ignitions. Splitting ignitions into sub-groups by ignition type (i.e. arson, brush pile, etc.) helps increase the sensitivity of a model (Syphard and Keeley 2015). However, this requires a much larger sample size due to the sub-groups. While this was not in the current study framework, future research should attempt to take this sub-sampling into account.

Another limitation with the models occurred in the 2001 model. The fire-behavior fuel-moisture dataset originating from the LandFire program (https://landfire.gov/) was

used for land cover. As with many publicly available datasets, some errors or assumptions occur. The biggest error in the land cover dataset (2001) was that much of the landscape deemed forest is actually agriculture. This issue was widespread throughout the datasets and difficult to correct. Since the error occurred in 2001, a reasonable representation for 2012 was still created.

Surprisingly, changes in CFL's for timber areas were lower than expected. Studies have found timber areas to be higher risk (Papakosta *et al.* 2017). While this trend is countered by the kind of increases in fuel loading found with shifts to timber, a standard deviation increase in fuel loading is not enough to completely offset the decrease found from timber. The changes in CFL's for timber areas might be due to higher live fuel moisture than reality. This may also explain some of the issues with the study's ability to represent the Bastrop Complex fire. Because the Bastrop complex occurred primarily in timber, the severity of predicted fire is lower without more extreme weather conditions (Dillon *et al.* 2011).

One last major limitation of model representations is the use of extreme weather over a complete fire season. The goal of this study was to understand the influence of development on fire risk, specifically focusing on extreme fire. However, non-catastrophic fires can still cause structural damage. Future research should use a complete fire season to better emulate the landscape as well as to better understand differences between extreme and normal fire weather.

While the study is limited by model representation, its design creates another area of limitations. The study area has fast growing development patterns into the WUI that has been subject to very few fire risk studies. However, the study area is small and not necessarily representative of the many different fire regimes in the United States, where

other factors may be more influential for fire risk. In addition to spatial constraints, there are also temporal constraints. The study only focused on two generations of fire risk and development shifts. Evidence suggests that development patterns are cyclical (Dietzel *et al.* 2005b). Future research studies should look at different spatial locations as well as longer temporal ranges to see if risk patterns cycle.

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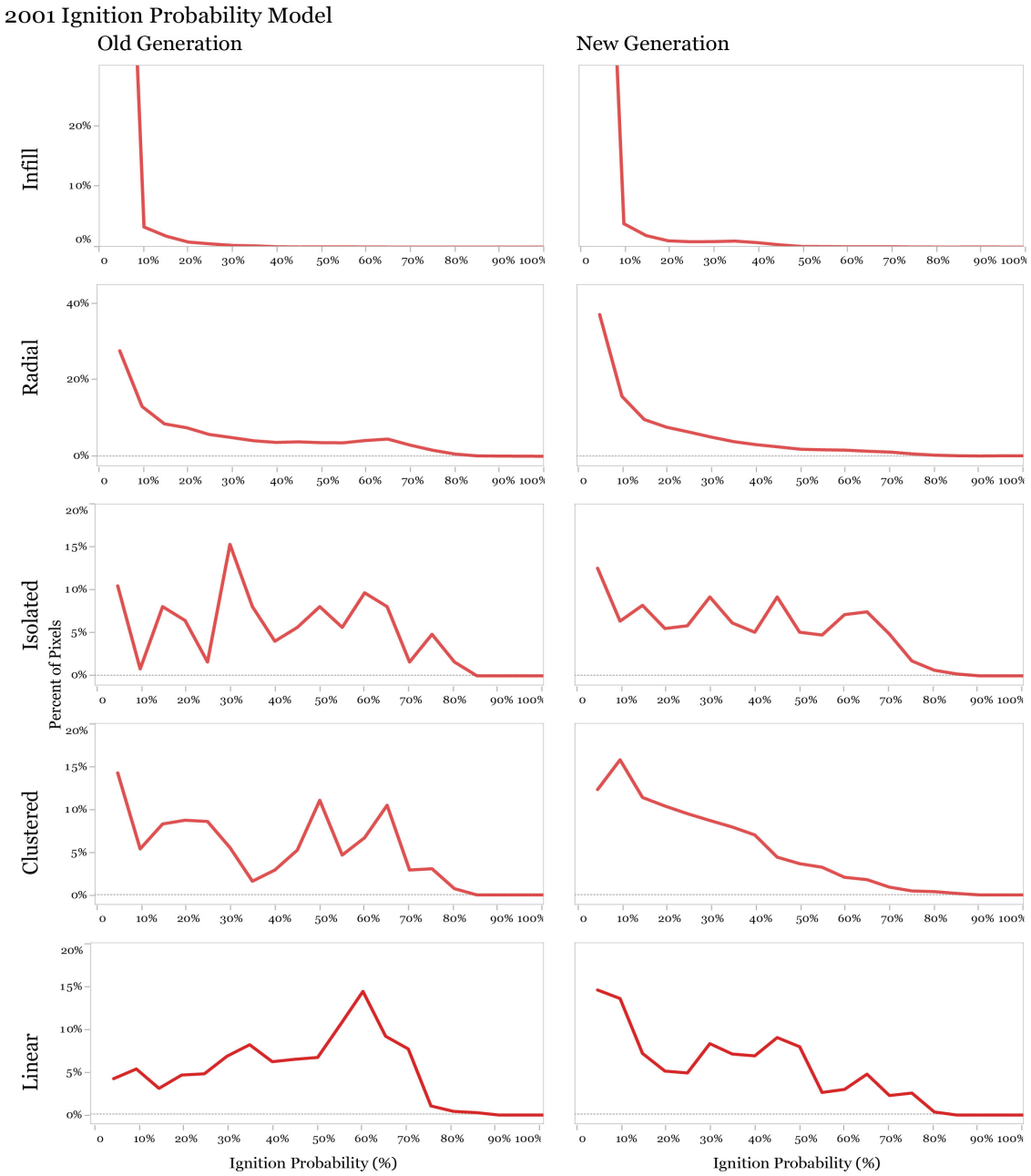
APPENDIX A

							Fuel Moisture					
DATE	ERC	Tempera-ture	RH	Wind Direction	10 Min Wind Speed	1 Min Wind speed	FM 1	FM 10	FM 100	FM 1000	FMH	FMW
9/10/2011	82	97	10	NW	5	9	2	3	7	10	2	74
9/9/2011	80	96	9	NW	6	10	2	3	7	10	2	76
9/8/2011	79	96	11	W	7	11	2	3	7	11	2	77
9/12/2011	79	103	13	S	7	11	3	4	8	10	3	74
9/11/2011	78	100	9	SW	7	11	2	3	8	10	2	74
9/7/2011	76	94	10	E	4	8	2	3	8	11	5	79
9/13/2011	76	104	15	S	7	11	3	4	9	10	3	74
9/6/2011	74	91	9	NW	6	10	2	3	8	11	9	81
9/14/2011	74	104	15	SE	7	11	3	5	10	10	3	74
10/1/2011	72	92	13	NW	5	9	2	4	10	11	2	80
10/2/2011	72	89	11	NE	5	9	3	4	10	11	3	79
9/5/2011	70	101	20	NW	9	13	4	5	9	12	11	82
9/15/2011	70	101	21	E	6	10	5	6	10	10	5	75
9/24/2011	70	96	19	SW	4	8	3	4	11	11	3	79
9/25/2011	70	101	15	S	10	14	3	5	11	11	3	78
10/3/2011	70	89	12	NE	6	10	3	5	10	11	3	79
9/4/2011	69	101	20	NW	12	17	3	4	10	12	13	83
8/29/2011	68	110	14	E	7	11	2	4	9	12	22	87
8/30/2011	67	109	12	E	6	10	4	5	9	12	20	86
9/20/2011	67	94	18	W	6	10	3	5	12	11	3	79
9/26/2011	67	104	16	SE	7	11	5	6	11	11	5	79
9/30/2011	67	98	22	N	7	11	3	5	11	11	3	81
10/4/2011	67	88	19	E	6	10	4	6	11	11	4	80
9/3/2011	66	102	24	NW	9	13	4	5	11	12	16	84
9/23/2011	66	96	26	W	6	10	4	5	12	11	4	80
10/5/2011	66	88	24	E	6	10	5	6	11	11	5	79
8/28/2011	65	110	17	NE	6	10	2	4	11	12	25	88
8/31/2011	65	103	21	SE	8	12	4	5	10	12	20	86
9/27/2011	65	102	23	S	6	10	5	6	11	11	5	79
9/2/2011	64	101	27	NE	9	13	4	5	11	12	18	85
9/16/2011	64	96	31	E	8	12	9	9	11	10	9	75
9/18/2011	64	95	40	SE	7	11	5	7	13	11	5	77
9/19/2011	64	95	32	NW	5	9	4	6	13	11	4	78
9/17/2011	63	91	41	E	5	9	8	8	12	10	8	76
9/21/2011	63	96	14	S	6	10	5	7	13	11	5	80

9/28/2011	63	98	27	S	5	9	4	6	13	11	4	81
9/29/2011	63	101	20	SE	5	9	5	6	12	11	5	81
8/20/2011	62	105	23	NE	8	12	4	6	11	12	28	88
9/1/2011	62	101	23	E	6	10	5	6	11	12	18	85

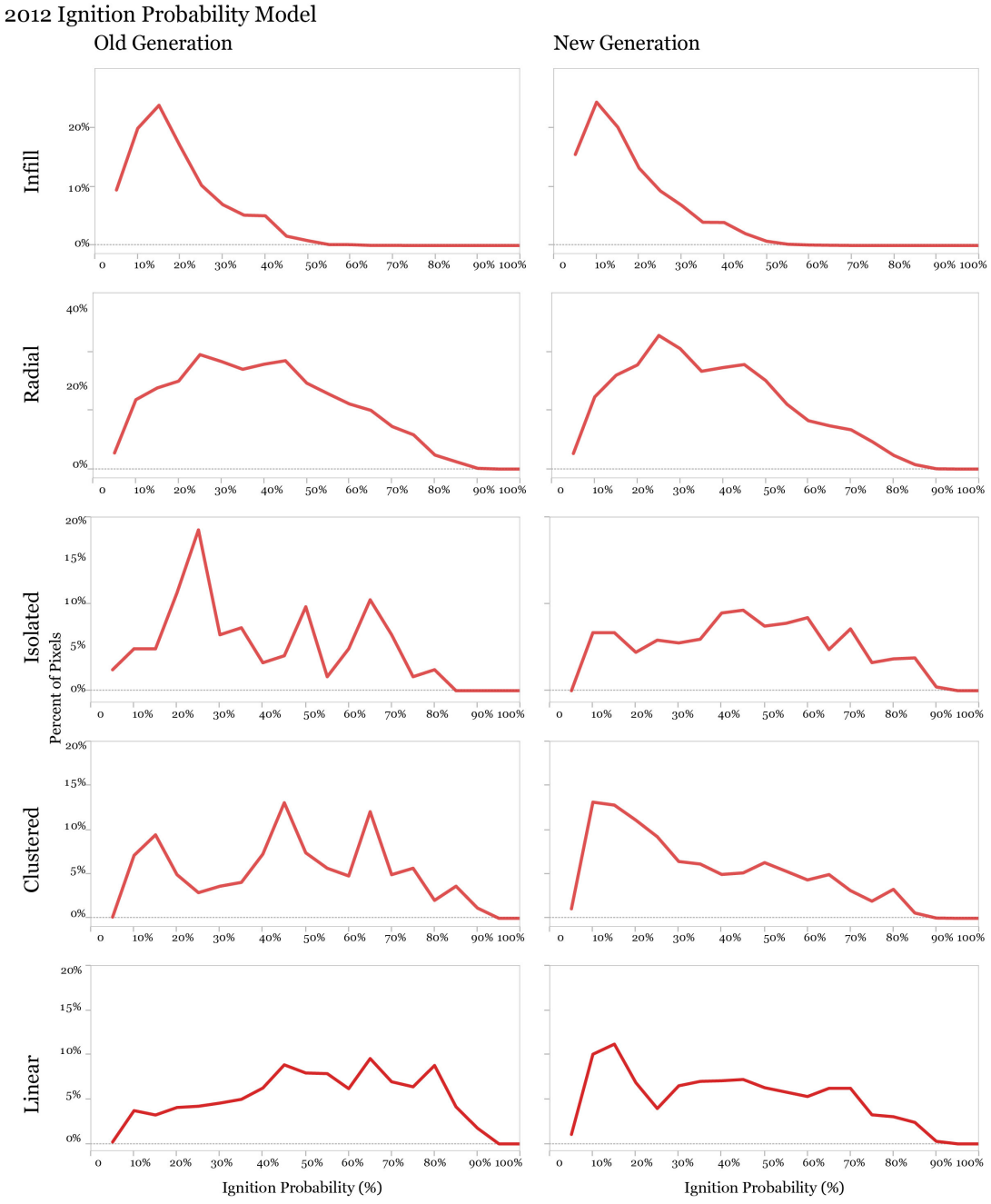
APPENDIX B

Histograms of Ignition Probabilites surrounding development types based on a 30m buffer for the 2001 Model.



APPENDIX C

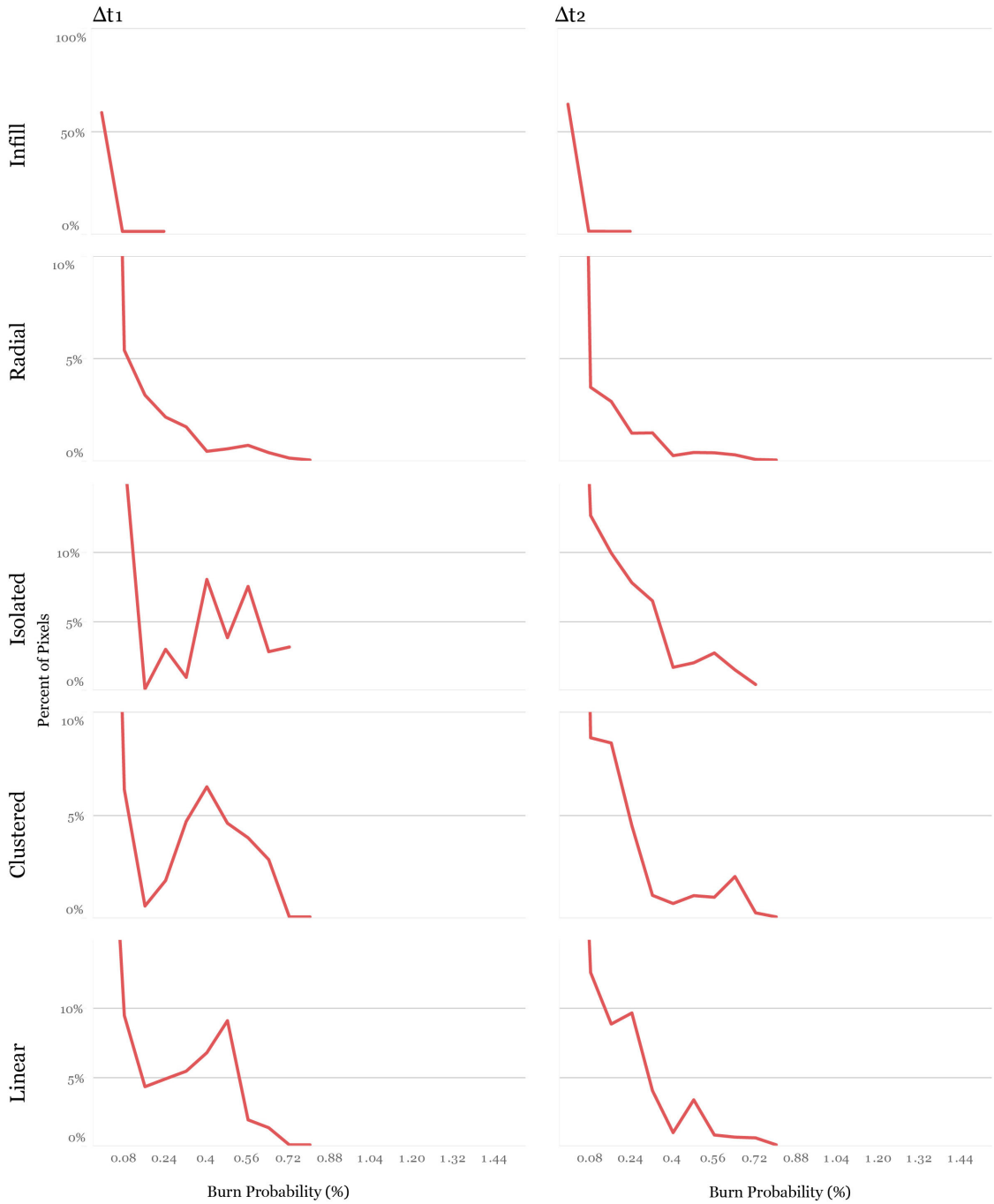
Histograms of Ignition Probabilites surrounding development types based on a 30m buffer for the 2001 Model.



APPENDIX D

Histograms of Burn Probabilites surrounding development types based on a 30m buffer for the 2001 Model. All development typtes have a high peak of p_{bp}=0, due to development being unburnable. Any interpretation of the results should focus on the graph where probabilities occur.

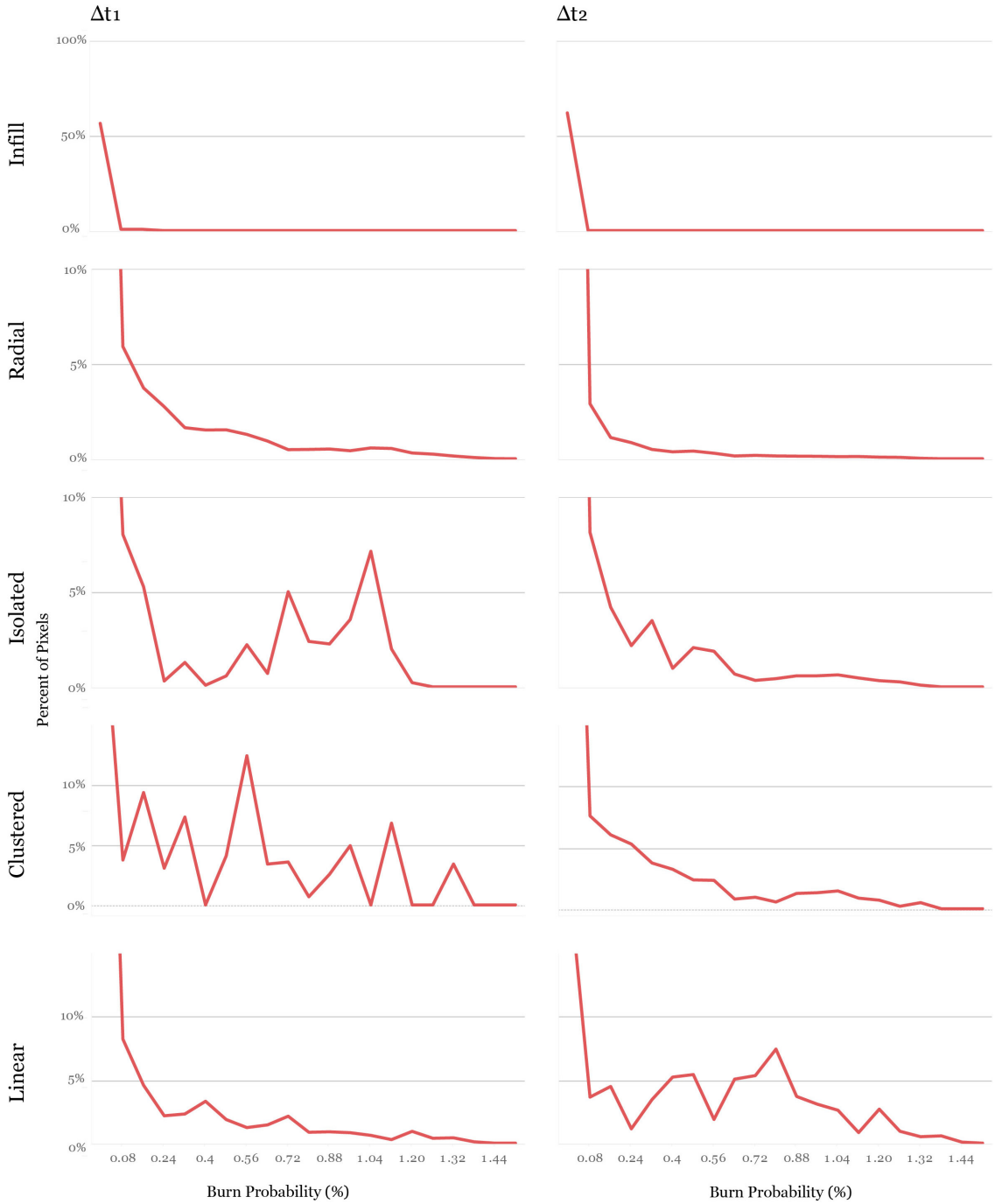
2001 Fire Simulation Model



APPENDIX E

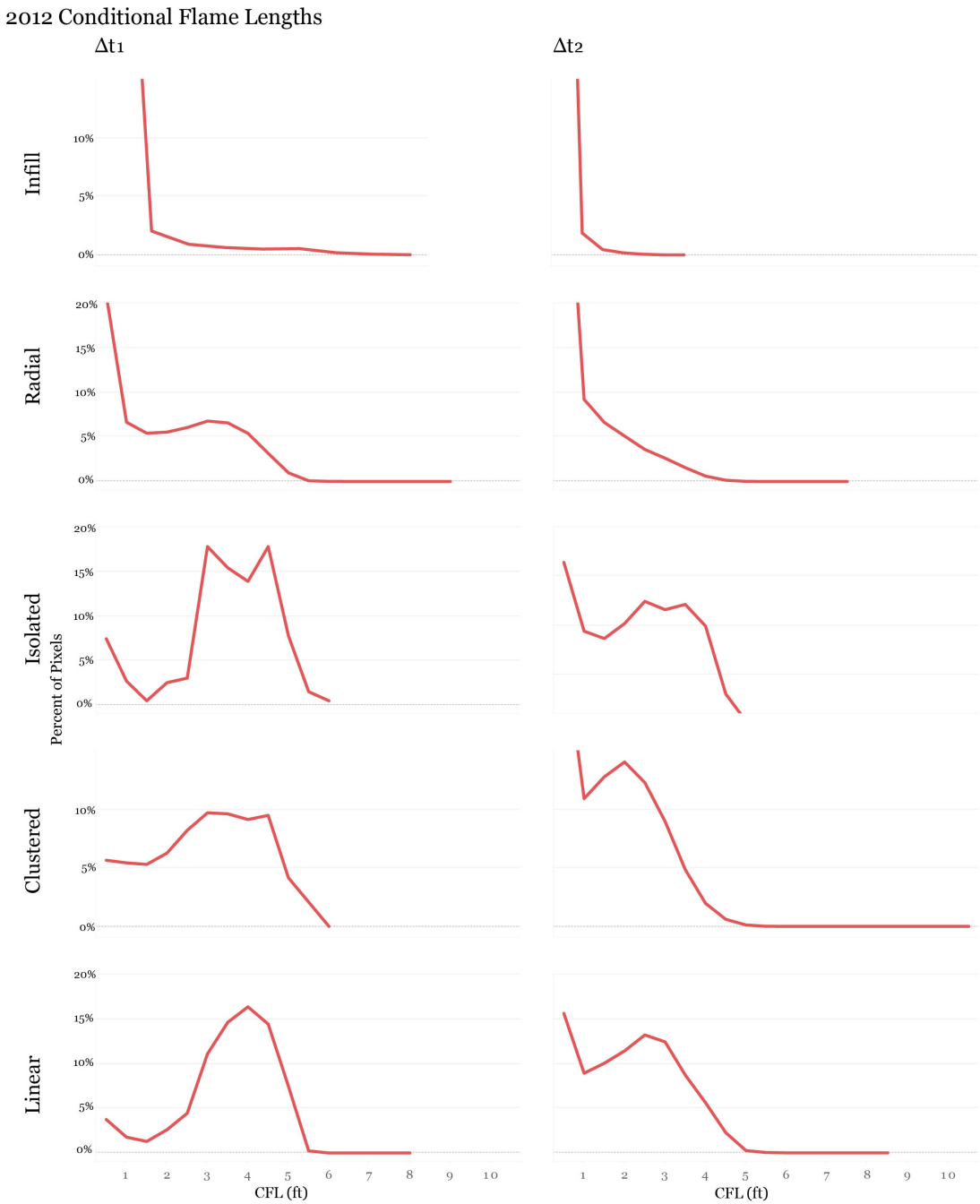
Histograms of Burn Probabilites surrounding development types based on a 30m buffer for the 2012 Model. All development types have a high peak of p_{bp}=0, due to development being unburnable. Any interpretation of the results should focus on the graph where probabilities occur.

2012 Fire Simulation Model



APPENDIX F

Histograms of Conditional Flame Length surrounding development types based on a 30m buffer for the 2012 Model. All development types have a high peak of p_{bp}=0, due to development being unburnable. Any interpretation of the results should focus on the graph where probabilities occur.



APPENDIX G

Histograms of Conditional Flame Length surrounding development types based on a 30m buffer for the 2012 Model. All development types have a high peak of p_{bp}=0, due to development being unburnable. Any interpretation of the results should focus on the graph where probabilities occur.