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Fire regimes across the western United States have been altered due to past land management and changing land use. Mitigating increased risks of wildfire occurrence in landscapes such as central Oregon requires landscape level management from both governmental and private organizations. Non-industrial private forest (NIPF) owners manage a relatively small area, but they are an extremely diverse group of land managers in Oregon and predicting their management decisions has traditionally been difficult. Encouraging NIPF owners to address increased fuel loads, a primary goal in reducing wildfire risk, must occur to reduce wildfire risk at a landscape scale. With the recent creation of LandTrendr, a Landsat image processing program, land managers can locate recent fuel treatments across a landscape with relative ease and limited resources. This approach to identifying fuel treatments, in addition to a logistic regression models created from survey data, are used to investigate the spatial correlations among treatment locations, wildfire risks, and the estimated costs of fuel treatments on NIPF parcels in central Oregon.

Remote Detection and Predicted Locations of NIPF Fuel Treatments in Central Oregon

by
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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Michael P. Hall, Author

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TABLE OF CONTENTS

TABLE OF CONTENTS (Continued)

TABLE OF CONTENTS (Continued)

LIST OF FIGURES

LIST OF FIGURES (Continued)

LIST OF TABLES

LIST OF TABLES (Continued)

Chapter 1: Introduction

Wildfires in the western United States have been the center of intense research focus and management debates over the past decades. Much of the scientific community agrees that regional wildfire regimes across the United States have been altered from their historic cycles, primarily due to the settlement of European Americans (Stephens 1998; Hessburg *et al.* 2005; Andrews *et al.* 2007; Climate Central 2012). Adding to the altered land management these settlers brought with them, more recent changes in regional climate and land use are also strongly correlated to altering fire regimes. In diverging from the historic fire regime, regions' ecologic, economic, and social systems are directly impacted (Quigley *et al.* 2001; Nelson *et al.* 2004; Safford *et al.* 2009). Scientists and policy makers have attempted to determine methods to lessen these increasing risks to both natural and human systems in the face of an apparent trend of more frequent severe wildfires in the eastern forests of the Pacific Northwest.

Often, the most desired and practical course of action to minimize fire risks is to implement fuel reduction treatments on the landscape (Fitzgerald 2005; Safford *et al.* 2009). As fire does not recognize ownership boundaries, land managers must consider both private and public lands when assessing the possibility of wildfire. Not only do land managers and policy makers face complications from the fragmented ownership of the region, but also from limited economic resources. Prioritizing the use of resources often relies on the implementation of some form of fire modeling for the landscape and the consideration of current land management (Keyes and O'Hara 2002; Stratton 2004; Andrews *et al.* 2007; Ager *et al.* 2012, 2013). While modeling and predicting wildfire movement and severity across the landscape has been extensively researched, and modeling tools are consistently improving, determining the locations of pre-existing fuel treatments often is labor intensive and cost prohibitive, especially where private lands are concerned. Researchers must currently rely on the use of surveys, ocular inspection of remote imagery, and or survey responses to determine the approximate locations of fuel treatments in a given area. The continuous advancement in the field of remote sensing provides economically accessible tools for researchers to replace traditional methods of fuel treatment observation. LandTrendr is one such product which could greatly increase researchers' ability to locate and describe fuel treatments.

This thesis addresses three research questions. First, can fuel reduction treatments on non-industrial private forestlands (NIPF) be identified with remotely-sensed data and the spatial analysis tool LandTrendr? Second, what factors influence NIPF owners' decisions to perform fuel reduction treatments and can they be used to create a reliable prediction model? In addition, can LandTrendr also be used to predict the placement of fuel reduction treatments? And third, within the study area, are there correlations among the placement of fuel treatments, fire risks, and treatment costs? And if so, can these correlations be used to inform policy decisions?

Chapter 2: Literate Review

Western Wildfires

Fire regimes across much of the United States have been altered from their historic cycles. Identifying and detailing historic fire regimes requires the use of a range of scientific disciplines. Through the use of dendrochronology, studies of soil sediments, and ecological transitional phase modeling, researchers have reliably reconstructed fire regimes across the United States. Climate change, alterations in land use, and varying land management policies have all had their effects on fire regimes (Cardille *et al.* 2001; Kauffman 2004; Stephens 2005; Hessburg *et al.* 2005; Climate Central 2012; Fettig *et al.* 2013). Land management approaches that European Americans brought with them as they propagated through the North American countryside directly influenced how wildfires were perceived and controlled. In some regions, such as the Midwestern United States, relatively frequent, low intensity, anthropogenic ignited wildfires were disrupted (Guyette *et al.* 2006; Hawbaker *et al.* 2013). Alternately, the dry coniferous forests of the inland Pacific Northwest had their frequent, low intensity and mixed severity, mostly naturally ignited wildfires suppressed (Quigley *et al.* 2001; Fitzgerald 2005). In both instances, the shift from the historic fire regimes had direct consequences on the ecology of the regions.

Fire dependent plant and animal communities are often altered and decline when fire regimes change. This can raise concerns from ecologists seeking to preserve and restore a region's historic ecosystems. In the dry forests of the Pacific Northwest, a regime of frequent, mixed severity surface fires sculpted the forested systems to have low tree densities and open understories (Fitzgerald 2005; Hessburg *et al.* 2005). Due to shifts in land management and land use, these conditions are increasingly rare with forested stands largely having shifted towards denser understories (Quigley *et al.* 2001; Stephens 2005). Attempts to re-establish pre-settlement fire regimes are often the best way to restore these communities. However, in the increasingly complicated wildland urban interface (WUI), this approach is rarely feasible due to risks to public health and human structures.

Difficulties facing fire management

Private development into previously intact forested landscapes has created unique challenges to managers hoping to reduce the general public's exposure to fire events and at the same time, restore fire dependent ecosystems (Kline and Alig 2005; Theobald and Romme 2007). The wildland urban interface (WUI) typically includes a mix of federal and state public lands and a mix of private lands dedicated to varying uses, but often including residential development on parcels of various sizes. People own parcels within the WUI for a number of reasons including the placement of vacation homes, permanent residences, or managing the parcel for ranching or timber products. Large timber companies, which have traditionally been the main form of industry on the private forest land, are often found in the WUI as well, alongside large acreages of publicly managed, state and federal lands (Kline *et al.* 2004; Busby *et al.* 2012; Fischer and Charnley 2012).

Aggregating the myriad of different land management objectives and approaches of these disparate owners into a single, coherent fire risk management plan is a looming obstacle (Busby *et al.* 2012). Once a plan is developed, implementation is often impeded by limited resources and the varying fuel and management conditions unique to each parcel within the plan (Haight *et al.* 2004; Schoennagel *et al.* 2009; Stockmann *et al.* 2010).

Private forestlands are a heterogeneous mosaic of hundreds, if not thousands, of individual owners with individual management objectives. At the coarsest scale, private forest parcels can be divided into two categories: industrial owners, and non-industrial private forest (NIPF) owners (Kuuluvainen *et al.* 1996; Kline *et al.* 2000). Industrial parcels can be generalized as typically performing management activities that increase parcels' investment returns. As businesses, the managers of these parcels typically perform actions that return revenue. While industrial forest managers are still a diverse group, they have been found to be much more likely to perform intensive, active management compared to NIPF managers (Rogers and Munn 2003; Kline and Alig 2005), that encompass a broad spectrum of owners with varying degrees of willingness to perform management actions.

Fuel Treatments

Effectiveness of Treatments

A general goal of fuel treatments is to reduce the severity of a wildfire event by removing available fuels and altering the stand conditions. Reducing a wildfire's severity directly correlates to a reduction in damage sustained to human structures and ecological resources from the fire within the treated parcel (Agee and Skinner 2005; Wei *et al.* 2008; Safford *et al.* 2009). A parcel's fuel treatment may also directly reduce the risk of severe wildfire for adjacent parcels which were not treated (Hummel and Calkin 2005; Wei *et al.* 2008). Landscape managers have the ability to influence wildfire behavior on both treated and neighboring parcels by strategically locating fuel treatments across their management areas. Fire models aid in predicting the most efficient way to place fuel treatments on a given landscape without considering individual managers' willingness or capability to follow the created prescriptions. When insight from fire models is considered, it has assisted land managers in reducing the risk of severe wildfires (Preisler *et al.* 2004; Agee and Skinner 2005; Busby *et al.* 2012).

Fuel treatments come in a variety of forms. Treatments include thinning to remove ladder and fuels and reduce canopy bulk density, understory mowing or herbicide treatments to remove ladder fuels and prescribed burning to remove small fuels which directly influence a fire's flaming front. Treatments may be completed individually or multiple treatments may be completed in coordination over time (Agee and Skinner 2005). Regardless, the fundamental goal is to decrease the risk of high intensity, and high severity wildfires (Agee and Skinner 2005; Agee and Lolley 2006; Mitchell *et al.* 2009).

Each treatment has negative impacts that need to be weighed by the land manager during their decision to decrease fire risk within a stand. Treatments can negatively impact stands' soil quality by increasing compaction or increasing erosion potentials. Some treatments are better able to target and remove ladder fuels or fine fuels which directly reduce a fire's intensity in the stand. Other treatments target the canopy reducing the potential for high intensity and severity crown fires (Raymond and Peterson 2005; Agee and Skinner 2005; Agee and Lolley 2006). Wildlife's response to treatments differs by species with some benefiting from treatments while others are put at a temporary disadvantage (Long 2013). Carbon stores are also impacted by fuel treatments, and in today's socio-political environment, land managers may be strongly encouraged to anticipate how to maintain and increase a stands ability to sequester carbon (Mitchell *et al.* 2009). Social response to a treatment can also be negative, with some finding the aesthetics of treatments unappealing (Busby *et al.* 2012). Typically, land managers hope to achieve a number of objectives at once during a fuel treatment, such as lowering risk of loss to fire by reducing the availability of fine fuels and decreasing canopy density. Combining treatments can make the most of mitigation expenses while accomplishing the most reduction in fire risk.

Average costs of fuel treatments are highly variable. Prescribed burning is typically the cheapest; mechanical thinning typically the most expensive (Calkin and Gebert 2006). Costs of overall treatment of a parcel can be especially high when multiple treatments are completed in coordination. Although prescribed burning is typically the least costly treatment approach, it can often only be applied following an initial mechanical treatment. That coordinated approach has been found to reduce fire risk more effectively than treatments without the use of prescribed burning (Raymond and Peterson 2005) or with prescribed burning alone.

Treatment Cost Estimates

The factors that influence the decision to complete one or more fuel treatments in a stand differ by land ownership. Managers of public lands have a focus on safety for visitors and neighboring properties, or protection and enhancement of wildlife habitat. Non-industrial private forestlands may be more concerned with protecting human structures, or providing the aesthetics that appeal to the individual owner. Industrial forestlands may be more concerned with only mitigating the risk of timber loss so as to preserve their financial investments. While the motivations for applying fuel treatments vary among owners, the costs of the projects are often a prominent factor in any decision. Estimating the costs of fuel treatments in a given landscape is often a complicated process; although not nearly as complex as predicting how those expected costs impact the management decisions of owners.

Estimating the financial costs of fuel treatments is seemingly straightforward goal with deceivingly convoluted processes. In modeling the costs on federal lands, perhaps the largest hurdle to overcome is incomplete, conflicting, or incorrect data records used in analyses (Calkin and Gebert 2006). Even correcting for such errors, many cost estimations suffer by not considering the financial burden of risk, and businesses' overhead fees (Hesseln 2000; Rummer 2008). These data gaps are more apparent for private sector work as individual contractors are reluctant to divulge how their costs are calculated and passed onto the land manager. In addition, cost estimates often lack metrics to incorporate non-market values which may heavily influence a manager's decision (Venn and Calkin 2008). Managers often rely on the quoted cost of a treatment, which can include considerations for fuel, travel distance, and work hours, and the loss of capital on the parcel, for example in the form of a structure or timber value, to make the decision about applying a fuel treatment (Venn and Calkin 2008; Stockmann *et al.* 2010).

Ideally, managers would be able to easily include non-market costs and benefits into their decision making framework when contemplating fuel treatments. Non-market evaluations may include considerations of aesthetic values, elements of risk avoidance, ecological impacts, or cultural values to name a few. Including these costs into estimates is more challenging for researchers, and thereby managers, and has resulted in a knowledge gap compared to market value estimates (Venn and Calkin 2008). Publications which attempt to detail non-market costs have used tools such as willingness to pay, or drawn from research in similar, but different, fields of study. The applicability of results from such studies is debatable, and fundamentally more research is needed to accurately reflect non-market costs (Venn and Calkin 2008). True costs of fuel treatments may be misrepresented by not including non-market values, but just as importantly, unmeasured benefits may also be missing from estimates as well. For these reasons, researchers' attempts to create fuel treatment cost estimators, such as the United States Forest Service's (USFS) Fuel Reduction Cost Simulator Software (FRCSS), should not be used to estimate the exact costs of a fuel treatment. Instead, these tools provide useful references for land managers to inform decisions.

However, as many of the purely economic evaluations are plagued by various shortcomings and inconsistencies (Rummer 2008), alternative methods for evaluating the benefits and costs of a treatment may prove helpful in providing land managers a more complete picture. By merely focusing on economic metrics such as net present value (NPV), perhaps significant values such as wildlife habitat or a given forest's resiliency to wildfire may be missed (Hummel and Calkin 2005). An alternative metric which could be tied to economic valuation could be a given landscape's change from historic range and variability of ecological traits (Venn and Calkin 2008). This may help incorporate non-market values into the decision making process without needing to directly estimate their economic value. However, this metric is difficult to estimate and likely to add complexity to an already onerous evaluation process.

Wildfire Modeling

Estimating the risk of a landscape to wildfire requires a number of variables, including topography, typical fire weather, and typical fuel conditions. Many models have been developed that utilize these basic variables to output expected fire behaviors (Stratton 2004; Keane *et al.* 2010; Ager *et al.* 2012, 2013). While some models use detailed physics-based approaches to predict the exact behavior of a single fire at a fine spatial scale, others utilize a Monte Carlo approach to summarize the results of hundreds of simulated fires on a larger spatial area (Preisler *et al.* 2004; Finney 2005; Carmel *et al.* 2009). These generalized results can be used to create a conditional burn probability which provides useful information for land managers. Depending on the spatial scale of the input datasets, the resulting fire risk map can potentially provide relatively fine scale results while still encompassing a large modeling area (Stratton 2004; Brillinger *et al.* 2006; Ager *et al.* 2010, 2012).

A fire's behavior is dependent on what is referred to as the fire behavior triangle; the three sides of the triangle are weather, topography, and fuel. Various variables detailing these three sides are the basic foundation required by all fire modeling software. Weather variables can include average wind speed, expected wind gusts and frequency, average wind direction, relative humidity, and the atmospheric inversion levels. Topography can be described by average slope, aspect, and elevation. Fuel characteristics include fuel moisture broken down by size class (1 hour, 10 hour, etc.), fuel type (grassland, shrub, dry coniferous, etc.), amount of fuel, and existing fuel breaks across the landscape (such as lava flows, streams, or roadways) (Finney 2006). Values for these variables can mostly be obtained from remote sensing (Riaño *et al.* 2002). If the modeler desires a fine spatial grain or the most recent conditions, such as for the modeling of an active wildfire, direct observations are required.

Monte Carlo models have been proven to provide useful approximations of fire risk for a single landscape. The study area is broken into pixels spatially determined by the input dataset's resolutions. Generally, if a modeler is using Landsat derived data, a scale less than 30 x 30 meters is not possible (Riaño *et al.* 2002). Typically the resolution is actually decreased to exponentially reduce computer processing time (Ager *et al.* 2007, 2010). After compiling the input data, it is input into the fire model. These models place a single random ignition within the study area, and model its behavior based on both the fire behavior data and user defined inputs such as fire duration, spatial resolution, and number of random ignitions (Ager *et al.* 2007, 2010). Only one ignition source is generated in a single iteration within a given model run. After modeling the defined iteration of fires, which is defined by the researcher and can range from the hundreds to tens of thousands, information such as conditional burn probability and flame length are output (Finney 2006; Ager *et al.* 2011).

Both conditional burn probability and flame length are metrics to estimate a pixel's given fire risk. Conditional burn probability is simply the number of times that the given pixel was classified as "burned" during the ignition modeling divided by the total number of fires, multiplied by 100 to give a percent (Finney 2005; Ager *et al.* 2011). While this result is not to be interpreted as a hard statistic, it does provide a metric to quantify the differences across a study area in terms of the general likelihood of a pixel experiencing a fire event. Flame length is the average estimated height that the active flaming front would achieve in a given pixel limited by the fuel conditions, fuel type, fire weather, and topography in the pixel. It can be interpreted as a metric to describe the intensity of a fire, which is defined as the energy released from the combustion of organic matter (Ager *et al.* 2011). This is not to be mistaken for fire severity, which describes the impact of the fire on the ecosystem post-burn (Finney 2006).

NIPF Management

NIPF owners can have an expansive, diverse number of management goals (Bliss 2003; Elwood *et al.* 2003; Berlin *et al.* 2006; Fischer 2012). Some owners may hold the recreational value of their parcel with the highest regard, while others may favor the aesthetics, or privacy of their parcel. Parcels could also have great value to owners harvesting forest products such as firewood or mushrooms (Kline *et al.* 2000). These differences in ownership values cause management approaches can greatly vary. Passive managers may not perform any direct actions, letting nature take its course on their parcel. Owners who are focused on the amenities of their parcel may perform FireWise actions to safeguard structures, or remove undesired vegetation that interferes with aesthetics or recreation (Carroll *et al.* 2004; Bright and Burtz 2006). Those who place higher values on the timber production of their parcel are more likely to perform silvicultural actions such as selectively thinning their stand to favor desirable timber species, understory removal to reduce competition with the overstory, or patch clear cuts to generate income as needed (Carroll *et al.* 2004; Bright and Burtz 2006; Domínguez and Shannon 2009; Fischer 2012). With all of these differences in values, they don't entirely capture the influences on an individual's management decisions.

In addition to their own motivations and beliefs, NIPF owners may be influenced by a variety of external factors. Observing what neighboring parcels have done, the ownership of those parcels, the types of forestry related educational material the owners are given or groups they communicate with (Andersson 2012; Fischer and Charnley 2012). An increased perception of risk has a positive effect on landowners willingness to conduct fuels treatment (Prestemon *et al.* 2002; Talberth *et al.* 2006; Busby *et al.* 2012; Fischer *et al.* 2014). Having the resources necessary to perform a management action, perhaps, has the most obvious impact on whether fuel treatments are performed. The availability of resources to pay for or complete fuels treatment, and the capacity to implement or oversee those treatments, are final key factor in NIPF adoption of fuel treatments (Andersson 2012; Fischer and Charnley 2012).

Policy Tools and their Evaluation

In recognition of the financial and operational challenges faced by many private landowners, a variety of state and federal programs have been created to facilitate active management by parcel owners. Cost sharing programs help reduce the financial cost of approved actions, while consultation services give NIPF owners the ability to craft forest management plans with their desired goals in mind (Vanbrakle *et al.* 2013; Butler *et al.* 2014). Tax incentives have been established in the form of reduced tax rates for forested parcels whose owners can show they have a current forest management plan (FMP), including a FMP that aims to improve fuel conditions.

Investigating the effectivness of these policy tools in increasing NIPF fuel reduction treatments is challenging (Venn and Calkin 2008). Active management levels before the use of the policy tools needs to be compared to the current level of treatments (Butler *et al.* 2014). This approach has two challenges that are apparent from research on federal lands: 1) past data for management actions on forest stands can be hard to obtain (Hummel and Calkin 2005), and 2) collecting data on the current levels of management for large forests can be unreliable (Rideout and Omi 1995; Calkin and Gebert 2006). Even with the large amount of data collected and maintained by federal agencies, issues like these persist and impede the ability for researchers to reliably model and evaluate management actions. These limitations are likely to be even more apparent for NIPF parcels, but they can be addressed by limiting the scope of a given study to spatial location that has past management history and is small enough to allow for direct observations of current management activities. Researchers could also rely on survey data instead of direct observations to ascertain the current levels of management (Venn and Calkin 2008; Butler *et al.* 2014), but this introduces a number of new complications which can be difficult to account for. Utilizing remote imagery in lieu of surveys or direct observations may provide a method for both past management actions (to the point that imagery was first collected) and current actions in a cost-effect method across much larger spatial scales (Preisler *et al.* 2004; Carver *et al.* 2006; Wei *et al.* 2008; Ager *et al.* 2010).

Satellite imagery has the potential to detect changes in vegetative cover over large spatial areas, although the temporal span is dependent on the type of imagery, and quality of data required by the researcher (Carver *et al.* 2006). For the purpose of vegetative cover, Landsat imagery has an adequate spatial resolution of 30 x 30 meters to potentially capture management actions. While a researcher could obtain Landsat imagery for free, a large time and money expense would be incurred by manually inspecting the data for signs of management activity. A number of tools to more quickly analyze and interpret satellite imagery have been developed (LaCroix *et al.* 2006; Cohen *et al.* 2010; Kennedy *et al.* 2010; Meigs *et al.* 2011; Moore *et al.* 2013), and LandTrendr is an example of such a tool. It is unique in that it allows for annual disturbance events to be detected from a series of Landsat imagery. This tool, if proven to effectively detect forest management actions, could allow for researchers and mangers to assess management actions without considerable resource investment.

LandTrendr

Basics of remote sensing & LandTrendr

Remote sensing allows researchers to obtain information across large spatial and temporal scales far more economically than could be achieved through direct observations. By utilizing instruments attached to a wide array of mounts, including aerial vehicles, satellites, and aqueous vehicles, a wide array of information can be obtained. Sensors can detect and record data such as light waves ranging from low frequency waves such as microwaves to high frequency gamma rays, sonic reflectance through the use of sonar equipment, or the reflectance of objects measured with lasers or light detection and ranging (LIDAR) equipment (Khorram *et al.* 2012). With these tools a satellite in Earth's orbit, for example, could measure cloud cover, weather patterns, areas of human development, vegetative cover, landscape elevation, heights of buildings or trees, approximate locations of underground mineral deposits, or even the vigor of a farmer's crops (Khorram *et al.* 2012). Depending on the type orbit in which this figurative satellite is in, this data could be collected for the entire globe over a coarse temporal scale, or for a select portion of Earth over a relatively fine temporal scale (Khorram *et al.* 2012). With a combination of both private and public satellites currently in various Earth centric orbits, researchers have an overwhelming smorgasbord of data available either for free (in the case of publicly funded satellites such as Landsat) or for fees (as in the case of DigitalGlobe).

Landsat 7 and Landsat 8, collect publicly available data from their onboard light sensors. The data is maintained and available for free through three web based catalogs: EarthExplorer-EE, GloVis, and LandsatLook Viewer (Society 2014). A number of recognized methods have been developed to address an array of research problems from the data. These range in complexity from the simple, artificial coloring of data from the non-visible portions of the light spectrum and manually inspecting the results, to complicated computer algorithms that can track and quantify temporal and spatial changes for a designated area across a given time scale. LandTrendr is an example of the latter, and has been recently developed and used in a growing number of publications to track landscape disturbances (Cohen *et al.* 2010; Kennedy *et al.* 2010; Meigs *et al.* 2011; Ohmann *et al.* 2012; Bright *et al.* 2014).

LandTrendr takes Landsat imagery and calculates yearly changes in spectral conditions which are then used to estimate changes in vegetative cover to detect disturbance events (Cohen *et al.* 2010; Kennedy *et al.* 2010; Meigs *et al.* 2011). Within a user defined focal area, LandTrendr samples a year's worth of Landsat imagery and for each pixel of the study area, the least obscured Landsat data is saved. This process is applied for the area with the result being a mosaic of pixels taken from a single year's Landsat imagery. Once a composite image is created for each year, LandTrendr then compares differences among years following user defined parameters. Specifically, LandTrendr examines differences in the shortwave- and near-infrared reflectance which best displays vegetative cover (Cohen *et al.* 2010; Kennedy *et al.* 2010).

The changes in the near-infrared spectrum between years are analyzed by an algorithm in LandTrendr which assesses the rate of change, both relative to the previous and future year, and a series of years. If the change in measured reflectivity is within the user-defined boundaries, then LandTrendr does not flag the change as a discrete disturbance event. When the change surpasses the parameters by either being abrupt, or prolonged long enough, LandTrendr then flags the pixel as having experienced a disturbance event (Cohen *et al.* 2010; Kennedy *et al.* 2010). The year of the disturbance, the resulting reflectivity, and the percent change in overall reflectivity are saved to be output within the results. Performing a LandTrendr analysis show the pixels, by year, that have experienced a disturbance event. From this process, a researcher can quickly and reasonably reliably locate changes in vegetative cover within a study area across a number of years.

In addition to locating the approximate locations of disturbance events, clues hinting at what the disturbance was can be teased out through further data analysis. By examining the reflectance following a disturbance event researchers can determine what the land cover changed to. Bare soil which can follow a fire event, urban development such as blacktop and housing additions, deforestation, reforestation, and even the loss or increase of overstory vigor can potentially be determined simply by examining the LandTrendr output. Performing this in depth analysis across a large study area, however, is time prohibitive. Currently, research is being performed to create an algorithm which will automatically handle this process and add the variable to the discrete disturbance event.

Chapter 3: Remote sensing used to map fuel treatments

Introduction

Through the use of remotely sensed data, researchers are able to sample larger spatial areas than could be accomplished through direct observation. Some remote data sources, such as satellite imagery, can also provide a fine temporal grain to the data. Many scientific fields now routinely employ remote sensing to accomplish an astonishing number of different analyses. Geologists can locate events such as past landsides covered by vegetation, and mineral deposits. Climatologists can observe global or local weather patterns across a large temporal scale, while meteorologists can use remotely sensed data to create the weekly forecast. Ecologists can map the location of vegetative cover and track its change over time (Khorram *et al.* 2012).

To use remotely sensed data, analysis software and tools have been, and continue to be, developed to accomplish specific needs. LandTrendr is one example which provides researchers the ability to map the spatial and temporal locations of disturbance events (Kennedy *et al.*). While this tool has been used to map events such as insect outbreaks, reforestation, and afforestation, it could also be used to identify management actions (Kennedy *et al.* 2010; Meigs *et al.* 2011; Bright *et al.* 2014). Knowledge of the location and age of management actions that have happened previously provides information for management of individual parcels that considers a larger landscape context. One area that LandTrendr could prove extremely useful is in wildland fire management. Landowners and managers, who hope to reduce the possibility of wildfire on their parcel, or the severity of a wildfire, could consider how their neighbors' fuel treatments, or lack thereof, would influence a wildfire in the area.

Previous research used LandTrendr to identify insect mortality (Meigs *et al.* 2011). In both prior research, and this project, the spatial extent of the LandTrendr analysis encompasses an entire landscape. At the time of writing, use of LandTrendr to locate fuel reduction treatments has not been documented. This chapter will answer the first research question: can remotely sensed data be used to reliably detect different forest management activities, including fuel reduction treatments?

Methods

Study Area

The study area is located in central Oregon. Its northern boundary encompasses the Warm Springs tribal lands and spans south to Klamath Falls (Figure 1.1). Four counties are included in this area: Klamath, Lake, Deschutes, and Jefferson. Approximately 55% of the land area is managed by federal agencies (48% U.S. Forest Service, 7% U.S. Bureau of Land Management), and 20% is privately owned. Within this 20%, there were at the time of this study approximately 11,700 non-industrial private forest (NIPF) parcels greater than 1 hectare (2.47 acres) with equal to or greater than 10% forested area.

Ecologically the area is diverse with cover types ranging from moist subalpine forests to arid shrub-steppe. Ponderosa pine (*Pinus ponderosa*) dominates the study area, covering roughly 33% of it. Fire regimes across the landscape vary as well, with fire rotations of 4-11 years in the ponderosa pine to 250 year rotation ages in mountain hemlock. Low-severity wildfires constitute the shorter rotation ages, while high intensity, high severity wildfires define the 250 year rotation age fires (Bork 1984; Simon 1991). Wildfires in the area typically are vast in scale, with only 10% of the fires between 1910 and 2002 accounting for 74% of the total burned area within Deschutes National Forest (Finney 2005).

Residents of the area experience wildfires seasonally. Two recent large fires attracted significant public attention. The B & B Complex Fire burned 36,733 hectares in 2003 (Zybach and Lapham 2004), and the Pole Creek fire burned 10,844 hectares in 2012 (Impacts of the Pole Creek Wildfire on Fish, Wildlife and Aquatic Habitat, and on Public Health 2014). Federal and state land managers in the area have historically had policies emphasizing fire suppression and exclusion, like much of the United States. Less frequent, larger, more severe wildfires are occurring across the landscape. Information concerning fuel treatments, homeowner preparedness, and general fire safety has been increasingly distributed by local governments, community groups, and public outreach organizations (McLean 1992).

Data Management

Known Locations of Management Actions

Two different datasets defining management actions were used in this assessment: one an agency catalog of federal land management in the study area, and the other a survey of NIPF owners within the area. Both datasets were assumed to detail the true locations of forest management actions.

The United States Forest Service's (USFS) Forest Service Activity Tracking System (FACTS) is a catalog of management actions on federal lands. The approximate locations, date on which the management action was drafted, the date the management action was completed, and the type of management action are recorded along with many other descriptive variables. Nineteen different management actions were recorded within this dataset, providing the ability to assess how differing levels of management were detected by LandTrendr.

The mail survey used in this project was sent to 1,451 NIPF owners within the study area. Of these, 388 were returned while 236 were undeliverable (response rate = 32%). Included in the survey were questions about the management actions that the respondent had conducted in any of the previous five years. Unlike the FACTS dataset, survey respondents were only asked about five management actions: understory mowing, thinning for timber value, thinning for fuel treatment, commercial timber harvest, and prescribed burning.

Predicted Locations of Management Actions

Results from a previously compiled LandTrendr analysis were obtained for the Forest, People, Fire (FPF) study area (Figures 3.1 and 3.2). The data's temporal range spans from 1985 – 2011, with a temporal grain of one year. Since the FACTS data spanned from 2000 – 2010, and the survey response data spanned from 2008 – 2012, the LandTrendr years used in the analysis were from 1999 – 2012. Using LandTrendr results from a year prior to the FACTS data allowed for a more accurate representation of on the ground disturbance events. The FACTS and LandTrendr data did not classify a calendar year in the same fashion. As the data from LandTrendr analysis had already been created, it was not possible to include data for calendar years past 2012.

Figure 3.1 – Map of Oregon with the study area outlined in bold. County lines and city limits are included for reference.

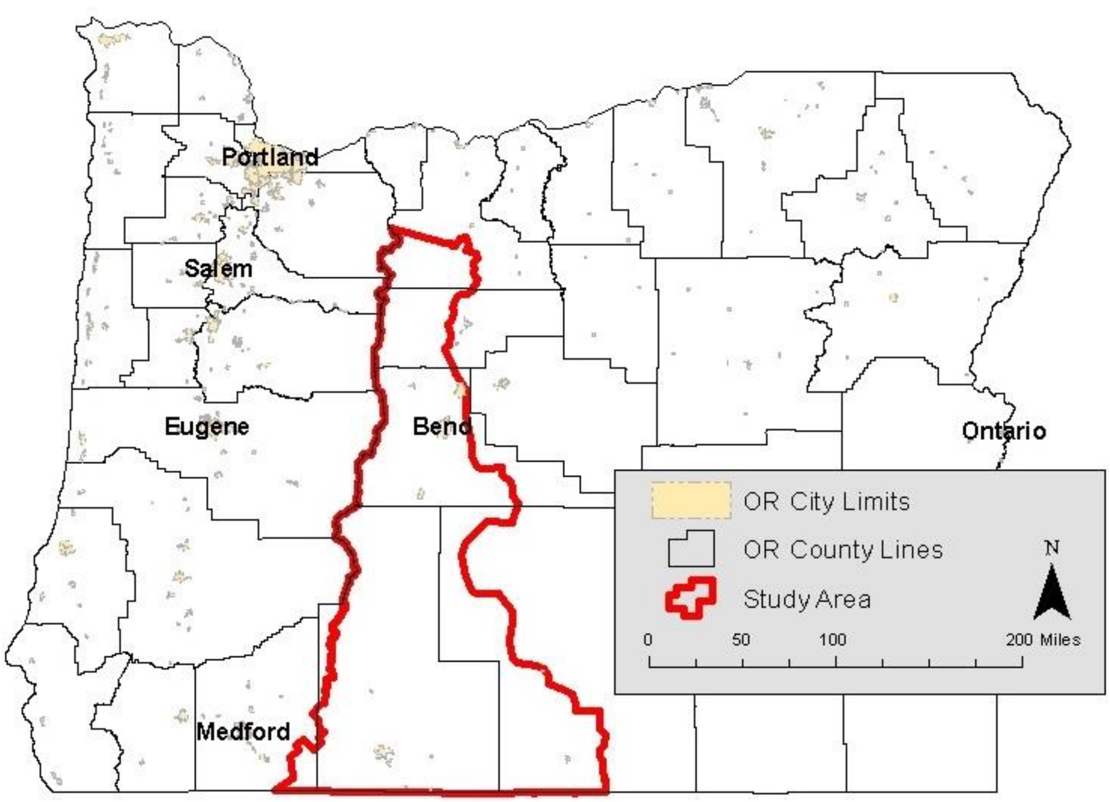
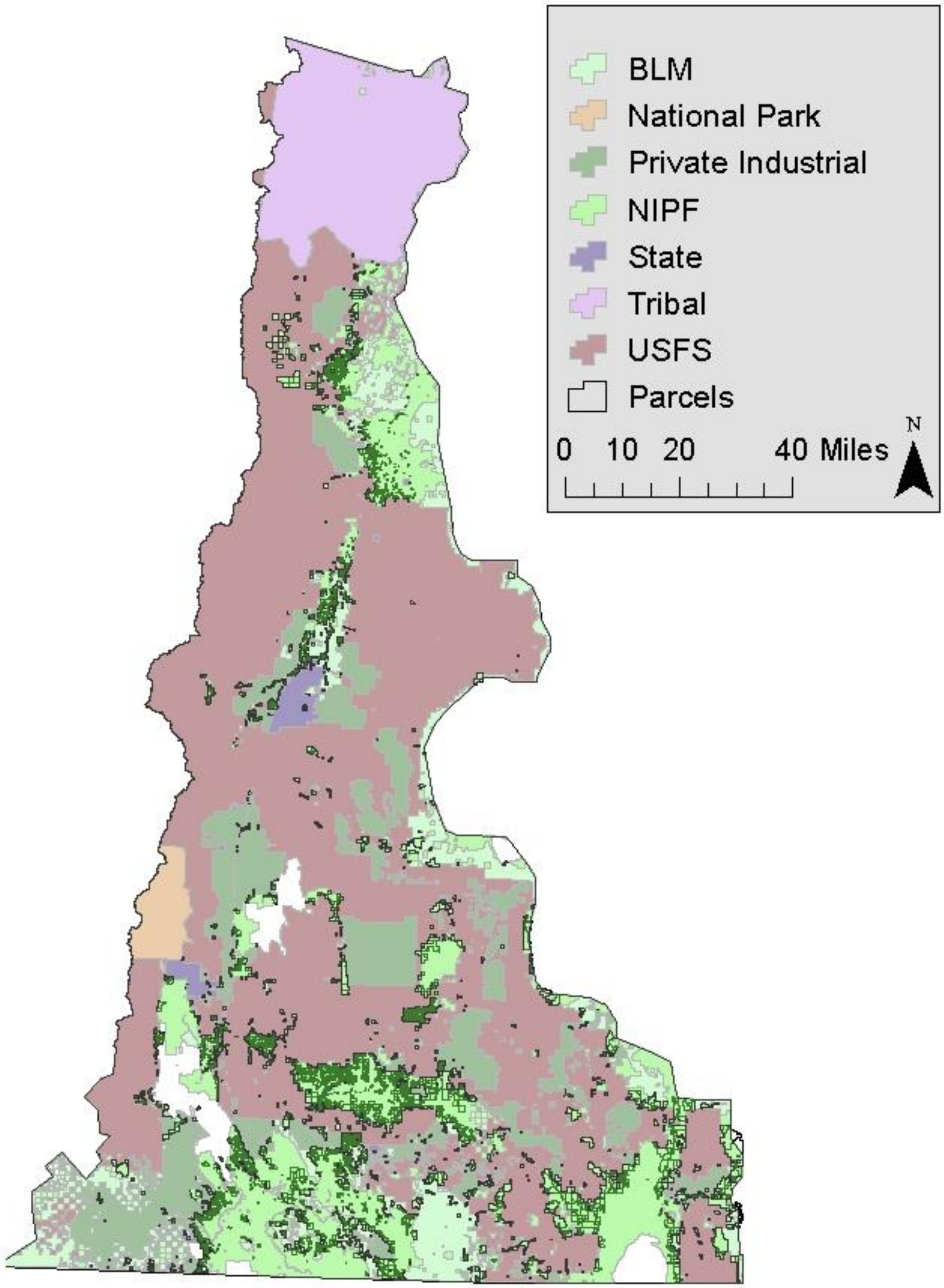


Figure 3.2 – Map of the study area showing ownership boundaries and the locations of the 11,700 NIPF parcels that met the study's size and percent forest cover requirements.



The LandTrendr data was a raster made up of 30 x 30 meter cells containing information such as the locations of disturbances, the year of the disturbance, and the approximate percent of the cell disturbed. Disturbance events included within the original data could have been the result of blow downs, commercial harvests, fire damage from wildfires and prescribed fires, insect induced mortality, or even the death of landscaping during periods of drought. At the time that data was collected, no methodology was available to reliability and accurately identify which agent was responsible for a given disturbance events at a landscape scale; inspecting each LandTrendr disturbance event through orthoimagery was not a viable option. The only statement that could be made about an event is that according to the LandTrendr analysis, a discernable change in the spectral reflectance of the pixel was capture from one year to the next.

To focus the LandTrendr data to include only disturbance events which could be reasonably defined as anthropogenic management actions, the data layer was filtered to eliminate fire disturbances and large mortality events due to insect infestations. A layer showing probable fire locations within the study area was obtained online from Monitoring Trends in Fire Severity (MTBS). This dataset had a 30 x 30 meter spatial resolution and included data for the years of interest. Only fires greater than or equal to 1,000 acres were recorded within this dataset. Using ArcMap v. 10.2, disturbance locations were removed via a mask to eliminate any disturbance pixel that overlapped with a fire event in the MTBS dataset. Small scale fires (< 1,000 acres) were left within the LandTrendr dataset due to the limitations of the MTBS data.

To remove probable insect infestations, a mask was again applied to remove any cells overlapping hand mapped insect mortality locations. Keith Olsen, a senior faculty research assistant with Oregon State University, inspected the data and identified probable insect induced mortality. He compared the LandTrendr disturbance layer to aerial orthoimagery obtained from the Oregon Explorer website. Only large areas of disturbance were inspected due to time restraints. Boundaries defining each disturbance polygon were created by hand in ArcMap. Three large bug kill areas were removed from the disturbance layer. The first of the three areas was approximately 2,307 acres, 23 miles west of Bend, OR. The second area was approximately 13,000 acres, 26 miles east of Crater Lake. The third area was approximately 3,631 acres, 18.5 miles south of Summer Lake.

The refined disturbance layer was recoded into binary variables so that 1 was the presence of a disturbance, and 0 was the lack of disturbance. A three pixel by three pixel moving window was then used to recode the processing cell to equal the sum of the grid (Figure 3.3). At this size, approximately two acres were used in the recoding at a time. Since the NIPF parcels examined within this study needed to be at least 1 hectare (2.5 acres), an entire parcel would not fall within a single frame. Multiple windows would need to be used to cover even the smallest parcel within this study, helping to ensure the capturing of a management action on these smallest of parcels.

1	0	0
0	**<u>0</u>**	1
1	1	0

Figure 3.3 - An example of the moving window used to recode the cleaned, binary LandTrendr data. In this example, the processing cell would be recoded from a 0 to the sum of all nine pixels, 4.

The resulting data layer consisted of pixels with values ranging from 0 to 9. Another recoding was performed to convert the data back into a binary format. Only pixels which had a value greater than or equal to 2 were coded as 1 (disturbance), while values of 0 or 1 were coded as 0 (no disturbance). The final result was a binary data layer which gave the approximate location for disturbance events which were equal to or greater than .016 hectares in size (two 30 x 30 meter pixels) within a 0.81 hectare (2 acres) range. Relatively fine scale detail was maintained from the original LandTrendr dataset, while still removing noise and small, remote disturbance events. It was important to maintain this fine scale of spatial detail because with the smallest parcels (1 hectare in size) the 10% forested requirement would only result in 0.1 hectares of forest. While this is much larger than the .016 hectares of disturbance maintained from the moving window analysis, a parcel owner may not have treated the entirety of their forested area within a given year. Legitimate management actions less than 0.1 hectares would be missed with a coarser spatial scale, negatively impacting future results.

Comparison to FACTS

Overlaying the cleaned LandTrendr data for 1999 – 2010 and the FACTS data in ArcMap allowed for an examination of LandTrendr's success at detecting various forms of management actions. Since the LandTrendr data was converted to a binary layer, the percent of a given management action's area that was detect by LandTrendr was easily accomplished by using the Zonal Statistics tool. The tool returned the percent of the management area overlapped by LandTrendr identified disturbances. The results for all management polygons were aggregated based on the type of action as recorded within FACTS. While FACTS potentially allowed for a clear comparison of which management actions were captured by LandTrendr, there were some major issues both with the FACTS and LandTrendr data which had to be overcome.

Comparison to Survey

Comparing the LandTrendr results to the survey data potentially provides a more reliable method than FACTS to confirm LandTrendr's ability to detect a number of management actions. The surveys included information on which types of management actions the respondent had performed on their parcel in the past five years. As this data is coming from the property owners themselves, the dataset is perhaps more reliable than the FACTS database. After reviewing the raw survey data and correcting for respondent errors, a similar approach to comparing the FACTS database was undertaken within ArcMap to compare the LandTrendr and survey results.

The survey data included information for 379 NIPF parcels within the study area (Figure 3.1). An apparent respondent error in the original data was corrected during data management. Two different questions within the survey inquired about the occurrence of a prescribed fire on their parcel. This was asked about at two different locations in the survey, with two different wordings. A small number of respondents answered “yes” to one question and “no” to the other. For these respondents, both questions were recoded as “yes”.

As worded in the survey, only management actions in the past five years that fall within the categories of “cut timber for sale”, “controlled burn/prescribed fire”, “tree thinning for timber value”, “tree thinning to reduce fire danger”, or “mowing or cutting the understory” were recorded. A separate portion of the survey asked if the respondent had any disturbance event on their property in the past five years. Included within these possibilities were “wildfire”, “controlled burn or prescribed fire”, “tree insect infestation or disease outbreak”, “construction of structures”, or “invasive plant establishment”. In examining the survey data the assumption that the respondents would be able to accurately describe the disturbance events on their parcel was not always found to be true.

With the collection of the original survey data, a unique identification number was assigned to each mailed survey and the parcel's owner information. To compare LandTrendr's results to the survey results, the unique survey identifier was used throughout the analysis to maintain the confidentiality of the respondent. To maintain respondent privacy, the entire NIPF dataset was used when performing analyses within ArcMap. Results of these analyses were examined in Excel by extracting only those parcels which had valid survey responses.

Manipulating the LandTrendr results was exactly the same as detailed for the FACTS comparison. The same three insect infestations were removed from the original dataset, as were suspected fire disturbances captured within the MTBS dataset. However, in matching with the survey stipulation that the management action had to occur within the previous five years, only LandTrendr results for 2008 – 2012 were considered. Including the 2008 data was necessary to account for the fact that the LandTrendr analysis did not follow the calendar year (Jan. 1st – Dec. 31st).

The cleaned, binary LandTrendr results were overlaid on the NIPF parcels. The mean value within each parcel was calculated with ArcMap's zonal statistics tool. Multiplying this number by 100 gave the percent of the parcel which was disturbed as reflected by the LandTrendr dataset. For parcels which had undergone a management action in the past five years, the detection of any disturbance was assumed to be the management action. A confusion matrix was created for the results detailing the success and failings of this analysis.

Results

Comparison to FACTS

There was high agreement between LandTrendr and the FACTS database. Of the 3,766 management polygons within the FACTS dataset, 3,517 of them were detected at some level by LandTrendr (93.4% success). Each individual polygon was deemed to have been successfully captured within LandTrendr if any of the FACTS polygons contained a disturbance within their drawn boundary. With this requirement, every management action in FACTS was detected at some level by LandTrendr (Table 3.1). Given the nature of the FACTS database, where management action polygons with ArcMap were often only partially disturbed, LandTrendr was assumed to be successful at labeling a management category when greater than 10% of the aggregate management area polygons for a discrete treatment were disturbed. All the management categories met this criterion, although certain treatments were more readily observed by LandTrendr.

Generally, the more disruptive the management action was to the overstory, the better it was captured within LandTrendr. Of the individual polygons within FACTS, LandTrendr detected 100% of the patch clearcut, selection cut, partial removal, shelterwood establishment cut, and group selection cut. Among these four management actions, LandTrendr showed that between 34% and 69% of the FACTS polygon was disturbed within the 11 years of LandTrendr data analyzed. Overstory removal cuts were the least detected, but LandTrendr still detected 76.5% of the managed areas. However, only 11% of the total managed area was labeled as disturbed.

Table 3.1 - Results by management action comparing LandTrendr's detected disturbances to the FACTS database from highest to lowest success rate. Area disturbed estimated from the 30 x 30 m pixel resolution of LandTrend.

	Number of management areas	Detected (at any level)	% LandTrendr detected	Cumulative management area (ha)	Area disturbed (ha) [%]
Patch clearcut	1	1	100	19	6 [34]
Selection cut	1	1	100	19	7 [36]
Partial removal	2	2	100	216	109 [50]
Shelterwood establishment cut	52	52	100	952	657 [69]
Group selection cut	19	19	100	153	133 [87]
Commercial thin	1392	1381	99.2	35,790	24,894 [70]
Overstory removal cut (from adv. regeneration)	61	60	98.4	1,221	713 [58]
Single-tree selection cut	194	190	97.9	4,950	3,243 [66]
Stand clearcut (w/ leave trees)	15	14	93.3	336	281 [84]
Thinning for hazardous fuels reduction	677	629	92.9	13,778	5,207 [38]
Stand clearcut	11	10	90.9	170	139 [82]
Shelterwood removal cut	85	77	90.6	1,826	279 [15]
Sanitation cut	65	58	89.2	1,310	364 [28]
Salvage cut	385	341	88.6	8,274	2,681 [32]
Shelterwood removal cut	66	58	87.9	1,411	374 [27]
Sanitation	468	398	85.0	8,183	1,793 [22]
Other stand tending	202	169	83.7	3,099	913 [29]
Special cut	53	44	83.0	1,159	489 [42]
Overstory removal cut (w/ residuals)	17	13	76.5	217	24 [11]

Comparison to Survey

There was less consistency between LandTrendr and the stated actions of landowners. Of the 379 surveys, 204 (53.8%) of the reported management actions were correctly labeled by LandTrendr (Table 3.2). Of the errors, 31 were false positives where LandTrendr indicated a disturbance but landowners did not report a disturbance event. Conversely, there were 144 false negatives (38.0%)—instance where a stated disturbance from a landowner was not identified by LandTrendr.

Table 3.2 – Confusion matrix showing the success of LandTrendr at detecting respondent reported management actions at any level (% of returned survey).

		LandTrendr detected disturbance event	
		Yes	No
Respondent reported treatment	Yes	97 (25.6)	144 (38.0)
	No	31 (8.1)	107 (28.3)

LandTrendr had difficulty detecting parcels with only one disturbance. (Table 3.3). Twelve of the 35 parcels (34.3%) with a single disturbance were identified by LandTrendr. None of the individual management actions reported by landowners was detected with greater than 50% success. The least successful, understory mowing (29% detection), was also the most likely of the three actions to not impact the overstory's canopy structure. The two actions which would have likely had the most direct impact the canopy, thinning for timber values and timber sale, were not represented within the sample population.

Table 3.3 – LandTrendr's success at detecting discrete management actions as reported by survey respondents.

Management action	Number of parcels	Number of successful detections	Percent successful (%)
Understory mowing	17	5	29
Thinning for fire values	12	4	33
Thinning for timber values	0	-	-
Controlled burn/ prescribed fire	6	3	50
Timber sale	0	-	-

Discussion

Results show that LandTrendr is able to accurately detect discrete management actions, with actions that impact the overstory being more likely to be detected than actions which do not impact the overstory. For instance, understory removal through mowing or a low intensity surface fire is less likely to be detected than selective thinning or crown disturbance. The size of the disturbance event also has an impact on the ability for LandTrendr to detect it. For instance, the FACTS comparisons showed that only 76.5% of overstory removal cuts were correctly identified. Presumably these removals caused clear disturbances to the overstory, but with an average disturbance area of only 1.4 ha (17 polygons with 24 ha disturbed), the size of the disturbance may have been too small for LandTrendr. The methods of removing noise from LandTrendr could also have contributed to this low number by being too conservative in what was retained as disturbance events.

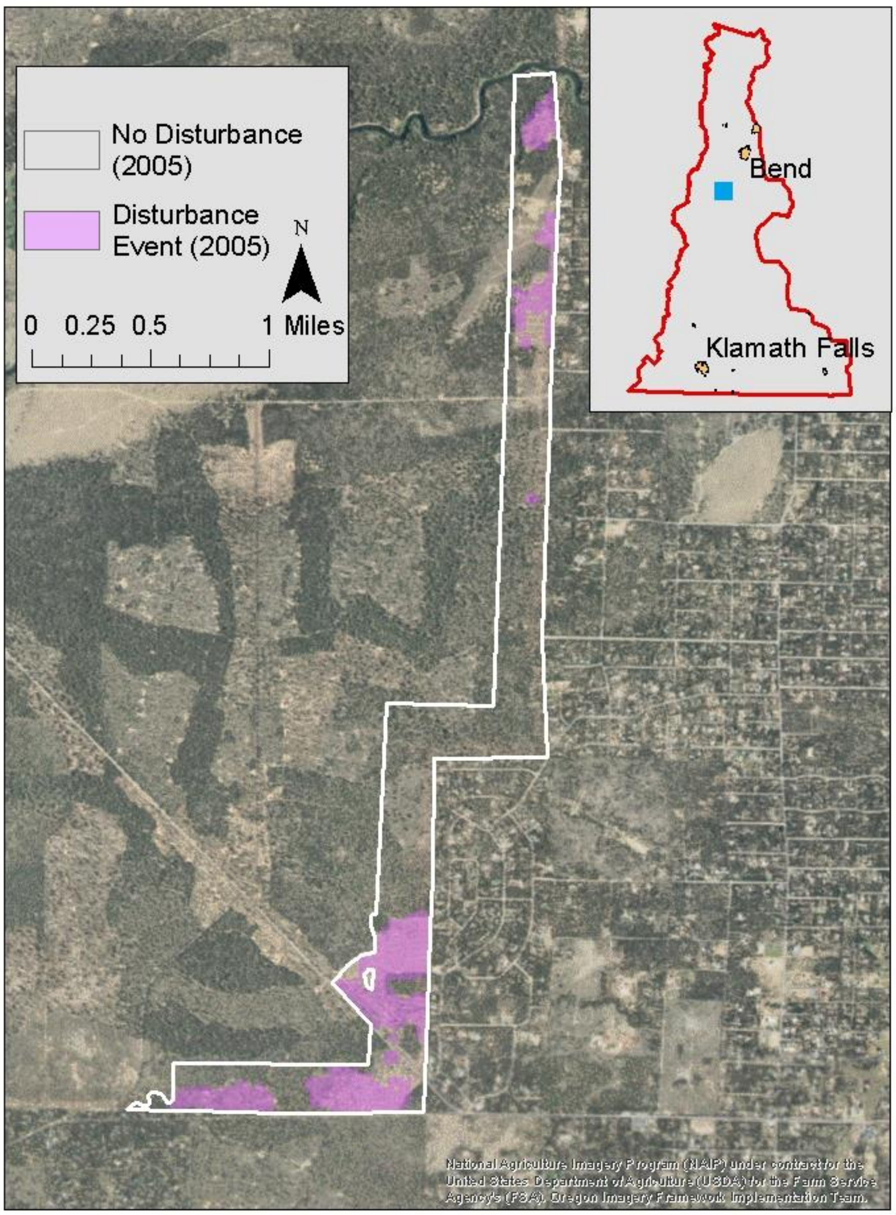
Considering the potential constraints from LandTrendr itself, or those defined by the user, researchers can use LandTrendr to quickly and accurately summarize land management actions for large spatial areas without resorting to manually inspecting the aerial imagery or field observations. As mentioned before, improving LandTrendr's ability to detect management actions while excluding other disturbance events is a next step to improve LandTrendr. Current work is being completed to reliably describe what type of mechanism caused the observed disturbance. Including this capability in the established ability for LandTrendr to capture disturbance events will make it a very useful tool for land managers, researchers, and policy creators who want to quickly and economically detail the management actions across a number of ownerships within a given area.

After the initial reformatting of the LandTrendr data, many large contiguous patches of disturbance, as well as a plethora of individual 30 x 30 meter cell disturbances remained. While the reliability of LandTrendr's detection of small disturbances occupying one 30 x 30 m pixel was not quantified in this project, the presence of these solitary cells was assumed to be inaccurate across the entirety of the study area. Potentially, these distinct disturbances could have been legitimate events, such as small patches of trees being blown down or perhaps a landowner planting a shade tree around a residence. However, it is also likely that a number of them were simply noise within the original dataset created from the LandTrendr analysis. Interpolation of the cleaned, binary data was done to remove both this possibility and to further focus on likely forest management actions.

Inconsistencies with the FACTS management polygons and actual management actions as observed through aerial imagery were noted while comparing the FACTS and cleaned LandTrendr layers. In a small handful of instances, disturbance patches were correctly (as confirmed with orthoimagery) detected just outside or only partially within the FACTS defined polygons. While potentially a fault of the FACTS database, it could also have been a result of obtaining the orthoimagery from the publicly available OregonExplorer website. This data, while free, is limited in its scope as only imagery for 1995, 2000, 2005, 2009, and 2011 were available. Errors could have been made in interpreting the locations of management actions which occurred during years not captured by the OregonExplorer data.

In addition to errors in the location of management polygons, FACTS appears to also have inconsistently recorded "dates of completion" within the database. Management actions may have occurred a few years after being recorded as "complete" within FACTS. Polygons of management actions within FACTS often times include large patches of land which appear to be in the process of being incrementally treated. A good example of this would be a large fuel reduction treatment just to the west of Bend, OR (Figure 3.4). Portions of this polygon have clearly had fuel reduction treatments performed, while larger portions appear unaltered. It is possible that the remaining area within the polygon was treated and is not detectable by aerial imagery. It could also be that the treatment area will require multiple years before the plan is fully implemented. However, since this study used the best, freely available data, the errors in the original dataset are acceptable for a landscape analysis so long as the limitations are considered when interpreting the results.

Figure 3.4 – Map showing the location of a FACTS fuel treatment recorded as having been completed in 2003 just west of Bend, OR. LandTrendr detected disturbances for 2005 are highlighted. Note that only a portion of the management area has been disturbed during this calendar year.



Using the survey data to assess LandTrendr's effectiveness introduced potentials for error. First, the LandTrendr data ended in 2012, while the survey responses could have reflected management actions up until 2013. This lack of temporal overlap directly reduced the accuracy of the survey comparison's reliability for detecting management actions which occurred in 2012 or 2013. This source of error was deemed acceptable within the constraints of this research project.

Concerning the survey responses themselves, inconsistent information was given by respondents when answering questions about prescribed or controlled burn disturbances on their parcels, and prescribed or controlled burn management actions. A number of respondents answered that a disturbance of a prescribed fire had occurred, but that a management action of a prescribed fire had not occurred, or *vice versa*. It is possible that some of these respondents may have been indicating that someone else's prescribed fire had accidently burned onto their property, where it was not originally intended to occur. As LandTrendr would potentially detect an intended prescribed burn and an escaped prescribed burn the same (assuming similar severities on both the intended and unintended parcels), if a respondent answered "yes" to either a disturbance of prescribed fire or the use of it as a management action, then both answers were altered within the original data to indicate a "yes" response.

Considering these sources of errors, the analysis in this chapter still clearly illustrates LandTrendr's ability to reliably capture disturbance events which impact the forest overstory. Additionally, there is strong evidence that management actions which create minimal, if any, impact on overstories can be detected. However, LandTrendr's ability to define the exact boundaries of such actions is weak at best. These results show that LandTrendr can be a valuable tool for researchers and land managers hoping to detect management actions on any parcels on a given landscape.

Conclusion

Remotely-sensed data have been shown to be useful in identifying management efforts—especially those that disturb the canopy. While there are concessions given to the spatial and temporal grain of the data, these shortcomings are being reduced through continuing advances in hardware. Improvements in the instruments used for remote sensing not only increases the quality of data sets, but it can also collect an ever increasing array of observations. Advances are also being made in the software which is used to sort and analyze the data once collected. Research questions continually push the envelope of how remotely sensed data can be utilized. LandTrendr is an example of a software package which takes traditional Landsat imagery and uses it to produce a novel data set which can directly inform questions on land management and policy.

To confirm LandTrendr's ability to detect management actions, the analysis's results were compared to FACTS and survey responses. Many of the recorded management actions in both FACTS and the survey data were accurately captured by LandTrendr. The FACTS management action which was identified with the least accuracy was the overstory removal cut (76.5% correctly identified) likely due the fragmented nature of the canopy that was removed, while five of the actions were identified with 100% success. LandTrendr's ability to accurately detect management actions based on landowner stated behavior was less successful (53.9% accurately labeled), the results were still encouraging. Refinements to the LandTrendr classification methodology could be made both in its ability to detect disturbance events and label the suspected cause of the disturbance.

With the relatively low success of identifying overstory removal cuts being caused by the size of the removal patches, LandTrendr could be indicating that the respondent analysis was lower due to decreased disturbance patch sizes. The amount of disturbance may also be preventing LandTrendr's ability to detect the management actions. In both cases, NIPF owners could potentially be performing ineffective fuel treatments. Additional research into this possibility should be pursued as it would inform policy actions which attempted to encourage NIPF owners to perform fuel treatments.

Chapter 4: Survey Analysis and Logistic Regression

Introduction

Investigating the views of non-industrial, private forestland (NIPF) owners has become increasingly important in forest science as landscape-level ecology often requires a coordinated management effort by public and private land managers. Natural processes rarely recognize ownership boundaries created by humans, and so researchers and managers interested in wildlife, forestry, ecology, or wildfire science must investigate the values and goals of all parcel owners within a landscape. Surveys of land owners and managers are often used to inform the understanding of how a landscape is actively managed, and how it may change in the near future.

Surveys can be costly research tools, to capture how respondents perceive their world. Creating models based on survey responses helps to inform a researchers' view on a given population. Models, adequately constructed, can be used to predict the behavior of landowners outside the survey sample. The ability to apply models outside of the sample allows for predicting the behavior of people, based on the established relationship in the model, without requiring the continual use of surveys. Models generalize a given process, with their results to be viewed as a useful tool and not a definitive truth. In social science, this fact is even more apparent as reliably and accurately predicting human actions would require a staggering amount of variables that, realistically, could never be captured by a single survey. However, the validity of a given model can be strengthened when used in conjunction with other tools, such as a LandTrendr analysis. This chapter will address the second research question of this project, what factors influence NIPF managers' decisions to apply fuel treatments? An effective model to predict the management behavior of NIPF landowners could better inform management actions in the mixed-ownership landscape of central Oregon.

Methods

Survey

Data for this analysis were drawn from a mail survey of non-industrial private forest landowners completed as part of the Forest, People, Fire project. Properties were determined to be NIPF parcels based on an ownership classification map created by the Oregon Department of Forestry. To be included in the sample population, the properties had to be equal to or greater than one hectare (2.47 acres) and have at least 10% forested area according to the U.S. Forest Service's Landscape Ecology, Modeling, Mapping, and Analysis (LEMMA) 2008 gradient nearest neighbor (GNN) dataset for the study area. A sample of 1,451 parcels was selected from the 11,700 NIPF parcels within Central Oregon. Respondents' stated demographic and land use values were compared to results from the United States Forest Service's (USFS) Woodland Owners Survey for Oregon. That comparison indicated that the characteristics of landowners in the sample were generally consistent with those of the broader NIPF landowner group. The sample appeared to be representative.

The 11 page survey consisted of a number of dichotomous questions as well as questions based on a 5-point scale, with 1 = not important to 5 = very important, similar to Elwood et al. (2003). Respondents were asked to identify management actions and disturbance events both on their parcel and neighboring parcels. Information on the owners' involvement in organizations offering technical silvicultural assistance and social groups was also collected. The 5-point scaled questions assessed the respondents' ownership values for the parcel. Other questions included in the survey assessed under what conditions a respondent would or would not consider future management actions on their parcel. For the purposes of this study, questions pertaining to land ownership values and types of management actions were used in addition to information on the types and numbers of land management organizations a respondent belonged to.

While the surveys covered a broad spectrum of information relating to management actions, and the incentives or influences guiding these actions, examination of the responses showed that insufficient numbers of respondents answered the more complex questions proposing different management scenarios. As such, results for these questions were not used within the analysis. As a whole, the sample size of approximately 380 was large enough to ensure a +/-5% sampling error in those questions which every respondent answered.

Survey Analysis

The survey responses were cleaned to remove incomplete and inconsistent responses. For instance, at two points within the survey the respondents were asked if a “controlled burn or prescribed fire” had occurred on their property within the past five years. Of the 388 surveys, a small number of respondents answered “yes” to one question, and “no” or “unsure” to the other. In these instances, it was assumed that “yes” was the correct answer and the data was adjusted accordingly. Errors in data entry were also corrected during this phase. No surveys appeared to be protest responses.

Several statistical tools contained within the Statistical Package for the Social Sciences (SPSS) were used to analyze the survey data. An exploratory factor analysis was used in the creation of the independent variable detailing respondents’ ownership values. A cluster analysis then grouped the respondents into categories based on similar values. This variable, along with ten others, were input into a logistic regression model. The dependent variable for the model was the presence or absence of a management action within the previous five years on the parcel. The remaining ten independent variables were collected from publicly available data sources, such as the U.S. Geological Society and U.S. Forest Service. FlamMap and the Fuel Reduction Cost Simulator (FRCS) – West were used to estimate a parcel’s fire risk and calculate its approximate fuel treatment costs respectively.

The binary dependent variables (Com_mgmt and Noncom_mgmt) was coded 1 = "management action" and 0 = "no management action". Management actions must have occurred within the previous five years (from the time of the survey, 2008 – 2012), and only actions that occurred on the individual's parcel were of interest for the purposes of this study. Management actions asked about in the survey were prescribed fires, thinning for lumber values, thinning for fuel reduction, understory mowing, and timber sales; of these five, thinning for lumber values and timber sale were the two actions reflected within "Com_mgmt". The remaining three management actions were captured within "Noncom_mgmt". A respondent must have performed no management actions within the past five years for the variable to be coded as zero.

Four logistic regression models (Eq. 4.1a, 4.1b, 4.2a, and 4.2b) were created so that each dependent variable could be examined using two different configurations of independent variables (Table 4.1). These models were built after consulting previous research which identified key influences on a landowner's willingness to perform a management action (Kline *et al.* 2000; Fischer 2012; Fischer *et al.* 2014). The independent variables in equations 4.1a and 4.1b used only data which could be obtained from publicly available sources while equations 4.2a and 4.2b required the use of survey responses. Creating this distinction was done to examine if the added cost and time of performing a mail survey improved the researcher's ability to accurately model the placement of management actions within the study area. If no difference was found between the two models, then some of the complexity of the methods could be removed in future projects. Determining a respondent's personal values with a larger, more complicated, and thereby more time consuming survey could be avoided.

(4.1a) Com_mgmt = 2008_BP + 2008_FL + Slope_Pct + Med_Ac + Lg_Ac + Perc_For + Fuel_trt_cost + constant

(4.1b) Noncom_mgmt = 2008_BP + 2008_FL + Slope_Pct + Med_Ac + Lg_Ac + Perc_For + Fuel_trt_cost + constant

(4.2a) Com_mgmt= 2008_BP + 2008_FL + Slope_Pct + Med_Ac + Lg_Ac + Perc_For + Fuel_trt_cost + Amenity + Passive + parcel_res + res_primary + constant

(4.2b) Noncom_mgmt = 2008_BP + 2008_FL + Slope_Pct + Med_Ac + Lg_Ac + Perc_For + Fuel_trt_cost + Amenity + Passive + parcel_res + res_primary + constant

Table 4.1. Names and descriptions of the independent variables for logistic regressions.

Variable Name	Variable Description (continuous or binary)
2008_BP	The estimated average conditional burn probability for a parcel as estimated by FlamMap (continuous)
Slope_pct	The average slope percent of the parcel based on the USGS DEM (continuous)
Sm_Ac	Dummy variable grouping parcels less than 1 – 4 hectares in size (binary)
Med_Ac	Dummy variable grouping parcels between 4 – 12 hectares acres in size (binary)
Lg_Ac	Dummy variable grouping parcels greater than 12 hectares in size (binary)
2008_FL	The estimated average flame length for a parcel as estimated from FlamMap (continuous)
Perc_For	The percent forest cover of a parcel based on GNN data (continuous)
Fuel_Trt_Cost	Estimated cost of a fuel reduction treatment as predicted by FRCS-West (continuous)
Tot_org*	Total number of land management organizations respondent belongs to (continuous)
Passive*	Binary variable with “true” (1) for those parcel owners with Passive land management preferences
Amenity*	Binary variable with “true” (1) for those parcel owners with Amenity focused land management preferences
Production*	Binary variable with “true” (1) for those parcel owners with Production focused land management preferences
Parcel_res*	Does the parcel have a residence (as a permanent structure) located on it?
Res_Primary*	Is the residence the respondent’s primary residence?

*Denotes variables obtained from survey data (Eq. 4.2a, Eq. 4.2b, Eq. 4.3a, Eq. 4.3b).

Grouping Respondents by Ownership Values

A variable describing an individual respondent's land use value was created from a 5-point scale, with 1 = not important to 5 = very important based on the survey presented in Elwood et al., 2003. Respondents ranked their interest in the privacy of their property, the value of timber resources on it, the aesthetic values, in addition to a number of other potential values. From this ranking, an exploratory factor analysis was performed to create three independent dummy variables measuring broader concepts, such as amenity or production based values. While some currently published studies used similar questions to create factor loadings, a confirmatory factor analysis was not possible due to the inability of determining exactly what factors were created from these studies.

Once the factors were established, a reliability analysis was used to assess the strength of the found relationships. From these factors, a cluster analysis was performed to group the respondents based on shared ownership values. Previous studies found that four clusters described ownership values for similar NIPF sample populations (Fisher 2012, Kuuluvainen et al. 1996). However, the results from creating two, three, and five groups were also investigated for this study.

After creating the ownership value variable from the survey data, the remaining independent variables were created from publically available databases (Table 4.1). Additional tools were required to transform some of the raw data into the variables required for the logistic regression models. These variables fell into two main categories: fire, and land cover variables.

Fire Variables

Conditional burn probability (CBP) and conditional flame length (CFL) were chosen to indicate each parcel's potential exposure to wildfire. Conditional burn probability is the percent a given pixel would burn within a user defined number of simulated random ignitions. For any pixel to have a value greater than zero, it must have burned at least once during the model run. Unlike real wildfires which ignore imaginary boundaries, fires that start outside the user defined boundaries of the study area are not considered in the model.

Conditional flame length (CFL) is calculated based on the fuel loads of each pixel, as well as topographic and weather variables. Like CBP, CFL required a pixel to burn at least once during the modeling process to give a result > 0. This is not true for urban areas, however, as they returned a 0 due to the lack of LandFire fuel load data for these areas. Since this variable describes the influence of fuels and topography at a given location, considering the user defined fire weather variables, mapping the results does not offer much insight into risk of fire occurrence. Areas which have a majority of trees have higher flame lengths, whereas areas dominated by grasses, scrub, or sagebrush have much smaller flame lengths. Instead, this variable describes fire risk by suggesting the intensity (not necessarily the severity) each pixel would experience during a wildfire.

Creating the average conditional burn probability (2008_BP) and flame length (2008_FL) for the study area required the use of ArcFuels and FlamMap. Fuel load data for the study area was acquired from the LandFire website. The 2008 dataset was used to best reflect conditions five years prior to the survey. This made the CFL and CBP variables consistent with the landscape which the respondents were experiencing at the time of the survey. The fire weather inputs (Table 4.2) used for the model run were adapted from those used in a previous fire research in the study area (Shaw *et al.* 2014).

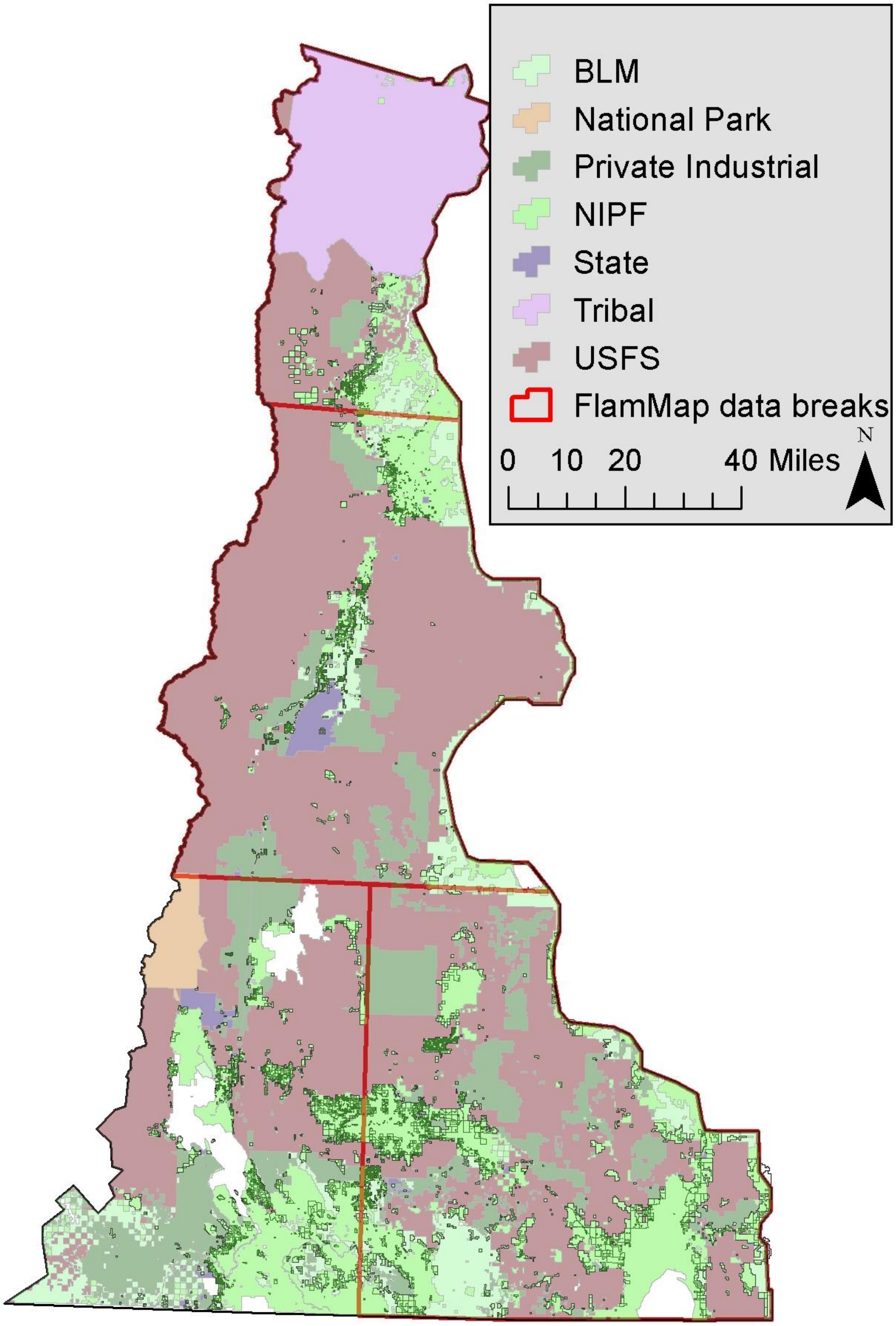
Table 4.2 - Fire weather characteristics, fuel conditions, and FlamMap model parameters for the conditional burn probability and conditional flame length model.

Weather conditions		Fuel conditions		FlamMap parameters	
		Fuel Class	Fuel Moisture (%)		
Wind direction	215°	1 hour	2	Num. of random ignitions	10,000
Wind speed	15 mph	10 hour	2	Resolution of calculations	$90m^2$
		100 hour	5	Simulation time	480 minutes
		Live herbaceous	60	Interval for minimum travel paths	500
		Live woody	90	Spot probability	10%
				Lateral search depth	6
				Vertical search depth	4

Because of computational limitations, two steps were taken to reduce processing time and error. First, the CFL and CBP output were recorded in 90 x 90 m pixels, which was larger than the input datasets which all had a 30 x 30 m resolution. Second, the study area was broken up into four sub-areas to complete the FlamMap analyses (Figure 4.1).

Due to this alteration, special considerations could have potentially been required to correct for the edge effect created within the CBP results. As mentioned within the results and discussion sections of this chapter, the CBP output was resampled to smooth the output's edges. No further corrections to the edges were deemed necessary.

Figure 4.1 – Regions used for FLAMMAP processing with land ownership information included for reference.



Treatment Cost

Estimating each parcel's fuel treatment cost (Fuel_trt_cost) was done in FRCS - West. Specific variables needed for this model to run were average yarding distance (ft.), number of chip trees removed, number of small log trees removed (total volume < 80 ft^3), number of large log trees removed (total volume > 80 ft^3), average slope of the parcel, the average bulk density of each of the three size classes being removed, treatment method, and the bole volume to be removed within each of the three size classes (ft^3). The model's inputs are entered in per acre averages, so the total acreage being treated did not need to be entered.

Stand characteristics were drawn from the GNN dataset. The average slope of the parcel was taken from the digital elevation model (DEM) of the study area. Distance to the nearest landing was estimated by assuming each parcel was a square with the length of each side determined by the total area of the parcel. The length of one side of the square was quartered to create a conservative estimate for a potential required road length. In general, larger parcels would likely require longer yarding distances to access log landings compared to smaller parcels. This assumed relationship was maintained with this process.

Fuel treatment prescriptions applied to the parcels (Table 4.3) in FRCS - West were created based on literature detailing effective fuel reduction guidelines within Central Oregon (Holmberg and Bennett 2008; Parker and Bennett 2008; Bennett and

Fitzgerald 2008a; b), as well as consultation with Dr. Stephen Fitzgerald, an Oregon State Extension Silvicultural Specialist. A target stand basal area of 60 ft^2/ac was set as the ideal stocking level post treatment. Stand densities based on the GNN data ranged from 182 ft^2/ac to less than 10 ft^2/ac. All parcels had a treatment performed on them to prevent a cost of $0 from entering the model. To prevent the creation of unreasonably high costs from the model, the most intensive treatment was applied only to parcels with greater than 120 ft^2/ac. Each treatment removed a larger amount of chip trees, which was assumed to remove more fine fuels and break up potential fuel ladders. This would create a more direct reduction in fire risk. In each treatment, some amount of the small and large trees were removed to give the owner the potential to offset the treatment cost through timber sales during the management action.

Table 4.3 – Treatment levels used to estimate the amount of fuel to be removed for each parcel within FRCS – West.

Treatment level (pre-treatment ft^2/ac)	Chip trees removed (%)	Small trees removed (%)	Large trees removed (%)
Low (0 – 59.9)	25	15	5
Moderate (60 – 119.9)	50	30	20
High (120+)	70	55	45

Land cover Variables

The average slope (Slope_pct) for each parcel was obtained from a DEM for the area. Parcels were grouped based on their area into three groups; “Sm_ac” ranged from 1 – 4 hectares, “Med_ac” ranged from 4 – 12 hectares, and “Lg_ac” included all parcels greater than 12 hectares (max in study = 2,099 hectares). The percent area covered by forest within each parcel ("Perc_for") was estimated in ArcMap using the GNN data created for central Oregon. A 30 x 30 meter binary raster detailing forest cover (1 = forest, 0 = non-forest) was used to create an average amount of forest cover for each parcel (0 – 1 scale). This result was then converted to a percentage.

The role of forestry organizations

In addition to these four equations, a fifth equation was created after the initial analysis to further investigate spatial relationships among data sets within the study area (Chapter 5). Equation 4.3a and 4.3b explore the influence that NIPF owner's use, or lack thereof, of forestry organizations has on the use of both fuel reduction treatments and commercial timber harvests. This additional variable, "tot_org", was the total number of management organizations that the respondent reported they belonged. It was left as a continuous variable, with a range of 0 – 4.

(4.3a) Com_mgmt= 2008_BP + 2008_FL + Slope_Pct + Med_Ac + Lg_Ac + Perc_For + Fuel_trt_cost + Amenity + Passive + tot_org + parcel_res + res_primary + constant

(4.3b) Noncom_mgmt = 2008_BP + 2008_FL + Slope_Pct + Med_Ac + Lg_Ac + Perc_For + Fuel_trt_cost + Tot_org + Ho_aso + Amenity + Passive + tot_org + parcel_res + res_primary + constant

Use of this variable was decided on after exploring why NIPF parcels within the northern two thirds of the study area differed in their fire risks, treatment costs, and use of fuel reduction treatments. From examining the differences among counties, it was found that NIPF parcels within Deschutes County were more likely to perform fuels treatments than parcels within Jefferson, Klamath, or Lake Counties. Among these counties, the average number of management groups that respondents belonged to differed the most, spurring the creation of Eq. 4.3a and 4.3b.

Results

Survey analysis

Of the 1,451 surveys mailed, 388 were returned while 236 were undeliverable (response rate = 32%). For the logistic regression modeling, 41 of the respondents did not fully answer the questions used in the analysis, further reducing the sample size to 347 (89% of respondents). However, these 41 respondents were not removed from the analyses done prior to the logistic regression model. The exploratory factor analysis, reliability analysis, and cluster analysis were performed with any respondent who answered the pertinent questions.

The exploratory factor analysis performed on the fourteen land ownership value questions suggested five discrete factors which could explain a respondent's value (Table 4.4). These five factors were defined as: amenities, non-forest value, forest value, proximity to town, and land value. A reliability analysis was performed on these factors to examine their strength (Table 4.5). Of the five factors, "proximity to town" and "land value" were insufficient to use in the future analyses ($\alpha < 0.65$), and were discarded. In all, 8 variables describing land use values were created from this process. Forest value, non-forest value, and amenity value were calculated for each respondent by averaging their responses on the 1 to 5 scale. The remaining five values which were not included in a factor were taken directly from the respondent's rating on the 5 point scale.

Table 4.4 - Exploratory factor analysis of reasons for parcel ownership, which describes a respondent's land use values.

Reasons for ownership	Factor loadings[1]				
	Factor 1:Amenities	Factor 2: Non-forest values	Factor 3: Forest values	Factor 4: Proximity to town	Factor 5: Land value
Privacy	.84				
Aesthetics	.78				
Recreation	.70				
Far from town	.68				
Residence	.66				
Ranching		.77			
Farming		.74			
Timber resources			.83		
Non-timber resources			.76		
Near to town				.83	
Available school system				.72	
Family land holding					.82
Land stewardship					.61
Land investment					.50
Eigenvalue	2.86	1.78	1.61	1.48	1.48
Percent (%) of total variance explained[2]	20.41	12.68	11.48	10.58	10.54

[1] Principal components factor analysis with Varimax rotation. Only factors with eigenvalues greater than 1 and items with factor loadings greater than .40 were retained in the final factor structure (Tabachnick and Fidell, 1996). Items coded on 5-point scales of 1 = not important to 5 = very important.
[2] Total cumulative percent (%) variance explained = 65.68%.

Table 4.5 - Reliability results for factors describing respondents' different values from their owning of NIPF parcels.

Values and variables[1]	Mean(M)	Std.dev. (SD)	Item total correlation	Alpha (α) if deleted	Cronbach alpha (α)
Non-forest value					.77
Importance of ranching	1.85	1.42	.64	-	
Importance of farming	1.55	1.15	.64	-	
Forest value					.70
Importance of timber	1.68	1.21	.55	-	
Importance of non-timber	1.45	.96	.55	-	
Amenity value					.79
Importance of residence	3.57	1.63	.55	.76	
Importance of recreation	3.39	1.52	.49	.78	
Importance of privacy	3.82	1.44	.75	.70	
Importance of aesthetics	3.66	1.44	.62	.74	
Importance of remoteness	2.47	1.54	.47	.79	
Proximity to Town					.56
Close to town	1.53	1.03	.39	-	
Quality of school	1.51	1.04	.39	-	
Land value					.52
Family landholding	2.84	1.63	.44	.22	
Land stewardship	2.91	1.56	.36	.37	
Investment	3.34	1.46	.21	.59	

[1] All variables were measured on a 5-point scale from 1 = "not important" to 5 = "very important".

These eight variables were input into a cluster analysis to create respondent groupings. Previous studies have found four categories of ownership values held by NIPF respondents (Fisher 2012, Kuuluvainen et al. 1996). However, in this study it was found that three groups produced the optimal result (Table 4.6). The three titles chosen to describe the make-up of these clusters were "production and amenity focused stewards", "amenity focused stewards", and "passive owners".

Table 4.6 - Ownership groupings created from a cluster analysis based on factors describing respondents' priorities for NIPF ownership.

		Owner Clusters[1]	
	Production and amenity focused stewards	Amenity focused stewards	Passive owners
Amenities	4.19	3.97	3.01
Non-Forest Resources	3.83	1.41	1.31
Forest Resources	2.80	1.46	1.28
Land Investment	4.00	3.00	3.00
Family landholding	4.00	3.00	2.00
Stewardship	4.00	4.00	2.00
School district	2.00	2.00	1.00
Near to town	2.00	1.00	1.00
Far from town	3.00	3.00	2.00

[1] All variables were measured on a 5-point scale from 1 "not important" to 5 "very important". Individuals within each group, in order of above columns, 41(14% of valid respondents), 127 (44% of valid respondents), and 121 (42% of valid respondents).

Fire modeling

CBP and CFL

Conditional burn probabilities and flame lengths for the survey respondents were extracted from the FlamMap results (Table 4.7). Since the fire model outputs fire data in 90 x 90 m pixels, the average value for pixels contained within each NIPF parcel were calculated using ArcMap. Conditional flame lengths include the height of the flame and the fuel being burned. So for fuel averaging 100 ft tall that burned with a 15 foot flame length, FlamMap would report that pixel as having an average flame length of 115 ft.

Table 4.7 – Conditional burn probability and flame length results for NIPF parcels within the study area, according to FlamMap.

		Conditional burn probability (%)	Conditional flame length (ft.)
Survey respondents	Mean	0.22	13.02
	Maximum	2.97	138.27
	Minimum	0.00	0.00

Fuel treatment cost

Costs varied greatly across the study area, ranging from \$0.11 to \$1,603.53 per acre (Table 4.8). As mentioned in the methods, every parcel was required to have a fuel treatment, even those far below this study's threshold basal density of $60 ft^2/ac$.

Table 4.8 – Fuel reduction costs for the respondent sample, and all NIPF parcels within the study area. Costs estimated using FRCS – West.

		Cost ($/ac)
Survey respondents	Mean	143.26
	Median	84.61
	Maximum	1,453.14
	Minimum	1.32

Logistic regressions

With Only Publically Available Data

Models Eq. 4.1a and 4.1b were created to investigate the factors that drive a parcel owner's use of a fuel treatment and commercial timber harvest using only variables that do not necessitate the use of a survey. These models rely only on variables that can be developed from publicly-accessible secondary data sources. The fit for both models was relatively weak, although the model for commercial timber harvests (Eq. 4.1b) was the better performing of the two (Table 4.10 and Table 4.12).

Table 4.9 - Logistic Regression of NIPF fuel-treatment behavior based on observable landscape variables[1] (Eq. 4.1a)

	β	Standard error	Wald χ^2	df	*p*-value	Odds
2008_BP	-81.486	63.129	1.666	1	.197	< .001
Slope_Pct	-.042	.014	8.419	1	.004*	.959
Med_Ac	-.212	.288	.543	1	.461	.809
Lg_Ac	.291	.268	1.177	1	.278	1.338
2008_FL	.006	.007	.861	1	.353	1.006
Perc_For	.155	.506	.094	1	.759	1.168
Fuel_Trt_Cost	.001	.001	1.226	1	.268	1.001
Constant	.348	.426	.668	1	.414	1.416

[1] Dependent variable: remotely sensed variables influence on management action, where 0 = no action taken, 1 = action taken. Nagelkerke R^2 = .060.

*Denotes values that are statistically significant (p < .05)

Table 4.10 - Logistic Regression of NIPF commercial timber harvest behavior based on observable landscape variables[1] (Eq. 4.1b)

	β	Standard error	Wald χ^2	df	*p*-value	Odds
2008_BP	-87.202	94.308	.855	1	.355	< .001
Slope_Pct	-.012	.022	.271	1	.603	.989
Med_Ac	1.099	.547	4.034	1	.045*	3.002
Lg_Ac	2.459	.455	29.209	1	< .001*	11.699
2008_FL	.013	.008	2.320	1	.128	1.013
Perc_For	.025	.814	.001	1	.975	1.026
Fuel_Trt_Cost	.002	.001	4.306	1	.038*	1.002
Constant	-3.411	.754	20.462	1	< .001*	.033

[1] Dependent variable: remotely sensed variables influence on commercial timber harvest, where 0 = no action taken, 1 = action taken. Nagelkerke R^2 =.224 .

*Denotes values that are statistically significant (p < .05)

For the prediction of fuel treatments, only the average slope of the parcel (Slope_Pct) was statistically significant (*p* = .007), with steeper sloped parcels less likely to have treatments applied to them (constant = -.042). No other variable was statistically significant (Table 4.9); however, the largest category of parcels (Lg_Ac) had an odds ratio of 1.501, suggesting that there may be a noticeable level of correlation to fuel treatments. However, the study's sample size may have not been adequate to show the statistical significance of this relationship.

The size of the parcel and the cost of a fuel treatment were statically significant in predicting the location of commercial timber harvests ($p < .05$). Parcels that were greater than 12 hectares in size were more likely to have a commercial harvest compared to either small (1 – 4 ha) or medium (4 – 12 ha) parcels (Table 4.10). The estimated cost of a fuel treatment, while significant ($p = .038$) appeared to have a weak, positive influence on the use of commercial timber harvest ($\beta = .002$).

Between the two models, Eq. 4.1b was more successful at correctly predicting the placement commercial harvests (Table 4.11 and Table 4.12). Overall, Eq. 4.1b successfully predicted the use of commercial harvests 86.8% while Eq. 4.1a was only able to successfully predict the use of fuel reductions 59.4%. The model correctly predicted no use of a fuels treatment for 39.5% of cases. The use of fuels treatment was correctly predicted in 75.8% of cases. This relationship was reversed for the commercial harvests, with 99% of parcels that did not perform a harvest being correctly predicted by the model. Only 10.6% of the relatively few parcels that did a commercial harvest were correctly identified by the model.

Table 4.11. Logistic Regression Classification Table[1] (Eq. 4.1a)

Observed	Fuel reduction treatment		Percentage correct
	No mgmt. action in the past 5 years	Mgmt. action in past 5 years	
No mgmt. action	62	95	39.5
Mgmt. action	46	144	75.8
Overall percentage			59.4

[1] Dependent variable: influence of remotely sensed data on fuel management action where 0 = no action taken, 1 = action taken. Independent variables: 2008_BP, Slope_Pct, Med_Ac, Lg_Ac, 2008_FL, Perc_For, Fuel_trt_cost (Med_ac and Lg_Ac are dummy variables).

Table 4.12. Logistic Regression Classification Table[1] (Eq. 4.1b)

Observed	Commercial timber harvest		Percentage correct
	No mgmt. action in the past 5 years	Mgmt. action in past 5 years	
No mgmt. action	291	3	99.0
Mgmt. action	42	5	10.6
Overall percentage			86.8

[1] Dependent variable: influence of remotely sensed data on commercial timber harvest where 0 = no action taken, 1 = action taken. Independent variables: 2008_BP, Slope_Pct, Med_Ac, Lg_Ac, 2008_FL, Perc_For, Fuel_trt_cost (Med_ac and Lg_Ac are dummy variables).

With survey data collected from landowners

Dummy variables detailing the ownership clusters were added to the previous logistic regression to create Eq. 4.2a and 4.2b. The addition of these variables improved the fit of both models, with Nagelkerke R^2s of 0.293 and 0.272 respectively (Tables 4.13 and 4.14). Similar to Eq. 4.1a, Eq. 4.2a found that the parcel's average slope was statistically significant correlated to the application of a fuel reduction treatment, holding all other variables constant (p = .016). The addition of ownership values showed that NIPF owners that had permanent residences on their parcels (p < .001) were less likely to perform fuel reduction treatments holding all other variables constant. Of these NIPF owners, those that lived on their parcel for their primary residence, however, were more likely to perform fuel reduction treatments (p = .025) holding all other variables constant.

Although the model fit for predicting commercial timber harvests improved slightly with the addition of survey data, the variables that were statistically significant predictors of commercial timber harvest remained the same. Large parcels (> 12 ha) were significantly more likely (p < .001), all other variables held constant, to contain these actions. Medium parcels (4-12 ha) also remained significant (p = .033). There also remained a statistically significant, though weakly positive, relationship between the cost of treatment and likelihood of having completed a commercial timber harvest (p = .007, β = .003).

Table 4.13 - Logistic Regression of NIPF fuel-treatment behavior based on observable landscape variables and survey data[1] (Eq. 4.2a)

	β	Standard error	Wald χ^2	df	*p*-value	Odds
Parcel_res	-1.383	.332	17.317	1	< .001*	.251
Res_primary	.758	.337	5.056	1	.025*	2.133
Passive	-.279	.301	.858	1	.354	.757
Amenity	-.237	.310	.581	1	.446	.789
2008_BP	-62.092	70.905	.767	1	.381	< .001
Slope_Pct	-.038	.016	5.834	1	.016*	.963
Med_Ac	-.014	.325	.002	1	.964	.986
Lg_Ac	.193	.301	.409	1	.522	1.212
2008_FL	.005	.007	.425	1	.515	1.005
Perc_For	.338	.569	.352	1	.553	1.402
Fuel_trt_cost	.001	.001	2.931	1	.087	1.001
Constant	1.832	.714	6.591	1	.010*	6.249

[1] Dependent variable: remotely sensed variables influence on fuel reduction, where 0 = no action taken, 1 = action taken. Nagelkerke R^2 =.293.

*Denotes values that are statistically significant (p < .05)

Table 4.14 - Logistic Regression of NIPF commercial timber harvest behavior based on observable landscape variables and survey data[1] (Eq. 4.2b)

	β	Standard error	Wald χ^2	df	*p*-value	Odds
Parcel_res	.391	.541	.521	1	.470	1.478
Res_primary	1.134	.527	4.632	1	.031*	3.107
Passive	-.683	.509	1.795	1	.180	.505
Amenity	.175	.411	.181	1	.671	1.191
2008_BP	-98.166	96.182	1.042	1	.307	< .001
Slope_Pct	-.012	.023	.243	1	.622	.989
Med_Ac	1.205	.564	4.558	1	.033*	3.335
Lg_Ac	2.524	.477	28.052	1	< .001*	12.477
2008_FL	.017	.009	3.651	1	.056	1.017
Perc_For	-.059	.840	.005	1	.944	.942
Fuel_trt_cost	.003	.001	7.193	1	.007*	1.003
Constant	-4.530	1.228	13.618	1	< .001*	.011

[1] Dependent variable: remotely sensed variables influence on management action, where 0 = no action taken, 1 = action taken. Nagelkerke R^2 =.272 .
*Denotes values that are statistically significant (p < .05)

Adding the respondent data not only improved the models' fits, but it also improved their predictive capabilities. Fuel treatments were located correctly 73.5% by Eq. 4.2a, with 78.9% of parcels which performed the action correctly identified and more than half (66.9%) of the parcels that did not perform the action identified (Table 4.15). Overall, 87.7% of parcels correctly had their use of commercial timber harvests predicted (Table 4.16). While 99.7% of the parcels without harvests were correctly predicted, only 12.8% of those that did perform management actions were predicted.

Table 4.15 - Logistic Regression Classification Table[1] (Eq. 4.2a)

Observed	Fuel reduction treatment		Percentage correct
	No mgmt. action in the past 5 years	Mgmt. action in past 5 years	
No mgmt. action	105	52	66.9
Mgmt. action	40	150	78.9
Overall percentage			73.5

[1] Dependent variable: influence of remotely sensed data on fuel reduction where 0 = no action taken, 1 = action taken. Independent variables: Parcel_res, Res_Primary, Passive, Amenity, 2008_BP, Slope_Pct, Med_Ac, Lg_Ac, 2008_FL, Perc_For, Fuel_trt_cost (Passive, Amenity, Med_ac and Lg_Ac are dummy variables).

Table 4.16 - Logistic Regression Classification Table[1] (Eq. 4.2b)

Observed	Commercial timber harvest		Percentage correct
	No mgmt. action in the past 5 years	Mgmt. action in past 5 years	
No mgmt. action	293	1	99.7
Mgmt. action	41	6	12.8
Overall percentage			87.7

[1] Dependent variable: influence of remotely sensed data on commercial timber harvest action where 0 = no action taken, 1 = action taken. Independent variables: Parcel_res, Res_Primary, Passive, Amenity, 2008_BP, Slope_Pct, Med_Ac, Lg_Ac, 2008_FL, Perc_For, Fuel_trt_cost (Passive, Amenity, Med_ac and Lg_Ac are dummy variables).

Adding management organizations

In both models Eq. 4.3a and 4.3b, the addition of a variable representing communication between the landowner and management organizations increased the models' fit (R^2 = .358 and .297 respectively) (Table 4.17 and Table 4.18). Fuel reduction treatments were significantly correlated to the average slope of the parcel (p = .036), the presence of a residential structure (p < .001), and if that residence was the NIPF owner's primary residence (*p* = .036). These findings were similar to Eq. 4.2a. For predicting commercial harvests, medium parcels (4 – 12 ha) were significantly correlated to harvests (*p* = .037), as were large parcels (*p* < .001), similar to Eq. 4.2b.

Table 4.17 - Logistic Regression of fuel reduction action with organization contact variable[1] (Eq. 2.3a)

	β	Standard error	Wald χ^2	df	*p*-value	Odds
Tot_org	.748	.180	17.354	1	< .001*	2.113
Parcel_res	-1.379	.344	16.026	1	< .001*	.252
Res_primary	.733	.349	4.414	1	.036*	2.082
Passive	-.349	.311	1.258	1	.262	.705
Amenity	-.284	.321	.783	1	.376	.753
2008_BP	-42.886	73.175	.343	1	.558	< .001
Slope_Pct	-.034	.016	4.385	1	.036*	.967
Med_Ac	.037	.333	.012	1	.911	1.038
Lg_Ac	.020	.314	.004	1	.949	1.020
2008_FL	.007	.008	.975	1	.324	1.007
Perc_For	.496	.583	.723	1	.395	1.641
Fuel_trt_cost	.001	.001	2.565	1	.109	1.001
Constant	1.367	.739	3.420	1	.064	3.922

[1] Dependent variable: remotely sensed variables influence on management action, where 0 = no action taken, 1 = action taken. Nagelkerke R^2 =.358.

*Denotes values that are statistically significant (p < .05)

Table 4.18 - Logistic Regression of commercial timber harvest with organization contact variable [1] (Eq. 4.3b)

	β	Standard error	Wald χ^2	df	*p*-value	Odds
Tot_org	.373	.159	5.488	1	.019*	1.452
Parcel_res	.514	.557	.851	1	.356	1.671
Res_primary	1.100	.537	4.200	1	.040*	3.005
Passive	-.727	.513	2.009	1	.156	.483
Amenity	.185	.416	.198	1	.657	1.203
2008_BP	-98.328	99.426	.978	1	.323	< .001
Slope_Pct	-.007	.024	.091	1	.763	.993
Med_Ac	1.248	.568	4.826	1	.028*	3.482
Lg_Ac	2.448	.484	25.620	1	< .001*	11.562
2008_FL	.018	.009	4.133	1	.042*	1.019
Perc_For	.153	.869	.031	1	.860	1.165
Fuel_trt_cost	.002	.001	5.651	1	.017*	1.002
Constant	-5.084	1.300	15.287	1	< .001*	.006

[1] Dependent variable: remotely sensed variables influence on management action, where 0 = no action taken, 1 = action taken. Nagelkerke R^2 =.297.
*Denotes values that are statistically significant (p < .05)

Model Eq. 4.3a's ability to correctly predict the presence or absence of fuel reductions was increased (Table 4.19), while Eq. 4.3b slightly reduced the ability to predict the locations of commercial harvests (Table 4.20). Parcels which had not performed a fuel reduction were slightly more likely to be correctly identified in Eq. 4.3a (67.5%) compared to model Eq. 4.2a, without the organization variable (66.9%). The locations of fuel treatments were also more accurately predicted by Eq. 4.3a compared to Eq. 4.2a (84.2% and 78.9% respectively). Equation 4.3b had an different relationship when compared to Eq. 4.3a; the predicted lack of a management action was less accurate

(98.0% in Eq. 4.3b compared to 99.7% in Eq. 4.2b), while harvests were more accurately predicted (19.1% to 12.8% respectively).

Table 4.19 - Logistic Regression Classification Table[1] (Eq. 4.3a)

Observed	Fuel reduction treatment		Percentage correct
	No mgmt. action in the past 5 years	Mgmt. action in past 5 years	
No mgmt. action	106	51	67.5
Mgmt. action	30	160	84.2
Overall percentage			76.7

[1] Dependent variable: influence of remotely sensed data on fuel reduction where 0 = no action taken, 1 = action taken. Independent variables: Tot_org, Parcel_res, Res_primary, Passive, Amenity, 2008_BP, Slope_Pct, Med_Ac, Lg_Ac, 2008_FL, Perc_For, Fuel_trt_cost (Passive, Amenity, Med_ac and Lg_Ac are dummy variables).

Table 4.20 - Logistic Regression Classification Table[1] (Eq. 4.3b)

Observed	Commercial timber harvest		Percentage correct
	No mgmt. action in the past 5 years	Mgmt. action in past 5 years	
No mgmt. action	288	6	98.0
Mgmt. action	38	9	19.1
Overall percentage			87.1

[1] Dependent variable: influence of remotely sensed data on commercial timber harvest action where 0 = no action taken, 1 = action taken. Independent variables: Tot_org, Parcel_res, Res_Primary, Passive, Amenity, 2008_BP, Slope_Pct, Med_Ac, Lg_Ac, 2008_FL, Perc_For, Fuel_trt_cost (Passive, Amenity, Med_ac and Lg_Ac are dummy variables).

Discussion

Of all the models created, those that used multiple variables obtained from survey data were most successful, with Nagelkerke R^2s ranging from .272 to .358 (Tables 4.13, 4.14, 4.17, and 4.18) compared to Eq. 4.1a and 4.1b, with a Nagelkerke R^2 of .060 and .224 respectively (Tables 4.9 and 4.10). Commercial timber harvests were less successfully predicted than fuel treatments with commercial harvest model fits ranging from .224 to .297 (Tables 4.10, 4.14, and 4.18). Fuel treatment models had fits ranging from .060 to .358 (Tables 4.9, 4.13, and 4.17). Based on this analysis, the ability to include landowner characteristics, estimated from survey data in this case, greatly improved model performance. Of statistical importance are variables detailing the number of organizations a respondent interacted with, and the presence and use of a permanent residence.

Constructing the independent variables from the remote data for the logit model proved to be the largest source of difficulty for these methods. Modeling the estimated cost of a fuel reduction treatment proved to be a challenging task that required a number of assumptions that need to be scrutinized. The fire risk variables, CFL and CBP, also proved their own unique difficulties. While generating these variables also required a set of assumptions, the true source of difficulty for these variables was from the hardware used in the analysis.

Using FRCS – West to estimate the cost of a fuel reduction treatment provided a standardized approach that could be replicated in future studies. The model used within this software required a number of variables, however, that leave a clear area for improvement. Distance to the nearest log landing is the variable that could use the most improvement. The method in this study to treat each parcel as a square and extrapolate a yarding distance from this assumption can be validated by assuming that larger parcels would require longer yarding distances. However, there is a host of instances where this assumption may not be accurate on a parcel by parcel examination. For instance, if a parcel that is 100 ha in area was only 10% forested (the bare minimum to be included in the NIPF sample), then only 10 ha of the parcel would be open to a fuel reduction treatment (by the method used within FRCS –West). The yarding distance in this parcel may very well be smaller than that of a parcel that is only 40 ha in size but 90% forested (36 ha of treatable area). Adding to the potential error in how the distance to a log landing were created are irregular shaped parcels. There again exists a large number of possible ways that parcels would invalidate the assumption used within these methods. While these are obvious sources of errors, for the purposes of this study which was to create a model at a landscape scale, it would be infeasible to correct them in any meaningful way.

Similarly, the application of preset levels of treatment based on the GNN recorded stocking of the parcel could be inappropriate based on the unique traits of a given parcel. An individual’s management objectives may not solely be to reduce the risk of fire occurrence and intensity on their parcel. For instance, a NIPF owner could wish to maintain a high level of stocking on their parcel regardless of fire risk to maintain the aesthetics. The inclusion of large trees in all treatment types was intend to mimic the probable sale of timber by the parcel manager during a treatment to help offset the treatment's cost. This, as well as the cost of removing lumber and biomass from the treatment site, are not included in the estimated cost. This level of scale is again unobtainable within a landscape level analysis and as such, the methods used in this chapter are adequate.

Modeling the fire risk variables, CFL and CBP, required a number of modeling assumptions, such as fire weather, fire behavior, etc., that are widely accepted within the field of fire science. For this project, however, the actual running of the fire model within FlamMap proved to be the source of error. Due to hardware limitations and the size of the area entered into FlamMap, smaller, sub-sections had to be created for the analysis to be completed. Random ignition fire modeling sets a preset number of ignition points within an area, and the results are unique to both that area and the specific model run. By splitting the study area into four sub-sections, four distinct models had to be run and their outputs were combined. This created obvious edge effects within the CBP, but would not have impacted CFL. To correct these effects, the fire model output was interpolated at a coarser scale to smooth the edges. Also, the boundaries of the sub-sections were created so that no NIPF parcels were near the edges. This helped to maintain the integrity of the CBP for the NIPF parcels themselves

Conclusion

Predicting the application of forest treatments on NIPF parcels can provide land managers insight into stand conditions at a landscape level. Direct observation of these actions is rarely feasible at such a broad scale. Instead, models, such as the logistic regressions created in this chapter, provide researchers and managers the ability to predict, with an acceptable degree of accuracy, how NIPF owners are likely to behave. In an attempt to streamline this modeling process further, models using only publically available satellite data were compared to models which used survey data in addition to the remote data. The two models based only on remotely sensed data (Eq. 4.1a and 4.1b), however, were found to be less effective at predicting the application of both fuel treatments and commercial timber harvests on NIPF parcels than models including survey data (Eq. 4.2a, 4.2b, 4.3a, and 4.3b).

Metrics of fire risk, CFL and CBP, were created in FlamMap. Due to hardware limitations, CBP, as reported in this study, requires the consideration that the methodology for calculating it was flawed. By splitting the study area into four smaller areas, as was required due to hardware limitations, the CBP values had areas of obvious edges. While the output was corrected to compensate for this limitation, it still requires acknowledgement. Conditional flame length does not suffer from the same handicap, as the metric is calculated based on the fire weather and fuel conditions, both of which remained constant during the fire modeling. Future research efforts could improve the fire risk variables used within these logistic regression models to further improve their predictive capabilities.

Equation 4.3a and 4.3b, which included survey data providing insights into the NIPF owner's ownership values, residential status on the parcel, and land management network, provided the most reliable predictions of management actions on NIPF parcels. The land ownership values of NIPF owners, as well as the total number of land management organizations to which they belonged, improved the base models' effectiveness with increases in both model fit and overall predictive accuracy. While both equations require the use of survey data, they still rely heavily on GIS and remotely sensed data. A concise survey could be used to obtain these specific variables, providing at least a potential reduction in labor in regards to this process. Alternatively, Eq. 4.1a and 4.1b could be used to provide insight into the placement of commercial timber harvests and fuel reduction treatments using only freely available, remotely sensed data. Fuel reductions are not predicted with much accuracy using this model, but it would provide at least some level of insight where none may have been prior to use of the model. Improvements to both the fire risk modeling, as well as the fuel reduction cost estimation, could further increase the effectiveness of the models' predictions.

Chapter 5: Comparing NIPF landscape treatments, fuel loading, and treatment cost

Introduction

Due to the generally increased risk of severe wildfires across the western United States, mitigation policies have been established by the federal, and even many state and local governments. While publically managed lands across a landscape are, in theory, able to be consistently managed based on the guiding principal of the management agency, private lands within the same landscape can have vastly differing approaches applied to them (Elwood *et al.* 2003; Berlin *et al.* 2006; Andersson 2012). NIPF owners make up a relatively small percentage of land managers within Oregon, but their influence on the landscape is greater than their numbers alone indicate (Bliss 2003). For researchers, land managers, and policy makers to best make decisions about wildfire management, they need access to the current conditions of the landscape in which their lands lie. By combining the results of Chapters 1 and 2 of this study, this chapter will create an analysis of NIPF management of wildfire risk at a landscape scale. Results from this can be used to further target Oregon's wildfire policies encouraging and aiding NIPF owners to implement fuel reduction treatments.

Cost-share programs to encourage fuel reduction treatments, free access to consultation from professional foresters, and expanding public understanding of the risks and benefits of wildfire are some methods that governments and land management organizations strive to decrease the prevalence of severe wildfires (Kline *et al.* 2000; Elwood *et al.* 2003). The effectiveness of these methods varies by regions of the U.S., the target group for the policy, and the action (*e.g.* tax incentives, professional aid, *etc.*) type (Kline *et al.* 2000; Elwood *et al.* 2003; Butler *et al.* 2014). Encouraging the creation of forest management plans through professional consultation has been shown to have little impact on actual forest management (Vanbrakle *et al.* 2013). Cost-sharing of fuel treatment costs have been controversial in the effectiveness of their application, as the location of fuel treatments could often be improved to both reduce landscape fire risk more efficiently, and reach a wider demographic of parcel owners (Butler *et al.* 2014). Public outreach does seem to provide some benefit to increasing the use of fuel reduction treatments, but it is not clear if the increase in treatments occurs in locations that are at the greatest risk of experiencing a wildfire (Carroll *et al.* 2004; Fischer and Charnley 2012; Fischer 2012). Within central Oregon specifically, there have been few studies examining the effectiveness of wildfire mitigation policies at a landscape level. Expanding this understanding can help policy makers and land managers use methods that achieve the maximum effectiveness for their cost.

By providing the tools to model both wildfire risks and the current locations of fuel treatments, policies and management decisions can be targeted to areas that are in the most need of a fuel reduction treatment. Considering the cost of a fuels treatment, the stand’s risk of experiencing a wildfire, and the location of recent fuel reduction treatments can be used to create a hierarchy of parcels most likely to both need a treatment and provide the largest benefit from the cost of treatment.

Methods

Mapping fuel treatment across all NIPF parcels

Model Predictions

Equation 4.3a proved to be the most effective model for predicting the location of fuel reduction treatments, but because that equation required the use of landowner characteristics that were estimated from only a sample of NIPF owners, it could not be applied to all NIPF parcels in the study area. Instead, Eq. 4.1a was used to predict the locations of fuel treatments on all NIPF parcels within the study area (Eq. 5.1). Values for each variable were extracted from the remotely sensed datasets as described in Chapter 4.

(5.1) Fuel_Treat =

Due to processing errors during data management within ArcMap, 291 of the original 11,700 NIPF parcels had to be removed from the sample. Some parcels proved to be so narrow that none of the 30 x 30 m grid data lay within their boundaries. Other parcels were lost for unclear reasons. One possible issue may have been the size of the data files being analyzed within ArcMap, which has been known to operate inconsistently with extensive datasets. After extracting the variables from the remotely sensed data, the predicted logit score, “Fuel_Treat” was calculated. These scores were then converted to odds ratios using Euler’s number (Eq. 5.2).

$$(5.2)\quad \text{Odds\_Ratio} = \frac{(2.718281828^{\text{Fuel\_Treat}})}{(1+2.718281828^{\text{Fuel\_Treat}})}$$

“Odds_Ratio” values ranged from 0 to 1. Parcels with values equal to or greater than 0.75 were recoded as “1” and labeled as having performed a fuel reduction treatment. Parcels with values less than 0.65 were coded as “0” and labeled as not having performed a fuel reduction treatment. The cut-off of 0.65 was chosen for the odds ratio to create a conservative estimate of fuel reduction treatments. Originally, 0.50 was used as the cut-off, but with this result 9,498 of the 11,700 parcels (81% treatment rate) were identified as having performed a fuel reduction treatment in the past five years. This number seemed much too high considering recent studies of NIPF owners, and so the more restrictive threshold of 0.65 was chosen. Now instead of an 85% treatment rate, it the model predicted that 16% of parcels had performed a treatment (1,927 out of 11,700). With the unique identifiers for the NIPF parcels, these results were entered into ArcMap as a spatial data layer.

LandTrendr Identifications LandTrendr

A second data layer was created within ArcMap by using output from LandTrendr. From the data for 2008 – 2012, the mean percent disturbance for each NIPF parcel was calculated using the zonal statistics tool. Since the LandTrendr layer was binary, the parcel averages ranged from 0 to 1 and could be interpreted as percent of parcel disturbed by multiplying the value by 100. Parcels which had a mean disturbance greater than or equal to 0.09 were classified as having performed a fuel reduction treatment. For mean disturbances less than 0.09, the parcel was labeled as not having performed a fuel reduction treatment. The value of 0.09 was decided upon by considering the size of both the cut-off for NIPF size and the size of each LandTrendr pixel. With one hectare being the minimum size a parcel could be in this study (10,000 m^2), approximately 11 LandTrendr pixels (30 x 30 m or 900 m^2) would fit inside its boundaries. If only one pixel was labeled as having been disturbed, the mean disturbance for a one hectare sized parcel would be 0.09 (1/11). While there is the potential that this method may incorrectly identify parcels, especially larger ones, as having not performed a fuel management action, this error was deemed acceptable considering the scale of the analysis.

Mapping landscape fire risks

Fire risk across the landscape was characterized by conditional burn probability and conditional flame length. These variables were created using ArcFuels and FlamMap as detailed in Chapter 2. A simplified scale was created for the two data sets to aid in the interpretation of the results (Table 5.1) using ArcMap's interface. Five categories, selected by natural breaks (Jenks), were created through this process. Ranging from "very low" to "very high", these scales are unique to this study area and do not directly correlate to previous rankings of CBP or CFL from wildfire literature.

Estimated cost of treatment

As detailed in Chapter 2, each parcel had the cost of a fuel reduction treatment estimated for it. The Fuel Reduction Cost Simulator (FRCS) – West software package was used to complete this analysis on all NIPF parcels. Due to the size of the sample, FRCS had to be run in three separate batches. In theory, this should not have resulted in any negative effects on the results; however, there were a number of parcels which were not calculated correctly for unknown reasons. Forty of the 11,700 parcels were removed from the analysis for this reason (0.3% of the sample). The costs of treatments were also simplified into five categories to increase the ease of the interpretation when viewed within ArcMap (Table 5.1). Natural breaks (Jenks) was again used to establish the bounds of each category.

Table 5.1. Details of the 5 groups created for each input variable from the data analysis for the 11,700 NIPF parcels within the study area.

Classification	Conditional burn probability (%)	Conditional flame length (m)*	Treatment cost ($/ac)
Very Low	0.00 – 0.26	0.00 – 18.13	0.10 – 93.97
Low	0.27 – 0.59	18.14 – 39.94	93.98 – 219.87
Moderate	0.60 – 1.10	39.95 – 67.61	219.88 – 402.17
High	1.11 – 2.22	67.62 – 101.16	402.18 – 786.71
Very High	2.23 – 4.00	101.17 – 214.39	786.72 – 1,603.53

* Conditional flame length includes the height of the vegetation that is burning, e.g. a flame height of 10 meters would read as 150 meters if the vegetation was 140 meters tall

Comparison of Treatment Locations, Fire Variables, and Treatment Costs

Once the five spatial data layers of fuel treatment cost, conditional burn probability, conditional flame length, and predicted fuel treatment locations (both LandTrendr and Eq. 2.3a) were entered in ArcMap, they were overlaid and inspected visually to ensure ease of interpretation of clusters of high and low values. Conditional burn probability and CFL were easy to interpret thanks to the interpolation performed in Chapter 2 on CBP and the 90 x 90 m resolution of CFL. When colored with a green (low) to red (high) scale, hot spots within the datasets stood out clearly. The continuous nature of these variables across the study area also made their interpretation easier. Upon closer examination of fuel treatment costs and estimated locations, additional steps had to be taken to enhance these data layers' readability.

Since the estimated fuel reduction costs and locations were contained only within the NIPF parcels, groupings detailed in Table 5.1 were not easily readable when viewed in conjunction with the other data layers. To further enhance the coherency of these two data layers, the Optimized Hot Spot Analysis tool within ArcMap was applied to them. This tool creates statistical weights detailing both “hot” (high values), “cold” (low values) spots, and statistically insignificant spots from the input dataset. With this tool applied to both fuel reduction costs and treatment locations the ability to easily interpret landscape scale hot spots was greatly enhanced. This tool was used on both the LandTrendr detected mean disturbance area (fuel treatment) per parcel, and the logistic regression predicted treatment locations. To work on the modeled locations, the continuous values for predictive probability were used instead of the binary recoding which used the 0.65 threshold.

Further data layers showing Oregon urban growth boundaries, county lines, federal land boundaries, and trees per hectare were added to ArcMap to aid in explaining the patterns in treatment locations, costs, and fire risks. The GNN data set was used to extract the trees per hectare layer. To identify hot and cold spots within this layer, inverse data weighting was applied with ArcMap.

Results

Estimated treatment locations

Parcels which had performed fuel reduction treatments within the previous five years were both predicted by model Eq. 2.1a and identified using LandTrendr. Each method produced different treatment maps, detailed below. Both methods were used when comparing the spatial distribution of fuel treatment costs and fire risk variables.

Model Predicted Treatments

Applying the logistic regression model to the remaining NIPF parcels within the study area creates a map of expected fuel reduction treatments (Figures 5.1 and 5.2). After removing the 40 parcels which resulted in an error, 1,927 parcels were identified as having performed a fuel reduction treatment (16.9% of 11,369). The remaining 9,442 parcels were predicted to not have performed a fuel reduction treatment within the previous five years.

Figure 5.1 – A close up of the northern portion of the study area showing the results of logistic regression modelling of fuel treatment locations.

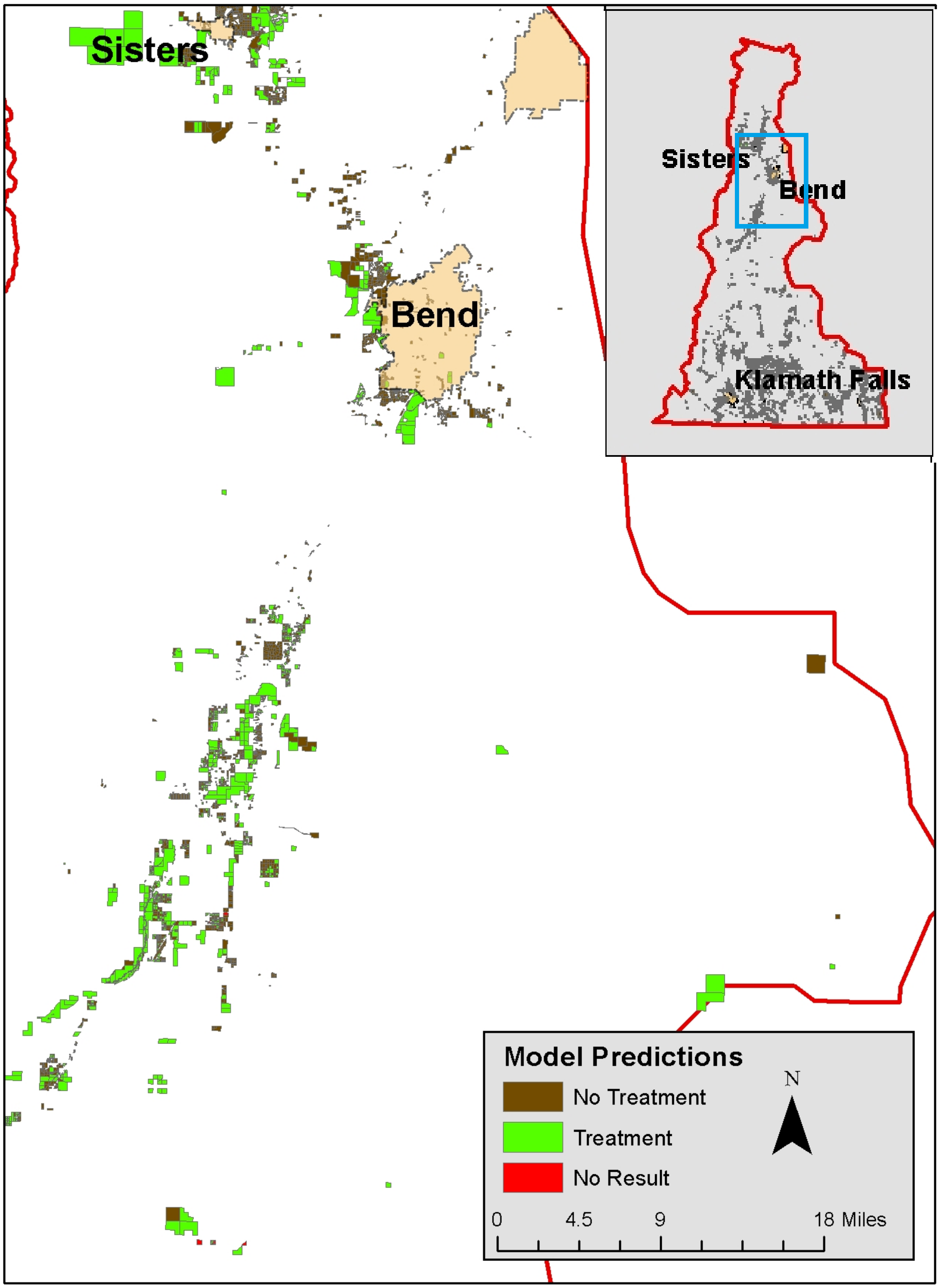
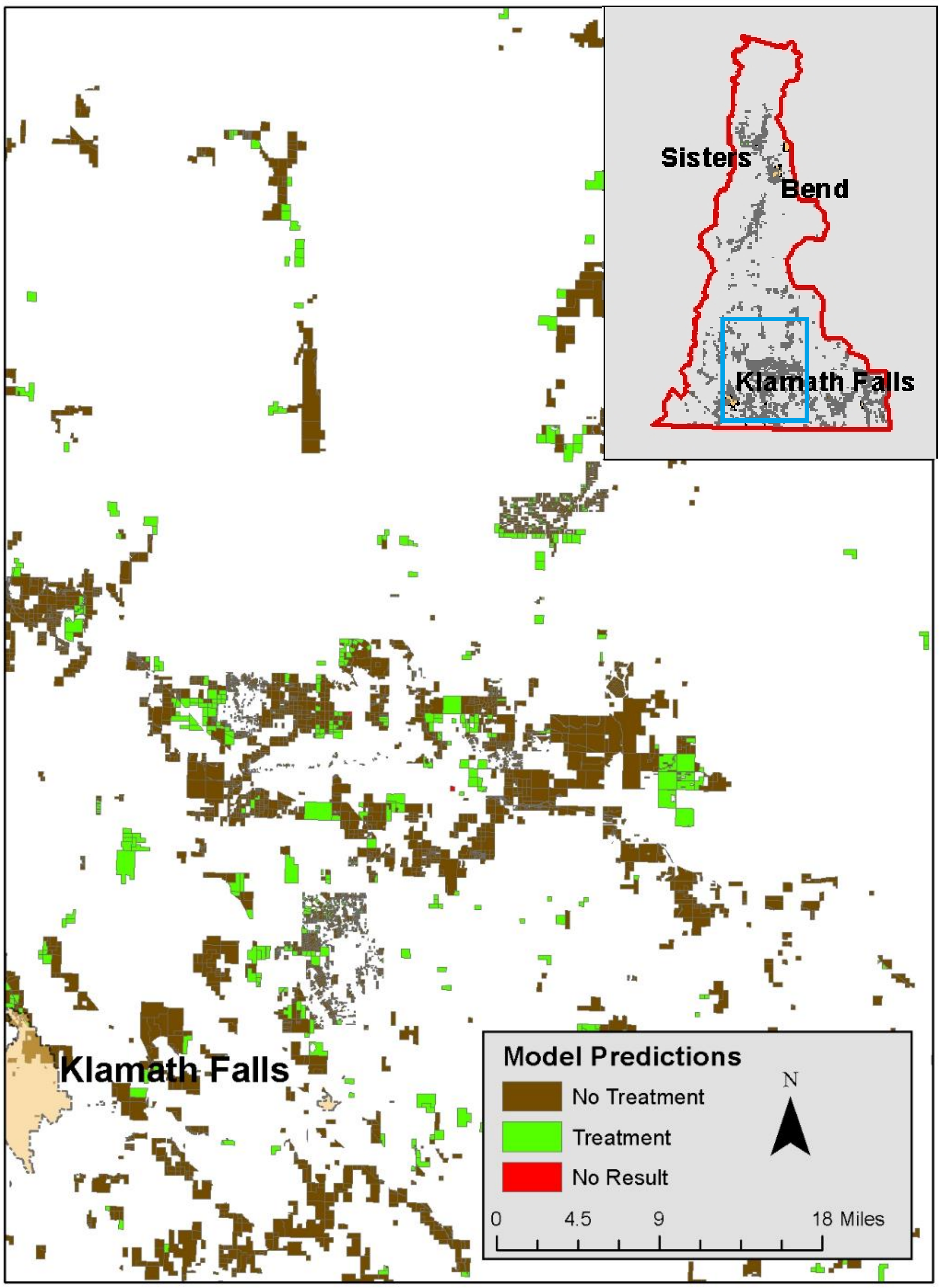


Figure 5.2 – A close up of the southern portion of the study area showing the results of the logistic regression modelling of fuel treatment locations.



A number of hotspots were identified through ArcMap's optimized hotspot tool. The northern and central NIPF parcels had concentrated areas of treatments (Figure 5.3) with 1,154 of the 1,927 treatments located here (10.2% of total NIPF parcels). Although NIPF landowners were most likely to do treatment in the North and central portions of the study area, the majority of NIPF parcels are located in the southern third of the landscape (7,388 or 65.0% of all parcels). There were a number of large cold spots where the lack of treatments were predicted (Figure 5.4). Of the 7,388 NIPF parcels within the southern area, only 733 were identified as having a fuel reduction treatment (6.8% of the total parcels). What few hot spots of fuel reductions were located within this area were typically centered on relatively isolated parcels that had small numbers of abutting parcels.

Figure 5.3 – A close up of the northern portion of the study area. Results of the hotspot analysis on logistic regression predicted fuel treatment locations are included.

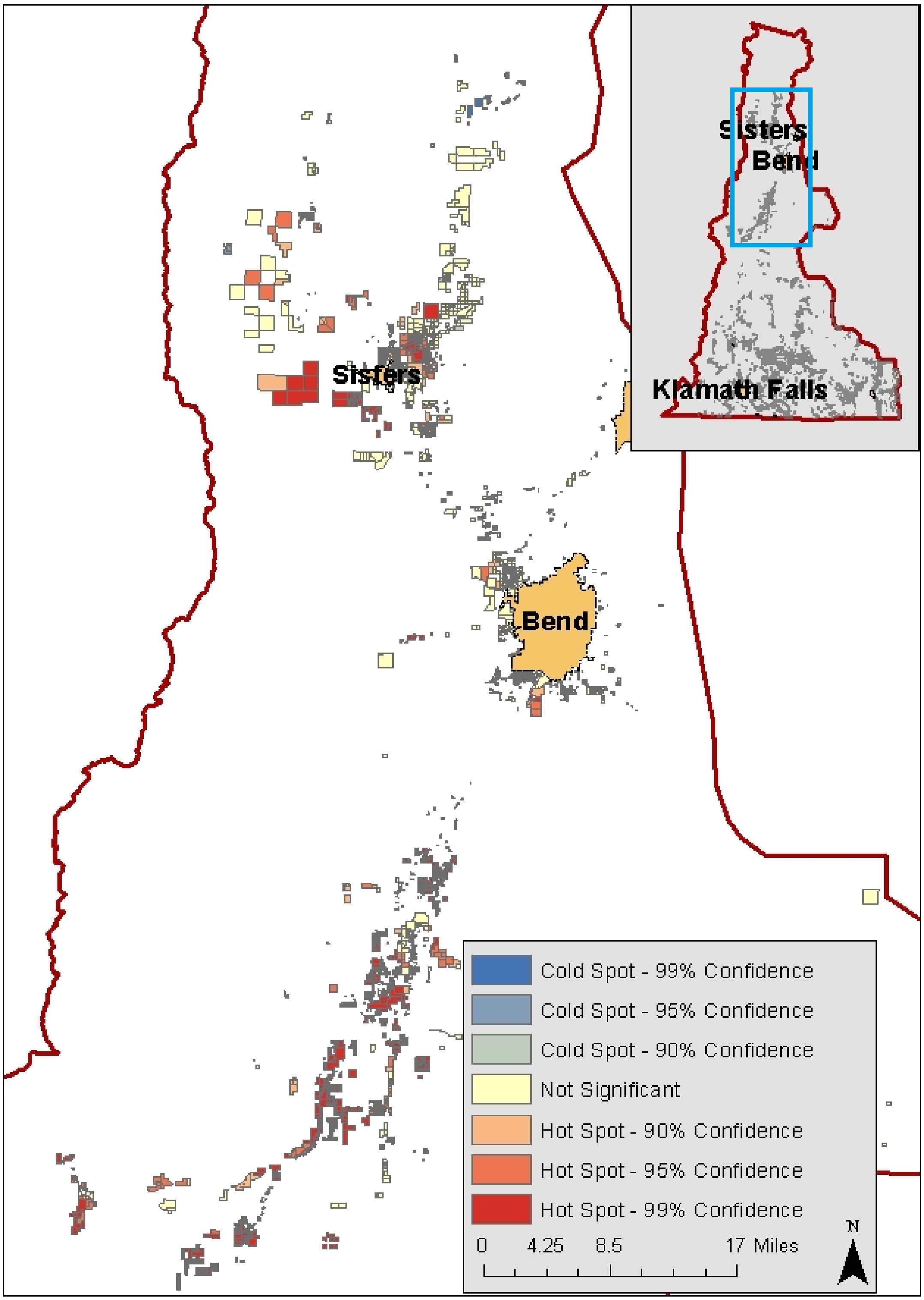
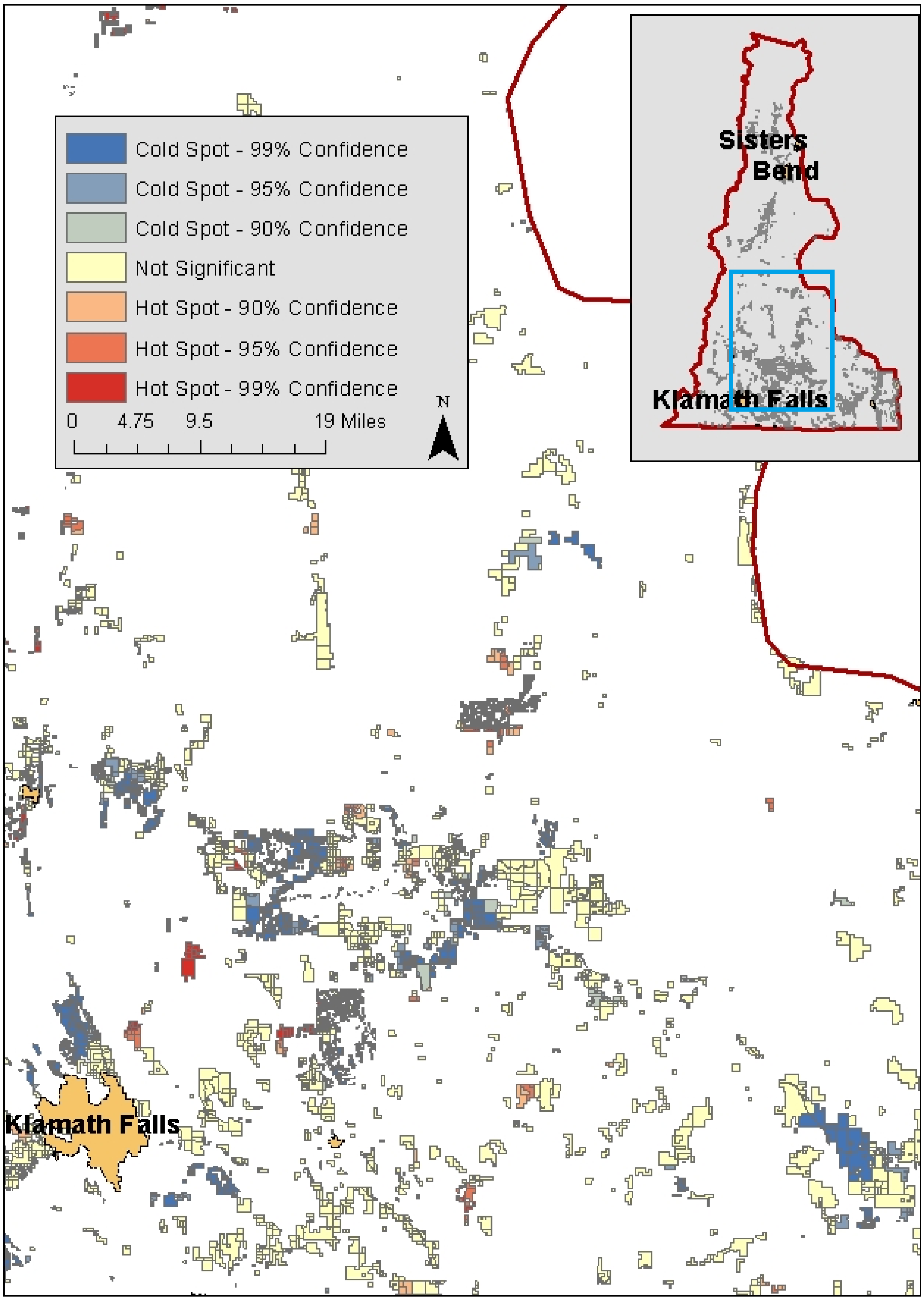


Figure 5.4 - A close up of the southern portion of the study area. Results of the hotspot analysis on logistic regression predicted fuel treatment locations are included.



LandTrendr Identified Treatments

By classifying parcels with a mean disturbance greater than or equal to 0.09, 1,258 parcels (11% of 11,369) were identified as having performed a fuel reduction treatment in the previous five years. Looking at the binary classification data, the spatial distribution of the results appears more random than that of the modeled output. The northern two thirds of the study area did have the majority of parcels identified as having performed a treatment (57.4%, or 722 of the 1,258).

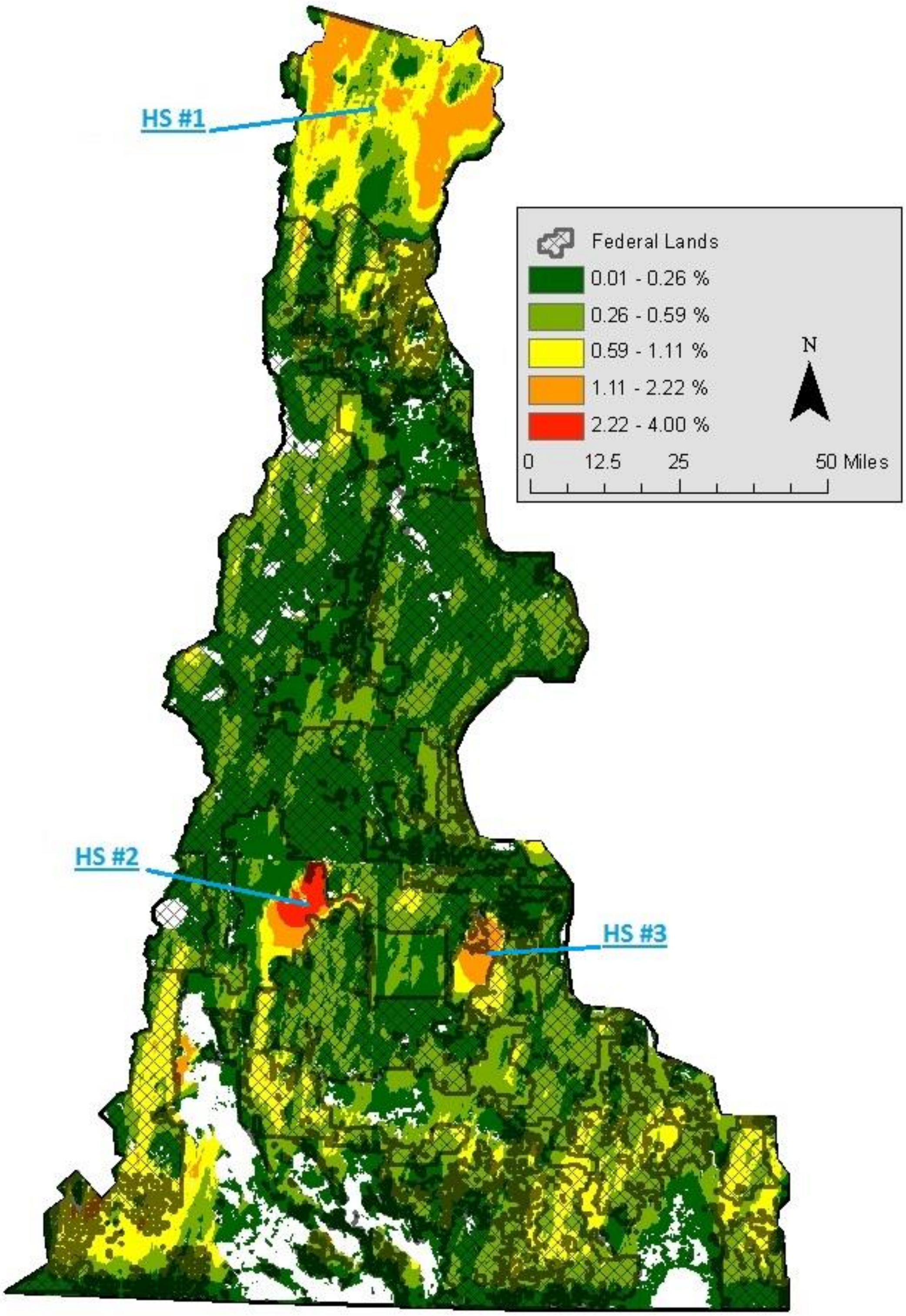
The majority of the parcels within the study area had a mean disturbance less than 0.09 during the years 2008 – 2012 (10,151, or 89.0%). For the purposes of this study, these results were assumed to describe parcels with no management action from 2008 – 2012. Parcels which had mean disturbances greater than 0.09 were assumed to have had some management action taken on the property. In total, 11.0% of the parcels had a management action as detected by LandTrendr (1,258 parcels).

Burn probability

Across the study area, the conditional burn probability was low (all values < 4%). This result was expected, as previous studies using the same modeling methods typically return low burn probabilities (Ager *et al.* 2010, 2012). However, the splitting of the study area in this model clearly impacted the CBPs (Figure 2.1). Distinct edge effects where relatively high burn probabilities immediately revert to low probabilities are visible when the data is examined in ArcMap. While this edge effect is undesirable, there were no NIPF parcels near enough to the few abrupt edges to be of concern.

Three main concentrations of relatively high CBP (Figure 5.5) are apparent. The northern tip of the study area has the largest contiguous area of increased risk of wildfire (HS #1). Located at this northern limit of the study area is the Warm Springs Indian Reservation. This area is characterized by generally rugged terrain, dense forests broken by numerous timber sales in the western half, and the beginning of the sagebrush steppe to the east.

Figure 5.5 – Conditional burn probability results as modeled in FlamMap. Hot spots of fire risk are labeled.



The second hotspot (HS #2) is located directly over Klamath Marsh National Wildlife Refuge. With the greatest conditional burn probabilities of the entire study area (greater than 2.2%), the wildlife refuge stands out on Figure 5.5 as the only area marked in red. About 145 NIPF parcels lay within the bounds of the elevated fire risk surrounding the wildlife reserve. The boundaries of the elevated fire risk correlate to the apparent boundaries of the wildfire refuge, with an artificial edge to the north due to the hardware limitations encountered when running FlamMap. It is likely that had the model been run with the study area as a contiguous landscape file, the elevated burn probability would have extended north for a short distance.

The third hotspot is located over Sycan Marsh, about 17 miles west of Summer Lake in the southeastern area of the study area. Like the wildlife refuge (HS #2), the elevated burn probability boundary mirrors closely the boundary of the marsh. Fifty NIPF parcels lay within the boundary of this hotspot. Unlike HS#1, this hot spot is contained near enough towards the center of the FlamMap model area that the total area of increased fire risk is represented on the map.

There is a noticeable difference in maximum fire risk between the northern two thirds and southern third of the study area. Southern forests have an average CBP of 0.3%, much lower than the maximum CBP of 4.0%, with a maximum CBP also of 0.3%. Parcels in the northern two thirds have an average CBP of 0.1%, but 31 of the 4,021 parcels have a CBP greater than 1.0%, with a maximum of 3.0%.

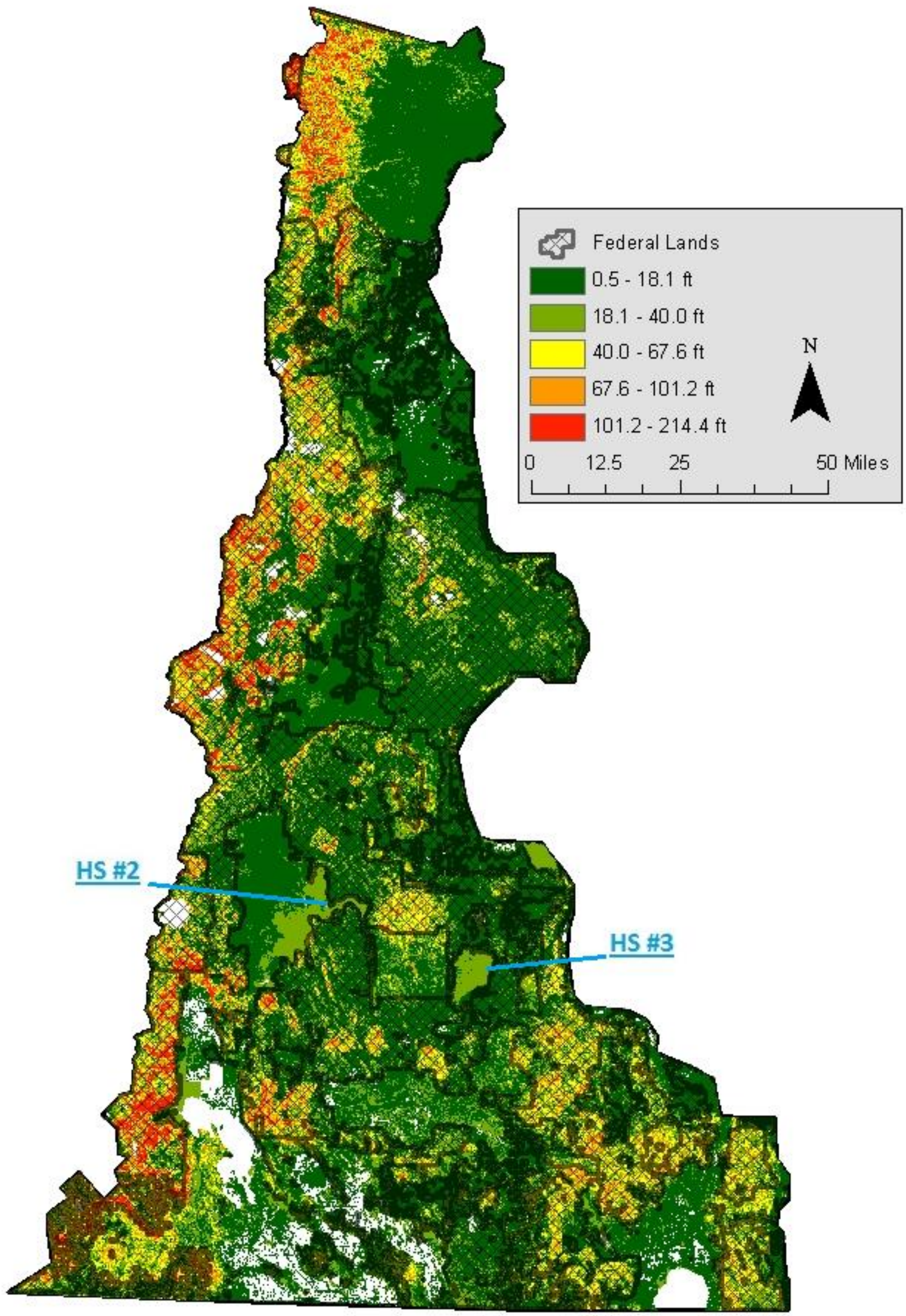
Conditional flame length

As CFL is directly correlated with the type and height of the fuel which is consumed by a modeled fire, the trees per hectare data layer was viewed to add insight into the output. Typically, areas with the least number of trees per hectare (between 0 and 184 stems/ha), also had the smallest average conditional flame lengths. The inverse of this, however, was not true. There were pockets throughout the study area which had the second highest concentration of trees/hectare but the second lowest flame lengths.

The average CFL for all the NIPF parcels was 12.7 m, with 106 parcels having flame lengths characterized as high or very high (>= 67.6 m). There was again a noticeable difference between the northern two thirds of the study area and the southern third. Maximum CFL for the northern parcels was 107.3 m, with a mean of 8.3 m. Southern parcels had a max CFL of 138.3, and a mean of 15.2 m.

Conditional burn probability hotspots #2 and #3 (Figure 5.6) had some of the smallest flame lengths in the study area. Though the risk of a fire occurrence in these areas was the highest within the study area, the expected fire was likely to be less intense than compared to other areas which would have modeled flame lengths in excess of 40 feet. Again, the flame length results include the average height of the vegetation which is burning.

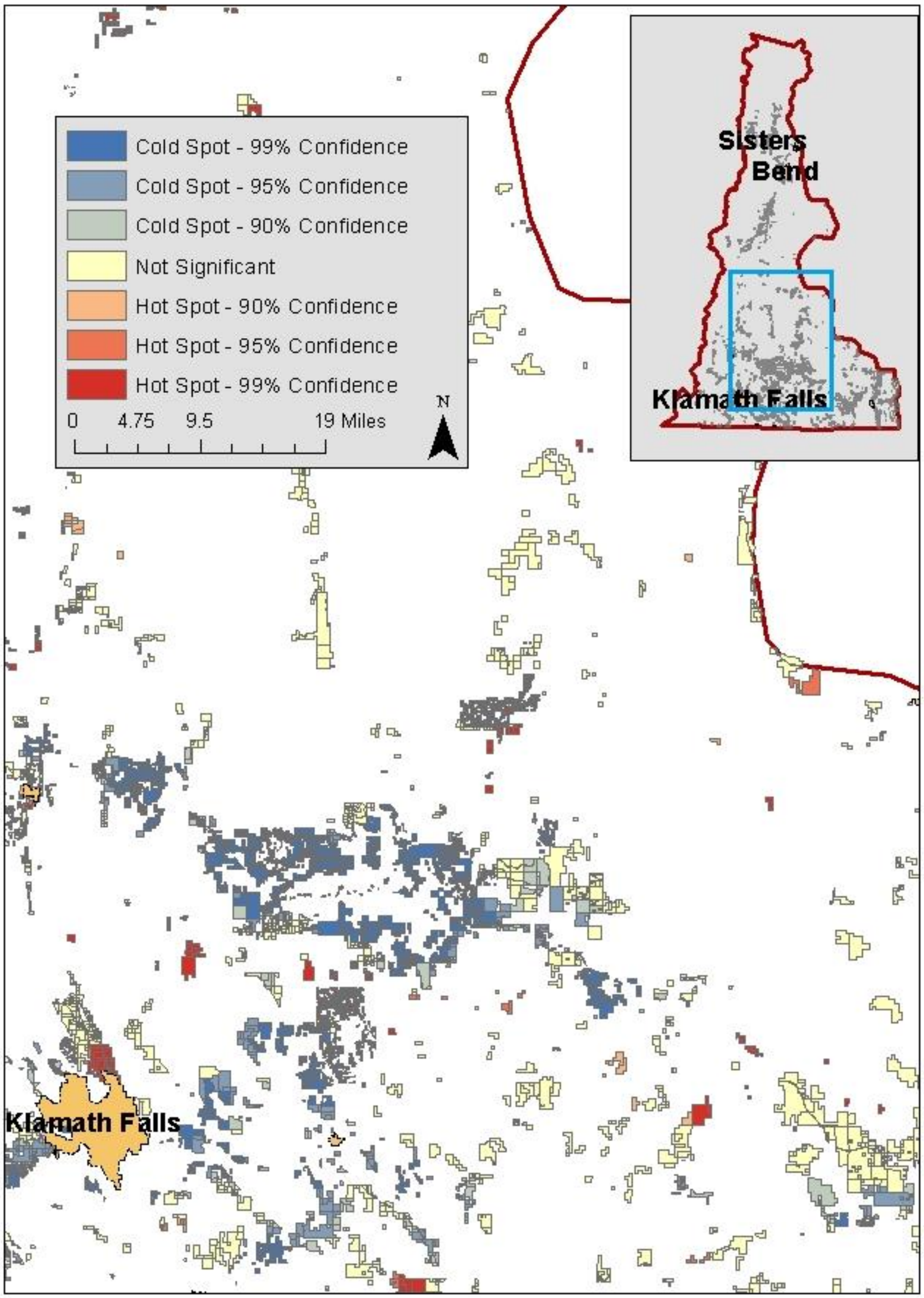
Figure 5.6 – Conditional flame length results for the study area as modeled in FlamMap. Locations of Hot Spot #2 and #3 are indicated for reference.



Treatment cost per acre

More than half of the parcels within the study area have an estimated fuel treatment cost under $95 per acre (6,520 parcels, 57.3%). The most expensive categories ($402.17 – 786.72 and $786.73 – 1,603.53) included 475 parcels (4.2%) and 0.8% (96 parcels) of the NIPF parcels respectively. The spatial distribution of the costs resulted in a number of small, concentrated hot spots (Figure 5.7), with the majority of parcels falling into statistical cold spots.

Figure 5.7 – A close up of the southern portion of the study area. Results of the hotspot analysis on estimated fuel treatment costs are included.



The 4,028 parcels in the northern two thirds had a maximum treatment cost of $1,603.53/ac, with a mean of $160.91/ac. Southern forests had both a smaller maximum, $1,420.66/ac, and a smaller mean cost at $112.93/ac.

Interaction of Treatment Locations, Costs, and Fire Variables

Model Predicted Treatments

Placing the hot spot analysis results for fuel reduction costs and the binary modeled locations over both CBP and CFL showed a number of interesting patterns upon visual inspection. For most parcels in the northern portion of the study area, the estimated fuel treatment cost appeared to have limited influence. Parcels with both high and low costs were predicted to have fuel treatments. The CFL and CBP also did not appear to have a direct influence over which parcels were treated. Again, both areas of low and high CFLs and CBPs were treated.

Southern parcels, however, show different patterns. Here, large numbers of parcels with low fuel treatment costs were not predicted to have performed one. Parcels which did perform fuels treatments typically were correlated with greater than average CFL, CBP, or both. These parcels also typically had fewer neighboring NIPF parcels, bordered instead by government managed lands and industrial forests. Estimated treatment costs did not appear to deter these parcels from having performed a treatment.

LandTrendr Identified Treatments

With fuel reduction treatments located through LandTrendr, the northern parcels showed a similar pattern to the modeled treatment locations. Estimated costs, CFL, and CBP did not appear to increase or decrease the potential for a given parcel to perform a fuel reduction treatment.

Southern parcels again shared similar patterns as described for the modeled treatment locations. Areas of highest treatment costs appeared to have very few of the treatments. The majority of the few treatments within this area also appeared to have some of the fewest NIPF neighbors. Parcels with higher than average CBP and CFL also seemed more likely to have performed a fuel treatment.

Discussion

Spatial Data Correlations

From a simple visual inspection of the data layers, there was a clear difference between the northern two thirds of the NIPF parcels and those in the south. For both treatment locations predicted by LandTrendr and the model, Jefferson and Deschutes counties had higher numbers of fuel treatments (Table 5.2).

Table 5.2 – Fuel reduction treatments according to logistic regression modeling and LandTrendr analysis, separated by county.

County	Num. of Treatments (model/LT)	Num. of no Treatments (model/LT)	% Of parcels treated (model/LT)
Deschutes	564 / 471	1,976 / 2,078	28.5 / 22.7
Jefferson	31 / 8	118 / 144	26.3 / 5.6
Klamath	1,265 / 732	6,686 / 7,247	18.9 / 10.1
Lake	67 / 47	662 / 682	10.1 / 6.9

These results led to the re-consideration of the logistic regression models in Chapter 2. When the survey data was separated out by county, it was found that respondents in Deschutes were much more likely to belong to land management organizations. This spurred the creation of Eq. 4.3a and 4.3b, which proved to be the most effective logistic regression models for predicting the placement of fuel reduction treatments.

Considering the recent, large wildfires that have occurred near the NIPF parcels within Deschutes and Jefferson Counties, the managers here may be more likely to perform fuel treatments for a number of reasons. Owners here may be more concerned with the risk of wildfire after having dealt with the effects of the B & B Complex and Pole Creek Fires. This may also correlate to the increased numbers of respondents within the survey population who belonged to land management organizations. Or perhaps the county governments are better at encouraging NIPF owners to perform management actions compared to Klamath and Lake Counties.

Within the northern portion of the study area, the differences in a parcel's CBP, CFL, and estimated fuel treatment cost did not seem to impact the probability that a parcel would perform a treatment. Looking at a breakdown of variables by treatment location, however, shows that this was in fact not the case (Table 5.3). For both modeled and LandTrendr detected disturbance locations, average CBP was higher for the parcels which did not receive treatments in the previous five years. This could be due to potential temporal overlap in the LandFire data and those datasets used to estimate the locations of fuel reduction treatments. The LandFire data, obtained for 2008, may actually have captured the post-treatment fuel loads of parcels which had performed fuel treatments. However, this is unlikely to have impacted all NIPF parcels as the predicted treatment locations included treatments over five years.

Average parcel size appears to correlate well with the use of a fuels treatment (Table 5.3). This result was expected as previous studies have shown similar trends (Ager *et al.* 2010, 2012). Only LandTrendr detected management actions in the south showed a different pattern, with the mean parcel size being 19.2 ha for those that performed treatments, and 21.8 for those that did not.

The average slope of parcels which had performed treatments was less than those which had not performed treatments. This trend was also expected due to previous studies (Berry and Hesseln 2004; Berry *et al.* 2006; Calkin and Gebert 2006). What is curious, however, is that in these studies slope is correlated with estimated treatment cost.

From this study's findings, however, average costs were estimated to be higher for parcels which had performed a fuels treatment. Further investigation and research would be needed to determine if this pattern is unique to the study area, or an artifact of the methods used to create the cost estimate itself.

Parcels' average percent forested did not appear to differ between parcels that had and had not performed a fuel reduction treatment. This was true for both the LandTrendr and model methods.

Table 5.3 – Descriptive statistics of NIPF parcel characteristics segregated by their location within the study area.

Treatment Classification (n)	CBP (%)				CFL (m)				Hectare				Trtmt Cost ($/ac)			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
LT Treat – North (657)	.13	.16	0	2.02	8.8	9.9	0	93.2	14.2	39.3	.8	515.3	167.53	201.93	0	1,479.33
Model Treat – North (1,156)	.11	.10	0	.59	11.2	12.4	0	107.3	21.6	46.4	.5	515.3	312.55	267.49	13.13	1,603.53
LT Treat – South (602)	.27	.22	0	1.21	14.8	15.6	0	137.3	19.2	62.1	1.0	1,052.1	108.77	122.25	0	1,037.66
Model Treat – South (773)	.15	.14	0	.89	25.3	23.9	0	138.3	31.0	52.0	1.0	470.0	247.57	215.61	1.11	1,420.66
LT No Treat – North (3,371)	.15	.23	0	3.0	8.23	8.43	0	107.32	13.0	44.2	0	978.8	159.62	182.51	0	1,603.53
Model No Treat – North (2,872)	.16	.26	0	3.0	7.16	6.23	0	68.01	9.8	41.7	0	978.8	99.87	81.59	0	706.82
LT No Treat – South (6,786)	.25	.20	0	1.52	15.2	13.6	0	138.3	21.8	76.4	0	2,090.7	113.30	122.81	0	1,420.66
Model No Treat – South (6,615)	.26	.20	0	1.52	14.0	11.4	0	137.3	20.5	77.5	0	2,090.7	97.19	95.05	0	786.72

Table 5.3 - continued

Treatment Classification (n)	Slope				% Forested			
	Mean	SD	Min	Max	Mean	SD	Min	Max
LT Treat – North (657)	2.1	2.7	0	23.9	79.3	22.4	11.1	100
Model Treat – North (1,156)	1.1	1.6	0	18.5	87.8	17.7	13.1	100
LT Treat –South (602)	4.2	3.9	0	21.1	69.4	28.3	8.7	100
Model Treat – South (773)	4.0	3.5	0	20.1	63.9	48.0	0	100
LT No Treat – North (3,371)	1.9	3.1	0	29.8	78.0	25.2	0	100
Model No Treat – North (2,872)	2.3	3.4	0	29.8	74.4	26.2	0	100
LT No Treat – South (6,786)	5.8	4.9	0	32.7	73.9	27.4	0	100
Model No Treat – South (6,615)	5.8	4.9	0	32.7	72.6	27.8	0	100

Fire Variables

As seen in Table 5.3, parcels which had performed a fuel reduction treatment had lower CBP on average. This result could be due to the fuel load data, or it could be tied to the fire model itself. Since the study area had to be broken into four sub-sections for the modeling process, it may be possible that the edges caused by this were enough to distort the mean values. If the study area had been entered into FlamMap as an entire landscape, these edges would not be present as each modeled fire could burn across the landscape freely. It was assumed that the edges were in locations which did not impact any parcel directly, but without being able to perform a model run for the entire study area at once this assumption could be flawed. It is unlikely, however, as the fire weather would have pushed the modeled fires to the northwest (wind direction) from the edges, which did not appear to impact any parcels directly.

Within the CBP data layer, two of the three clear hot spots were located on nature preserves, potentially due to the nature of fuels located in these areas (more grass and shrub cover than surrounding matrix). Some of the increased risk of wildfire occurrence surrounding these areas enters onto small numbers of NIPF parcels, but none of these parcels were predicted to have performed a fuel treatment by either the logistic regression model or LandTrendr. At a landscape scale, the CBP does appear to be slightly elevated in the southern portion of the study area, although it does not appear to be different between those parcels that had performed a treatment and those that did not (Table 5.3). This was not expected as some studies have shown that as a land owner's awareness of fire risk increases, the probability that the owner will use a treatment also increases (Bar Massada *et al.* 2009; Fischer and Charnley 2012; Fischer *et al.* 2014). This trend may not be occurring within the study area, or perhaps the variance in CBP is not enough to display this pattern. Alternatively, it may be that CBP does not reflect the NIPF manger's interpretation of fire risk. Creating and validating a variable that can be obtained without survey data that is a stand-in for an individual's interpretation of fire risk would greatly enhance both the logit model, and future research efforts.

Further Investigation

As mentioned earlier, there was a clear pattern of increased fuels treatments by county, with Jefferson and Deschutes counties having higher percentages of NIPF parcels with treatments. Including the additional spatial data of urban growth boundaries and governmental lands also resulted in the illumination of patterns.

Urban growth boundaries obtained from the Oregon Department of Land Conservation and Development included boundaries for cities such as Bend, Paisley, and Sisters. What few NIPF parcels that fell within these boundaries were not predicted to perform fuels treatments by either method. This is expected since as urbanizing areas, these parcels were isolated pockets of forested land typically surrounded by built-up land. The fire variables, which were built of fuels data that did not include urban structures, did not have values for much of the urban growth areas. What is more interesting is that NIPF parcels nearest to the boundaries also were also not predicted to perform fuels treatments by the logistic regression model. LandTrendr, however, did detect hot spots of management activity on these parcels. The LandTrendr identified treatments may also be included disturbances associated with urban development, such as construction, irrigation activities, *etc*., creating false positives for fuel reduction treatments.

The urban growth boundaries also typically fell in areas of lower CFP and CBP than the surrounding landscape. Increased fragmentation in the fuel structure is likely the cause of this trend. Urban structures such as buildings and roads were not included in the fuels data for the fire model creating an artificial level of fragmentation. Even if these elements had been included, other urban features such as parking lots, roads, or irrigation ditches would act as fuel breaks. The relatively smaller towns, such as Sisters, Chiloquin, Redmond, and even Bend, however, were unique in that they had large patches of CBP of equal scale to their surrounding landscape within their boundaries. This may be a result of the lack of urbanized areas within these urban areas, or the prevalence of green spaces which would have provided fuel loading data for the fire model.

Looking at how CBP and CFL correlated among ownership categories within the study area, it is clear that federal lands contain both higher average CFL and CBP (Figures 3.5 and 3.6). These areas were intermixed with hot spots of trees/ha, although the areas with the highest trees/ha did not also have the highest CFL values. Intuitively this would make sense, as areas with the highest trees/ha on federal lands are likely areas of planting and regrowth following a timber sale, which would in turn have smaller

CFL's as the vegetation in these areas would be shorter. Again, CFL is modeled to include both the fuel's height and the flame height, so shorter, and potentially younger, trees would have smaller flame lengths than taller, and potentially older, trees. The patches of the highest CFL's fell on areas with relatively fewer trees/ha, which could indicate that these areas were characterized by taller, more mature stands that had undergone competition and disturbance events to reduce their densities.

Conclusion

Investigating the results of the logistic regression model, LandTrendr analysis, and the variables used in the creation of the logit model itself can give insight into which NIPF parcels were in need, or are in need, of fuels treatments. There were a number of patterns that were apparent within this study that could inform management and policy decisions for central Oregon. From spatial datasets, pockets of high elevated fire risk, high and low expected costs of fuel treatments, and the potential willingness of an owner to perform a fuel treatment can be ascertained quickly to inform policy and management decisions.

In the case of this study, there were only two areas with very high fire risk based on conditional burn probability. Both areas were public nature preserves and only a small number of NIPF parcels neighbored these areas. Parcels near urban areas largely had low fire risks, with parcels closer to federally managed lands having increased CBP's. This proximity to the public lands likely had a direct influence on both the parcels' fire risk and their application of fuel treatments as this has been shown in other studies (Fischer and Charnley 2012).

Overall, parcels within Jefferson and Deschutes counties were more likely to have performed a fuel reduction treatment than parcels in the southern counties of Lake and Klamath. The average fire risks (both CBP and CFL) for parcels that performed fuels treatments in the northern counties were lower than the average risk of southern parcels that treated. Also, the average cost of these treatments was higher in the north than in the south, and yet those parcels were still more likely to perform a fuels treatment. It was assumed at first that parcels which had higher treatment costs and lower fire risks would in turn be less likely to perform fuels treatments. This was not the case in this study.

This difference between Jefferson and Deschutes counties and Klamath and Lake Counties requires further investigation and research efforts. A preliminary exploration of the data hints at one possible hypothesis to explain the difference being the increased rates of NIPF owner involvement in land management organizations in the north compared to the south. Additional work to refine the methods by which fuel reduction treatments were located, both by LandTrendr and the logistic regression model, could also help detail differences among NIPF parcels.

LandTrendr and the logistic regression model, Eq. 2.1a presented in this study, can help inform wildfire policy decisions and management actions. With a small number of software tools, managers and researchers can identify information about a landscape's current wildfire management needs. Directing policy tools to areas with increased fire risks can improve the rates that NIPF owners perform fuel reduction treatments. Land managers can plan their own management actions while considering how a wildfire would move across a landscape with greater ease by using LandTrendr. Obtaining the locations of pre-existing fuels treatments on nearby parcels could allow land managers to locate the most effective placement of their own treatments. Continued research in the use of LandTrendr, and the analysis methods presented in this study, could improve not only wildfire management, but potentially any forest management scenario by easily expanding a manger’s view to a landscape level.

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