



AN ABSTRACT OF THE THESIS OF

Aaron R. Gagnon for the degree of Master of Science in Sustainable Forest Management  
presented on December 10, 2015

Title: Economic Benefit from Allowing Wildfires to Burn in Federal East-Side Cascade Forests

Abstract Approved:

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In this thesis I examine the question: can allowing a wildfire to burn this year result in a net positive economic gain? To answer this question I created 2,500 multiple sets of paired scenarios (called a fire of interest) which consist of ignitions, vegetation growth, and timber harvest over the course of 100 years. Each set had a unique ignition timing and location. Each pair within a set was identical in ignition timing, location, and growth, but the fire of interest was treated with suppression in one instance and was allowed to burn in the other. All future fires were assigned suppression attempts.

For the economic analysis, I used dollar values associated with harvest revenue of green trees and suppression costs. Timber harvests were implemented every ten years to provide revenue. Timber salvage was not considered in this thesis. Costs were incurred by suppression attempts on all future ignitions. The idea was to compare the discounted revenue/costs from the let burn scenario to the suppressed scenario over 100 years.

The result was one discounted net value for each paired simulation and the data produced a large number of positive net benefits. Interpreted loosely, a positive net benefit translates to a net economic benefit from allowing the original fire to burn. I used this value as the dependent variable in a regression to test the relationship between the net benefit and characteristics that influence fire behavior.

I also developed a non-monetary method to evaluate the landscape. I did this by creating a Restoration Index that compares current and future stand structure distributions to a baseline condition. The Restoration Index uses succession classes to determine deviations from a pre-

determined resilient state by comparing composition and density between stands. Only ponderosa pine was considered in the Restoration Index.

This thesis is an early step in a process aimed at helping Forest Service land managers determine whether there is a potential economic value to allowing a wildfire to burn. It provides the foundation for future research to expand on landscape variability, multiple spatial and stochastic factors, and dynamic programming methods.

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December 10, 2015

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Economic Benefit from Allowing Wildfires to Burn in Federal East-Side Cascade Forests

by

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A THESIS

Submitted to

Oregon State University

In partial fulfillment of  
the requirements for the  
degree of

Master of Science

Presented December 10, 2015

Commencement June 2016

Master of Science thesis of Aaron R. Gagnon presented on December 10, 2015.

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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.

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Aaron R. Gagnon, Author

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## INTRODUCTION

Wildfire management on National Forest lands has undergone many changes over the past 100 years. As a result of catastrophic fires in 1910 (where over 2 million acres burned and 78 lives were lost), the Forest Service implemented a policy of fire suppression. Early Forest Service land managers saw fire as a threat to both human life and forest resources. A policy was implemented in 1935 to extinguish all fires by 10am the following morning. This set the stage for fire management over the remainder of the century.

The resulting wildfire exclusion drastically changed the composition and structure of western forests. This is especially true of dry ponderosa pine (*Pinus ponderosa*) forests east of the Cascades in the Pacific Northwest. Historically, many of these forests were dominated by large, open expanses of ponderosa pine (Agee 1993, Youngblood 2004). Ponderosa pines have thick lower bark and high crowns that are created by the regular shedding of branches as the tree grows. Surface vegetation was sparse and mainly consisted of grasses and brush with small amounts of litter and branches (Fitzgerald 2005). Limited surface fuel, coupled with regular intervals of dry season lightning, created an environment conducive to frequent surface fires that would keep excess fuels from cumulating.

Wildfire suppression policy caused the composition and structure of ponderosa pine forests to change. Without regular light burning, surface fuels accumulated and more shade tolerant trees produced ladder fuels in the understory. These changes created a greater continuity of fuel from the surface into the canopy (Fitzgerald 2005). Competition for nutrients and resources increased. This led to higher stress, mortality, and the increased probability of bark beetle attacks and other diseases. Stressed trees and increased fuel levels resulted in more intense fires covering larger areas.

Consequently, federal expenditures on wildfire suppression are increasing (Calkin 2005). By 2008, approximately 50% of the Forest Service budget was allocated to wildfire suppression and yearly expenditures routinely exceeded \$1 billion. Geoffrey Donovan, an economist with the Forest Service, analyzed the cost of accumulated fuels that wildfires managed in the past. If the

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goal was to mechanically treat all of the ponderosa pine stands well outside of their historic variability, it would cost \$12 billion and take over 25 years to complete (Donovan 2007). Over the past 10 years, the average Forest Service total appropriation for hazardous fuels reduction is approximately \$300 million/year (Hoover 2015). This has led many economic researchers to study how to minimize fire suppression and prevention costs given limited resources.

Operations research is a discipline that deals with how to most efficiently allocate resources. Specialists are continually working to find the most cost effective means to mitigate the effects of wildfire. Much research has gone into the optimal placement of fuel treatments to limit the damage from wildfire. However, little research has been conducted into optimal use of fuel treatments to restore fire resilient forests. The problem of optimally placing a fuel treatment is computationally challenging because there are a limitless number of combinations of vegetation characteristics and fire attributes that can occur over time.

Another way to lower the cost of both suppression and prevention is to allow some wildfires to burn. While it's easy to see how letting a wildfire burn would reduce both current and future suppression expenditures, it may not be obvious how it reduces prevention costs. When a surface fire burns with excessive surface fuels, it removes some (or all) of those fuels without incurring expensive mechanical costs (Schmidt et al. 2002).

In this thesis I explore the question: under what conditions does allowing a fire to burn produce a positive net benefit? Using Monte Carlo methods I generate many simulations consisting of wildfires, harvests, and stand growth over time. Allowing a fire to burn can provide benefits in the form of suppression cost savings but can also affect discounted revenues from reasonable harvest plans based on current Forest Service practices. I also explore the effect of letting a current wildfire burn on restoring a landscape to pre-settlement conditions.

This study is a follow-on analysis of an earlier study by Houtman et al. (2013). In that study, researchers integrated a fire simulation model, a simple state-transition simulation model, and a suppression cost estimation model in order to examine long-term landscape level effects of

allowing a current fire to burn. This was done by comparing two scenarios: 1) allowing a current fire to burn versus 2) suppressing the same fire. The landscape resulting from each of these events was then tracked over a 99-year period in which suppression was attempted on all subsequent naturally occurring ignitions. The end result was an estimate of the discounted value of suppression cost savings.

My thesis extends Houtman et al. (2013) by adding timber harvest, constructing a Restoration Index, and using regression analysis to explore the conditions under which the benefits of allowing a fire to burn exceed the costs. I used a study area in which Forest Service land managers would be open to the idea of allowing a wildfire to burn given favorable weather conditions and proximity to public structures. This area lies in the southern portion of the Bend Fort-Rock District of the Deschutes National Forest. The parcel consisted of an area approximately 72,000 ha in size and is populated primarily by lodgepole pine (*Pinus contorta*) and ponderosa pine (*Pinus ponderosa*).

## **LITERATURE REVIEW**

There have been many studies that attempt to identify the historical structure and vegetation associated with pre-settlement eastside Cascade forest range. Early 20<sup>th</sup> century photos depict open park-like stands of ponderosa pine (Franklin and Dryness 1988). There was very little surface fuel and trees had thick bark and high limbs. Using early 1900 forest inventory plot information, Powell (2005) summarized forest conditions for five ponderosa pine-dominated stands in northeastern Oregon. These summaries include information on trees per acre, basal area per acre, and stand density index during either 1910 or 1912.

Ironically, Thorton Munger (1917), an early Forest Service research scientist, described just such a forest structure. He believed fire damaged the existing trees and retarded regeneration. Shaw and Kotok (1924) also believed that by permitting fires to burn on pine forests, managers were not allowing the stand to produce to its full capacity. The blanket of young growth following 20+ years of suppression management was evidence of a healthy forest.

Historically, ponderosa pine forests east of the Cascades were subject to high-frequency, low-intensity fires (Agee 1993). Mean fire return intervals typically fell in the range of 16 – 38 years (Bork 1985). According to Wright and Agee (2004), the area burned in a given fire was typically small in size and only covered larger areas in times of significant drought. Changes in the ecological structure of the forest during the early 20<sup>th</sup> century were mainly due to cattle grazing, which removed surface fuels, selective logging, which remove large fire resistant trees, and active fire suppression (Hessburg and Agee 2003). As a result of these intense management practices the ponderosa pine fire regime changed over time. Currently the fire regime in many of these stands is low-frequency, high-intensity (Schmidt et. al 2002).

One of the first arguments to suggest that fire suppression could have a negative effect on ponderosa pine forests came from Meyer (1934). When Meyer examined stands of selectively cut ponderosa pine, he observed clumping and overstocking in areas associated with the cut. He postulated that these clumps were producing at 10% of normal yields for a comparable site index. Weaver (1943) believed that periodic fires and pine-beetle attacks operated together to control the density and composition of ponderosa pine forests. As the Forest Service followed the aggressive fire suppression policy with authorization for unlimited spending on wildfire (Omi 2005), Weaver noticed shade-tolerant species dominating the understory and an increase in pine-beetle outbreaks. Weaver (1943) concluded that, if ponderosa pine is the desired species, then fire should be employed as a tool.

There are numerous options to consider when attempting to restore a fire-resilient forest. Agee (2002) proposed four actions: reduce surface fuels, increase height to live crown, keep large fire resistant trees, and decrease crown density. Methods to accomplish fire resilience include prescribed burning (Walstad et. al 1990), thinning (Graham et. al 2004), and mowing (Fitzgerald 2005). While these methods have proven useful, cost continues to be a major obstacle. Costs per hectare can go well into the thousands of dollars and the amount of area that must be treated in order to be effective is on a landscape level. Therefore, many projects will go unfunded (Donovan and Brown 2007). A different approach is to use natural fire to help restore pre-

settlement conditions in ponderosa. For example, Miller (2003) considered using a decision process to determine if wildfires could provide benefits if allowed to burn.

Youngblood (2004), using the Pringle Butte Research Natural area, identified reference conditions for restoration of ponderosa pine forests on deep pumice soils. By investigating age, size, and spatial patterns of old growth trees, Youngblood was able to develop density parameters for pre-settlement dry ponderosa pine forests. To aid with computer-based vegetation modeling, state-and-transition models were developed within LANDFIRE (2011) to provide expert-informed development of vegetation over time. LANDFIRE is a fuels characteristics mapping program used by many federal agencies to provide up-to-date spatial data for various fire research projects. A key aspect to the restoration process was the reintroduction of fire to eliminate high stem densities and reduce surface fuels.

An early attempt to develop a framework for cost-benefit analysis applied to fire and fuel management was Sparhawk's (1925) least Cost plus Loss ( $LC + L$ ) model. This model was the first attempt at basing fire management decisions on net value. The objective was to minimize the cost of fire suppression plus the net damage due to fire. This model did not include any potential benefits that could result from fire. Simard (1976), using classical production theory, modified the model to reflect any changes that might provide a benefit of fire. Rideout and Omi (1990) extended this idea to include both inputs and outputs with regards to fire management. Their model is called Cost plus Net Value Change ( $C + NVC$ ). Donovan (2007) also used the  $C + NVC$  method to study the impact of uncertainty on wildfire decision-making processes.

The advantage of the  $C + NVC$  model is that it accounts for both pre-suppression and suppression costs and incorporates beneficial and detrimental net value changes in a static environment. The limitation of these models is that they are static and fire is a dynamic process. Optimality of a current decision is dependent on future fire events and the decisions made when they have been realized. In order to facilitate this procedure, a form of dynamic optimization may be employed to assist with the decision making process.

The basis for dynamic economic optimization is the Bellman equation. Bellman (1957) uses the principle of optimality to maximize the attainable sum of current and future rewards. When future events are uncertain, the Markov Decision process is used to represent probabilities of future outcomes based on the likelihood that a particular state transitions to a future state given a possible action. To accomplish this, multiple future scenarios are generated from one particular action to approximate the expected value of a future state (Powell 2009). It is this expected value that is used as the framework for my decision making process.

## **ANALYTICAL METHODS**

One goal of this project is to analyze the change in Net Present Value (NPV) of the landscape when a wildfire is allowed to burn. Given a fire-generating ignition at time zero, herein after referred to as the fire of interest, two separate actions were considered: let the fire burn ( $x_0 = 0$ ) and suppress the fire ( $x_0 = 1$ ). For a given fire, each scenario was simulated over a period of 100 years multiple times using Monte Carlo methods to generate sequences of future ignitions and harvests. Suppression efforts were attempted for each future fire in the years following the fire of interest. Timber harvests were conducted every 10 years to generate revenue. Also, ponderosa pine forest structure was evaluated at 20, 50, and 100 years using a Restoration Index to evaluate deviation from a desired state.

The Fort Rock Ranger District of the Deschutes National Forest has multiple management objectives. In this analysis I focused on two: 1) net revenue and 2) restoration of pre-European settlement conditions. Net revenue is defined as the revenue from timber harvests less the cost of fire suppression. I define the value of the landscape as the sum of the net present value of net harvest revenue less the cost of fire suppression discounted to the present<sup>1</sup>. Restoration is defined by the succession class distribution of the ponderosa pine cover type across the landscape<sup>2</sup>.

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<sup>1</sup> I used the Oregon Department of Forestry pond value for the 3<sup>rd</sup> quarter 2011 less the “rule of thumb” harvest and haul cost

<sup>2</sup> Alternative restoration objectives could be used, e.g. total area in which fire could be allowed to burn.



**Equation 1**

$$v = \sum_{t=1}^{T-1} e^{-rt} (H(s_t) - C(s_t)) + e^{-rT} V_T + c(s_0, x_0 | x_0 = 1)$$

Where:

- $T - 1$  Total time periods for each simulation.
- $T$  Ending time period.
- $r$  Real discount rate of 4% (Row et al. 1981).
- $H(s_t)$  Net harvest revenue in each period  $t$ .
- $C(s_t)$  Cost of fire suppression in each period  $t$ .
- $c(s_0, x_0)$  Cost of suppression for the fire of interest. I assume this is zero if the fire is allowed to burn.
- $V_T$  Ending value of the landscape at time period  $T = 99$ .
- $x_0$  Variable describing whether or not the fire was allowed to burn ( $x_0 = 0$ ) or if there was a suppression attempt ( $x_0 = 1$ )
- $w_t$  Vector of weather and ignition variables for each time period  $t$ .
- $s_t$  Vector of state-transition variables for each time period  $t$ . These include vegetation and landscape characteristics.  $s_t$  can be further broken as follows<sup>3</sup>:

$$s_0 = S(s_0, w_0)$$

$$s_1 = S(s_1, w_1, x_0)$$

---

<sup>3</sup> Simulation models are used to represent the state-transitions.

$$s_{t+1} = S(s_t, w_t) \text{ for } t = 1 \dots T-1$$

Net value change ( $\Delta v$ ) is defined as the difference in the discounted value of the landscape when a suppress effort will be attempted and when it is allowed to burn. Based on Equation 2 it is rational to let a fire burn at  $t = 0$  if the benefits of letting the current fire burn exceed the costs.

### Equation 2

$$\Delta v = v(s, w | x_0 = 0) - v(s, w | x_0 = 1)$$

When  $\Delta v > 0$ , the loss in harvest revenue due to letting the fire of interest burn is less than the reduction in suppression cost. If  $\Delta v$  is the only criteria, it is optimal to let the fire of interest burn.

When  $\Delta v < 0$ , the reduction in suppression cost from letting the fire of interest burn is less than the loss in harvest revenue. If  $\Delta v$  is the only criteria it is optimal to suppress the fire of interest.

The following equation breaks equation 2 down into its four component parts.

### Equation 3

$$\Delta v = \left[ \sum_{t=0}^{T-1} e^{-rt} \langle H(s_t | x_0 = 0) - H(s_t | x_0 = 1) \rangle \right] - \left[ \sum_{t=1}^{T-1} e^{-rt} \langle C(s_t | x_0 = 0) - C(s_t | x_0 = 1) \rangle \right] + [e^{-rT} \langle VT x_0 = 0 - VT x_0 = 1 \rangle] + [cs_0, x_0 | x_0 = 1]$$

The first term in brackets of Equation 3 describes the change in harvest revenue when comparing the let burn to the suppress scenario ( $\Delta H$ ). The second term describes the reduction in suppression cost when comparing the let burn to the suppress scenario ( $\Delta C$ ). The third term describes the discounted value of the harvestable timber at the end of the 100-year period. The fourth term is the cost of suppressing the fire when the initial decision is to suppress,  $x_0 = 1$ .

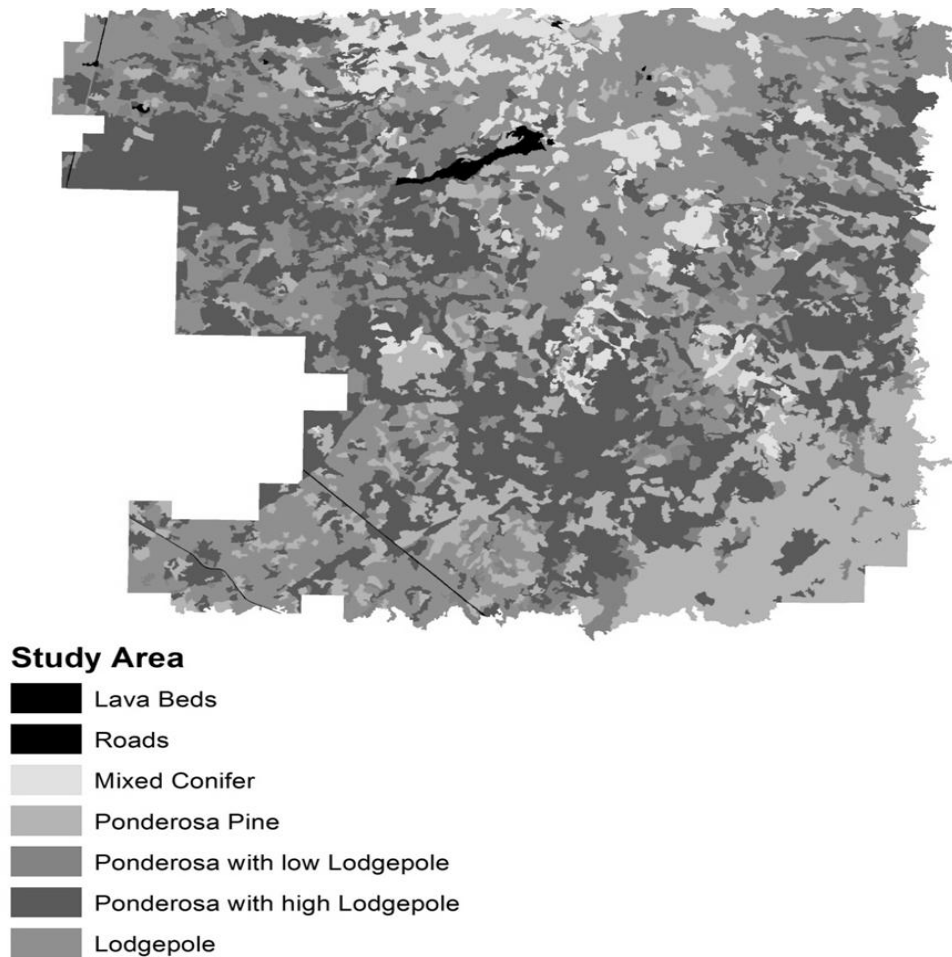
The main objective of this analysis is to explore how conditions known at the time of ignition (e.g. location, time of year, vegetation, etc.) affect the net value change ( $\Delta v$ ) of allowing a fire to burn given that future fires will be suppressed:

**Equation 4**

$$\Delta v_0 = f(s_0, w_0)$$

**INITIAL LANDSCAPE**

The study area is 72,305 contiguous hectares on the southern flank of Newberry Crater in the Deschutes National Forest. The area is bordered on the north by the heavily-visited Newbery Crater National Monument, on the south and east by arid sagebrush steppe, and on the west by private lands, including La Pine, and Highway 97.



**Figure 1: Map of Study Area**

The landscape is characterized by a shallow deposit of pumice and ash resulting from the eruption of Mt Mazama which occurred over 7000 years ago. The elevation is approximately 4300 ft, with the exception of the northern portion which rises with Newberry Crater. Most precipitation occurs in the form of snow during the winter and spring seasons. The summer and early fall are dominated by hot temperatures and dry weather. The topography and climate are conducive to intense summer storms which can produce dry lightning.

The vegetation is dominated by high elevation mesic-type of nearly pure stands with relatively little understory. For the purposes of this paper, stands are classified by Plant Association Groups (PAG). A PAG is defined as grouping of trees and plants that occur together in similar environments (Grenier 2010). To simplify the vegetation classification process, only the 3 most common PAGs were chosen to represent the study area: ponderosa pine (PP), lodgepole pine (LP), and mixed conifer (MC). Approximate distributions by PAG are as follows: PP 44,164 ha (61%), LP 23,152 ha (32%), and MC 4,561 (6%). Each PAG is then sub-categorized by density and, in the case of ponderosa pine, encroachment of lodgepole pine.

The initial landscape consists of 5,122 stands of varying sizes. Stands are homogeneous units comprised of tree lists. Tree lists were derived from FIA inventory plots (USDA 2000) using the gradient nearest neighbor method (Ohmann and Gregory 2002). Assignment of tree lists and processing of data into stands was accomplished at the Western Wildland Environmental Threat Assessment Center in Prineville, Oregon (Alan Ager and Nicole Vaillant, personal communication, 11/7/2009). Each stand had a corresponding tree list assigned to it for the study area initialization.

Using information from Mike Simpson (email communication, Mike Simpson, Ecologist, 8/8/2011), I developed a program to place each of the tree lists into succession classes by analyzing the composition of each tree list (Appendix B). Determination of succession class is based on diameter at breast height (DBH), size and density class, and canopy cover. Each tree list was then assigned a succession class. Representative tree lists were then selected to describe

each succession class on the initial landscape<sup>4</sup>:

### 1. Ponderosa pine PAG

- a. Initiation: Early development structure consisting of seedling/sapling trees. Approximately 0-20 years old. One representative tree list was chosen for landscape initialization.
- b. Young-Dense: Mid development structure consisting of medium-sized trees with canopy closure greater than 40%. Trees approximately 20-125 years old. Two representative tree lists were selected: PP with 0-10% LP and PP with greater than 10% LP.
- c. Young-Open: Mid development structure consisting of medium-sized trees with canopy closure less than 40%. Trees approximately 20-125 years old. Two representative tree lists were selected: PP with 0-10% LP and PP with greater than 10% LP.
- d. Old-Open: Late Development structure consisting of large-sized trees with a canopy closure less than 40%. Trees typically older than 125 years. Three representative tree lists were selected: 0% LP, less than/equal to 10% LP, and greater than 10% LP.
- e. Old-Dense: Late Development structure consisting of large-sized trees with a canopy closure greater than 40%. Trees typically older than 125 years. Three representative tree lists were selected: PP with 0% LP, less than/equal to 10% LP, and greater than 10% LP.

### 2. Lodgepole pine PAG

- a. Initiation: Early development structure consisting of seedling/sapling trees. 0-20 years old.
- b. Old-Dense: Late Development structure consisting of medium-sized trees with a canopy closure greater than 40%. Generally greater than 20 years old.
- c. Old-Open: Late Development structure consisting of medium-sized trees with a canopy closure less than 40%. Generally greater than 20 years old.

### 3. Mixed Conifer PAG

- a. Initiation: Early development structure consisting of seedling/sapling trees. Generally 0-20 years old.

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<sup>4</sup> Mixed conifer and lodgepole pine consisted of one initial representative stand per succession class.

- b. Young-Dense: Mid development structure consisting of medium-sized trees with canopy closure greater than 40%. Generally 20-125 years old.
- c. Young-Open: Mid development structure consisting of medium-sized trees with canopy closure greater than 40%. Generally 20-125 years old.
- d. Old-Open: Late Development structure consisting of large-sized trees with a canopy closure less than 40%. Generally older than 125 years.
- e. Old-Dense: Late Development structure consisting of large-sized trees with a canopy closure greater than 40%. Generally older than 125 years.

To place each of the selected stand types on the landscape, all of the existing stand types were categorized by the percent cover for every species. The representative tree list that had the closest characteristics to the existing stand was used to represent the initial vegetation in that stand. For example, if an existing PP stand had 37% percent total cover with 7% LP, then succession class Young-Open, with 0 – 10% LP was selected to populate that stand. This method was applied to all forested stands on the landscape. The initial landscape was populated with 19 total stand types.

## **RESTORATION INDEX**

A policy of wildfire suppression continues to convert ponderosa pine stands to a fire regime more conducive to high intensity, high severity fires. Removing fire from trees adapted to frequent, less intense fires resulted in a mixture of both higher densities and divergent species compositions compared to those of pre-fire suppression forests. In this thesis, I analyze how the structure and composition of ponderosa pine stands change following a wildfire where there is no attempt at suppression. To do this, I developed a restoration index,  $R$ , that represents how ponderosa pine stands evolve over time following a wildfire. I then compare that development to stands in which the same fires were suppressed.

### **Equation 5**

$$\Delta R = (R|x_0 = 0) - (R|x_0 = 1)$$

The restoration index indicates how current stand attributes compare to a desirable set of attributes. To define “desirable”, I use the historical characteristics described in LANDFIRE (see below). It is understood that many definitions of “desirable” exist for species composition. For this analysis, I use the more fire-resilient stand structure that characterized pre-settlement eastern Cascades ponderosa pine forests as a baseline. Only ponderosa pine stands were chosen because their structure is the best-documented negative species transformation following human intervention. Lodgepole pine trees do not develop in open stands and their anatomy is not resistant to fire (Agee 1993). Also, mixed conifer stands typically develop with shade-tolerant trees at higher elevations and in significantly different fire regimes than that of ponderosa pine (Agee 1994). Therefore, lodgepole pine and mixed conifer were not included in the restoration index.

To represent the restoration objective, I created a restoration index based on the deviation from a baseline succession class distribution of ponderosa pine. The restoration index is expressed as the sum of squared deviations of ponderosa pine succession classes from the baseline succession class (Equation 6). Changes in succession class distribution were recorded throughout each simulation. As a stand develops over time, changes in structure are the result of factors including mortality, size class and canopy development, in-growth, and disturbance from fire and harvesting. Percent area in each succession class over the landscape was reported for years 0, 20, 50, and 100.

### Equation 6

$$R_t = \frac{1}{5} \left[ \sum_{n=a}^N (X_{nt} - X_n^*)^2 \right]$$

Where:

$n$  Index for succession classes (described below)

$X_{nt}$  Percent area in succession class  $n$  at time  $t$

$X_n^*$  Desired percent area in succession class  $n = 1 \dots 5$

$a$  Succession class type

Equation 6 is used as a measure of deviation from the desired succession class distribution at a point in time (squared to magnify the deviations). The smaller the restoration index ( $R$ ), the closer the simulated landscape is to the desired succession class distribution. The initial landscape has a score of 504.72. A score of 0 indicates a landscape that is perfectly matched to the desired landscape. The highest possible score is 2480. This would indicate a landscape that is 100% dominated by either Young or Old-Dense succession classes.

The baseline condition<sup>5</sup> was derived from the state-and-transition model called BioPhysical Settings (BPS) which was developed as a part of LANDFIRE. BPS is based on literature and expert opinion and is used to represent pre-settlement vegetation in most species throughout the western United States. The initial and baseline ponderosa pine distributions on the landscape are given in Table 1. Using Table 1, 45% of the landscape should be in the Old-Dense ponderosa pine succession class. Since only 6.22% of the landscape labeled ponderosa pine is actually in Old-Open, there is a potential deficit of 38.78% (or 17,127 ha) in this succession class.

Ponderosa Pine					
Succession Class			Landscape Coverage		
Develop	Canopy	Cover	Initial	Baseline	Deviation
Initial	All	All	9.22%	10.00%	-0.78%
Young	Dense	> 40%	36.45%	5.00%	31.45%
Young	Open	≤ 40%	37.62%	35.00%	2.62%
Old	Open	≤ 40%	6.22%	45.00%	-38.78%
Old	Dense	> 40%	10.49%	5.00%	5.49%

**Table 1: Ponderosa pine distribution by succession class. Landscape coverage depicts the actual area covered compared to an ideal, or pre-settlement, forest structure. Open <40% and closed >40% canopy coverage when viewed from above.**

<sup>5</sup> Percentage area representing the baseline condition is not spatially limited to a defined area. It is used in this thesis to represent a percentage of the total landscape.



## TIMBER HARVEST BENEFITS

Timber harvests were incorporated into the simulation to examine the tradeoff between suppression cost savings and the loss of timber value from allowing a fire to burn. Timber harvests were implemented at the end of each 10-year period based on current management practices in the Deschutes National Forest (personal communication, Barbara Schroeder, Forester, 8/3/2011). Using current management strategies, along with the Deschutes National Forest Plan (1990), I derived a target harvest volume. I then devised a method to identify contiguous areas of similar stand structures and created a harvest priority schema for the resulting stands.

For simplicity, the basis for the harvest selection process was at the pixel (30m x 30m) level<sup>6</sup>. Pixels were prioritized and selected until either a minimum threshold was reached or maximum number of pixels was attained. This selected unit (hereinafter referred to as a stand) was then marked for harvest and the volume (BDFT) recorded. Stands were selected for harvest until either the target harvest volume was reached, or until stands with harvestable timber were exhausted. The foundation for prioritization was based on cover type, density, succession class, and time since last harvest.

Stand Density Index (SDI) is used to determine a relationship between tree per acre (TPA), quadratic mean diameter, and basal area (Reineke 1933). SDI is a method to measure the density of a stand without having to determine an age. Cochrane (1994) devised a method to determine harvest levels using Upper/Lower Management Zones (UMZ/LMZ). Most species have management zones based on a percentage of a “fully stocked” stand. The UMZ, which is 75% of “fully stocked”, is the density at which a suppressed class of trees develops. LMZ, or 67% of UMZ (50% of fully stocked), is the management goal where enough vegetation is removed to allow an efficient use of site resources. Since mortality, mainly due to mountain pine beetle, has

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<sup>6</sup> See Appendix C for detailed explanation of the harvest selection process.

resulted in densities below UMZ for ponderosa pine, Cochrane (1994) developed a critical density based on site index (SI).

Using Cochrane's method I devised three SDI categories (0, 1, 2) for ponderosa pine and two SDI categories (0, 1) for both lodgepole pine and mixed conifer. SDI 0 means the stand is considered open and there is no competition for site resources. SDI 1 begins when a stand reaches its minimum harvestable volume and ends at the species fully stocked volume. There is limited competition for resources and shade-tolerant trees begin to infiltrate the stand. SDI 2 is considered overstocked because extreme competition occurs and there is an excess of fuel and fuel ladders have developed. Only stands with an SDI of 1 or 2 were considered for harvest.

Management strategies were determined by cover type. Ponderosa pine and mixed conifer were managed on uneven-aged rotations. Following standard Deschutes National Forest silvicultural practices, only trees in diameter classes 11 – 21” were harvested using the LMZ as a target management density. The maximum harvest unit size was 40 acres and the managers were assumed to rely on natural regeneration from mature seed sources. Lodgepole pine was managed on an even-aged rotation. Selected stands were clearcut. The maximum harvest unit size for this analysis was 60 acres and managers were assumed to rely on natural regeneration.

Succession class also played a role in establishing harvest eligibility and levels. Both young and old dense stands were given a higher priority than young and old open stands. Dense ponderosa pine stands, for example, covered a greater percentage of the landscape. Therefore, in order to help manage the landscape for restoration, dense stands were prioritized higher than open stands. Initiation level stands (Succession Class A) were not considered for harvest.

Time since last harvest was the last factor in determining harvest criteria. The highest priorities were reserved for those stands with a time since last harvest of 100 years or greater. The next higher priorities consisted of time since last harvest of 90 years. This continued down to 20 years. Stands harvested less than 20 years prior to selection were not considered for harvest.

The volume harvested per acre was determined by species, succession class, SDI, and time since last harvest<sup>7</sup>. The Forest Vegetation Simulation model (Dixon 2002) was used to determine harvest volume for each priority classification. At the end of each 10-year period, contiguous areas were selected for harvest. Harvestable stands<sup>8</sup> account for approximately 95% of the study area. For simplicity, all stands were labeled as harvestable for this analysis.

Total harvestable volumes were based on the 10-year average of the Deschutes National Forest (2010) Allowable Sale Quantity (ASQ). ASQ is the chargeable component of a timber sale and consists of material suitable as saw timber (i.e. not firewood or chipable material). The average yearly ASQ for the entire Deschutes National Forest was approximately 27.3 Million Board Feet (MMBF). Since my area accounted for 10.1% of the entire landscape area, I assumed a harvest of at most 10.1% of this average (or 2.73 MMBF) per year on the study area. For a 10-year entry the defined maximum allowable harvest per decade is 27.3 MMBF for this study area.

When the selection process for a harvest was complete, the total value for the harvest was recorded for use in the Net Present Value equation for the landscape. Log prices were determined using Oregon Department of Forestry 3<sup>rd</sup> quarter 2011 prices from Region 5 – Klamath Unit. Ponderosa pine and mixed conifer used an average log price of \$340/MBF and an average harvest and haul cost of \$175/MBF. This yielded a net revenue of \$165/MBF. Lodgepole pine used an average log price of \$275/MBF and an average harvest and haul cost of \$125/MBF. This resulted in a net revenue of \$150/MBF. The values for all future harvests were discounted using a 4% real discount rate.

## **FIRE SIMULATION**

To determine the extent of fire spread, I simulated fire on the landscape using FARSITE. FARSITE (Finney 1998) is a deterministic fire spread model used to simulate wildfire behavior across a landscape. It accounts for both the spatial and temporal effects of fire and reports both

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<sup>7</sup> See Appendix D for a full description of the harvest priority table.

<sup>8</sup> Harvestable stands are defined as timber producing and available for forest management. Stands labeled as non-harvestable include stands which may contain endangered species or are associated with high use recreation.

area burned and fire intensity across a landscape. Wildfire behavior and spread are simulated using weather and landscape attributes, which includes fuel type and terrain. FARSITE produces three outputs for each simulation: burned in a surface fire, burned in a crown fire or not burned. There are six required pieces of information required to run FARSITE:

1. Landscape (vegetation/fuel and topography)
2. Wind (speed and duration)
3. Weather (temperature and humidity)
4. Ignition (location)
5. Fuel moisture (percentage)
6. Fire duration (described below)

Characteristics of the vegetation are described in the *Initial Landscape* section above.

Development of vegetation over time in response to growth, fire, and harvest is described below in *Updating the Landscape*. The sources of data for the remaining attributes are described later in *Generating Future Events*.

Suppression cost estimation was based on the size of the fire at containment: small, medium, or large. Typically, 98% of ignitions are suppressed shortly after being reported (Mark Finney, personal communication, February 4, 2011). In this case the fire is small (less than 0.4 ha or 1 acre) and assigned a cost of \$710. This was based on the average of all fires less than 0.4 ha for my study area over a 20-year period. Medium size fires are those that escaped initial attack and grew to between 0.4 and 121.4 ha (300 acres). The cost for a medium sized fire used a weighted average between the initial attack cost and the value computed by the suppression cost model (below).

For large fires (over 121.4 ha), I used a suppression cost model developed by Gebert et al. (2007) and later modified by Matt Thompson (personal communication, 8/23/2010). This model estimates suppression cost as a function of conditions at the start of a fire.

**Equation 7**

$$\ln\left(\frac{\text{cost}}{\text{acre}}\right) = 4.040437 + 0.019546(\text{ERC}) - 0.32068(\ln\_Acresburned) - 0.26234(\text{Disttown}) \\ + 0.142163(\text{Housingvalue}) + 0.113394(\text{Slope}) + 0.360279(\text{Elevation}) \\ - 0.14305(\text{COS Aspect}) - 0.05089(\text{SIN Aspect})$$

Where:

ERC: Energy Release Component. Index related to BTU (energy) output per unit area at the head of the fire.

Acres Burn: ( $\ln\_total$  acres burned). Total acres within the fire perimeter.

Town: ( $\text{disttown}$ ). Distance to La Pine.

Home Value: ( $\text{housingvalue}$ ). Total value of homes within 20 miles.

Slope:  $\text{LN}(\text{slope})$ . Slope at the point of origin (%).

Elevation:  $\text{LN}(\text{elevation})$ . Elevation at the point of origin (ft).

COS Aspect: Cosine of aspect in 45° increments from origin.

SIN Aspect: Sine of aspect in 45° increments from origin.

**UPDATING THE LANDSCAPE**

Vegetation was updated at the end of each simulation year. This was accomplished using a look-up table that links each starting state with a transition type to determine the post-transition state. The look-up table tracks attributes of vegetation as they evolve over time. Any group of attributes that can be assigned to a pixel (30m x 30m grid point) is called a state. Attributes of a pixel at the beginning of a year (old state) are transitioned to a pre-determined set of attributes from the look-up table at the end of the year (new state). A transition occurs when attributes of

the vegetation change following one of four possibilities: vegetation growth, surface fire, crown fire, or harvest. A fifth outcome is that the attributes do not change. In this case the vegetation attributes remain the same but the time-in-state decrements by one year, moving it one year closer to a grow transition.

To create the look-up, I expanded on the version developed by Houtman et al. (2013). My expanded version tracked attributes that were relevant to implementing harvests and incorporate more ecosystem dynamics. I added the attributes stand density index (SDI) and succession class. I also included transitions to represent lodgepole pine encroachment into unburned ponderosa pine stands. Lodgepole pine encroachment was tracked using the Plant Association Group to monitor the species composition of each unit over time (explained below). Fire and Fuels Extension of the Forest Vegetation Simulator (FVS-FFE) simulated tree growth to generate post-transition states for each initial state. Because FVS-FFE is too slow to run interactively, the look-up table was pre-processed to account for all possible future scenarios.

The transition attributes comprise three main groups (Table 2): (1) attributes required by FARSITE to determine both fire spread rate and intensity; (2) attributes related to the density and succession class; (3) the dominant species composition of the stand (PAG)<sup>9</sup>. The attributes used in the lookup table were subdivided into suitable ranges (Table 3) and each pixel on the initial landscape was assigned a set of attribute values (initial state). The ranges were based on examination of the full extent associated with each characteristic. Each range produced similar fire behaviors.

Fuel	Stand	Cover type
Canopy Cover (%) Canopy Height (ft) Canopy Bulk Density (kg/m <sup>3</sup> ) Canopy Base Height (ft) Fuel Model (Scott/Burgan 2005)	Stand Density Index (TPA) Succession Class	Plant Association Group (PAG)

**Table 2: List of attributes included in the lookup table. Fuels are used in the FARSITE fire simulation process. Stand characteristics define qualities about the stand for harvest. Cover type tracks vegetation types across the landscape.**

<sup>9</sup> Variables used to prioritize timber for harvest, determine volume harvested, and compute the restoration index.

In order to transition pixels to a new state, I used a growth simulator to project the future characteristics of the vegetation. The Forest Vegetation Simulator (FVS) is a deterministic individual tree growth and yield model used by land managers to develop reliable forest management strategies. FVS bases tree growth on standard inventory data and localized growth rates. The geographic region I used to simulate the growth rates was the Southern Oregon variant (2002).

For this project, FVS was used to grow all initial states, as represented by archetype tree lists used in the development of the look-up table. The purpose of the lookup table was to track how vegetation changed over the course of the 100-year period. This was accomplished by growing each tree list for 100 years. Each initial state was simulated for 100 years using FVS. This output was then placed into a range to be used in the lookup table (see lookup table section). FVS was also employed to determine harvest volumes and the post-harvest growth of candidate stands.

Canopy Cover (%)		Canopy Base Height (ft)	
Range	Value	Range	Value
0.0 – 0.1	0	0 – 1	0
0.1 – 10	5	1 – 5	3
10 – 40	25	5 – 15	10
40 – 75	55	15 – 25	20
75 - 100	90	25 +	30

Canopy Height (ft)		Canopy Bulk Density (kg/m <sup>3</sup> )	
Range	Value	Range	Value
0 – 5	5	0.0 – 0.01	0.0
5 – 45	25	0.01 – 0.05	0.03
45 – 90	65	0.05 – 0.1	0.08
90 +	100	0.1 – 0.2	0.15
		0.2 – 0.35	0.28

**Table 3: Ranges and assigned values for the for the lookup table transitions. The range of values were assigned after observing the maximum values following multiple FVS simulations. These ranges also represent characteristics of the vegetation in each state**

FFE-FVS operates in conjunction with FVS by using keywords to predict the effect of fuel dynamics and fire behavior on stand development. While FFE-FVS does not simulate fire spread

or assign fire probabilities, it does measure potential fire intensities associated with input stand and fuels conditions. I used FFE-FVS to simulate varying levels of wind and temperature to determine the effects of crown and surface fires on fuels.

Because fire suppression has allowed for the increased spread of lodgepole pine into ponderosa pine stands, I devised a method to account for this during the transition phase. A pixel never changed its initial PAG classification. This is because PAG is dependent on abiotic characteristics. However, ponderosa pine pixels did vary by the amount of lodgepole pine present. These units were allowed to modify throughout the 100 simulations as follows:

1. 0% lodgepole pine: if this pixel is not adjacent to a lodgepole PAG, it remains 0% lodgepole pine regardless of whether a growth, fire, or harvest event occurred. If this pixel was adjacent to a lodgepole pine PAG, it will transition to 0-10% lodgepole cover in 20 years without a fire or harvest event.
2. 0 – 10% lodgepole pine: if this pixel has no fire event in 30 years, it will transition to a >10% lodgepole pine PAG. If there is a surface fire, it will transition to 0% lodgepole pine post-surface fire PAG. If there is a crown fire, it will transition to a 0% lodgepole pine post-burn PAG.
3. >10% lodgepole pine: if this pixel has no fire or harvest event, it will remain in this PAG. If there is a surface fire, it will transition to 0-10% lodgepole pine post-surface fire PAG. If there is a crown fire, it will transition to a 0% lodgepole pine post-burn PAG.

While the lookup table is extensive, it only captures the variation associated with a limited number of tree lists assigned to the initial landscape. Because of this limitation, fuel models tracked by the forest growth simulator could underestimate the actual fuel loads. This has the potential to result in uncharacteristically low-intensity fires during the FARSITE fire simulations.



## GENERATING FIRE EVENTS

Multiple 100-year trajectories of future fires were simulated for each fire of interest. Two scenarios were simulated for each trajectory – one in which the fire of interest was allowed to burn and one in which it was suppressed. The output for each pair of simulations was used to evaluate  $\Delta v$  and  $\Delta R$ . The expected net value change,  $E[\Delta v]$ , was based on the average  $\Delta v$  for the 10 sample pathways that were simulated for each fire of interest.

In this section, I briefly describe how the set of 100-year trajectories of future fires was developed. For a detailed description, see Houtman (2013). The trajectory of fire events over the 100 years for each simulation was determined using Monte Carlo methods. Ignition traits were drawn from Forest Service historical human and lightning-generated ignition data. Traits included date of ignition, location, and whether or not the ignition resulted in fire spread.

Weather attributes (temperature, humidity and precipitation) were also drawn from historical data. Wind attributes consisted of wind speed and direction. These data were obtained from the remote Automated Weather Station (RAWS) at Cabin Lake, OR. A randomly selected weather year was chosen for each year of fire simulations. Ignitions were assigned a date (and the weather for that date) from historical frequency. Only 24 years of data were available so the variation in weather was limited throughout the simulations.

Since FARSITE requires user input for fire end dates, a method was developed to choose dates appropriately. For fires that were allowed to burn, end dates were chosen based on thresholds of fire-weather characteristics. For fires that were suppressed, end dates were identified by a regression developed by Finney et al. (2009) that uses several fire and weather attributes to determine whether or not suppression was successful every day following an ignition until the fire was out.

## DECISION REGRESSION

In this section I analyze the change in value following multiple simulated fire events on a historically fire-dependent portion of the Deschutes National Forest dominated by ponderosa pine. The future landscape structure is likely to be different depending on whether the fire of interest is suppressed or allowed to burn. Analyzing these differences and assessing the likely occurrence of a particular outcome can help a federal land manager understand when it might make sense to allow a real-time wildfire to burn. To do this, I generate the difference in value of letting the fire of interest burn to suppressing the same fire of interest ( $\Delta v$ ). I then used regression analysis to explore the conditions under which net value change is positive.

The data consisted of 2,500 fires of interest (FOI). A FOI is a fire at time zero on the initial landscape. For each FOI, I created 10 sample pathways. Each FOI and its associated sample pathways were simulated twice. One simulation suppressed the fire ( $X_o = 1$ ) and the other let the fire burn ( $X_o = 0$ ). This produced a total of 25,000 pairs of simulations for the landscape. The difference in each pair of simulations generated an estimate of  $\Delta v$  following Equation 3. For each FOI, I generated the expected value of the net value change ( $E[\Delta v]$ ) which is simply the average  $\Delta v$  over its 10 sample pathways.

My regression analysis examined the relationship between factors that drive fire behavior (independent variables) and the resulting value (dependent variable) following numerous simulations. I did this by constructing a pooled panel regression to explore conditions under which a let burn decision could generate positive net value change on this landscape. Equation 9 shows the regression and its component parts. For simplicity, dummy variables are only shown by group. For example,  $D_{Month}$  is a dummy variable for the month the fire occurred (October being the omitted variable).

For the dependent variable I used expected net value change for a particular fire of interest (FOI),  $E[\Delta v]$ . The result is 2,500 values for  $E[\Delta v]$  derived from 25,000 paired simulated values of  $\Delta v$ . Since each FOI had one set of unique fire attributes, using  $E[\Delta v]$  helped eliminate the

uncertainty associated with each future outcome. Therefore, using  $E[\Delta v]$  as my dependent variable allowed me to focus on the fire attributes by averaging  $\Delta v$  over the 10 sample pathways for each FOI. The data for the regression analysis were constructed as follows.

### Equation 9

$$E[\Delta v] = \beta_0 + \beta_1 X_{ERC} + \beta_2 D_{Month} + \beta_3 D_{Cover Type} + \beta_4 X_{Wind Speed} + \varepsilon$$

Where:

$E[\Delta v]$	Expected change in value of the landscape.
$X_{ERC}$	Energy Release Component for the fire of interest.
$D_{Month}$	Dummy variable for month fire of interest occurs.  1 if month equals May, June, July, August, or September.  October is the omitted variable.
$D_{Cover Type}$	Dummy variable for cover type fire of interest occurs.  1 if cover type equals, PP, PP (0-10% LP), PP (>10% LP), or LP.  MC is the omitted variable.
$D_{Wind Speed}$	Wind speed at the time of ignition.

The independent variables were chosen based on two factors. First, they must be derived from information a land manager would have relatively easy access to in the event of a fire. The assumption is that the point of ignition is observed and the weather is documented in a reasonable amount of time for the land manager to make a decision. Second, these characteristics produced the most significant results with limited multicollinearity and provided a reasonable first attempt at predicting future values.  $E[\Delta v]$  is used in two ways. First, the values at the time of ignition (independent variables) were regressed against  $E[\Delta v]$  to determine if there was a

relationship. Second, the coefficients were used to determine whether or not a future fire is likely produced a net positive or negative future value.

Using attributes associated with the landscape at the time of disturbance, I developed the framework for a decision making process using both actual and simulated features of our landscape. Wind speed, likely ignition occurrences, and energy release component were generated for all fire events using replicated conditions based on historical weather data. Fuel models were produced for all stands using a growth and yield model (FFE-FVS). Together these variables are regressed on the expected change in value ( $E[\Delta v]$ ) for each fire of interest. An analysis of the coefficients will follow to determine what qualities of the landscape have the most importance in predicting future fire management decisions.

## RESULTS

The first objective of this thesis is to examine expected net value change from allowing a fire of interest to burn and then to understand under what conditions it is likely to be positive, i.e.  $E[\Delta v] > 0$ . The second objective is to explore the effect of a let burn decision on the distribution of ponderosa pine succession classes relative to pre-European settlement conditions. Therefore, the results are presented in two parts.

Part 1 focuses on the analysis of the quantifiable data. First, I compare how harvest revenue and suppression costs affect the landscape expected change in value ( $E[\Delta v]$ ) between the let burn and suppress scenarios. Second, I focus on the decision making process. I use information related to the fire of interest to explore using regression analysis as a tool in assessing under what conditions there is a higher probability of a positive net benefit if a fire of interest is allowed to burn. In Part 2, I examine how the Restoration Index changes in ponderosa pine stands as a result of allowing a fire of interest to burn.

## Part 1

### Change in Value

The change in value of the landscape from allowing a wildfire to burn,  $\Delta v$ , is used to help determine when a current fire could have a suppression attempt or not. A positive value of  $\Delta v$  represents a future suppression cost saving which exceeds a loss of timber revenue when the current fire is allowed to burn. This is due to larger benefits in terms of future harvest revenue, greater future suppression cost savings, or some combination of both.

To reduce variation across pathways, my analysis was conducted on the expected value of each fire of interest over the 10 pathways ( $E[\Delta v]$ ). This allowed me to eliminate some of the uncertainty associated with a particular fire ( $\Delta v$ ) and focus on how attributes of a particular fire ( $E[\Delta v]$ ) affect the outcomes. Values were evaluated in 2011 dollars and discounted over the course of 100 years.

I separated  $E[\Delta v]$  into its component parts: suppression cost and harvest revenue. Each part revealed information about what determines whether the net value change will be positive or negative. Table 4<sup>10</sup> summarizes the results.

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<sup>10</sup> Initial suppression cost and the change in value of the ending landscape are omitted from  $E[\Delta v]$ .

	Net Value Change (\$) $E[\Delta v]$	Change in Suppression Cost (\$) $E[\Delta C]$	Change in Harvest Value (\$) $E[\Delta H]$
# OBS	2500	2500	2500
Mean	657,046.95	-473,789.32	74,678.29
Range	-743,740.61 to 10,229,529.18	-3,974,996.31 to 634,534.42	-432,934.44 to 618,474.81
95% CI	-1,070,676.75 to 2,384,770.64	-1,559,263.12 to 611,684.48	-113,195.75 to 262,552.32
% > 0	93.28%	13.76%	78.52%

**Table 4: Summary of expected value of the 10 pathways for each FOI (2,500 observations).**

Net Value Change ( $E[\Delta v]$ ) shows the overall value of the landscape if the fire of interest was allowed to burn. A positive value for  $E[\Delta v]$  suggests a net benefit and signifies that it may be optimal to allow the fire of interest to burn. Interestingly, the data shows an overwhelming percentage of positive values. Since  $E[\Delta H]$  and  $E[\Delta C]$  are components of  $E[\Delta v]$ , each of these parts are further broken to help determine what factors may play a more defining role in the values of  $E[\Delta v]$ . A detailed breakdown of the values for  $E[\Delta H]$  and  $E[\Delta C]$  is contained in the Discussion section below.

Change in harvest revenue ( $E[\Delta H]$ ) approximates the amount of harvest revenue gained from allowing the fire of interest burn. The overall range was -\$432,789 to \$618,475, yet only 21% of the results were negative. A negative  $E[\Delta H]$  reflects a situation where harvest revenue was greater when the fire of interest was suppressed.

In contrast, change in suppression cost saving ( $E[\Delta C]$ ) estimates the amount of future suppression dollars saved if the fire of interest is allowed to burn. When compared to  $E[\Delta H]$ , the overall range was quite large (-\$3.97M to \$.634M). The outcomes were positive 14% of the time. A positive  $E[\Delta C]$  is the result of higher future suppression costs when the fire of interest

was allowed to burn. Consequently, 86% of the outcomes produced a savings in future suppression costs when the fire of interest was allowed to burn.

### Decision Regression Analysis

The purpose of this regression is to explore conditions that may help a land manager determine whether a fire should be suppressed or not. The basic assumptions are that the fire occurs in an area designated as available to let burn and the necessary inputs (weather, fuel conditions, land features, etc.) are accessible to the land manager. In this analysis, I regressed the expected change in value ( $E[\Delta v]$ ) resulting from the multiple simulations on those features. Figure 2 shows the distribution of  $E[\Delta v]$ .

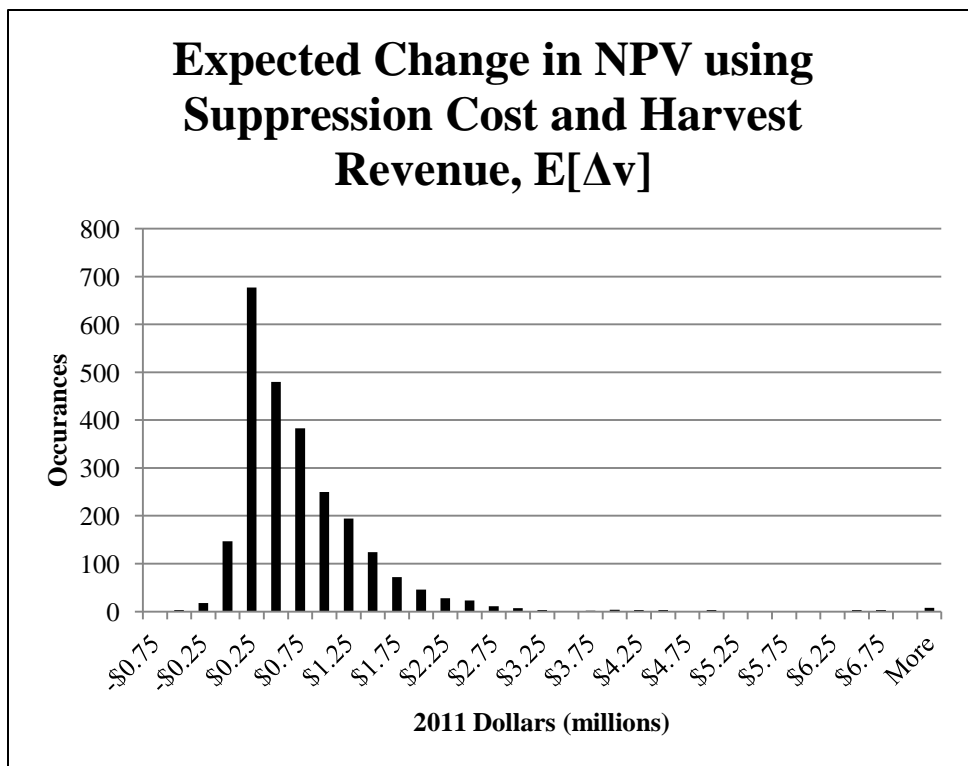


Figure 2: Change in Expected Net Present Value of Suppression Cost and Harvest Revenue,  $E[\Delta v]$ , over 2,500 paired simulations in dollars (2011).

Table 5 summarizes the coefficients resulting from regressing the expected change in value ( $E[\Delta v]$ ) on landscape and weather independent variables with a harvest level of 27.3M BDFT. Nominal data, namely month the ignition occurred and the plant association group, included reference variables to account for the dummy variable trap. October was removed for month of ignition and unknown/barren was removed for plant association group.

	Coefficient	T-Stat( $E[\Delta v]$ )
Intercept	-749471.89	-8.30***
ERC	6445.11	9.26***
May	367828.32	4.93***
June	678166.27	10.02***
July	802631.61	13.11***
August	633733.53	10.63***
September	228181.00	3.27***
Mixed Conifer	496758.72	6.15***
PP Pure	314481.21	5.35***
PP < 10% LP	270120.89	3.06***
PP > 10% LP	287380.97	5.34***
Lodgepole	377167.02	7.06***
Wind Speed	9832.83	3.45***
Standard Error	799762.39	
Adjusted $R^2$	.1428	
F - Statistic	35.72	

**Table 5: Coefficients for Expected Value ( $E[\Delta v]$ ) Regression.** \*\*\* = 99%, \*\* = 95%, \* = 90% confidence levels.

All of the coefficient estimates were highly significant and positive<sup>11</sup>. This is especially true for those coefficients positively correlated with fire intensity and size (ERC and wind) and, hence, future suppression costs relative to the reference case. The indication is, given the low harvest levels imposed, that future suppression cost savings dominate the net value change associated with any particular ignition. In other words, any fire that reduces future fuel levels, given my imposition of a suppression policy in all future periods, will result in a suppression cost savings.

Coefficient estimates not directly related to fire behavior also produced positive values. This suggests that both month of ignition and vegetation characteristics (PAG) are producing fires that

<sup>11</sup> A regression analysis was also performed for the 25,000 paired simulations,  $\Delta v$ , and the coefficient estimates were the same, the standard errors were smaller, and  $R^2$  was lower.



reduce future fuel levels and, therefore, are reducing future suppression costs. Consequently, any fire that is likely to be big will be more financially beneficial.

$R^2$  was extremely low and the Standard Error of the regression was large, thereby suggesting a model with very little predictive power. The F-Stat, on the other hand, produced a large value. This indicates a relationship between the independent variables and the outcome. The bottom line is that while the outcomes are highly variable, the model may be useful in a planning context. This may benefit a land manager when trying to decide under what conditions a let-burn decision may be more likely to produce a more financially beneficial result.

## Part 2

### Restoration Index

Restoration Index is an attempt to measure how the landscape composition (e.g. ponderosa pine) compares to a baseline pre-settlement forest composition over time. The values were tracked at years 20, 50, and 100 for each simulation and plotted to show the distribution over time. I then investigated how the values changed in both the let burn and suppress scenarios. Values were analyzed using all of the pathways and average of the pathways. The purpose is to examine if allowing a fire to burn can have a positive net impact on the Restoration Index.

All simulations were based off the original landscape, which had a Restoration Index of 505. Output can be compared to either the Restoration Index of 505 or by comparing the difference between let burn and suppression outcomes for the same fire of interest. The statistical values for both the let burn and suppression scenarios at 20, 50, and 100 years are displayed in Table 6.

A. Restoration Index for all Fires of Interest and Pathways						
	Let Burn			Suppress		
Year	20	50	100	20	50	100
Range	74 - 1208	74 - 1278	23 - 1559	88 - 1209	78 - 1278	21 - 1573
Mean	874	805	773	1090	885	833
Median	928	861	791	1187	1032	847
S. Deviation	273	303	348	233	333	364

B. Restoration Index for the Average of each Fire of Interest						
	Let Burn			Suppress		
Year	20	50	100	20	50	100
Range	115 - 1197	418 - 1199	383 - 1213	422 - 1201	521 - 1199	453 - 1221
Mean	874	805	773	1090	885	833
Median	915	810	774	1100	886	832
S. Deviation	211	123	123	84	105	117

**Table 6: Observations of Restoration Index for A. All Fires of Interest and their associated Sample Pathways, and B. the average of the Pathways for each Fire of Interest.**

The data outline a few important trends over time. In only 20 years, the mean Restoration Index increases significantly (874 - let burn; 1090 - suppress) regardless of whether the fire of interest was suppressed or not. This extreme shift is most likely due to two factors: lack of variability in the initial landscape and many stands quickly transition to dense succession classes early.

As the simulations continued forward in time, the mean Restoration Index decreases for each scenario. While future harvests may play a small part in the reduction, I believe that future fires escaping suppression attempts along with natural vegetation transitions play a dominant role. This is most likely due the limited harvest volumes used for the model.

## DISCUSSION

In the Results sections, it was shown that expected net value change ( $E[\Delta v]$ ) produced a large percentage of positive values. In order to help understand what may have caused this, I broke  $E[\Delta v]$  into its component parts,  $E[\Delta H]$  and  $E[\Delta C]$ . Separating these components allowed me to see what factors, if any, have more of an influence over  $E[\Delta v]$ . Ultimately, an understanding of how these factors drive the sign of  $E[\Delta v]$  can help federal land managers better determine where to focus future management strategies. In particular, those strategies which may provide a future positive net economic benefit and potentially reduced future suppression costs.

Harvest revenue,  $E[\Delta H]$ , produced an unexpectedly high number of positive values. A positive value occurs when harvest revenues are greater if the fire of interest is allowed to burn. There are

a number of possible reasons for this. For one, harvest selection occurred using a prioritization process and was based on availability. The program may have simply selected higher value timber harvests in the let burn pathways. In the end, the timber harvests were small enough to not generate an appreciable difference in value between the two scenarios.

At such low timber harvest levels, harvest revenue only played a small role in determining the expected net value change  $E[\Delta v]$ . Because average ASQ is well below the Deschutes Forest Plan annual projected average, there was always sufficient harvestable timber to meet the allowable cut target. Future fire scenarios rarely impacted available harvest requirements.

In other words, the average ASQ did not provide enough harvestable BDFT to make any appreciable difference in the overall change in value over the 100 years. On average, less than a 1,000 ha were harvested in each ten-year period. This quantity was not enough to allow a significant divergence in the amount harvested between the two scenarios. Since the 10-year cap on harvesting is set at 27.3M BDFT, each scenario harvested the maximum amount over 95% of the time. To impact expected value of net value change,  $E[\Delta v]$ , either the amount of allowable harvest in each 10-year period would have to be increased or there would need to be more frequent harvests.

A closer look at the magnitude of suppression cost,  $E[\Delta C]$ , reveals that it contributes more weight to expected net value change. Harvest revenue, on the other hand, is limited in its influence over net value change. For example, when analyzing the expected net value change, timber revenue will have little to no effect unless the suppression cost savings fall in the range of approximately -\$400,000 to \$600,000. While this does occur 67% of the time, harvest revenue's impact will not change  $E[\Delta v]$  unless its absolute value is greater than the suppression cost saving.

Of the fires allowed to burn in year zero, the average size was 7,245 ha and the largest was 52,358 ha. Therefore, approximately 10% of the landscape burned on average in year zero. Over 90% of the burned area recorded in year zero were surface fires. Surface fire not only provided

more future suppression cost savings by allowing fire to reduce surface fuels, they help to redistribute vegetation structures across the landscape. The preponderance of surface fires most likely affected timber harvests. Surface fires can help reduce competition for resources by allowing for more growth in the un-burned larger trees. This may have contributed to larger harvest revenues (overwhelming positive  $E[\Delta H]$ ) produced in the let burn scenario as compared to the suppression scenarios.

The underlying intent of this thesis is to lay the foundation for a model that can provide a decision support tool to help federal land managers predict when there may be an option to restrain suppression efforts on future wildfires. By comparing benefits and costs between letting a fire burn and suppressing a fire, I begin to explore how a wildfire can impact future harvest revenues and suppression costs.

Regression analysis provides the baseline for this cost/benefit investigation. Factors affecting fire behavior were regressed on simulated future expected values. This helped determine how much influence fire behavior variables have on potential future cost savings. The coefficient estimates are presented in the Results Section above. What follows is an analysis of the relationships between the coefficient estimates and their potential effect on future cost savings.

The coefficient estimate for Energy Release Component (ERC) is highly significant. The values for ERC range from 0 to 100. As ERC increases, the potential fire intensity rises. A positive coefficient suggests that a one unit increase in ERC increases the net value by \$6,445. Therefore, the larger the ERC value, the higher possibility of a larger area burned which could result in lower future suppression costs. This relationship provides evidence that it may be optimal to allow a fire to burn when the ERC is higher.

I next investigated how the timing of the ignition affected value. All coefficient estimates are significantly greater than zero regardless of the month the ignition occurred. The coefficient estimates for each month indicate that it is less likely to be optimal to let burn in October than in any other month. The coefficient estimate for July is the largest, indicating that it is more likely

to be optimal to let burn in July than in any other month. An ignition occurring in May or September is less likely to affect net value change. Ignitions occurred less frequently during the months of May, September, and October.

Cover type, as defined here by plant association group (PAG), also displayed coefficient estimates that were significantly greater than zero. The largest estimates occurred in mixed conifer and lodgepole pine. The coefficient estimates show that an ignition in ponderosa pine appears to be significantly less likely to be financially optimal to let burn than one that ignites in mixed conifer or lodgepole pine. In other words, characteristics of mixed conifer and lodgepole pine stands tend to produce more future financially optimal fires.

On average, ignitions occurring in both lodgepole pine and mixed conifer burned 20% more area than any of the three ponderosa pine PAGs when no suppression attempt was made. This could be the result of increased fuel loads associated with years of fire suppression. The coefficient estimates could also be an indicator of decreased future suppression costs associated with allowing current fires to burn. If a current fire were allowed to burn, future suppression costs should be curtailed by reducing the future area capable of burning, thereby contributing to a greater likelihood of a future financial gain.

Wind speed at the time of ignition was also analyzed. As wind speed increases so does fire intensity and rate of spread. Wind speeds greater than 15 mph at the time of ignition produced fires approximately 15% larger in area than those with wind speeds less than 15 mph. Like stated above, more area burned in the fire of interest has a higher likelihood of reducing future suppression costs. This coefficient estimate indicates that as wind speed increases, it becomes more optimal to let the fire of interest burn.

Next, I address how the model can help with the decision making process. The overall intent of the regression is to predict a statistically valid ending change in value ( $\Delta v$ ), and consequently  $E[\Delta v]$ , on the overall landscape following an ignition. Given known landscape and weather attributes at the time of ignition, a federal land manager can use that information to acquire a

likely cost/benefit assessment if the fire is allowed to burn. The question then becomes how valid is the assessment and to what degree of certainty can the manager place on making a valid decision as to whether to let burn or suppress?

As Table 5 illustrates above, the model produces conflicting results. The model produced highly significant coefficients (high F-statistic) that are clearly correlated with  $E[\Delta v]$ . However, the Adjusted  $R^2$  is relatively low and the Standard Error is extremely high. This suggests a model that has very little predictive power. The low  $R^2$  reveals low explanatory power with the model, while the high Standard Error states outcomes can vary significantly.

Additionally, I propose a means of valuing the forest based on a restoration index. State and transition models were used to group stands into succession classes based on tree size and density. These succession classes can play a role in determining how to value a landscape based solely on its composition, i.e. if the goal is non-monetary valuation.

As stands develop over time, the mean Restoration Index decreases. However, the mean does not decrease below the initial landscape value of 505. When analyzing those pathways that do reach Restoration Indices of 505, over 90% of those pathways had fires which escaped suppression efforts late in their 100 year cycle. 70% of those escaped fires were over 15% of the landscape in burned area. This opens up the question as to whether allowing more fires to burn could have more of a positive impact on Restoration Index.

If the goal is to manage to a more fire resilient forest structure, then Restoration Index can help federal land managers determine future treatment timing and locations. Future simulations should take into account Restoration Index when determining let burn scenarios. For example, placing a let burn policy at certain intervals in the future may help decrease densities associated with shade tolerant species infiltrating ponderosa pine stands experiencing fire exclusion. This model could be used to simulate many possible futures to help determine when the highest probabilities of success are for designing a more fire resilient forest.

## CONCLUSION

There are a number of limitations in the model. The most apparent is the lack of variability in the initial landscape. While there was enough data provided by the FIA plots to create a significant amount of initial variability, I was limited by processing times. In order to create the look-up table containing all possible future outcomes, simulations were needed for all potential wildfires, harvests, and growth outcomes. The volume of the simulations limited the number of stands I could use to populate the initial landscape. Pre-processing work could be alleviated by incorporating a program to analyze stands at the end of the season. This would ideally provide the necessary information to populate the look-up during the simulation.

Harvest levels did not play as important a role as they could have because there was simply too much available timber for harvest. Typically, political, and even economic, concerns will direct how much timber is harvested and when. I would propose analyzing how harvesting more timber than currently permitted would affect the value of future landscapes.

Another concern with the program is how crown fire was generated. Because of limitations in variability contained within its algorithm, FARSITE tended to underestimate crown fire. This may have been the result of a lack of variability in or misrepresentation of the vegetation characteristics used in determining transition tables and used as inputs to FARSITE.

Even with these limitations, I believe the simulator is a beneficial initial step in planning a let-burn policy. Choosing an area to let-burn is not a simple process. Increasing values at risk are high concern for federal land managers and the wildland urban interface is increasing along boundaries. Therefore, a let-burn candidate would have to meet a number of criteria. Any area where managers have the opportunity to burn would have to be away from areas of significant risk.

Federal land managers would also have to take into account all of the local features in the landscape. Elevation, aspect, slope, fuel characteristics, etc. are all important factors in

determining fire behavior. Time sensitive values, such as weather, are also important in determining whether to allow a landscape to burn or not. Even if a landscape is a good candidate, an unusually hot and/or dry weather pattern may prompt managers to suppress an ignition that would otherwise been left to burn. Factors such as these are outside the scope of this project.

In this analysis, I focus only on economic values related to green timber harvesting and wildfire suppression costs. I also provide a framework to value the landscape based on departures from a restoration index. This is just one tool to help the land manager. As this project continues forward, others will work towards broadening the capabilities of the program. One such method will be to introduce Approximate Policy Iteration while simulating let burn versus suppress future scenarios. Other possibilities include creating a more sophisticated let burn policy than the dichotomous choice. Examples of other possible strategies include revisiting decisions over the life of a particular fire, more emphasis on values at risk, or accounting for the potential rate of spread or direction of a particular fire, and examining how timber salvage will affect the decision making process.



## APPENDIX A

### Ponderosa pine succession class distribution

	Development	% Cover	DBH Range	% Desired	% Actual	Difference
A	Early	0 – 40%	< 5"	10%	9.22%	-0.78%
B	Young-Dense	> 40%	5 – 21"	5%	36.45%	31.45%
C	Young-Open	10 – 40%	5 – 21"	35%	37.62%	2.62%
D	Old-Open	10 – 40%	> 21"	45%	6.22%	-38.78%
E	Old-Dense	> 40%	> 21"	5%	10.49%	5.49%

### Mixed conifer succession class distribution

	Development	% Cover	DBH Range	% Desired	% Actual	Difference
A	Early	0 – 40%	< 5"	10%	2.20%	-7.80%
B	Young-Dense	> 40%	5 – 21"	5%	34.35%	29.35%
C	Young-Open	10 – 40%	5 – 21"	30%	47.19%	17.19%
D	Old-Open	10 – 40%	> 21"	45%	13.96%	-31.04%
E	Old-Dense	> 40%	> 21"	10%	2.30%	-7.70%

### Lodgepole pine succession class distribution

	Development	% Cover	DBH Range	% Desired	% Actual	Difference
A	Early	0 – 40%	< 5"	25%	16.88%	-8.12%
B	Old-Dense	> 40%	≥ 5"	55%	33.91%	-21.09%
C	Old-Open	10 – 40%	≥ 5"	20%	49.21%	29.21%

**Table 7: Distribution of the initial three cover types (PAG) by succession classes over the entire landscape.**

## APPENDIX B

### A. Steps for determining the Succession Class of both ponderosa and pine and mixed conifer

#### Step 1: Determine the Size Class of the stand

	Size Class
a. Is the canopy closure of the stand less than 10%?	1
b. Are there 10 or more trees per acre of DBH 21"+?	3
c. Do the trees of diameter class 21"+ have a canopy closure plurality?	3
d. Do the trees of diameter class 5 – 20.99" have canopy closure plurality?	2
e. Is the canopy closure of trees in the diameter class 5"+ greater than the canopy closure of trees in the diameter class 0 – 4.99"?	2
f. Is the canopy closure of trees in the diameter class 0 – 4.99" greater than the canopy closure of trees in the diameter class 5"+?	1
g. Is the canopy closure of trees in diameter class 21"+ greater all other classes?	3
h. Is the canopy closure of trees in diameter class 5 – 20.99" greater all other classes?	2
i. Is the canopy closure of trees in diameter class 0 – 4.99" greater than all other classes?	1

	Size Class
Seedling/Sapling (.1 – 4.99" DBH)	<b>1</b>
Small(5.0 – 20.99" DBH)	<b>2</b>
Large (21"+ DBH)	<b>3</b>

#### Step 2: Use Size Class and Canopy Cover to determine Succession Class

	Canopy Cover $\leq$ 40%	Canopy Cover > 40%
Size Class 1	<b>A</b>	
Size Class 2	<b>C</b>	<b>B</b>
Size Class 3	<b>D</b>	<b>E</b>

**B. Steps for determining the Succession Class of lodgepole pine**

**Step 1:** Determine the Size Class of the stand

	<b>Size Class</b>
a. Is the canopy closure of the stand less than 10%?	1
b. Do the trees of diameter class 5"+ have a canopy closure plurality?	2
c. Do the trees of diameter class 0.0 – 4.99" have a canopy closure plurality?	1
d. Is the canopy closure of trees in the diameter class 5"+ greater than the canopy closure of trees in the diameter class 0 – 4.99"?	2
e. Is the canopy closure of trees in the diameter class 0 – 4.99" greater than the canopy closure of trees in the diameter class 5"+?	1

	Size Class
Seedling/Sapling (.1 – 4.99" DBH)	<b>1</b>
Pole, Small, Large(5.0"+ DBH)	<b>2</b>

**Step 2:** Use Size Class and Canopy Cover to determine Succession Class

	Canopy Cover ≤ 40%	Canopy Cover > 40%
Size Class 1	<b>A</b>	<b>A</b>
Size Class 2	<b>C</b>	<b>B</b>

**Table 8: Steps for determining succession class for A. Ponderosa pine and mixed conifer, and B. Lodgepole pine.**

## APPENDIX C

The method for choosing harvestable stands was determined at the pixel level. The selection was based on a C++ ranking technique called priority queue. First, the program randomly selected a candidate pixel (30m x 30m grid point) from the highest priority pixels available. All neighboring pixels (those touching at least one side) were sent to the priority queue and ranked by priority number, perimeter, and order. The next candidate pixel selected was removed from the priority queue. All non-selected pixels remained in the queue. As long as a pixel remained in the queue, it was still a candidate.

Harvests occurred every ten years starting with year zero. The steps for choosing harvested areas are as follows:

1. Assign a priority to each pixel on the landscape from 31 to 0 (0 is un-harvestable).
2. Randomly choose one pixel from the highest available priority group<sup>12</sup>.
3. Look at each pixel adjacent to (shared sides) the randomly chosen pixel.
4. Choose the adjacent pixel with either:
  - a. Same priority (if more than one pixel qualifies, use first pixel checked)
  - b. Highest number of sides touching other chosen priority pixels (alternate criteria for more than pixel qualifying).
5. Repeat steps 3 and 4 until either:
  - a. Reach the maximum allowable harvest area of 180 pixels (approximately 40 acres),  
or
  - b. Run out of qualifying pixels and do not meet minimum required harvest area of 90 pixels (approximately 20 acres).
6. Repeat step 2 through 5 until either:
  - a. Reach the maximum allowable cut of 27.3 MBFT, or
  - b. All possible combinations for the harvest in question have been exhausted.

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<sup>12</sup> All harvested units were marked and not allowed to be chosen for any other harvest event during the year in question only.

## 7. Apply harvest (See Updating the Landscape).

Occasionally, due to limited availability, selected pixels within a priority class were too small to form a harvestable stand. The two main reasons for this were prior harvest or fire. This would result in small numbers of pixels (less than 180) being isolated and, therefore, not harvested with similar priority pixels. To overcome this issue, higher priority pixels were allowed to be included with the harvest selection of lower priority pixels. This could only occur within the same cover type (species).

## APPENDIX D

Priority (High to Low)	Cover	Stand Density Index (SDI)	Succession Class	Time Since Harvest	BDFT
31	PP	2	5	100	6355
				90	5509
				80	4672
				70	4170
				60	3562
				50	2335
				40	1625
				30	932
				20	483
30	LP	1	2	100	7123
			3		4689
29	PP	1	5	100	2997
			2		2741
28	PP	1	3	100	1616
			4		1276
27	MC	1	5	100	5136
			4		1317
			3		1616
			2		3226
26	LP	1	2	90	6553
			3		4223
25	PP	1	5	90	3861
			2		2917
24	PP	1	3	90	1591
			4		1211
23	MC	1	5	90	4339
			4		1293
			3		1591
			2		3305

Priority (High to Low)	Cover	Stand Density Index (SDI)	Succession Class	Time Since Harvest	BDFT
22	LP	1	2	80	5861
			3		3684
21	PP	1	5	80	4454
			2		2742
20	PP	1	3	80	1551
			4		1189
19	MC	1	5	80	3670
			4		1324
			3		1551
			2		3134
18	PP	1	5	70	3735
			2		2444
17	PP	1	3	70	1534
			4		1156
16	MC	1	5	70	2971
			4		1322
			3		1534
			2		3025
15	PP	1	5	60	3043
			2		2002
14	PP	1	3	60	1388
			4		1136
13	MC	1	5	60	2503
			4		1025
			3		1388
			2		1317
12	PP	1	5	50	2408
			2		1765
11	PP	1	3	50	1282
			4		1016

Priority (High to Low)	Cover	Stand Density Index (SDI)	Succession Class	Time Since Harvest	BDFT
10	MC	1	5	50	2155
			4		930
			3		1282
			2		2690
9	PP	1	5	40	1929
			2		1241
8	PP	1	3	40	1176
			4		1006
7	MC	1	5	40	1650
			4		906
			3		1176
			2		2010
6	PP	1	5	30	1486
			2		886
5	PP	1	3	30	849
			4		921
4	MC	1	5	30	1446
			4		851
			3		849
			2		1368
3	PP	1	5	20	1043
			2		507
2	PP	1	3	20	488
			4		821
1	MC	1	5	20	1113
			4		740
			3		488
			2		1112

Table 9: Harvest priority table



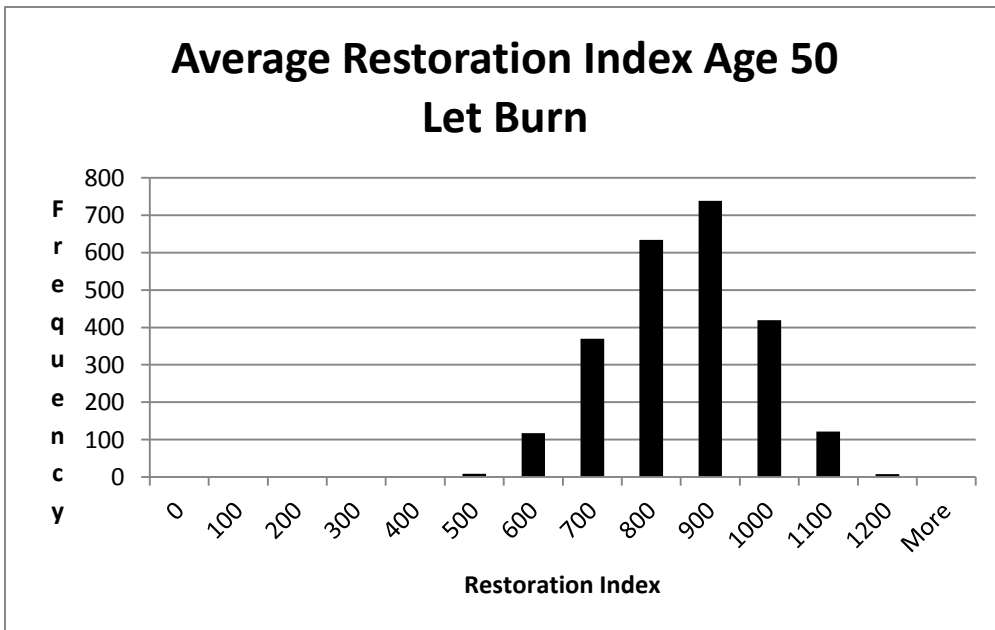
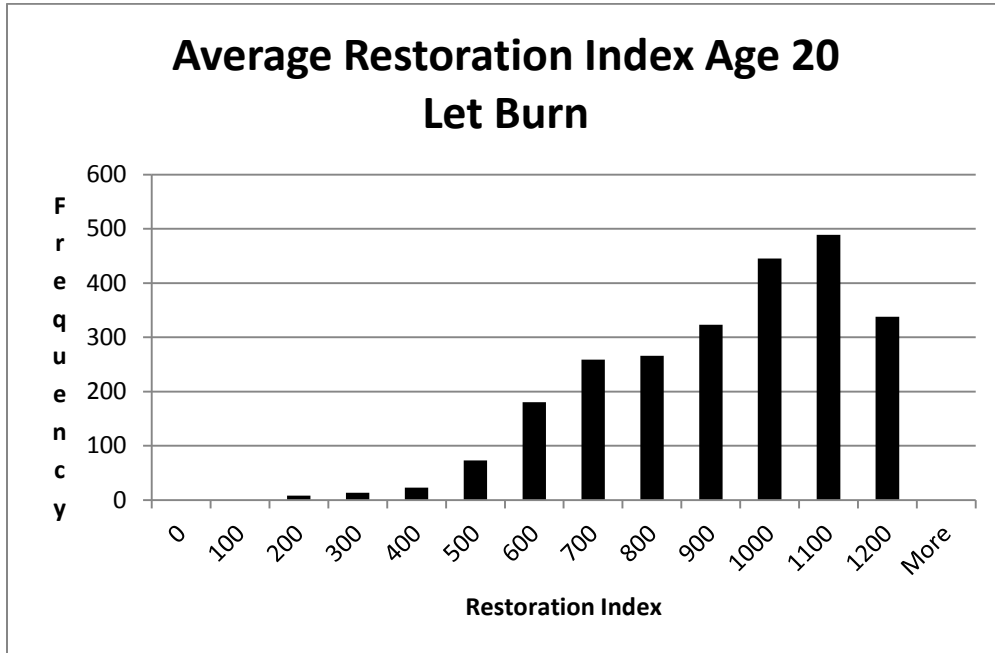
## APPENDIX E

A. Restoration Index for all Fires of Interest and Pathways						
Let Burn			Suppress			
Year	20	50	100	20	50	100
Range	28 – 1208	7 – 1231	25 – 1553	93 – 1209	42 – 1232	19 – 1538
Mean	867	801	658	1094	882	732
Median	921	891	616	1190	1052	685
S. Deviation	280	315	363	232	329	395

B. Restoration Index for the Average of each Fire of Interest						
Let Burn			Suppress			
Year	20	50	100	20	50	100
Range	35 – 1201	53 – 1177	169 – 1186	422 – 1203	477 – 1177	369 – 1215
Mean	867	801	658	1094	882	732
Median	901	809	654	1103	884	728
S. Deviation	221	137	144	83	104	129

**Table 10: Restoration Index. A. All Fires of Interest and associated Sample Pathways, and B. the average of the Pathways for each Fire of Interest**

**APPENDIX F**



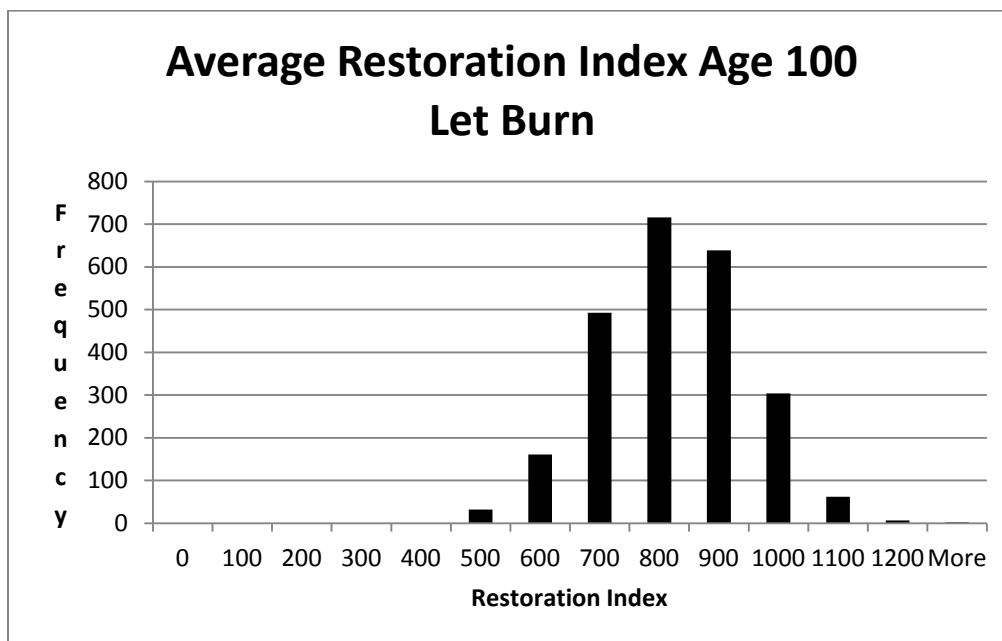
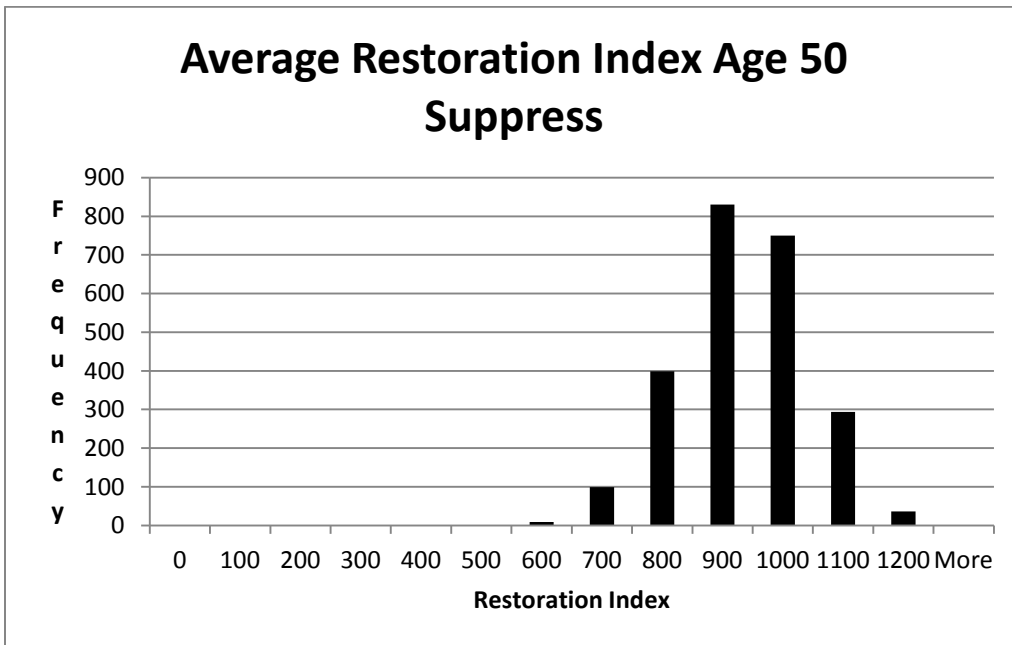
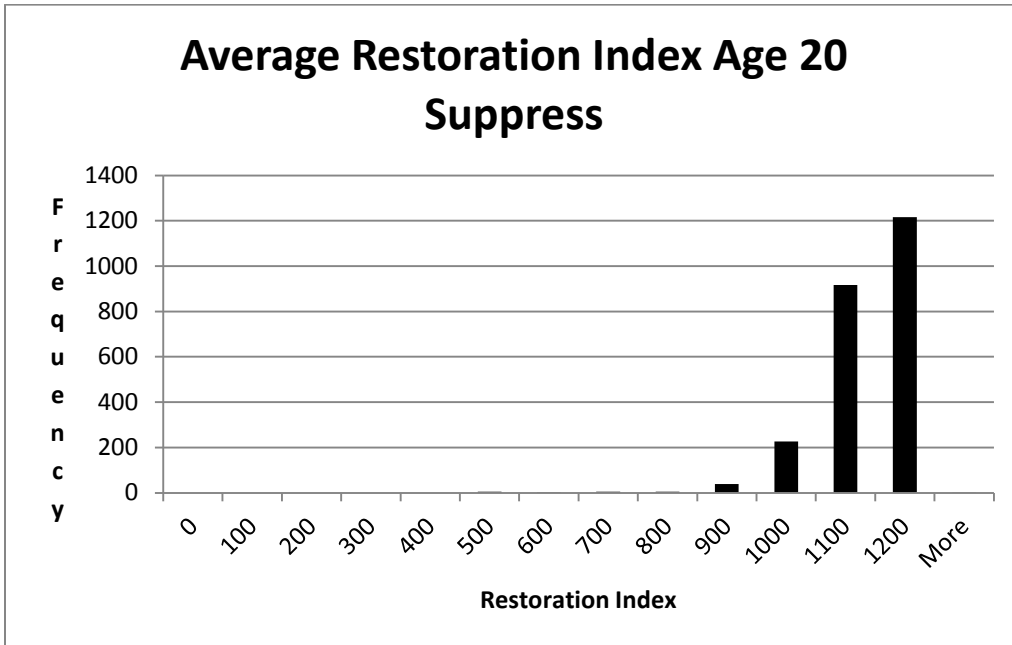


Figure 3: Average Restoration Index for the let burn scenario over 100 years.



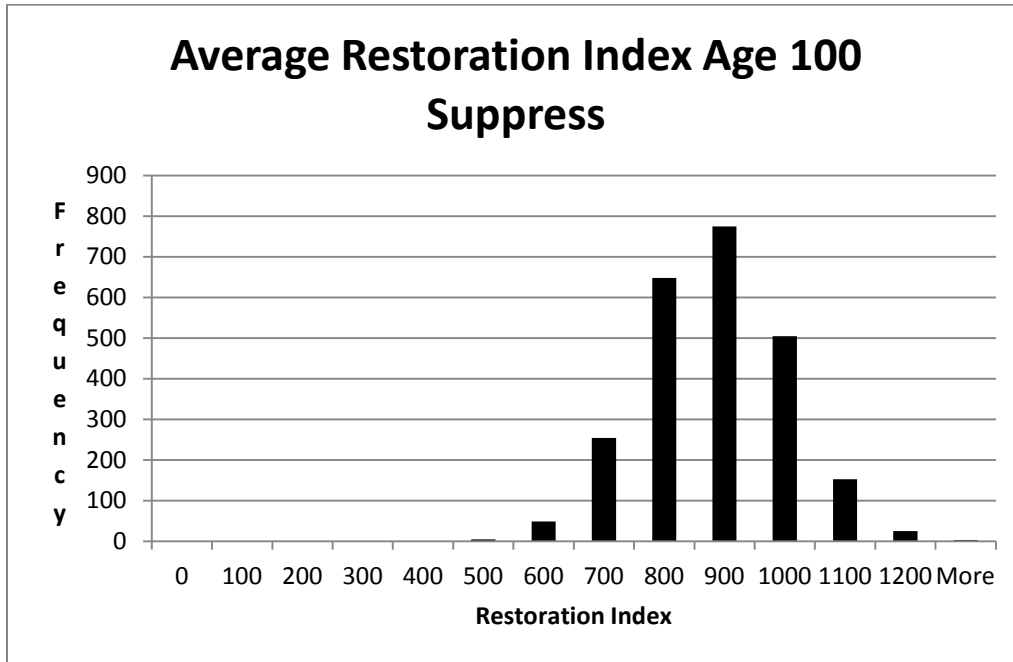


Figure 4: Average Restoration Index for the suppress scenario over 100 years.

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