The Effects of Climate Change on Tradeoffs Among Forest Ecosystem Services

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Abstract

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Tradeoffs Among Forest Ecosystem Services

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DRAFT

Forests provide ecosystem services in concert with one another. Multi-objective optimization has been a successful approach used to determine forest management schemes that maximize the simultaneous provision of ecosystem services. Climate change is predicted to impact forests and their ability to provide ecosystem services; however, no studies have determined how the relationships between managed ecosystem services will change with climate. This study addresses that question using a scenario-based approach. I consider a study system in the Deschutes National Forest with competing objectives: providing habitat for the northern spotted owl, reducing fire hazard, and ensuring water quality of the watershed. I compare the tradeoffs among the objectives under three climate scenarios which vary in their intensity of assumed climate change.

I find that ...

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GLOSSARY

CLIMATE PROJECTION: The IPCC defines a climate projection as a model-derived estimate of future climate. *See* CLIMATE SCENARIO[50].

CLIMATE SCENARIO: The IPCC defines a scenario as a coherent, internally consistent and plausible description of a possible future state of the world. Herein, I use this term synonymously with CLIMATE PROJECTION, since climate projections often underlie climate scenarios [50].

CLUSTER: Here, a set of contiguous forest stands whose combined area exceeds 200 ha

ECOSYSTEM SERVICE: Benefits that people receive from ecosystems, divided into four categories: supporting, provisioning, regulating and cultural [5]. Examples include food, soil formation, water purification, carbon storage, recreation, and education.

PARETO EFFICIENT: A solution to a multi-objective mathematical program is said to be Pareto efficient if no component of the solution can be improved without compromising another component.

STAND DENSITY INDEX (SDI: A measure of ...

ACKNOWLEDGMENTS

DRAFT

Thank you to all who contributed to my earning this degree.

DEDICATION

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To ma femme and my family

Chapter 1

ASSESSING CHANGES IN TRADEOFFS AMONG ECOSYSTEM SERVICES IN THE DESCHUTES NATIONAL FOREST

1.1 Introduction

Forests play an important role in global ecological, social, and economic processes. They provide ecosystem services such as carbon storage, purification of water and air, wildlife habitat, recreation opportunities, and generate raw materials for goods such as food and lumber [18]. In managed forests, the extent to which forests provide these services depends in part on management practices. Optimal forest management seeks to ensure the sustained provision of these ecosystem services [1].

Like other ecosystems, forests will undergo changes as a result of the changing climate. Researchers anticipate new spatial distributions of tree species [36], increased sediment delivery to streams [31], and increasing disturbance regimes such as wildfires, drought, and insect infestation [65]. As this transformation occurs, forests' ability to provide ecosystem services will change. Increased frequency of disturbance regimes will impact forests' ability to store carbon [7] and provide wildlife habitat [46]. Water supplies that rely on forests' filtration capabilities may be impacted by the rising sediment levels predicted by [31].

Optimal forest management must consider the effects of the changing climate, because the time scale of forest development is of the same order as that on which climate change is predicted to operate [34]. Optimal forest management will likely differ under alternative future climates [41]. Decisions that would once have resulted in optimal achievement of ecosystem services, now under different climatic conditions, may no longer do so. Without consideration of climate change, forest management plans may restrict forests' potential to provide ecosystem services most effectively.

Many studies have addressed the impacts of climate change on forest ecosystem services in isolation[65][7][46]. However, because forests provide these ecosystem services in concert with one another (see, for example, [63]), it is necessary to also understand how climate impacts the tradeoffs that exist among them. How does an increase in any one ecosystem service alter our ability to acquire an amount of another? Relationships such as a marginal sacrifice in one service for substantial improvement in another may no longer exist under a new climate. To better ensure the sustained provision of ecosystem services, we must understand how these tradeoffs evolve with climate.

1.1.1 A hypothetical scenario

To understand how tradeoff relationships impact management strategies and ecosystem service provision, consider the following hypothetical scenario in which a forest serves as prime habitat for a threatened bird species. The forest manager's primary objective is the conservation of this species, but the manager also performs the minimum amount of harvests necessary to negate the costs of property ownership from timber sales. To determine which stands to harvest, the manager ran an analysis, ignoring climate change, that suggested the harvest of a small set of stands near the northern perimeter of the forest as it was most accessible, served only as mediocre habitat for the bird species, and was dense with merchantable timber.

Now, climate change is reducing the area of the forest that is suitable habitat for the threatened bird species. Much of the species' remaining habitat is the area on the northern perimeter of the forest that has traditionally been harvested. Simultaneously, longer growing seasons and warmer temperatures are increasing the timber stock of other areas of the forest, making the northern stands less relatively advantageous to harvest. The manager, unaware, continues harvests in the northern stands, damaging much of what remains of the bird species' habitat.

With each ecosystem service modeled in isolation, this conflict is not fully understood, and optimal alternatives will not be discovered. Modeled in concert, however, the forest manager would have realized that these objectives do not strongly conflict with one another - if the manager were to move the harvests to the stands near the forest's eastern perimeter, his harvests would increase only slightly while also retaining nearly all of the bird species's suitable habitat. In other words, a marginal sacrifice in one ecosystem service allows for a significant improvement in another. Without knowledge of this tradeoff structure, the manager is unnecessarily impeding the bird species's climate-driven rangeshift.

It is the impact of climate change on such tradeoff structures that I investigate in this work. I consider as a case study an area in the Deschutes National Forest known as the Drink Planning Area, or the Drink area, in which we attempt to maximize the provision of the following ecosystem services: area of habitat available to the northern spotted owl, water quality in the watershed, and reduction in fire hazard.

1.2 Methods

1.2.1 Study area

I selected for the study system the Drink Planning Area which consists of 7056 ha on the east slopes of the Cascade Mountain Range in the Deschutes National Forest (see Figure 1.1). This area makes for an adequate study system, because it provides conflicting ecosystem services which the US Forest Service seeks to simultaneously optimize.

The first objective is the reduction of fire hazard rating through the use of silvicultural treatments. The USFS chose this objective because one third of the Drink area comprises the municipal watershed for the cities of Bend, OR and Sisters, OR (see Figure 1.2) which have a combined population of approximately 90,000. Wildfires pose a threat to the watershed as they cause soil water repellency, surface runoff, and debris torrents [35].

In addition, approximately 43% of the Drink serves as habitat for the northern spotted owl (NSO) (*Strix occidentalis caurina*) (Figure 1.2). The USFS is required to protect the NSO since it is threatened and therefore protected by the Endangered Species Act of 1973

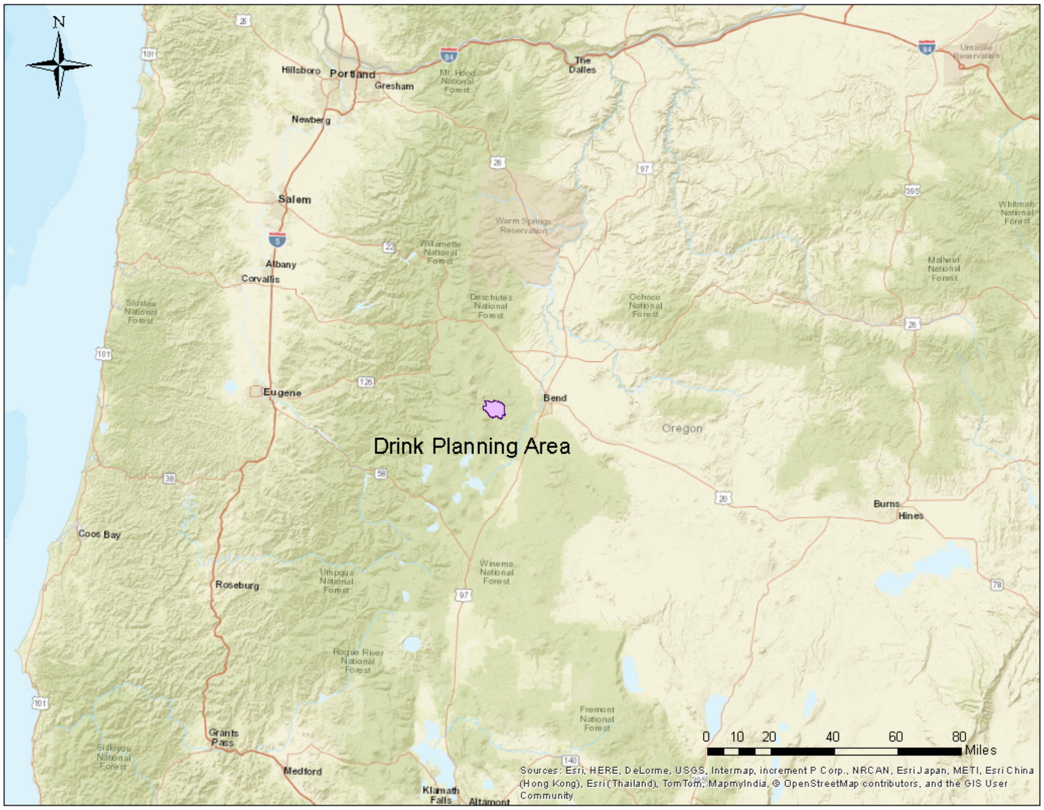

Figure 1.1: Overview of the study system, the Drink Planning Area (in purple), consisting of 7056 ha in the Deschutes National Forest.

[11]. The protection of NSO habitat is the second objective considered in this analysis.

Lastly, I aim to minimize the sediment delivered to the watershed as a result of the treatments applied to reduce fire hazard. While the treatments intend to provide long-term protection of the quality of the watershed, they also have the potential to introduce short-term increases in sediment delivery [49].

To accomplish long-term reduction in fire hazard rating for the area, I formed a strategic plan for silvicultural treatments to apply across the Drink. The treatments may be applied in each of two 20-year time periods (2015-2035 and 2035-2055) and to each of the 303 management units that comprise the Drink. The division of the management units (stands) was performed *a priori* by the Forest Service. The decision as to which treatment to perform

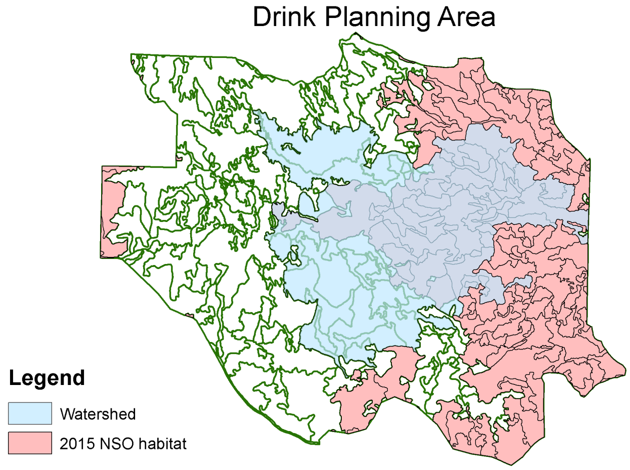

Figure 1.2: Location of the municipal watershed and the suitable NSO habitat in the Drink area at the beginning of the planning horizon (2015). Interior polygons are the 303 management units.

on a stand is entirely dependent on silvicultural characteristics; the rules used to determine the treatment applications can be found in Appendix B.

To assess the treatments' long-term efficacy, I measured the fire hazard of the Drink at the end of an 80-year planning horizon (2015-2095). I measured the area of NSO habitat at the end of each planning period to ensure that the application of treatments did not negatively impact the habitat available for the NSO. Finally, the short-term sediment contributions from performing the treatments were measured at the time of treatment, which is assumed to be at the midpoint year in the planning period (2025 for period 1, 2045 for period 2). The planning horizon including the time of these events is shown in Figure 1.4.

The three objectives are inherently in conflict with one another: fuel treatments drive short-term peaks in sediment delivery and potentially reduce owl habitat; minimizing short-term sediment delivery entails fewer treatments and therefore a higher fire hazard; maximizing owl habitat may require forgoing fuel treatments and again lead to higher fire hazard. In this study, I will determine how climate change impacts the tradeoffs that exist among these objectives.

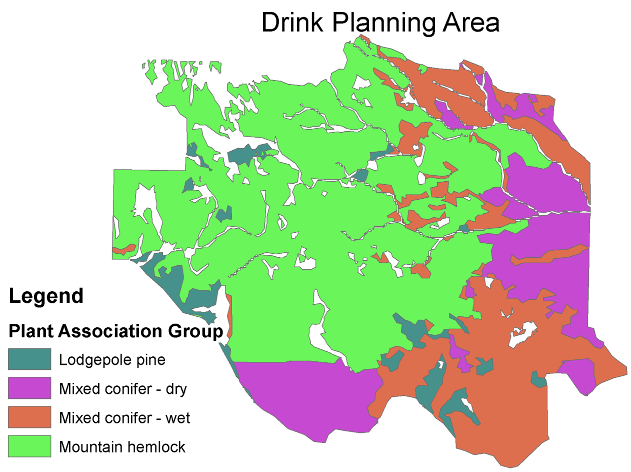

Figure 1.3: Plant association groups in the Drink Planning Area selected for treatment by the US Forest Service.

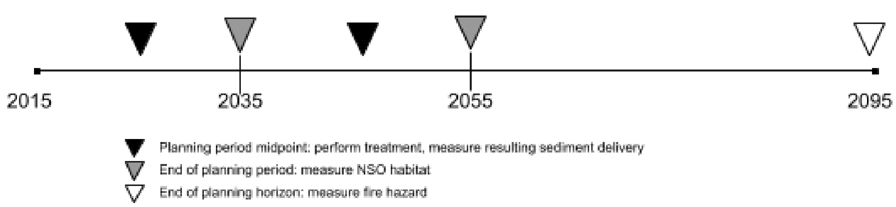

Figure 1.4: The planning horizon used in the analysis spans the 80 year period from 2015 to 2095. Treatments may be performed in the first period, the second period, both, or neither. Treatments are assumed to be performed at the mid-point years of each period (black triangles). Sediment delivery is measured on treatment years. Stands' suitability for NSO habitat is measured at the end of the planning periods (gray triangles), and fire hazard at the end of the planning horizon (white triangle).

1.2.2 Climate Scenarios Considered

To determine the impacts of climate change on the tradeoff structure between ecosystem services, it is first necessary to define how the impacts of climate change will be captured in the analysis. Here I use the method employed by the IPCC, namely, a scenario analysis. In a scenario analysis, multiple alternative futures are considered and no prediction is made as to which scenarios are more likely than others. There is no attempt to quantify the probability of realization of any one scenario, much like how IPCC does not attempt to quantify the probability that any particular climate model is the correct prediction of the future climate.

The alternative future climates I consider here are climate scenarios from the IPCC's Fifth Assessment [34]. Given the large number of potential future climates considered by the IPCC (see [25]) combined with the computational complexity involved in the study of each one, I selected a small subset of future climate scenarios for my analysis. I will refer to these three scenarios as "None", "Ensemble RCP 4.5", and "Ensemble RCP 8.5".

The first scenario, "None", is the assumption of no climate change. While the number of studies incorporating climate change is increasing, this is still the assumption used for many modern studies such as [55], from which this study is derived. Because it has served as the basis for many studies and assumes a static environment resembling today's, the "None" climate scenario serves as a good control against which to compare the other two climate scenarios.

As their names suggest, the second and third scenarios are ensembles. Each ensemble is comprised of 17 global circulation models (GCMs) used in the IPCC's Fifth Assessment (AR5). The selection of component GCMs in the ensembles was performed by the USFS's Climate-FVS [22] team. The list of the 17 scenarios included in the ensemble can be found in [14]. Each component GCM has a corresponding climate surface which contains a vector of 35 climate parameters at over 11,000 global locations for three time periods. The climate surfaces for the ensembles were created by averaging the values of all component GCMs for each climate parameter and each time period for each location. The result is a climate surface that, while temporally sparse, is spatially robust. This configuration is appropriate for use in the Drink area given its variability in elevation and slow vegetation growth.

The two ensembles are comprised of the same 17 GCMs, but the assumed representative concentration pathways (RCP) in the component GCMs differ. The RCP indicates the additional radiative forcing (in W/m^2) above pre-industrial levels, with higher values of forcing indicative of more severe climate change. The GCMs in the Ensemble RCP 4.5 scenario assume 4.5 W/m^2 of additional radiative forcing, and the GCMs in the Ensemble RCP 8.5 scenario assume 8.5 W/m^2 of additional radiative forcing.

I chose these three scenarios because they represent a range of predicted climate change severity, from a $0°C$ warming by the year 2100 under the "None" scenario to a $2.6 - 4.8°C$ warming under RCP 8.5 [34].

1.2.3 Determining tradeoff relationships between ecosystem services

Given a selection of climate scenarios, I determined the tradeoff relationships between ecosystem services under each scenario using multi-objective mathematical optimization [61]. This approach allocates resources so as to maximize a set of objectives subject to a set of constraints on the resource allocation. The objectives here are the ecosystem services that the USFS prioritized for the Drink area (see §1.2.1). The optimal management of these resources will be Pareto efficient and result in optimal provision of the ecosystem services.

To allocate the resources, the multi-objective optimization model assigns values to each of a set of decision variables. Here, the decision variables are on which stands and in which period to perform silvicultural treatments. This assignment is captured by the set of decision variables $x_{i,r}$. The model assigns $x_{i,r} = 1$ if stand $i \in I = \{0, 1, \ldots, 302\}$ (zero-indexed numbering for the 303 management units that comprise the Drink) is to be treated according to schedule $r \in R = \{0, 1, 2, 3\}$, where

- $r = 0$ is the decision not to treat the stand in either period in the planning horizon,
- $r = 1$ is the decision to treat the stand in the first period,

- $r = 2$ is the decision to treat the stand in the second period, and
- $r = 3$ is the decision to treat the stand in both periods.

The decision of which type of treatment to perform is not handled by the model; it is determined through the vegetation characteristics as described in §B.

The set of constraints on the decision variables is comprised of logical constraints, accounting constraints, and those imposed by the USFS. Logical constraints include those such as that one stand cannot be assigned to both be treated in no periods and also be treated in both periods (Equation 1.10). Accounting constraints track a quantity and are often used in conjunction with other constraints (or the objective function) to bound (or optimize) that quantity. See, for example, equations 1.11 and 1.13. Finally, constraints imposed by the USFS include those such as labor restrictions limiting the number of hectares that may be treated in a planning period (such as Equations 1.13 and 1.14).

I built a multi-objective model for each of the three climate scenarios. The result of each is a set of Pareto efficient solutions, each of which details a set of management actions to perform in order to attain a certain achievement in the three ecosystem services. Studying the solutions' achievements in the ecosystem services allows provides information on the tradeoff relationships between them.

Acquisition and projection of data

In order to formulate the models, I had to first acquire data. The data required included - for each climate scenario, each time period and each stand - a measure of fire hazard rating, determination of suitability for NSO habitat, and the amount of sediment deposited in the municipal watershed as a result of performing the silvicultural treatments.

For a measure for fire hazard rating, I chose the one employed by Kushch in CITESVETLANA'SMSWHENAVAILABLE. This metric suited this study, because it was developed specifically for the Drink area and was deemed appropriate by the Drink's fire specialist. This metric uses a combination of fire characteristics from Anderson's fuel models [4] to

Fuel Model	**Fire Hazard**	Group	Flame length (m)	Rate of spread (m/hr)	Total fuel load (tons/ha)
4*	**5**	Shrub	5.79	1508.76	32.12
5	**4**	Shrub	1.22	362.10	8.65
8	**1**	Timber	0.30	32.19	12.36
9*	**2**	Timber	0.79	150.88	8.65
10	**2**	Timber	1.46	158.92	29.65
11*	**2**	Logging Slash	1.07	120.7	28.42
12	**4**	Logging Slash	2.44	261.52	85.50
13	**5**	Logging Slash	3.20	271.58	143.57

Table 1.1: Fire hazard rating system used here, originally employed by CITESVETLANA'SMSWHENAVAILABLE.
* denotes fuel models in the extended set, not originally present in CITESVETLANA'SMSWHENAVAILABLE.
The fuel model column refers to the Anderson fuel model ratings [4].

assign a fire hazard rating: flame length, rate of spread, and total fuel load. I extended the rating system to include fuel models in this study that were not present in CITESVETLANA'SMSWHENAVAILABLE. See Table 1.1.

To determine the initial fire hazard ratings of each stand, I used the 2012 GNN structure map (`http://lemma.forestry.oregonstate.edu/data/structure-maps`) from Oregon State University's Landscape Ecology, Modeling, Mapping & Analysis (LEMMA) group. The LEMMA group provides this data in a format compatible with the USFS's Forest Vegetation Simulator (FVS). I mapped the plots from the LEMMA database to the stands in the Drink area in order to produce tree and stand lists. I used these lists with FVS's database extension to import this data into FVS and then used Climate-FVS with the Fire and Fuels Extension[53] (FFE) to simulate the stands' vegetation forward 80 years under each climate scenario. The output provides the fire characteristics necessary to compute the fire hazard ratings.

NSO habitat suitability was determined according to the following characteristics as specified by the USFS. Any area meeting the following would be considered ideal NSO habitat:

1. elevation less than 1830 m

2. the presence of trees with DBH no less than 76 cm

3. canopy closure of at least 60%

4. greater than 200 ha in size

I attained a digital elevation model from the US Department of Agriculture's GeoSpatial Data Gateway to compute average stand elevation and check for the first criterion. I checked the second and third criteria using the vegetation data produced by FVS. If the first three criteria are met but the area is less than 200 ha in size, it is still classified as NSO habitat but is penalized by a factor of $e = 0.5$. Since stands were generally less than 200 ha in size, the last criterion required the enumeration of all clusters of stands whose combined contiguous area exceeded 200 ha. The model checks whether all stands in such a cluster meet the first three criteria to determine whether the penalization is required.

I obtained the required data on sediment delivery using the Watershed Erosion Prediction Project (WEPP) online GIS tool [28]. This tool takes as input soil textures, treatment types, years of simulation, and custom climate data. I obtained soil texture data for the Drink area from the USDA's Soil Survey Geographic (SSURGO) database. Treatment types are those specified in §B, and the years of simulation correspond to the treatment years in the model's planning horizon.

The climate data used in the Climate-FVS and WEPP simulations was obtained through the Climate-FVS climate data server [15].

The Multi-objective Optimization Model

The first objective in the model is to minimize the cumulative fire hazard rating of the Drink area at the end of the 80-year planning horizon:

$$Minimize \quad F = \sum_{i \in I} \sum_{r \in R} F_{i,r} x_{i,r} \tag{1.1}$$

In equation (1.1), I sum over all stands $i \in I$ and all treatment prescriptions $r \in R$ to obtain a cumulative fire hazard metric F, which measures the total fire hazard rating of the Drink area at the end of the planning horizon. The coefficients $F_{i,r}$ are the area-weighted fire hazard ratings for each stand $i \in I$ at the end of the planning horizon if stand i is assigned to treatment prescription $r \in R$.

The second objective is to minimize the peak short-term sediment delivery that results from performing treatments in either period one (S_1) or period two (S_2):

$$Minimize \quad S = \max\{S_1, S_2\} \tag{1.2}$$

The last objective is to maximize the minimum area of northern spotted owl habitat at the end of each planning period, O_1 and O_2, for periods 1 and 2, respectively.

$$Maximize \quad O = \min\{O_1, O_2\} \tag{1.3}$$

The objectives are subject to the following constraints. First, I defined the accounting variables for the area of NSO habitat available at the end of each planning period:

$$\sum_{i \in I_{\omega,1}} \left(a_i p_{i,1} + e a_i \left(\sum_{j \in R_{i,1}} x_{i,j} - p_{i,1} \right) \right) = O_1 \tag{1.4}$$

$$\sum_{i \in I_{\omega,2}} \left(a_i p_{i,2} + e a_i \left(\sum_{j \in R_{i,2}} x_{i,j} - p_{i,2} \right) \right) = O_2 \tag{1.5}$$

The set of stands in the sum $i \in I_{\omega,t}$ are those that meet the first three criteria for NSO habitat under at least one treatment prescription $j \in R_{i,t}$, where $R_{i,t}$ is the set of treatment prescriptions for stand i such that it meets the first three NSO habitat criteria at the end of planning period t (where $t \in \{1,2\}$). If a stand i does not meet these criteria under any treatment prescriptions (if the set $R_{i,t} = \{\emptyset\}$), then $i \notin I_{\omega,t}$. If the model assigns a stand $i \in I_{\omega,t}$ a treatment prescription $j \in R_{i,t}$, then stand i meets the first three NSO habitat criteria at the end of planning period t, and the variable $x_{i,j} = 1$. If, in addition, the stand i is part of a cluster of stands all meeting the first three NSO habitat criteria at the end of period t and whose combined contiguous area is greater than 200 ha, then the variable $p_{i,t} = 1$. Notice that when $p_{i,t} = 0$, the stand's contribution is discounted by $e = 0.5$, and when $p_{i,t} = 1$ it is not.

Next, I defined the accounting variables for the sediment delivery that results from the performance of the prescribed management actions in each planning period.

$$\sum_{i \in I} \sum_{r \in 1,3} s_{i,1} x_{i,r} = S_1 \tag{1.6}$$

$$\sum_{i \in I} \sum_{r \in 2,3} s_{i,2} x_{i,r} = S_2 \tag{1.7}$$

The coefficients $s_{i,t}$ are the amount of sediment (in tonnes) that would result from treating stand i in time period t.

In order to control the trigger variables $p_{i,t}$ indicating a stand's inclusion in a 200 ha cluster of NSO habitat at the end of period t, I used the following two constraints:

$$\sum_{i \in D_c} \sum_{j \in R_{i,t}} x_{i,j} - |c| q_{c,t} \geq 0 \qquad \forall t \in \{1,2\}, c \in C \tag{1.8}$$

$$\sum_{c \in C_i} q_{c,t} - p_{i,t} \geq 0 \qquad \forall t \in \{1,2\}, i \in I_{\omega,t} \tag{1.9}$$

$c \in C$ are the clusters of stands whose combined area is greater than 200 ha. A cluster c contains the set of stands $i \in D_c$. Equation (1.8) specifies that all stands $i \in D_c$ within a cluster $c \in C$ must be assigned a management prescription such that they meet all NSO habitat criteria at the end of planning period t in order for the cluster trigger variable $q_{c,t}$ to take value 1.

Equation (1.9) specifies that if no cluster $c \in C_i$ - the set of clusters that contain site i - meets NSO qualifications at the end of period t, then the trigger variable $p_{i,t}$ must take value

0. If a cluster $c \in C_i$ does meet NSO qualifications at the end of planning period t, then the sense of the NSO objective function (1.3) will draw up the value of the variable $p_{i,t}$ to 1.

I also imposed the logical restriction that each stand may be assigned to at most one treatment prescription.

$$\sum_{r \in R} x_{i,r} = 1 \qquad \forall i \in I \tag{1.10}$$

Next, I ensured that the area treated in each time period is less than a pre-specified maximum area A. Here I used a value of $A = 6000$ acres, or 2428 ha:

$$\sum_{i \in I} \sum_{r \in 1,3} a_i x_{i,r} = H_1 \tag{1.11}$$

$$\sum_{i \in I} \sum_{r \in 2,3} a_i x_{i,r} = H_2 \tag{1.12}$$

$$H_1 \leq A \tag{1.13}$$

$$H_2 \leq A \tag{1.14}$$

Equations 1.11 and 1.12 define the accounting variables for the areas treated in time periods 1 and 2, H_1 and H_2, and equations 1.13 and 1.14 impose the upper bound.

Finally, I specified fluctuation constraints to bound the difference in the area treated in each time period:

$$\ell H_1 - H_2 \leq 0 \tag{1.15}$$

$$-u H_1 + H_2 \leq 0 \tag{1.16}$$

I defined a maximum of 20% areal fluctuation between the time periods. That is, $\ell = 0.8$ and $u = 1.2$.

Together with the binary specifications on the variables (equation (1.17)), the complete model is

$$
\begin{aligned}
&Minimize\\
&\qquad F = \sum_{i \in I} \sum_{r \in R} F_{i,r} x_{i,r}\\
&\qquad S = \max\{S_1, S_2\}\\
&Maximize\\
&\qquad O = \min\{O_1, O_2\}
\end{aligned}
$$

Subject to:

$$
\begin{aligned}
\sum_{i \in I_{\omega,t}} \left(a_i p_{i,t} + e a_i \left(\sum_{j \in R_{i,t}} x_{i,j} - p_{i,t} \right) \right) &= O_t \qquad \forall t \in \{1,2\}\\
\sum_{i \in I} \sum_{r \in 1,3} s_{i,r} x_{i,r} &= S_1\\
\sum_{i \in I} \sum_{r \in 2,3} s_{i,r} x_{i,r} &= S_2\\
\sum_{i \in D_c} \sum_{j \in R_{i,t}} x_{i,j} - |c| q_{c,t} &\geq 0 \qquad \forall t \in \{1,2\}, c \in C\\
\sum_{c \in C_i} q_{c,t} - p_{i,t} &\geq 0 \qquad \forall t \in \{1,2\}, i \in I_{\omega,t}\\
\sum_{r \in R} x_{i,r} &= 1 \qquad \forall i \in I\\
\sum_{i \in I} \sum_{r \in 1,3} a_i x_{i,r} &= H_1\\
\sum_{i \in I} \sum_{r \in 2,3} a_i x_{i,r} &= H_2\\
H_t &\leq A \qquad \forall t \in \{1,2\}\\
\ell H_1 - H_2 &\leq 0\\
-u H_1 + H_2 &\leq 0\\
x_{i,r}, p_i, q_c \in \{0,1\} \quad \forall i &\in I, r \in R, c \in C
\end{aligned}
\tag{1.17}
$$

1.2.4 Model solution

In general, solving a bounded and non-degenerate multi-objective optimization problem with N objectives produces a set of objective vectors (also called "solutions") $\mathbf{z} \in Z$ where $\mathbf{z} = \langle z^1, \ldots, z^N \rangle$. The set of solutions Z is referred to as the Pareto-optimal frontier or efficient frontier or, simply, frontier. The solutions comprising an efficient frontier have the special relationship such that no component of a solution $\mathbf{z}^i$ can be improved upon without one of the other components $\mathbf{z}^j$ $(j \neq i)$ degrading. This quality is known as Pareto efficiency. For example, this relationship in the current problem means that further reducing the value of fire hazard in a solution would result in either additional sediment deposits, a reduction of NSO habitat, or both.

Thus the efficient frontier provides information on the tradeoff structure that exists between ecosystem services. Parameterizing and solving the above model for each of the climate scenarios generates three frontiers: Z_{None}, $Z_{4.5}$, and $Z_{8.5}$ for the None, Ensemble RCP 4.5, and Ensemble RCP 8.5 scenarios, respectively. Since climate is the only thing that differs between the models and their resulting frontiers, the comparison of frontiers provides insight into how climate impacts the tradeoff structures between the ecosystem services.

To solve the models, I wrote my own implementation of Tóth's Alpha-Delta algorithm [60] utilizing the IBM ILOG CPLEX optimization engine. The Alpha-Delta algorithm finds the optimal set Z by iteratively slicing the N-dimensional objective space with a tilted $N-1$ dimensional plane. To derive the frontiers, I used an alpha parameter of $\alpha = .01$ and delta parameters of $\delta_{Hab} = 1$ ha and $\delta_{Sed} = 2$ tonnes for the NSO habitat and sediment delivery objectives, respectively.

1.2.5 Comparing Tradeoffs under each Climate Change Scenario

No standardized procedure exists for comparing frontiers or measuring the conflict between objectives within a frontier. To address the former, I drew on methods used in the field of evolutionary multi-objective optimization (EMO). To address the latter, I applied methods used for objective pruning in many-objective optimization.

Comparing frontiers

Researchers in the field of EMO develop algorithms to generate a set of non-dominated solutions that best represents the true Pareto-optimal frontier [19]. To test their algorithms, they use them to solve a benchmark multi-objective optimization problem and compare their resulting frontiers to the known Pareto front for that problem [39]. There is no assurance of optimality of the solutions derived using these algorithms, so they require a means of comparing the resulting frontiers to determine if one algorithm produces a "better" non-dominated frontier than another. Zitzler et al. provide a review of comparison methods in [70]. These methods aim to quantify certain traits about a frontier that can be used to measure their success in approximation of the true frontier.

My motivation in comparing frontiers is different from EMO in that, rather than comparing non-dominated sets produced by solving identical models, I compared frontiers generated by similar models that have the same structure but different parameterizations. As a result, not all comparison methods are applicable. For instance, the indicator for the number of Pareto points contained in the frontier does not make sense in my case, since all points on my frontiers are Pareto-optimal. However, other comparison methods still have value here. I chose a subset of these methods: the additive binary epsilon and binary hypervolume indicators, and the unary distance, additive unary epsilon, unary hypervolume, and unary spacing indicators.

Note that use of some comparison methods for the frontiers requires the normalization of the objective space. This is because the climate scenarios may significantly alter the bounds on the achievable values of the ecosystem services, resulting in frontiers whose objective spaces will not necessarily overlap and with incomparable distributions of solutions within. The chosen normalization of each frontier is the unit hypercube, with each objective bounded between 0 and 1, yielding a frontier bounded by $[0, 1]^N$. Without loss of generality, I convert all objectives to maximization, define the nadir solution to be at the origin and the ideal solution to be at the point $\vec{\mathbf{1}}$. The nadir solution $\mathbf{z}_{\text{nad}}$ of a frontier of points $z \in Z$ is defined as the objective vector with components

$$\mathbf{z}^i_{\text{nad}} = \inf_z \{z^i\} \quad \forall 1 \leq i \leq N \tag{1.18}$$

and the ideal solution is the objective vector with components

$$\mathbf{z}^i_{\text{ideal}} = \sup_z \{z^i\} \quad \forall 1 \leq i \leq N \tag{1.19}$$

Additive binary epsilon indicator $I_{\epsilon_+ 2}$ Given two frontiers, Z_1 and Z_2, the additive binary epsilon indicator is defined as [70]

$$I_{\epsilon_+ 2}(Z_1, Z_2) = \inf_{\epsilon \in \mathbb{R}} \{ \forall \mathbf{z}_2 \in Z_2 \; \exists \mathbf{z}_1 \in Z_1 : \mathbf{z}_1 \succeq_{\epsilon_+} \mathbf{z}_2 \} \tag{1.20}$$

where $\succeq_{\epsilon_+}$ is the additive ϵ-dominance relationship:

$$\mathbf{z}_1 \succeq_{\epsilon_+} \mathbf{z}_2 \iff \forall 1 \leq i \leq N : \epsilon + \mathbf{z}^i_1 \geq \mathbf{z}^i_2 \tag{1.21}$$

That is, ϵ is the minimum amount by which all components of all solutions in one frontier Z_1 must be increased such that every solution $\mathbf{z}_2 \in Z_2$ is weakly dominated by at least one solution $\mathbf{z}_1 \in Z_1$. See Figure 1.5.

Unary hypervolume indicator I_{H1} and binary hypervolume indicator I_{H2} For a frontier Z comprised of solutions $\mathbf{z} = \langle z^1, \ldots, z^N \rangle$ and with the objective space defined such that the origin is the nadir point, then the volume of a single solution $\mathbf{z}_i$ is the volume of the hyperrectangle r_i whose diagonal corners are the origin and the solution $\mathbf{z}_i$. The hypervolume of the frontier is the volume of the union of the hyperrectangles corresponding to the solutions in the frontier:

$$I_{H1}(Z) = \text{vol}\left(\bigcup_{i=1}^{|Z|} r_i \right) \tag{1.22}$$

Then define the binary hypervolume indicator of two frontiers Z_1 and Z_2 as [69]

$$I_{H2}(Z_1, Z_2) = I_{H1}(Z_1 + Z_2) - I_{H1}(Z_2) \tag{1.23}$$

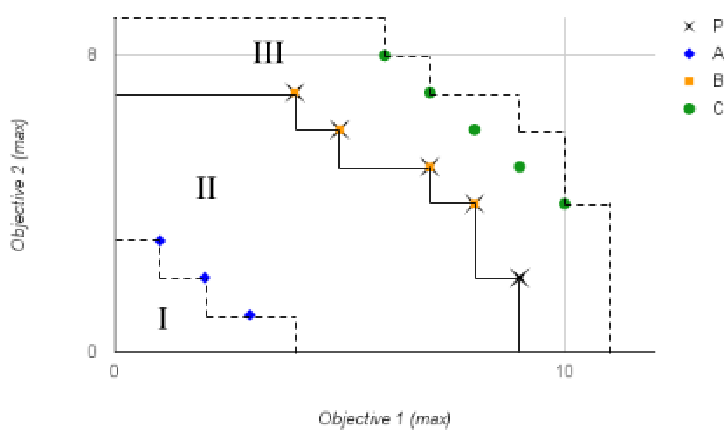

Figure 1.5: Depiction of the additive binary epsilon indicator I_{ϵ_+2} and the additive epsilon dominance relationship $\succeq_{\epsilon_+}$.

$$I_{\epsilon_+2}(P, A) = -4 < 0 \qquad I_{\epsilon_+2}(P, B) = 0 \qquad I_{\epsilon_+2}(P, C) = 2 > 0$$

Region III is ϵ_+-dominated for $\epsilon = 2$; region II is ϵ_+-dominated for $\epsilon = 0$; region I is ϵ_+-dominated for $\epsilon = -4$. Note that region II also encompasses region I, and region III encompasses region II.

Relation	Solutions		Frontiers	
Strictly dominates	$\mathbf{z}^1 \succ\succ \mathbf{z}^2$	$\mathbf{z}_i^1$ is better than $\mathbf{z}_i^2 \quad \forall 1 \leq i \leq N$	$Z_1 \succ\succ Z_2$	$\exists \mathbf{z}^1 \in Z_1 \succ succ\mathbf{z}^2 \quad \forall \mathbf{z}^2 \in Z_2$
Dominates	$\mathbf{z}^1 \succ \mathbf{z}^2$	$\exists 1 \leq i \leq N : \mathbf{z}_i^1$ is better than $\mathbf{z}_i^2$, and $\mathbf{z}_i^1$ is not worse than $\mathbf{z}_i^2 \quad \forall 1 \leq i \leq N$	$Z_1 \succ Z_2$	every $\mathbf{z}^2 \in Z_2$ is dominated by at least one $\mathbf{z}^1 \in Z_1$
Better			$Z_1 \rhd Z_2$	every $\mathbf{z}^2 \in Z_2$ is weakly dominated by at least one $\mathbf{z}^1 \in Z_1$ and $Z_1 \neq Z_2$
Weakly dominates	$\mathbf{z}^1 \succeq \mathbf{z}^2$	$\mathbf{z}^1$ is at least as good as $\mathbf{z}^2$ in all objectives	$Z_1 \succeq Z_2$	All solutions in $\mathbf{z}^2 \in Z_2$ are weakly dominated by a solution $\mathbf{z}^1 \in Z_1$
Incomparable	$\mathbf{z}^1 \Vert \mathbf{z}^2$	Neither $\mathbf{z}^1$ nor $\mathbf{z}^2$ weakly dominates the other	$Z_1 \Vert Z_2$	Neither Z_1 nor Z_2 weakly dominates the other

Table 1.2: Definitions of dominance relations between solutions and frontiers, reproduced from [70].

Name of indicator	Relation					
	$\succ\succ$	$\succ$	$\rhd$	$\succeq$	$=$	$\Vert$
I_ϵ	$I_\epsilon(Z_1, Z_2) < 1$	-	$I_\epsilon(Z_1, Z_2) \leq 1$ $I_\epsilon(Z_2, Z_1) > 1$	$I_\epsilon(Z_1, Z_2) \leq 1$	$I_\epsilon(Z_1, Z_2) = 1$ $I_\epsilon(Z_2, Z_1) = 1$	$I_\epsilon(Z_1, Z_2) > 1$ $I_\epsilon(Z_2, Z_1) > 1$
I_{H2}	-	-	$I_{H2}(Z_1, Z_2) > 0$ $I_{H2}(Z_2, Z_1) = 0$	$I_{H2}(Z_1, Z_2) \geq 0$ $I_{H2}(Z_2, Z_1) = 0$	$I_{H2}(Z_1, Z_2) = 0$ $I_{H2}(Z_2, Z_1) = 0$	$I_{H2}(Z_1, Z_2) > 0$ $I_{H2}(Z_2, Z_1) > 0$
I_d	-	-	-	-	-	-
I_s	-	-	-	-	-	-

Table 1.3: Tests using indicators to determine dominance relationships between frontiers [70]. While general tests of dominance relationships may not be avaiable for some metrics (any cell with '-'), conclusions may still be drawn. For instance, $I_d(Z_1) < I_d(Z_2) \Rightarrow Z_2 \not\rhd Z_1$.

where $I_{H1}(Z_1+Z_2)$ is the unary hypervolume indicator of the merged frontier consisting of all solutions from frontiers Z_1 and Z_2. The binary hypervolume indicator provides the volume of frontier Z_1 that is not contained within frontier Z_2. Larger values of I_{H1} correspond to frontiers occupying larger fractions of the objective space, indicating less conflict between the objectives. For frontiers Z_1 and Z_2 in comparable scales (that is, in normalized objective spaces), if $I_{H2}(Z_1, Z_2) > I_{H2}(Z_2, Z_1)$ this indicates less conflict between objectives in Z_1 than in Z_2. I_{H2} can also be used to determine other dominance relationships between frontiers (see Tables 1.2 and 1.3).

I developed a custom algorithm to solve for the unary hypervolume idicator. The details of the algorithm may be found in §A.

Unary distance indicator I_d The unary distance indicator used for the analysis is analogous to the unary distance indicator described in [17], but instead of computing the distance to a reference Pareto frontier I measure the average distance from the frontier to the ideal solution:

$$I_d = \frac{\sum_{\mathbf{z}\in Z} ||\mathbf{z}^{\text{ideal}} - \mathbf{z}||}{N} \tag{1.24}$$

Smaller values of I_d correspond to frontiers that are closer to the ideal solution, which implies less conflict between the objectives.

Unary Spacing Indicator I_s The unary spacing indicator, or Schott's spacing metric[54], computes the standard deviation of the distance between points in the frontier, defined as

$$I_s = \sqrt{\frac{1}{N-1}\sum_{\mathbf{z}\in Z}(d_z - \bar{d})^2} \tag{1.25}$$

where

$$d_z = \min_{\mathbf{y}\in Z, \mathbf{y}\neq\mathbf{z}} ||\mathbf{z} - \mathbf{y}|| \tag{1.26}$$

and $\bar{d}$ is the average of all d_z. In EMO, the spacing indicator provides a measure of an algorithm's ability to search the frontier space uniformly. Here, the spacing metric provides a measure of the flexibility afforded to the decision maker under each climate scenario. Larger spacing metrics imply larger sacrifices between decisions and less flexibility.

Quantifying conflict between objectives within a frontier

The above methods provide frontier-level metrics of conflict and tradeoffs. To determine the degree of conflict between two objectives within a single frontier, we employ an approach used in many-objective optimization. Given the increased difficulty in solving many-objective optimization problems [38], researchers in this field seek to reduce the number of objectives considered in the model. To determine which objectives most strongly influence the shape of the frontier, they compute the correlation between each pair of objectives [20]. The objective pairs with the most negative correlation are most in conflict. To rank the relative conflict between objectives in each climate scenario, I compute their Pearson correlation coefficients:

$$\rho_{X,Y} = \frac{\text{cov}(X,Y)}{\sigma(X)\sigma(Y)} \tag{1.27}$$

where, for objectives x and y, X and Y are

$$X = \{\mathbf{z}_x^1, \mathbf{z}_x^2, \ldots, \mathbf{z}_x^{|Z|}\} \tag{1.28}$$

$$Y = \{\mathbf{z}_y^1, \mathbf{z}_y^2, \ldots, \mathbf{z}_y^{|Z|}\} \tag{1.29}$$

1.3 Results and Discussion

DRAFT

The frontiers for each climate scenario can be found in Figure ...

1.4 Conclusion

DRAFT

I find that climate change has positive impacts on the tradeoff structure between managed ecosystem services in the Drink Area ...

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Appendix A

COMPUTING A FRONTIER'S HYPERVOLUME INDICATOR

Given a set of Pareto optimal solutions $\mathcal{P}$ to a multi-objective mathematical programming model with a set of objectives O of cardinality $N := |O|$, this algorithm computes the volume V of the objective space bounded by the Pareto frontier defined by the solutions $x \in \mathcal{P}$. The objectives are assumed to be normalized so that the objective space is the N-dimensional unit hypercube with the origin and the point $\vec{\mathbf{1}}$ defining the nadir objective vector and the ideal objective vector, respectively. That is, all objectives are assumed to be maximized with bounds $[0, 1]$.

The algorithm projects the objective space into $N-1$ dimensions by eliminating the dimension associated with an (arbitrarily-chosen) objective $p \in O$. The set of objectives is $\overline{O} := O \backslash \{p\}$. It is assumed that $x \in \mathcal{P}$ are sorted in descending order according to p. The algorithm proceeds by sequentially adding solutions to the $(N-1)$-dimensional space, and calculating the contribution to the frontier volume as a product of the volume contribution in $N-1$ dimensions and its achievement in objective p.

Let $\overline{V_x}$ be the $(N-1)$-dimensional volume contribution of solution x and x_p be the achievement of solution x in objective p. Further, let F be the set of non-dominated solutions in $N-1$ dimensions. I compute the N-dimensional volume of the frontier V as follows.

Figure A.1: Algorithm to compute the unary hypervolume indicator of a Pareto frontier.

$V \leftarrow 0$
$\overline{V} \leftarrow 0$
$F \leftarrow \emptyset$
for all $x \in \mathcal{P}$ **do**
    $\overline{V}_x \leftarrow \prod_{o \in \overline{O}} x_o - \overline{V}$
    for all $f \in F$ **do**
        if $f_o < x_o \forall o \in \overline{O}$ **then**
            $F \leftarrow F \backslash \{f\}$
        end if
    end for
    for all $o \in \overline{O}$ **do**
        $F_{x,o} := \{\, f \in F : f_o > x_o \,\}$
        Sort $f \in F_{x,o}$ in ascending order by their oth component, f_o
        $v_i \leftarrow x_o$
        for all $f \in F_{x,o}$ **do**
            $v_t \leftarrow f_o$
            $\delta_o := v_t - v_i$
            $\overline{V}_x \leftarrow \overline{V}_x + \delta_o \prod_{\sigma \in \overline{O} \backslash \{o\}} f_\sigma$
            $v_i \leftarrow v_t$
        end for
    end for
    $F \leftarrow F \cup \{x\}$
    $\overline{V} \leftarrow \overline{V} + \overline{V}_x$
    $V \leftarrow V + x_p \overline{V}_x$
end for

Appendix B

TREATMENT SPECIFICATIONS FOR THE DRINK AREA

Vegetation conditions were assessed at the midpoint of each planning period. If a set of conditions as listed in Table B.1 were met, then the corresponding treatment was applied. Otherwise, no action was taken.

Table B.1: Rules governing treatment assignments.

SDI[1]	**CBD**[2]	**TPH**$_{<18}$[3]	**Fuel model**[4]	**BA**$_{\mathrm{MHD+WF},>46}$[5]	**Treatment**
		Lodgepole pine (LPD) plant association			
< 87	N/A	N/A	N/A	N/A	**Prescribed burn**
≥ 87	> 0.037	> 49	≥ 10	N/A	**Thin, pileburn slash and fuels**[6]
			< 10	N/A	**Thin, pileburn slash**
		Mixed conifer wet (MCW) or mountain hemlock (MHD) plant associations			
< 87	N/A	N/A	N/A	N/A	**Prescribed burn**

[1] Stand Density Index, calculated in metric units (trees per ha).

[2] Crown bulk density (kg/m^3)

[3] Number of trees per hectare whose diameter at breast height (DBH) is less than 18 cm

[4] According to the Anderson rating system[4]

[5] Basal area in m^2 of all mountain hemlock (MHD) and white fir (WF) trees with DBH $> 46cm$.

[6] Pileburning slash involves removal of thinned trees only, while pileburning slash and fuels also involves removal of materials that were on the ground before thinning (Wall, Powers, 2012; personal communication)

≥ 87	> 0.037	> 49	$= 10$	> 7.5	**Thin, pileburn slash and fuels, prescribed burn**
				≤ 7.5	**Thin, pileburn slash and fuels**
			> 10	N/A	**Thin, pileburn slash and fuels**
			< 10	N/A	**Thin, pileburn slash**
		≤ 49	$= 10$	≥ 7.5	**Prescribed burn**
	≤ 0.037	N/A	$= 10$	≥ 7.5	**Prescribed burn**
	N/A	N/A	$\in \{6, 8, 9, 10\}$	N/A	**Prescribed burn**[7]
Mixed conifer dry (MCD) plant association					
< 87	N/A	N/A	N/A	N/A	**Prescribed burn**
≥ 87	> 0.037	> 49	$\in \{10, 11\}$	N/A	**Thin, pileburn slash and fuels, prescribed burn**
			≥ 12	N/A	**Thin, pileburn slash and fuels**
			< 10	N/A	**Thin, pileburn slash**
		≤ 49	$\in \{10, 11\}$	N/A	**Prescribed burn**
	≤ 0.037	N/A	$\in \{10, 11\}$	N/A	**Prescribed burn**
	N/A	N/A	$\in \{6, 8, 9, 10\}$	N/A	**Prescribed burn**[7]

[7] Only if prescribed burn was assigned in period 1 (applies to period 2 treatment assignments only)