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Private forest owners face an increasing risk of economic damage from extreme wildfires as the climate becomes warmer and drier. This thesis empirically estimates the influence of climate on private forest owners' management decisions using plot-level data in the Pacific states of the U.S. Econometric models are specified where the probability of precommercial thinning is a function of climate variables, timber productivity and fire risk. The results of the empirical analysis suggest that a forest stand with high timber productivity and land value are more likely to be thinned, indicating that the net private benefits of thinning are higher on more productive stands. This study also projects the marginal change in the probability of thinning in response to climate changes involving temperature and precipitation. Forest stands that occur in areas with current high fire risk and low forest rent are projected to be less likely to be thinned under future climate change. The result implies that stands with high fire risk will potentially be even more prone to fire if private forest owners make fuel management decisions driven by private economic motivations. Furthermore, the result

implies a higher risk of spreading wildfire across an entire landscape because management on a private forest stand interacts with neighboring forest stands**.** This study contributes to the economics of forest fire management under climate change by providing empirical evidence of landowners’ management response to climate.

Impacts of Climate Change on Fuel Management Decisions and Implications for Fire Risk

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

Nozomi Kato, Author

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CONTRIBUTION OF AUTHORS

Dr. David Lewis made substantial contributions to the design and review of all the manuscripts in this thesis.

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DEDICATION

To Akira, Hana, and Satoru, who always made me stay positive throughout the two years in graduate school. I can overcome any difficulty if you are with me.

1. Introduction

Management of fire is one of the most important issues in forest management. With climate change, forest owners face an increased risk of extreme forest fires (Abatzoglou & Williams, 2016). Fires can cause great economic loss by burning marketable trees that could otherwise have been used for timber. One of the regions where there is a growing concern is the Pacific states of the U.S., which is one of the largest national producers of timber products. Research targeting the Western U.S. has identified major factors accounting for an increase in fire risk due to climate change. Drier and warmer climate will result in lower fuel moisture and extended fire seasons (Halofsky et al. 2020). Early spring snowmelt will also drive longer fire seasons by releasing moisture carried in snowpack, which leads to low moisture content of fuels (Westerling 2016, O'Leary et al. 2016). The impacts of these factors on fire risk is particularly large in regions with sufficient fuels (Sheehan & Bachelet, 2019) as such fuels lose moisture and become flammable.

Increased fire risk is likely to motivate private forest owners to take adaptive actions such as precommercial thinning and prescribed burns. These management activities can raise the economic value of forestland by encouraging growth of desirable trees and enhancing health of the forest. At the same time, thinning and prescribed burns contribute to preventing wildfire spread by reducing flammable fuel loads. A change in fire risk adds to the factors private forest owners take into consideration when they make management decisions to maximize their profits. While such management decisions are likely made to maximize the value of a particular forest stand by a private forest owner, they also affect the entire landscape by altering fire spread. Likewise, management actions by a landowner's neighbors alter fire spread and affect land value. Fire can travel from one stand to another with the spread rate depending on the amount of fuels and weather. Because of spatial interactions that fire causes, the value of fuel treatment in one location depends partly on its effect on fire risk elsewhere (Lauer et al. 2019).

This study empirically analyzes fuel management decisions by private forest owners in response to climate in the Pacific states of the US – Washington (WA), Oregon (OR), and California (CA) – and how such decisions further affect fire risks in forest landscape. The following two steps are taken for analysis. First, the effects of climate on private forest owners' management decisions are estimated by using the plot-level data provided by USDA Forest Service Forest Inventory and Analysis (FIA). The FIA data is collected by annual inventory on plots in forestland across the U.S. to determine the extent, condition, volume, growth, and use of trees. It has been used for various studies analyzing natural resource management, wildlife habitat, or anthropogenic activities in relation to the status and change in forests. For the dependent variable of management choice, the Pacific Northwest (PNW) FIA data customized to the Pacific states is used since it includes an attribute of treatment that is more detailed than the national FIA data. It specifies what management activity, including precommercial thinning, has occurred since the last measurement at each plot. Second, changes in management decisions are projected by substituting projected values of climate variables in the model estimated in the first step. In addition, the study method applies cross-sectional Ricardian framework to assess climate change impacts on forest rents. The Ricardian framework is one of the empirical approaches economists have taken to quantify economic impacts of climate change (Auffhammer, 2018). Based on the estimation, this study attempts to draw implications for fire risks under a future climate change scenario.

This study is the first empirical econometric analysis of the link between climate and fire management conducted at the plot level. It provides empirical evidence of how private forest owners have made fire management decisions in response to the climate and stand conditions that they face. Providing this new empirical evidence contributes to forest fire management, which faces a challenge of managing increasing fire risk under climate change.

2. Literature Review

There have been a number of studies in the Western U.S. aiming to contribute to understanding management decisions by forest managers to adapt to climate change. In this chapter, I will review such previous studies to draw insights for this study to analyze climate change impacts on a certain management activity. The previous studies are categorized into four different approaches.

2.1 Climate Change Impacts on Wildfire

Adaptation of forest management starts with predicting and understanding fire risk under climate change (Keenan, 2015). Studies have been done to predict wildfire probabilities in the Western U.S. and found that the major contributer of fire is dry and hot weather, and sufficient biomass or fuels. Preisler and Westerling (2006) focused on large fire events and developed a statistical model for prediction by relating historic fire occurrence data to indexes representing climate. Results indicate that the drier and hotter an area is, the more prone it becomes to a large fire. Sheehan and Bachelet (2019) assessed risk of biomass loss by two drivers – fire and vegetation shift – in western Oregon and Washington. Their mapped results show that fire is influential in biomass loss in the southern part and northeastern corner of their study area in the next 20 years, where current biomass is high. Through time the area where fire imposes a high risk of biomass loss is expected to expand to the north and upslope as fire becomes more frequent with rising temperature. As the resolution of analysis becomes finer, the relationship between the environment and fire gets more complex. Parisien et al. (2012) estimated wildfire probability using historical data of burned areas at high-resolution. Their fine-scale analysis did not find any of the climate variables having a dominant link to fire. It indicates complexity in the area-specific relationship between the environment and wildfire across the Western U.S.

2.2 Effects of Management on Fire Risk

In addition to stand characteristics and area-specific conditions of a forest stand, management activities also influence fire risk. Forest owners recognize the changing environment and react to such changes by implementing management activities. Natural resource management with flexibility to respond to uncertainties is called adaptive management. Williams (2011) discussed the importantce of implementing adaptive management for natural resources to improve management by the feedback between learning and decision making. With regard to forestland management, Millar et al. (2007) suggested such measures as removing fuels around the highest risk or highest value areas, lowering stand density, and diversifying tree species as approaches to enable forest ecosystems to accommodate uncertainties of climate change impacts. They also argued that managers should stay informed about influences of management activities to make further decisions. Focusing on tree plantations, Odion et al. (2004) analyzed how management activity influenced the fire regime in northwestern California and southwestern Oregon. They found that fire severity was twice as high in plantation forests as in multi-aged ones. Referring to the fact that plantations are often established after high-severity fire and that plantations account for one-third of roaded area, they pointed out the possibility of increase in the size and severity of future fires as climate becomes warmer.

2.3 Interaction of Wildfire with Economics of Timber Management

Private forest owners make management decisions to opitimize their private benefit of owning land. Since a wildfire results in loss of timber, an increase in fire risk under climate change will affect forest owners' optimal management choices. Amacher et al. (2005) analyzed influences of fire risk on management activities of nonindustrial private forest owners with different assumptions of the relationship between fire arrival rate and stand age. Under the scenario that forest owners implement fuel treatment activities such as thinning and prescribed fire, their simulation results show that landowners respond to higher fire risk by lengthening the timber rotation age. They also evaluated how the management choices affect forest owners' welfare and found that fuel treatment brings about large welfare gains if fire risk rises with stand age. If not, large gains are limited to the cases with high fire risk. Lauer et al. (2017) added spatial and intertemporal interactions of fire management to an analysis of optimal forest management decisions in southwestern Oregon. They solved a dynamic problem of optimal management options using stochastic dynamic programming, which accounts for fire's ability to spread between stands as well as managers' decision to adjust to a post-fire landscape. They found a trade-off between shortening rotation age to secure on-site timber value and extending it to lower the risk of spreading fire to adjacent stands because younger stands have higher fire risk. With regard to fuel treatment, the likelihood of a stand receiving treatment rises if there are higher timber values at risk on surrounding stands. Lauer et al.'s (2017) analysis also highlights the fact that fuel management on one stand creates external benefits to adjacent landowners by lowering the risk of spreading fire. Thus, when conducted based purely on private benefits and costs, fuel management will be inefficiently low due to the incentive for landowners to ignore the benefits of their fuel management on others.

2.4 Economic Models of Forest Management Adaptation

Wildfire risk, forest owners' management choices, and economics of forest all interact with one another under climate change, and management activities have feedback effects on the economic value of forest. Empirical analyses have been done to link forest owners' response to climate change and the economic value of forestland based on fine-scale data of actual management activities. Hashida and Lewis (2019) analyzed adaptation behavior of private forest owners in terms of their choice of tree species to regenerate post-harvest in the Pacific states of the U.S. Estimated results indicate that forest owners adapt to climate change by shifting away from Douglas-fir to species more suitable to future climate such as hardwoods and ponderosa pine. Since these species are less valuable than Douglas-fir, the estimated changes in forest composition imply that climate change lowers the market value of forestland. Mihiar (2018) linked the market value of forest to climate by establishing a functional relationship between climate and land rent, and the resulting probability of changing land use. Results indicate that forest profitability rises with higher precipitation and maximum summer temperature, though there is significant spatial heterogeneity across the conterminous U.S. The rise in economic value of forest, however, is not as influential as non-climate drivers of land use change in increasing forest land. Finer (2019) also analyzed marginal effect of climate on private forestland value in Oregon under future climate projections using real-market value estimates for parcels of timberland. She integrated the fact that privately managed forestland tends to be at lower wildfire risk into her empirical estimation of private forestland values. Results showed that proximity to public forests together with low precipitation imposes high fire risk on a stand and that changing management of public forest improves the value of adjacent private forest.

2.5 Reflection of Insights from Reviewed Literature

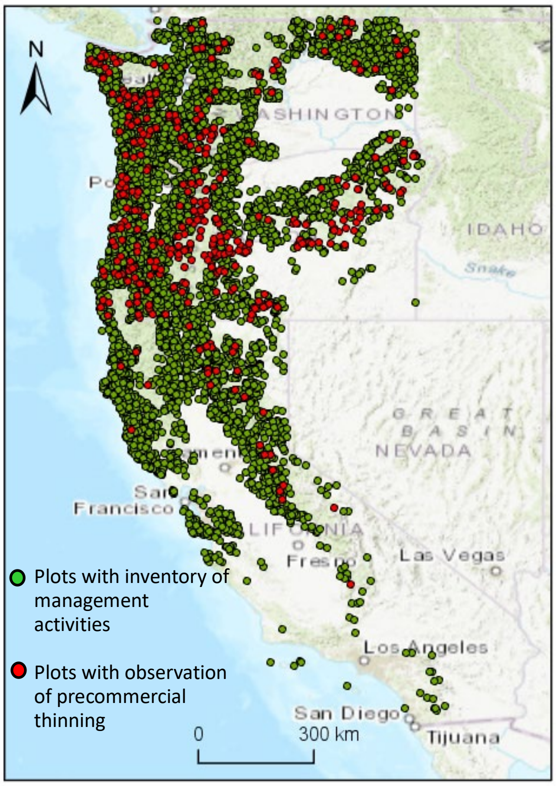
This study builds on Hashida and Lewis (2019), which analyzed climate change impacts on private forest owners' choices of tree species. They estimated a discrete choice model with explanatory variables of forest rent and climate measures. The potential forest rent that a landowner could earn from replanting different species is a driver of private forest owners' choice of management activities. This study aims to further clarify interaction among private forest owners' management decisions, forest rent, and climate change impacts. It analyzes how climate influences forest rent and the result is then integrated into a model to estimate the probability of a landowner choosing pre-commercial thinning, which is widely viewed as a fire management tool. Hashida and Lewis did not model pre-commercial thinning decisions, so this thesis extends their research by broadening the analysis to consider how fire management may respond to climate chante. This study aims to draw implications from an empirical analysis of how forest owners respond to their current climate through fire management decisions, particularly pre-commercial thinning that lowers fuel loads by reducing forest density.

3. Data

This study relies on plot-level data of forestland provided by USDA Forest Service Forest Inventory and Analysis (FIA) for the dependent variable of forest management choices and some of the explanatory variables of site characteristics. Each plot is measured every 10 years, i.e. the data on management activity indicates whether a certain management activity was implemented within the previous 10 years from an inventory year. There are four categories of landowner classes; forest service, other federal, state and local government, and private and Native American. For this analysis, plots owned by either state and local government or private are used. With regard to the attribute of forest management activity, the PNW FIA program that customizes the FIA national database to Alaska (AK), California (CA), Oregon (OR), and Washington (WA) collects data with more detailed categories of treatment. One of the categories specific to the PNW FIA data is precommercial thinning. Thinning is defined by the U.S. Forest Service as an intermediate treatment to reduce stand density of trees and its primary purpose includes improvement of growth and enhancement of forest health. Thinning also has the effect of a fuel treatment. The U.S. Forest Service lists abundant fuel as one of the contributors to the increased size, severity, and frequency of wildfires. Reduction of hazardous fuel is therefore one of the important measures of fire management. The National Strategy (Forests and Rangelands 2014), which provides a guideline for all stakeholders to manage wildfires, names thinning as a measure that needs to be actively used to reduce fuel in the Western region. Under climate change, thinning will play an even more important role. Warmer and drier conditions will likely increase the frequency and extent of fires due to lower fuel moisture and longer fire seasons (Halofsky et al. 2020). For this study, precommercial thinning is selected as a dependent variable representing forest owners' management choices to adapt to climate change. Out of 5,721 privately owned plots[1] with an inventory of management activities, precommercial thinning is performed on 323 plots. Figure 3.1 shows all the plots with an inventory of management activity and those with observation of precommercial thinning over the study area of WA, OR, and CA. Most of the pecommercially thinned plots are in WA and OR, particularly in the western part of OR and WA.

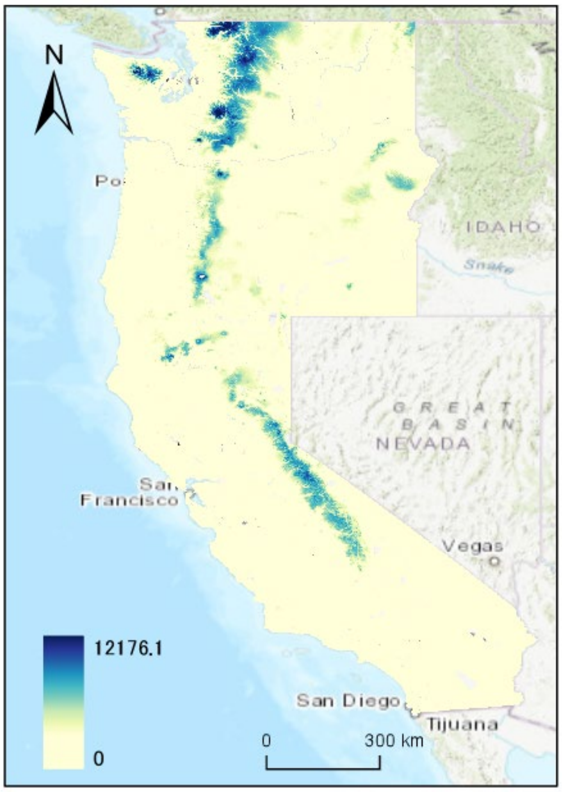
[1] These include the same plot with different inventory years. The same plots are used in Figure 3.3 to 3.5 in this chapter.

Figure 3.1 Privately owned plots with inventory of management activities and those with observation of precommercial thinning



To create a variable to represent the amount of snowpack near each plot, a dataset of continuous values covering all the study area is used so that a value can be extracted for each plot of the FIA data in the study area. Actual measurement of snowpack, however, is point data only available at a measurement station. The Snow Data Assimilation System (SNODAS) by the NOAA National Weather Service's National Operational Hydrologic Remote Sensing Center (NOHRSC) (2004) provides mapped data of snow parameters estimated based on measured values from 2004 to 2017. Among several parameters included in the SNODAS data, snow water equivalent (SWE) or the amount of liquid water contained within a snowpack is used for this study. Particularly, SWE data on April 1 each year are used to represent spring snowmelt, which is strongly associated with increase of fire risks (Preisler and Westerling 2006; O'Leary et al. 2016). Figure 3.2 shows the average of SWE on April 1 from 2004 to 2017. While a number of studies point out that SNODAS overestimates SWE (Lv, Pomeroy, and Fang 2019; Brennan et al. 2020; Massey et al. 2011), it does not affect the results of this study because its interest is in spatial and temporal variation in the data.

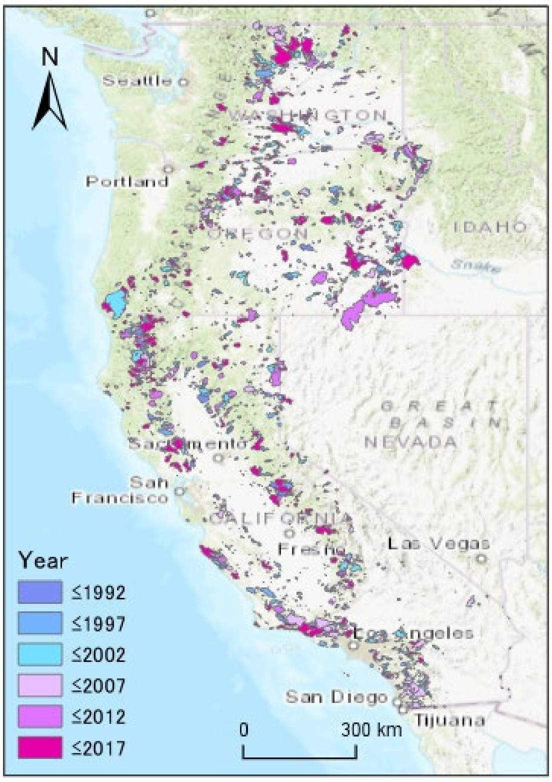
Figure 3.2 Average SWE of April 1 between 2004-2017 (mm)



Data by the Monitoring Trends in Burn Severity (MTBS) project (Eidenshink et al., 2007) is used to make a variable measuring the proportion of burned areas by wildfires. MTBS maps large fires in the U.S. from 1984 to present with burn severity and extent. The data is at a 30 meter resolution and includes all fires 4.05 square kilometers or greater in the western U.S.

and 2.02 square kilometers or greater in the eastern U.S. The dataset used for this study consists of polygons of burned areas with attributes including areas burned, a year when a fire started, and fire type. Figure 3.3 shows burned areas by wildfires between 1986 and 2017[2] based on MTBS data over the study area. The data shows that wildfires have become more frequent in the last 10 years and area burned by each wildfire has become larger.

Figure 3.3 Burned areas by wildfires from 1986 to 2017

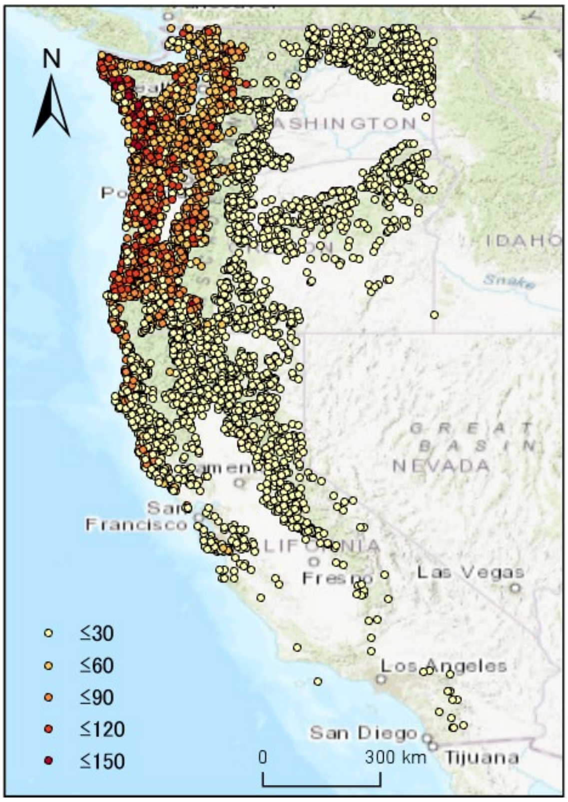


To represent the economic value of forestland used to produce timber, a measure of annualized timber rents are used. Rents are computed by each county and by six forest types – Douglas fir, fir/spruce/mountain hemlock, hemlock/Sitka spruce, ponderosa pine, other

[2] Out of the available MTBS data of time period of 1984-2017, 1986-2017 is used for the analysis.

softwoods, and hardwoods. The rent data is estimated by Hashida and Lewis (2019). They described regional average rents as a function of forest growth, timber prices by forest type, and site productivity. Timber prices exhibit regional variation across 18 such price regions defined by each of the three Pacific states' agencies that collect price data. Site productivity, or inherent capacity of forest land to grow industrial wood, is divided into seven classes as defined in the FIA data. For each forest type and site productivity classses by price region, Hashida and Lewis (2019) first estimated yield curves by specifying a non-linear growth equation by von Bertalanfy (1938), and then used the FIA plot-level data to estimate the relationship between stand volume and age. When combined with the respective price data, the yield curves are used to compute approximate Faustmann optimal rotation periods with an assumption of a discount rate of 5%. Annual per-acre rents are calculated using the maximized present value derived from the optimal rotation periods. Figure 3.4 shows rent at each plot depending on its forest type and county. The west side of the Cascade Range in WA and OR stands out with the highest rents across the Pacific states, while most of the other plots have rents less than USD 30/acre/year.

Figure 3.4 Forest rent at each plot ($/acre/year)



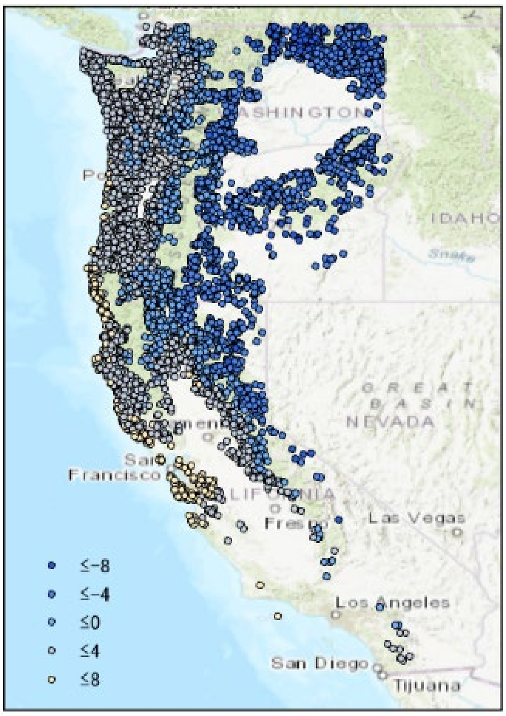
Climate variable data is also drawn from Hashida and Lewis (2019). As climate metrics observable to the forestland owners, they selected total precipitation and mean temperature during the growing season[3], the maximum temperature in the warmest month (August), and minimum temperature in the coldest month (December). They calculated the plot-level 30-year average from 1981 and 2010 of these parameters based on normal monthly data from the Parameter-elevation Regression on Independent Slopes Model (PRISM). Figure 3.5 shows a set of maps with a range of values of climate metrics at each plot as well as the

[3] Growing season months are those that have growing degrees days above 10°C (50°F), which are determined at a regional level that represents varying climate zones. Regional climate data are from National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center.

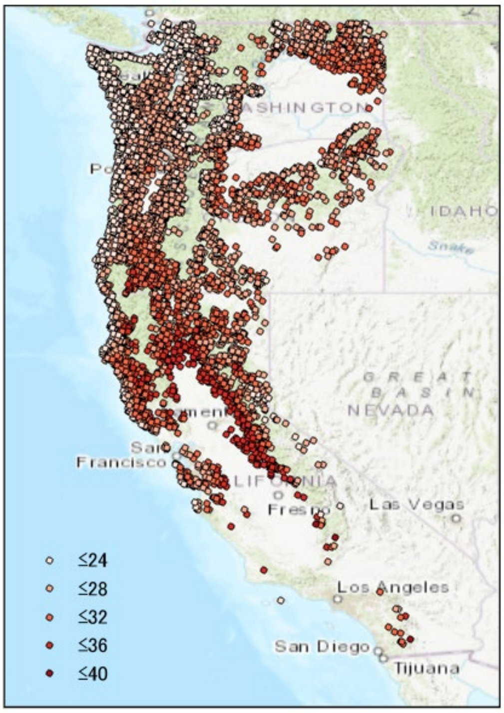
county average of the values calculated by taking a weighted average of all the plots in each county. Minimum temperature tends to be lower in the east side of the mountain ranges in all the three states. Maximum temperature tends to be higher in west of the Sierra Nevada Mountains in CA, while maximum temperature in WA and OR tends to be lower in the west side of the Cascade Range. Precipitation is higher in the western portion of WA and OR and the eastern part of CA in the mountains. For a future projection of these climate variables up to 2050 and 2090, Hashida and Lewis (2019) used RCP 8.5, a high-emission pathway where greenhouse gas emissions and concentrations continue to increase without any mitigation target. The projected values are derived from the US National Center for Atmospheric Research Community Climate System Model (CCSM) 4.

Figure 3.5 Plot- and County- level climate metrics

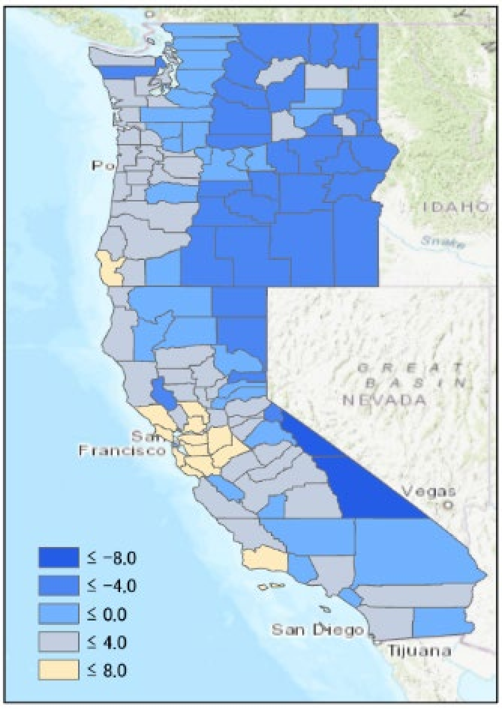
a.1 Minimum temperature in December at each plot (°C)



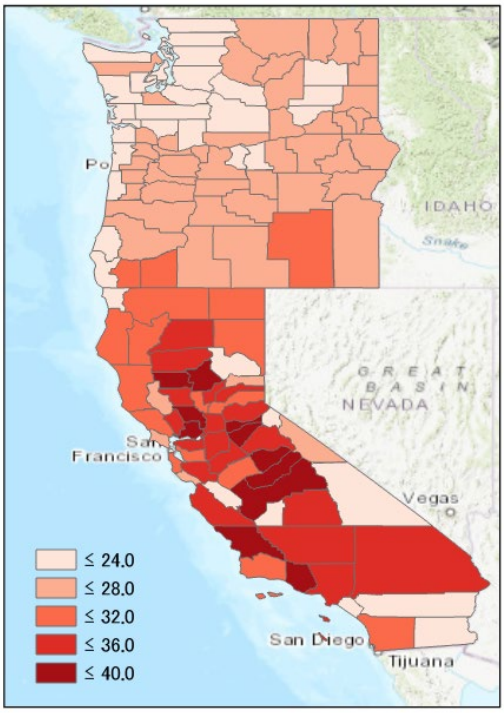
a.2 Maximum temperature in August at each plot (°C)



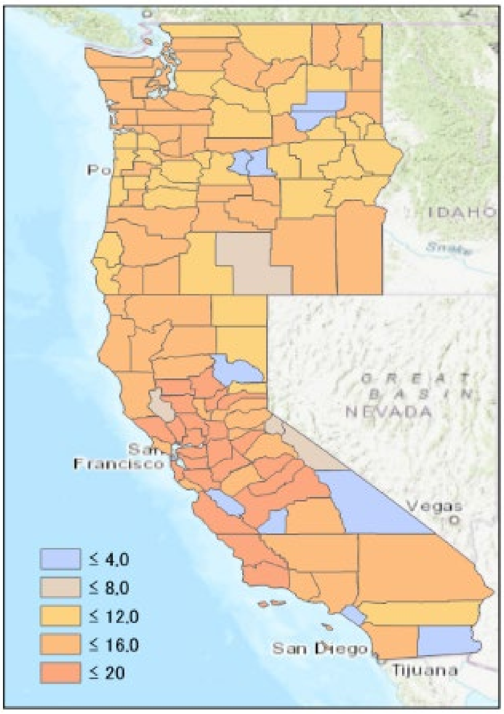
b.1 Minimum temperature in December by county (°C)



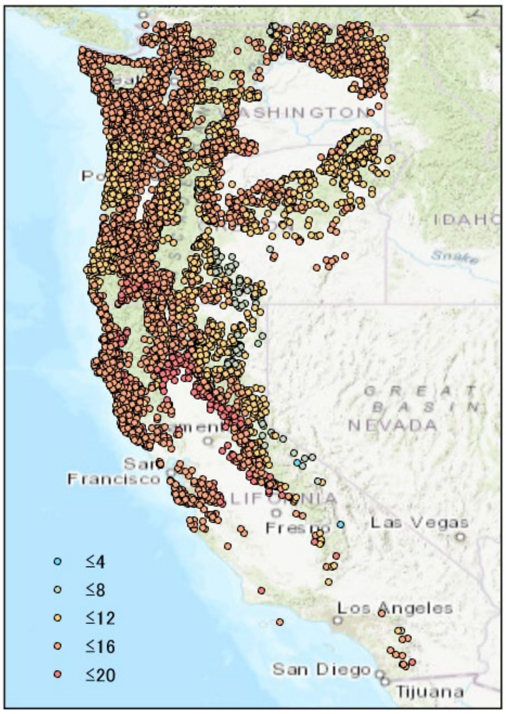
b.2 Maximum temperature in August by county (°C)



b.3 Mean temperature during the growing season by county

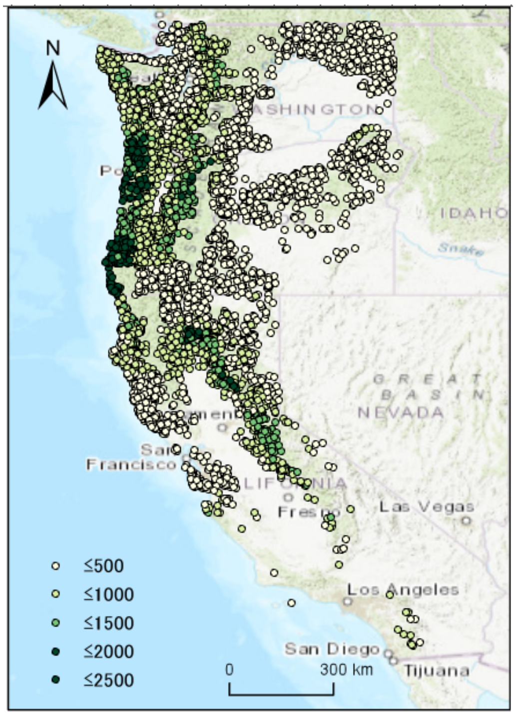


a.3 Mean temperature during the growing season at each plot (°C)



b.4 Total precipitation during the growing season by county (mm)

a.4 Total precipitation during the growing season at each plot (mm)



4. Methods

4.1 Development of Econometric Model

4.1.1 Dependent Variable to Represent Management Decisions

This analysis attempts to clarify interaction among private forest owners' management decisions, the economic value of forestland, and climate change impacts. As a dependent variable to represent management decisions by private forest owners to adapt to climate change, two options are considered; 1) precommercial thinning and 2) prescribed fire. Like thinning, prescribed fire is implemented as a fuel treatment and lowers risk of fire.

A binary variable of whether a stand has been thinned is created based on the FIA data customized for the Pacific Northwest. The data has an attribute of how a stand has been treated, which includes different types of cut, site preparation, regeneration, and precommercial thinning. The variable has a value of 1 if a stand has been thinned in the last ten years from an inventory year and 0 otherwise. The variable for the second option is the number of prescribed fires implemented near a plot based on the MTBS data. To approximate a plot where a prescribed fire takes place, a 1 km buffer is created around each plot by ArcGIS and the number of data points of prescribed fire within each buffer is counted. Data points that do not fall in any of the 1km buffers are snapped to the closest buffer. The number of prescribed fires, however, is limited. There are only 18 privately- or state- owned plots that have both an observation of implementation of prescribed fires and management activities. The first option of precommercial thinning, therefore, is chosen as the dependent variable representing management decisions by private forest owners to adapt to climate change. This binary dependent variable is expressed as *thinning*.

4.1.2 Impacts of Climate on Thinning through Rent

A linear probability model is developed to describe *thinning* as a function of explanatory variables such as the economic value of a stand, climate metrics, and other stand characteristics. Explanatory variables included in the models in this section are described in Table 4.1.

Table 4.1 Description of explanatory variables in models (1) to (6)

Variable	Description
fortyp_rent	County-level timber rent depending on forest type
climate	An unspecified variable to represent climate at a plot
fire_risk	An unspecified variable to represent wildfire risks at a plot
tmax_08_cnty	County-average maximum temperature in August
tmin_12_cnty	County-average minimum temperature in December
tmean_gs_cnty	County-average mean temperature in the growing season
precip_gs_cnty	County-average precipitation in the growing season
rent_cnty	County-average rent by weighing percentage of each forest type
tmean_gs	Plot-level mean temperature in the growing season
precip_gs	Plot-level precipitation in the growing season

To analyze how the economic value of forestry and climate change influences the probability of thinning, the model should include forest rent and climate metrics as explanatory variables. As stated by Lauer in an analysis of forest management under fire risk (2017 p. 37): "The cost of the fuel treatment is only justified if it is exceeded by the expected value created by changing the fire arrival probabilities across the landscape." Therefore, fuel treatments like thinning are hypothesized to be more likely to be adopted in landscapes with high timber values. Fuel treatment decisions are also a function of the risk of fire spread (Lauer et al. 2017), and so a variable to represent the risk of wildfires should also be included in a model of forest owners' fuel management decisions. A simple linear probability model is as follows:

$$thinning = \alpha_0 + \alpha_1 fortyp\_rent + \alpha_2 climate + \alpha_3 fire\_risk + u \qquad (1)$$

While thinning is described as a function of rent, climate, and fire risk, rent can also be a function of thinning since thinning promotes the growth of trees and improves timber value. The variable of rent can be described by a simple structural equation as follows:

$$fortyp\_rent = \beta_0 + \beta_1 thinning + \beta_2 climate + \beta_3 fire\_risk + v \qquad (2)$$

Model (1) and (2) suggest that the variable of rent is determined simultaneously with thinning, the primary dependent variable of interest. Model (1), therefore, is likely to be affected by simultaneity bias which induces correlation between the rent variable and the error term. To remove the endogeneity, a reduced form needs to be obtained by replacing the variable of rent with an appropriate function of exogenous variables that affect rent. By substituting *thinning* in model (2) with the right hand side of model (1), the rent variable is described by a reduced-form model:

$$fortyp\_rent = \{\alpha_0\,\beta_1 + \beta_0 + (\alpha_2\,\beta_1 + \beta_2)climate + (\alpha_3\,\beta_1 + \beta_3)fire\_risk + \beta_1\,u + v\}/(1- \alpha_1\,\beta_1) \quad (3)$$

The reduced-form relationship between rent and climate in (3) is commonly known as the Ricardian model. The Ricardian model was developed to analyze the economic impact of climate change on agricultural land prices (Mendelsohn et al. 1994). A simplified Ricardian model with only climate explanatory variables is developed by referring to the forestry Ricardian model developed in Mihiar and Lewis (2020). They describe the net returns to forestry by county as a function of multiple climate variables, and estimate the model using county-level data across the conterminous U.S. This study also uses county-average data of forest rent and climate for a Ricardian analysis, focusing on the Pacific states of WA, OR, and CA. Since both maximum temperature in August (*tmax_08_cnty*) and minimum temperature in December (*tmin_12_cnty*) is highly correlated with mean temperature in growing season (*tmean_gs_cnty*), only precipitation (*precip_gs_cnty*) and mean temperature in the growing season are included. The quadratic form of each of the climate metric is also included to check how the influence of each parameter on rent changes as its value changes. The Ricardian model is a reduced-form model with only exogenous explanatory variables and is described as follows:

$$rent\_cnty = \gamma_0 + \gamma_1 tmean\_gs\_cnty + \gamma_2 tmean\_gs\_cnty^2 + \gamma_3 precip\_gs\_cnty + \gamma_4 precip\_gs\_cnty^2 + w \quad (4)$$

Estimates of model (4) show that both climate metrics positively influence rent at a diminishing rate at less than a 5% significance level (Table 5.2). Data for the rent variable *rent_cnty* in this Ricardian analysis and that for *fortyp_rent* in model (1) to (3) are at a different scale. While *rent_cnty* is an average value of each county, *fortyp_rent* is a value determined for each forest type and site class within a county. Although measurement scale of variables is different, a functional reduced-form relationship between rent and climate informed by model (4) can be applied to the variables of rent and climate in model (3) to obtain the following:

$$fortyp\_rent = \{a_0 \beta_1 + \beta_0 + (a_2 \beta_1 + \beta_2) tmean\_gs + (a_2 \beta_1 + \beta_2)\, tmean\_gs^2 + (a_2 \beta_1 + \beta_2) precip\_gs + (a_2 \beta_1 + \beta_2) precip\_gs^2 + \beta_1 u + v\}/(1- a_1 \beta_1) \quad (5)$$

By substituting *fortyp_rent* in model (1) with the right hand side of model (5) and simplifying, the following model (6) is obtained. The model reflects the fact that climate influences thinning directly by altering fire risk, and indirectly through its impacts on rent.

$$thinning = \pi_0 + \pi_1 tmean\_gs + \pi_2 tmean\_gs^2 + \pi_3 precip\_gs + \pi_4 precip\_gs^2 + \pi_5 fire\_risk + x \quad (6)$$

4.1.3 Variables of Fire Risk and Stand Characteristics

In addition to the climate parameters in model (6), a variable to represent how early snow melts in spring is included to further analyze the influence of climate on forest owners' management decisions. Snow water equivalent (SWE) is subject to climate change and its decrease in spring leads to a higher risk of wildfire as mentioned in chapter 3. The earlier that snow melts in spring, the longer a dry season becomes, which increases fire risk. Therefore, SWE on April 1st is extracted for each plot from the data provided by SNODAS. Since the data is available only from 2004, the 10-year average is taken for plots measured after 2013. As for those plots measured before 2013, an average between 2004 and the inventory year is taken. In such case, the number of years on which average is taken is less than 10 years and becomes shorter as the inventory year gets closer to 2004. While this variable reflects precipitation in winter, it is distinct from the precipitation variable in model (6), which is during the growing season or typically summer to fall.

To control for the risk of wildfire recognized by private forest owners, a variable is created using ArcGIS based on historical data of wildfire provided by MTBS. A 10km and 20km buffer is created for each plot and then the total of burned areas by wildfire within each buffer is calculated. Rather than the proportion of burned areas in a 10km buffer, that in a 10-20km ring buffer is used because a higher proportion in a 10km buffer results in a larger loss of trees, which leads to a management activity other than thinning. It is calculated by subtracting burned areas as well as total areas of 10km buffers from those of 20km buffers and then divide the difference of burned areas by that of total areas. This variable is created based on the data between 10 to 20 years ago from the inventory year of a plot to assure reflecting the impacts of wildfires occurred before a plot is measured.

The model also includes two additional variables capturing characteristics of a stand that might explain forest owners' decisions to thin a stand. The first one is a plot-level measure of productivity of a stand, which is one of the factors to determine the value of forest. The variable is binary with 1 for a productive stand and 0 for an unproductive one. It is created based on an attribute of estimated site productivity in FIA data, which has seven classes of productivity in terms of cubic feet per acre per year. A threshold is set at 120 cubic feet, below which is considered unproductive. The second one is stand age. Plots with an observation of stand age less than 20 years old and more than 200 years are dropped, for they are either too young to thin or too old to apply a usual management decision. A quadratic form is also added because influences of stand age on thinning are likely to be nonlinear.

The additional variables explained above are listed in Table 4.2.

Table 4.2 Description of explanatory variables in model (7)

Variable	Description
swe_avg	Average of SWE on April 1st of the last 10 years from an inventory year for plots measured after 2013, and of the years between 2004 and an inventory year for plots measured before 2013
prop_burned	Proportion of areas burned by wildfires within a 10-20km ring buffer of a plot between 10 and 20 years ago from an inventory year
productivity	Binary variable: 1 if productive (>120 ft^3/acre/year) and 0 otherwise
stdage	Stand age (years)

With these additional variables added to model (6), the final econometric model to estimate the probability of thinning is as follows:

$$thinning = \pi_0 + \pi_1 tmean\_gs + \pi_2 tmean\_gs^2 + \pi_3 precip\_gs + \pi_4 precip\_gs^2 + \pi_5 swe\_avg + \pi_6 prop\_burned + \pi_7 productivity + \pi_8 stdage + \pi_9 stdage^2 + x \qquad (7)$$

In addition to this linear probability model, a probit model with the same dependent and explanatory variables is also run to check robustness of model (7). Marginal effects of each explanatory variable in the probit model are compared with the estimated coefficients of model (7).

4.2 Robustness check on SWE variable using a Bayesian method

To analyze the impacts of climate on management decisions, an explanatory variable of SWE is included in model (7) in addition to other climate variables such as temperature and precipitation in the growing season. It represents the timing of snowmelt in spring. However, the amount of snow in spring can be less recognizable to private forest owners as having an influence to fire risk compared with temperature and precipitation. A hypothesis can be made that forest owners do not respond to the SWE variable. A robustness check on this variable is implemented to see if accounting for forest owners' response to SWE provides the same value estimated by the econometric model (7). If the hypothesis cannot be rejected, then the question is if the number of observations is large enough to counteract the initial belief. If true, the hypothesis can then be rejected.

To test this alternative assumption, a Bayesian method is used. A hypothesis as a starting point of a Bayesian analysis is called a "prior" and the one made above is specifically called an "uninformative prior". The hypothesis that private forest owners do not respond to SWE, or zero response by forest owners, provides no previous information with regard to influences of SWE on management decisions. The initial belief is updated by measuring the influence of each observation of SWE on management decisions to the distribution of probability of the SWE coefficient. The updated distribution is used as a new prior for the next observation. A distribution obtained after looping this process through all the observations is used to test the null hypothesis. According to the Bayes theorem, posterior distribution is described as:

$$P(\theta/D) = [P(D/\theta)*P(\theta)] / P(D) \qquad (8)$$

where $P(\theta/D)$ is a posterior distribution, $P(\theta)$ is a prior distribution, $P(D/\theta)$ is the likelihood of data D if θ is true, and P(D) is the likelihood of data D. In this analysis, D is the set of independent variables, including the variable of interest SWE variable (*swe_avg*). $P(\theta)$ is an uninformative prior modeled as a uniform [-1, 1] distribution with zero mean and a range assumed to include the true coefficient value. $P(\theta/D)$ is compared with the coefficient of the SWE variable estimated by the econometric model (7) to check if it is converged to a value close to the econometric estimate.

4.3 Changes in Management Decisions under Climate Change

By using the estimated models of (4) and (7) above, the influence of climate change on forest rent and private forest owners' management decisions is projected. To estimate how changes in climate would alter county average forest rents, the marginal effects of mean temperature and precipitation in the growing season on rent for each county are obtained from model (4). County-level marginal effects of these climate variables are then multiplied by the difference between 30-year averages and projection of each of these climate variables. The change in rent is described with the total differential as follows:

$$\Delta rent\_cnty = \frac{\partial rent\_cnty}{\partial tmean\_gs\_cnty}\Delta tmean\_gs\_cnty + \frac{\partial rent\_cnty}{\partial precip\_gs\_cnty}\Delta precip\_gs\_cnty \quad (9)$$

where $\Delta rent\_cnty$ is the change in county average rent, $\frac{\partial rent\_cnty}{\partial tmean\_gs\_cnty}$ and $\frac{\partial rent\_cnty}{\partial precip\_gs\_cnty}$ are marginal effects of county average mean temperature and precipitation on rent, respectively. $\Delta tmean\_gs\_cnty$ and $\Delta precip\_gs\_cnty$ are the changes in county average mean temperature and precipitation, respectively.

Changes in rent due to changes in mean temperature and precipitation in the growing season are summed to get the total. They are calculated for two time periods of climate change projection, 2050 and 2090. Changes in management decisions in terms of the probability of implementing precommercial thinning are estimated in the same way. The marginal effects of mean temperature and precipitation in the growing season on the probability of thinning are multiplied by changes in these climate variables under climate change for each county. The change in the probability of thinning is described as follows:

$$\Delta thinning = \frac{\partial thinning}{\partial tmean\_gs\_cnty}\Delta tmean\_gs\_cnty + \frac{\partial thinning}{\partial precip\_gs\_cnty}\Delta precip\_gs\_cnty \quad (10)$$

where $\Delta thinning$ is the change in the probability of thinning, $\frac{\partial thinning}{\partial tmean\_gs\_cnty}$ and $\frac{\partial thinning}{\partial precip\_gs\_cnty}$ are marginal effects of county average mean temperature and precipitation on the probability of thinning, respectively.

5. Results

5.1 Relationship between Thinning and Rent

This section begins by quantifying the relationship between rent and thinning, as developed in equation (1). However, as discussed in chapter 4, rent and thinning are likely to be simultaneously determined, and so regressing thinning on rent is done as a means of exploring the correlation between the two variables in order to provide context into the reduced-form results that are presented later in this section:

$$thinning = \gamma_0 + \gamma_1 fortyp\_rent + \gamma_2\, fire\_risk + \gamma_3\, swe\_avg + \gamma_4\, prop\_burned + \gamma_5\, productivity + \gamma_6\, stdage + \gamma_7\, stdage^2 + e \qquad (11)$$

Results of OLS regression of this linear probability model are shown in Table 5.1. The estimated coefficient of *fortyp_rent* is positive (0.00026) and statistically significant ($P<0.01$). The higher a forest rent is, therefore, the more likely a stand is thinned in the study area, controlling for stand age, productivity, and a select set of fire risk variables. Results confirm that a theoretical assumption of higher likelihood of thinning at a forest stand of a higher value applies to the data used for this study.

Table 5.1 Estimated coefficients of the model with rent as an explanatory variable (dependent variable = a binary indicator for whether plot was thinned)

Variable	Est. coefficient
fortyp_rent	0.00026***
stdage	-0.00223***
stdage^2	0.00001***
productivity	-0.00035
swe_avg	-3.22e-06
prop_burned	-0.00016**
Intercept	0.10591***
Summary Statistics	
Observations	3,823
F(6, 3816)	11.03
Prob > F	0.0000
R-squared	0.0434
Root MSE	0.13926

Note: ** and *** denote significance at the 5% and 1% levels, respectively.

Although rent is significantly correlated with thinning, it is endogenous because it is simultaneously determined with thinning as explained in Chapter 4. An explanatory variable of rent therefore needs to be replaced with exogenous variables in a reduced-form. The Ricardian model (2) is set up to describe rent as a reduced-form function of two climate variables, mean temperature and precipitation in the growing season at county level. The purpose of developing model (2) is to examine how climate is likely to affect rent, which informs the eventual reduced-form relationship between thinning and climate described in model (7).

5.2 Relationship between Rent and Climate

Table 5.2 presents OLS estimates of the Ricardian model (2), using data aggregated to the county-level. The estimates show that both climate variables positively affect rent at a diminishing rate. The results, however, only show the coefficients estimated from all the observations of each variable. Therefore, marginal effects are taken to examine the relationship between rent and each of the climate variables over the range of the dataset (Figure 5.1).

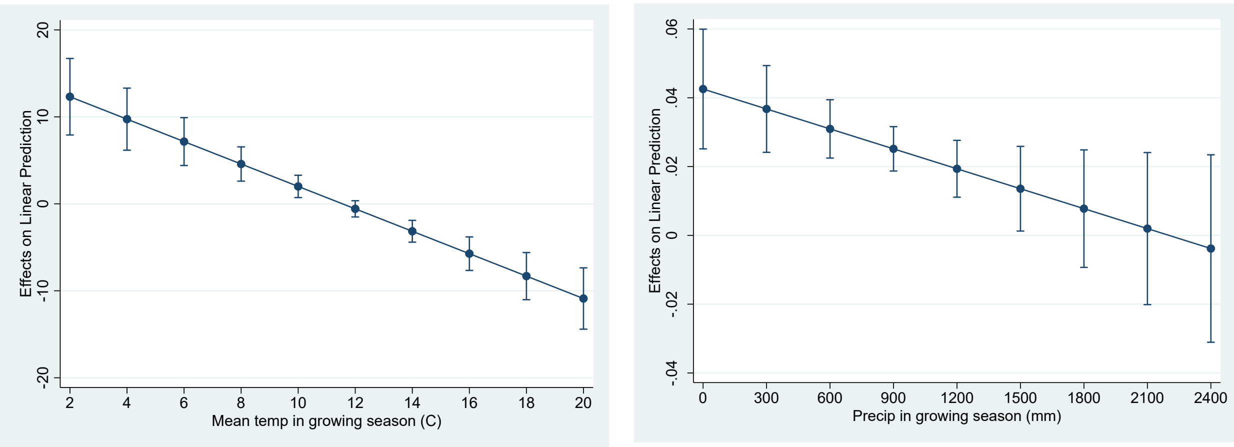
Table 5.2 Estimated coefficients of county-level Ricardian model (dependent variable = county-average rent to timberland)

Variable	Est. coefficient
tmean_gs	14.8944 ***
precip_gs	0.0425 ***
$tmean\_gs^2$	-0.6445 ***
$precip\_gs^2$	-9.66e-06 **
Intercept	-75.2876 ***
Summary Statistics	
Observations	123
F(4, 118)	25.90
Prob > F	0.0000
R-squared	0.4345
Root MSE	18.739

Note: ** and *** denote significance at the 5% and 1% levels, respectively.

Figure 5.1 Marginal effects of climate variables on rent with 95% confidence intervals, evaluated at alternative levels of the climate variables

a. Mean temperature in the growing season b. Precipitation in the growing season



Based on results of OLS regression as well as marginal effects, rent is concave with respect to mean temperature in the growing season. An increase in temperature raises rent when evaluated at lower temperature, and lowers rent when evaluated at warmer temperature. From the first derivative of model (4), the mean temperature at which its influence on rent turns from positive to negative is 11.55°C. Therefore, a temperature rise in areas of colder climate raises rents, while a temperature rise in areas of warmer climate lowers rents. Rent is also concave with respect to precipitation in the growing season. The marginal effect of precipitation is positive at all the levels of precipitation observed in the data. Thus, a wetter climate raises rents while a drier climate lowers rents in the study area.

The results in this section indicate that changes in climate have clear impacts on rents to timberland that vary regionally by the level of climate. Together with the results showing the relationship between thinning and rents in the previous section, they suggest that climate could impact thinning through its effect on rent.

5.3 Estimates of Probability of Thinning

The results of the Ricardian model above show that forest rents can be well explained by the two climate variables, as growing season temperature and precipitation explain more than 43% of the variation in county-level mean rents. Given the endogeneity of rent in the thinning equation from (1), the reduced-form model (7) is used to estimate the probability of thinning as a function of climate and fire risk variables where the right hand side of model (4) substitutes for the variable of rent. In addition to value of a stand, the climate variables in model (7) represent risk of wildfires. Since a drier and hotter climate in general makes an area more prone to a large fire (Preisler & Westerling, 2006), precipitation and mean temperature should indicate fire risk at a stand. Climate variables in model (7), therefore, influence private forest owners' management decisions through two different avenues; through the rental value of a stand and through the risk of wildfires. For example, while warmer temperatures may directly increase risk of wildfires, the results from the Ricardian model in section 5.2 also suggest that warmer temperatures can lower the rents to timberland, which could therefore lower the probability of thinning if landowners are less likely to thin land that has become less commercially valuable.

Table 5.3 shows OLS estimates of model (7). The estimated coefficient of *precip_gs* is positive and significant at less than 10% level. *precip_gs* and *precip_gs*^{2} are jointly significant as result of F-test on these variables is 0.001. *precip_gs*^{2} is negative and significant at less than 1% level. While the estimated coefficient of *tmean_gs* is insignificant, result of F-test on *tmean_gs* and *tmean_gs*^{2} is 0.10, indicating that the null hypothesis that *tmean_gs* and *tmean_gs*^{2} are jointly zero can be rejected at 10% significance level.

The productivity variable has a positive (0.0089) and statistically significant ($P<0.005$) effect on the probability of thinning. High quality stands have an approximate 0.9 percentage point higher probability of being thinned compared to low quality stands. To put this into perspective, the sample average probability of being thinned is 2.1%. The estimate of *swe_avg* suggests that the more snowpack a stand has in spring, the less likely it is to be thinned. It is significant at less than 10% level but not at 5% level. The result of *prop_burned* is negative and statistically significant ($P<0.005$) contrary to a theoretical expectation that more areas burned by wildfires in surrounding stands motivate a private forest owner to implement thinning to reduce risk of wildfire spreading to his own stand. This result could reflect that rents are lower in regions that experience more frequent burns, and this model includes some unobserved drivers of rent. As shown in Figure 3.1 in Chapter 3, more plots are thinned in the western part of WA and OR, which matches with regions where forest rent is higher. These regions are also where areas burned by wildfires are small. This likely bias causes the estimated coefficient of *prop_burned* to be negative.

Table 5.3 Estimated coefficients of the model to predict the probability of thinning

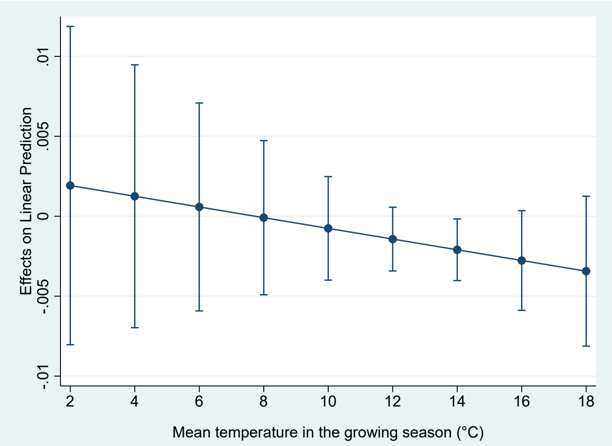
Variable	Est. coefficient
tmean_gs	0.00259
precip_gs	0.00001 *
tmean_gs^2	-0.00017
precip_gs^2	-9.66e-06 ***
stdage	-0.00242 ***
stdage^2	0.00001 ***
productivity	0.00894 **
swe_avg	-0.00002 *
prop_burn	-0.00016 **
Intercept	0.11197 ***
Summary Statistics	
Observations	3,743
F(9, 3733)	7.61
Prob > F	0.0000
R-squared	0.0432
Root MSE	0.1408

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

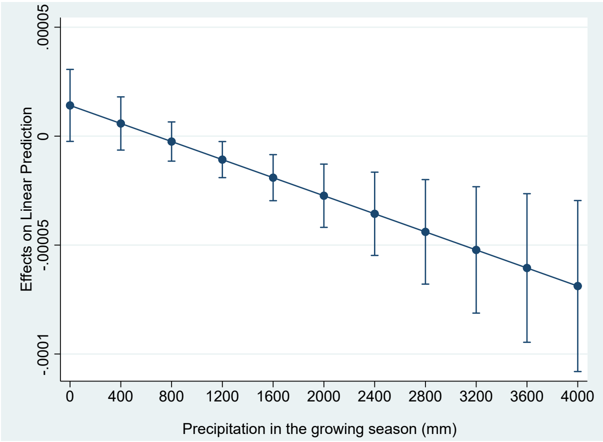
Marginal effects of climate variables are taken to examine effect of changes in climate on the probability of thinning over the range of data (Figure 5.2). Marginal effects of *tmean_gs* are insignificant at all levels within the range of data, which suggests that I fail to reject the null that *tmean_gs* has no effect on the probability of thinning over the study area. Marginal effects of *precip_gs* are insignificant when evaluated at drier climates, indicating that marginal changes in precipitation does not affect the probability of thinning in areas where it does not rain a lot. When evaluated at a wetter climate, the marginal effects of *precip_gs* are negative and significant ($p<0.05$). An increase in precipitation is likely to lower fire risk and therefore it lowers the probability of thinning. In contrast, a decrease in precipitation raises fire risk and accordingly it raises the probability of thinning.

Figure 5.2 Average marginal effects of climate variables on probability of thinning with 95% confidence intervals (linear probability model)

a. Mean temperature in the growing season



b. Precipitation in the growing season



5.4 Results of Probit Model

A probit model with the same variables as in the linear probability model (7) is run to check robustness of model (7). While model (7) includes a quadratic form of *tmean_gs, precip_gs,* and *stdage*, whether to include these variables in quadratic form in the non-linear probit model is checked by a likelihood ratio test. Results suggest that the null hypothesis that $tmean\_gs^2$, $precip\_gs^2$, and $stdage^2$ are jointly zero can be rejected at less than 1% significance level but the null that *tmean_gs*^{2}and *precip_gs*^{2} are jointly zero cannot be rejected ($p<0.05$). Therefore, *stdage*^{2} is included in the probit model, while *tmean_gs*^{2}and *precip_gs*^{2} are not.

Table 5.4 shows results of the probit model with those of model (7) for comparison. Parameters on *stdage* and *productivity* are significant in the probit model but the magnitude of their marginal effects at means differs from that of the estimated coefficients of model (7). Parameters on *swe_avg* and *prop_burn* become insignificant in the probit model, indicating a lack of robustness of these variables across the linear probability and probit models.

Table 5.4 Estimated coefficients of the probit model and linear probability model

Variable	Linear prob. model	Probit model	
	Est. coefficient	Est. coefficient	Marg. effects at means
tmean_gs	0.00259	-0.05130	-0.00074
precip_gs	0.00001*	-0.00017	-2.47e-06
tmean_gs^2	-0.00017	-	-
precip_gs^2	-9.66e-06***	-	-
stdage	-0.00242***	-0.04838***	-0.00037***
stdage^2	0.00001***	0.00021	-
productivity	0.00894**	0.27334**	0.00446**
swe_avg	-0.00002*	-0.00078	-0.00001
prop_burn	-0.00016**	-0.01424	-0.00023
Intercept	0.11197***	0.31920	-

Summary Statistics

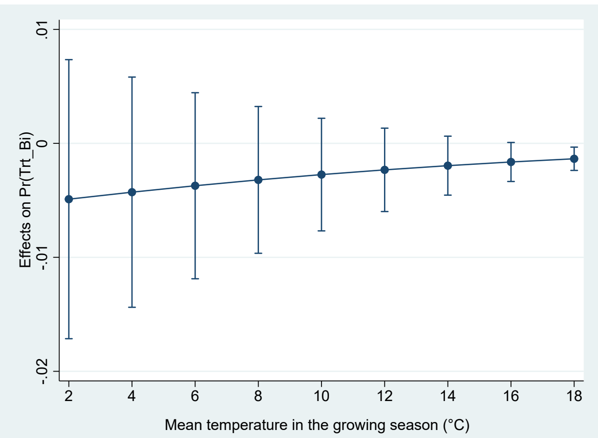
Linear prob. model		Probit model	
Observations	3,743	Observations	3,743
F(9, 3733)	7.61	LR chi-sq(6)	135.81
Prob > F	0.0000	Prob >chi-sq	0.0000
R-squared	0.0432	Pseudo R-sq	0.1988
Root MSE	0.1408		

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

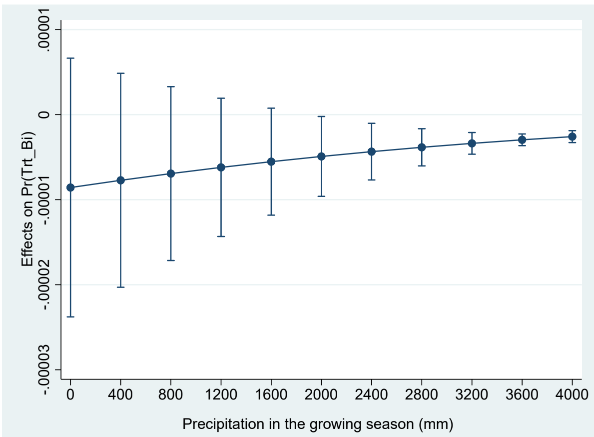
With regard to climate variables *tmean_gs* and *precip_gs,* marginal effects are taken to examine their relationship with the probability of thinning (Figure 5.3). *tmean_gs* is insignificant at all levels within the range of data, which is the same as the linear probability model as shown in Figure 5.2-a. The marginal effect of *precip_gs* finds the same pattern as that in the linear probability model (Figure 5.3-b) - it is negative and significantly different from zero (p<0.05) in wetter climates. Increases in precipitation therefore lowers the probability of thinning because it lowers fire risk, while decreases in precipitation raises the probability of thinning. In drier climates, however, the estimated marginal effect of *precip_gs* is insignificant and does not affect the probability of thinning.

Figure 5.3 Average marginal effects of climate variables on thinning with 95% confidence intervals (probit model)

a. Mean temperature in the growing season



b. Precipitation in the growing season



5.5 Results of robustness check on SWE variable

Table 5.5 shows results of the Bayesian analysis on the SWE variable. Results of the econometric model (7) are also included in the table for comparison.

Table 5.5 Results of the Bayesian analysis

Variable	Est. coefficient	
	Linear prob. model	Bayesian model
tmean_gs	0.00259	0.00195
precip_gs	0.00001*	0.00001
$tmean\_gs^2$	-0.00017	-0.00015
$precip\_gs^2$	-9.66e-06***	-1.06e-08
stdage	-0.00242***	-0.00242
$stdage^2$	0.00001***	0.00001
productivity	0.00894**	0.00893
swe_avg	-0.00002*	-0.00003
prop_burn	-0.00016**	-0.00016
Intercept	0.11197***	0.11710
Summary Statistics		
Observations	3,743	
F(9, 3733)	7.61	
Prob > F	0.0000	
R-squared	0.0432	
Root MSE	0.1408	

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The coefficient of the variable converges to -0.000026, which is very close to what is estimated by the econometric model, -0.000022. This result suggests that influence of the hypothesis, or initial belief, is rejected as updates occur. It also suggests that the number of observations used for this study is large enough to produce a statistically robust result. The data tells us that private forest owners do respond to earlier snowmelt by implementing precommercial thinning. It is, however, only along the mountain ranges where there is some snowpack. Private forest owners in such areas recognize earlier snowmelt as a factor to increase fire risk in addition to other climate variables.

5.6 Impacts of Climate Change on Management Decisions

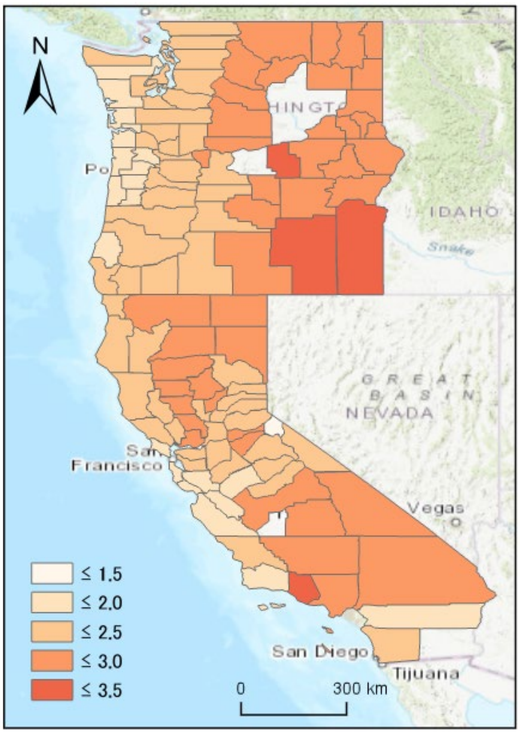
Using the estimated models, impacts of climate change on forest rents and the probability of thinning is projected. Climate change is reflected through the variables of mean temperature and precipitation in the growing season. Figure 5.4 shows how these two climate variables change in each county under climate change. The projection of these climate variables linked to each FIA plot comes from Hashida and Lewis (2019). I calculated the county-level values based on downscaled data of a global climate model under a climate scenario of RCP8.5.[4] Mean temperature rises all over the study area with a range between 1.4 and 3.1°C in 2050 and 2.9 and 5.6°C in 2090. Inland counties tend to have a higher magnitude of change. Precipitation increases in most of the counties in the east side of Cascade Range in WA and OR, while it decreases in many of the counties in the west side. The magnitude of the negative change is particularly large in the southwest part of OR. In CA, precipitation decreases in the

[4] The downscaled data is at 1km resolution and created by the ClimateWNA model developed by the Center for Forest Conservation Genetics at the University of British Columbia (Wang, Hamann, Spittlehouse, & Murdock, 2012).

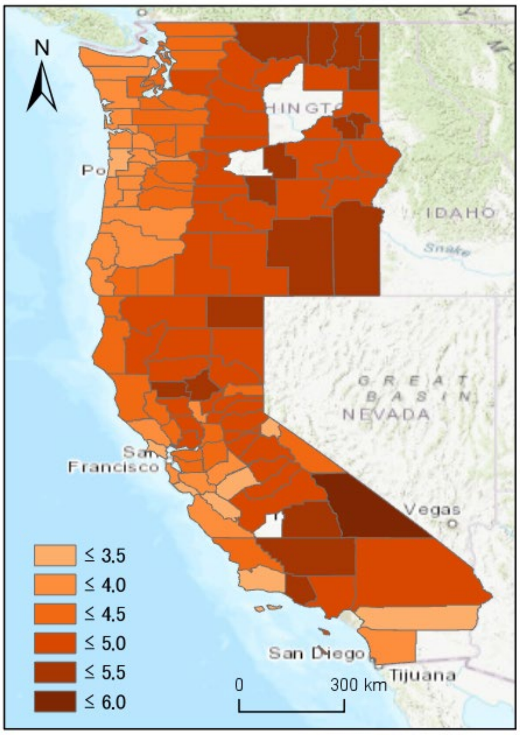
north and middle part of the state.

Figure 5.4 Changes in climate metrics

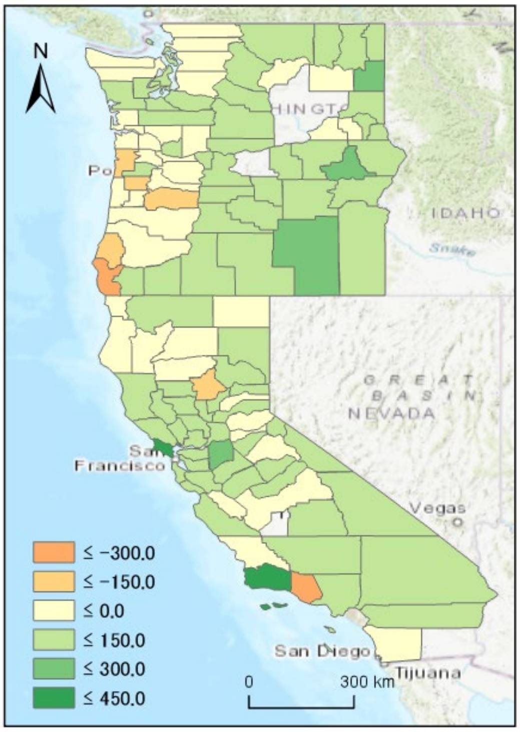
a.1 Mean temperature (2050) (°C)



a.2 Mean temperature (2090) (°C)



b.1 Precipitation (2050) (mm/year)



b.2 Precipitation (2090) (mm/year)

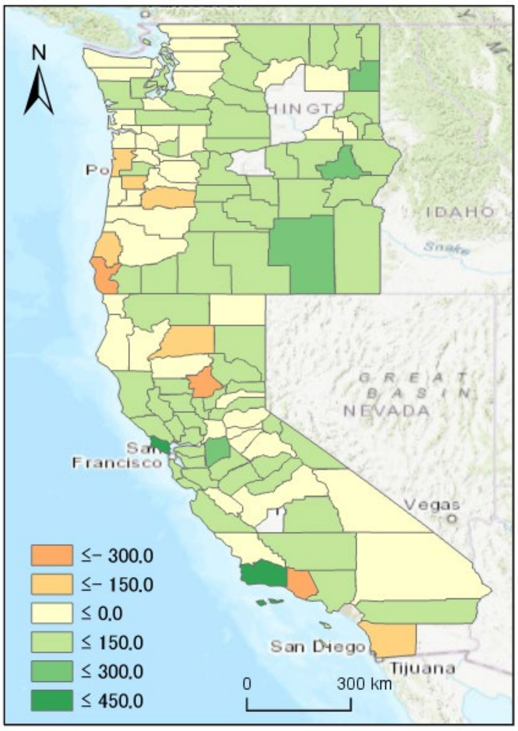
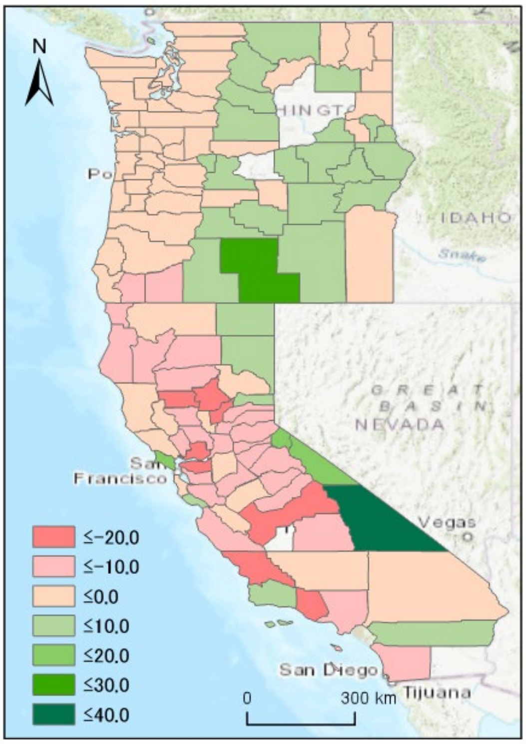


Figure 5.5 shows the projected change in rent by county under climate change in 2050 and 2090, using the estimated parameters from the Ricardian function. The projected change in rents reflects the combined effects of projected changes in both mean temperature and precipitation in the growing season. Mountain ranges in the study area distinguish the change in rent. Rent is generally projected to go down in the west side of the mountain range and projected to go up in the east side. This tendency is consistent with Hashida and Lewis (2019), who found that private forest owners are less likely to plant Douglas-fir, the highest value species, under climate change in western WA and OR. The magnitude of the negative change is larger in CA than that in WA and OR. The projected drop in rent is less than 10 USD/acre/year in 2050 and 15 USD/acre/year in 2090 in most of the counties with negative change in WA and OR. In CA, many of counties have much larger projected decreases in rent. In WA and OR, counties with a projected increase in rent generally coincide with those regions east of the Cascades that do not currently have significant amounts of Douglas-fir. In CA, very little land is projected to have an increase in rent.

Figure 5.5 Change in rent under climate change (USD/acre/year)

a. 2050



b. 2090

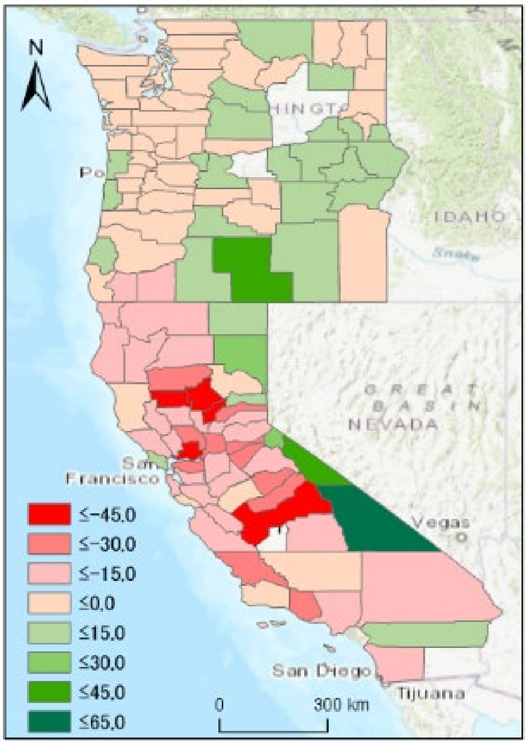
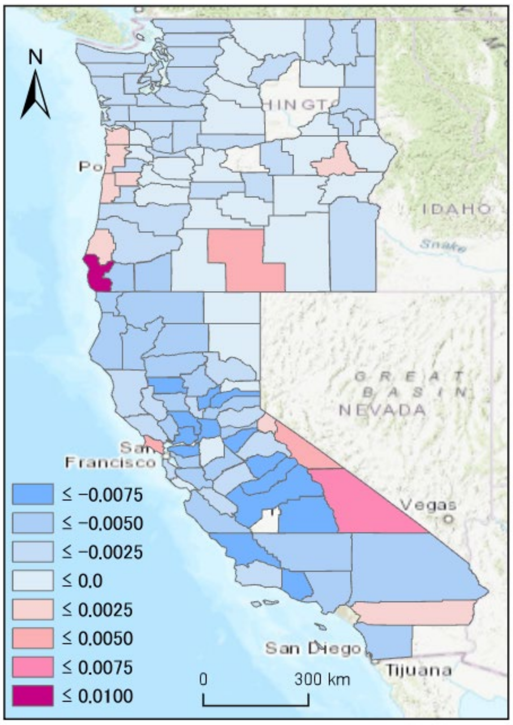


Figure 5.6 shows the projected change in the probability of thinning under climate change both at the county and the plot level. Standard errors of the total effects at each plot is calculated with the delta method to examine the significance of combined changes in temperature and precipitation. Figures 5.6.b.2 and 5.6.c.2 show only the plots with total effects of mean temperature and precipitation at less than 10% significance level. County-level maps of 5.6.a.1 and 5.6.a.2 show the projected climate impacts on thinning has a very similar geographic pattern as the projected change in rent. A stand is projected to be less likely to be thinned in counties that are projected to have a negative impact of climate change on rent.

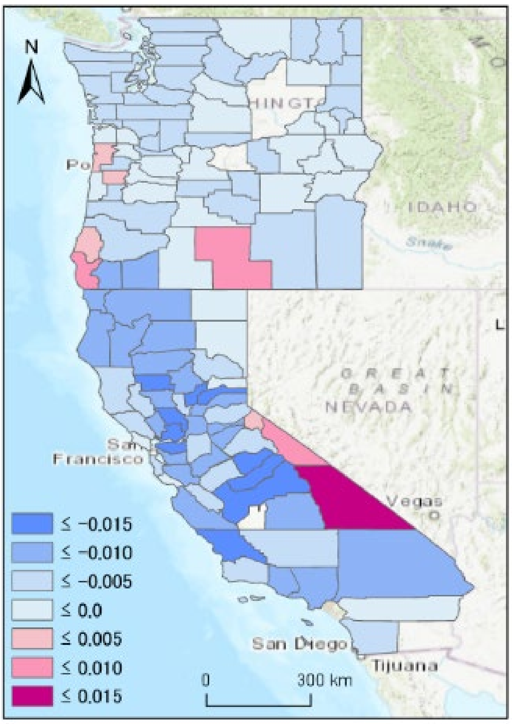
Plot-level maps of 5.6.b.1 and 5.6.c.1 show the tendency of lower probability of thinning in most plots. The map of plots that have climate impacts on the probability of thinning that are statistically significant (p<0.1) in 2050 (figure b.2) indicates that the probability of thinning rises at some plots. Those plots are mostly along the coast of OR where precipitation decreases at a particularly large extent. In 2090, all the plots that have a statistically significant climate impact on the probability of thinning (p<0.1) have a negative effect. The magnitude of the negative effect is especially large for plots in the northeast corner of WA and southwest part of OR. In these regions, an increase in precipitation lowers fire risk, which outweighs the effect of mean temperature rise to increase fire risk and lowers the probability of thinning.

Figure 5.6 Change in the probability of thinning under climate change

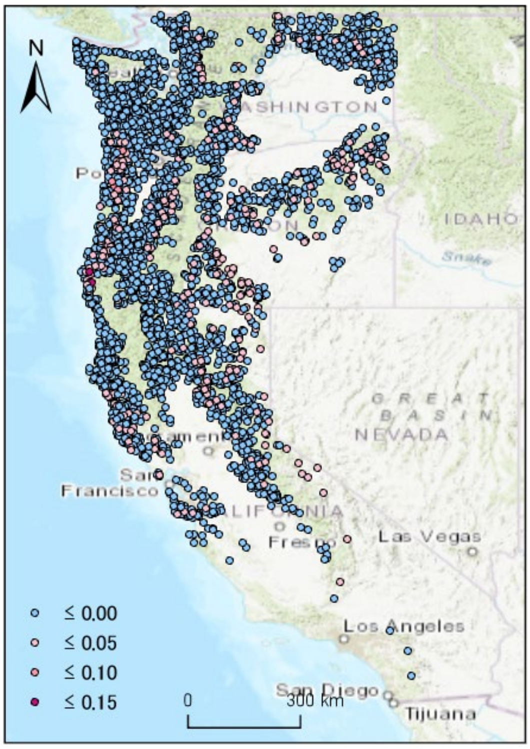
a.1 Changes at county level (2050)



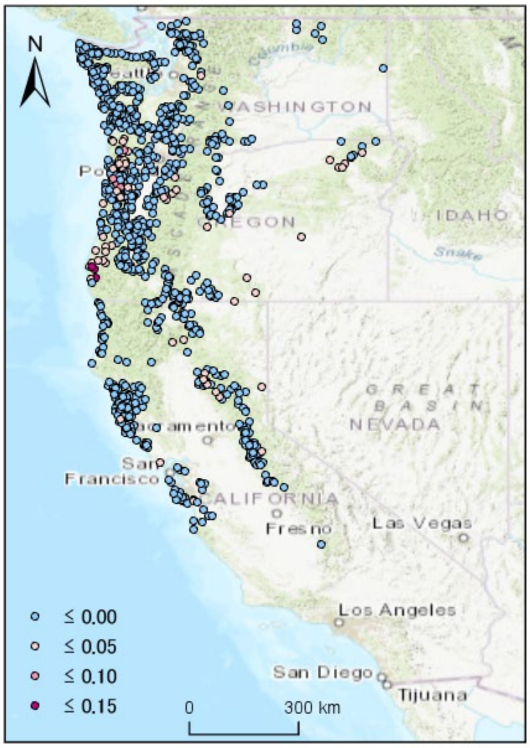
a.2 Changes at county level (2090)



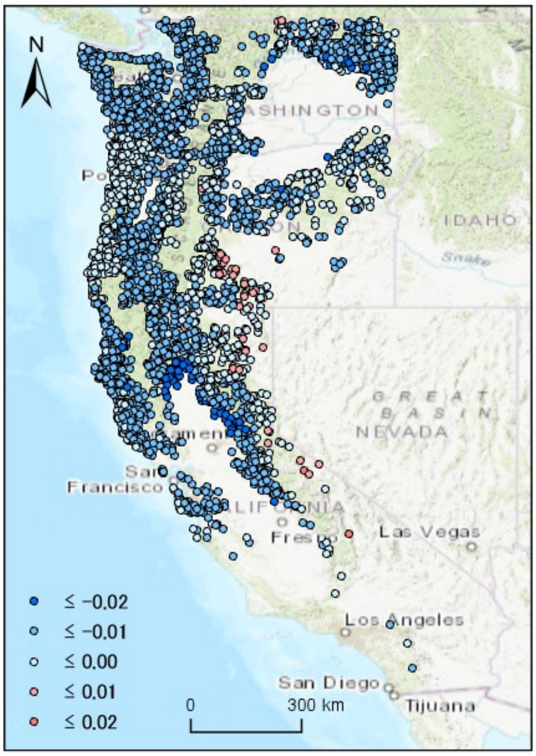
b.1 Changes at plot level (2050)



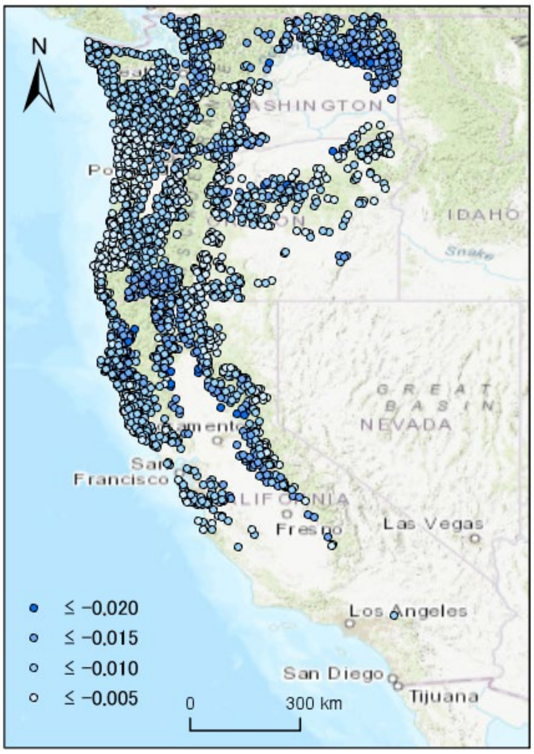
b.2 Changes at plot level with
10% significance (2050)



c.1 Changes at county level (2090)



c.2 Changes at plot level with
10% significance (2090)



6. Discussions and Conclusions

This study aims to empirically estimate the influence of climate on private forest owners' decisions of fuel management at the plot level across the Pacific states of the U.S. The management response of private forest owners to climate affects the risk of spreading wildfire across an entire landscape through interaction with neighboring forest stands, and so private management actions generate social costs and benefits. The results of the empirical analysis suggest that a forest stand with characteristics associated with high timber productivity and land value (moderate temperature, sufficient precipitation, high site class) is more likely to be thinned. A higher rent is partly explained by a higher precipitation, which facilitates growth. If a stand has characteristics that lead to relatively low productivity and economic value to timber, it will be less likely that the significant cost of thinning will be outweighed by private benefits to landowners. Within the study area, western WA and OR have moderate temperatures and a wetter climate that leads to much higher forest rents than the other portions of the Pacific states. Western WA and OR are also the region where there has been few large wildfires over the last three decades, while the rest of the Pacific states have experienced significant recent wildfire activity. Results presented in this thesis also suggest that private forest owners along the mountain range, where forest rents are high, respond to earlier snowmelt as one of the factors to increase fire risk. However, proportion of burned areas in surrounding stands, which tends to be large in regions with low forest rents, do not necessarily motivate private forest owners to implement precommercial thinning as a fire response. This finding implies the importance of policy support or incentive for private forest owners to implement precommercial thinning in a stand of a low timber value. Such support will contribute to creating a forest landscape that is less prone to extreme fires.

This study also estimates the marginal change in the probability of thinning in response to climate change. Projected precipitation decreases in the western part of WA and OR raises fire risk and therefore raises the probability of thinning. The probability of thinning is also influenced by climate variables through their influences on rent. A projected decrease in precipitation together with a projected increase in mean temperature in the growing season is estimated to lower forest rents particularly in inland of CA, where the probability of thinning drops most significantly within the study area. These areas are also where large wildfires have constantly taken place over the last three decades. The estimated results imply that the areas with already high fire risk will become even more prone to fires under climate change if private forest owners make fuel management decisions driven by economic motivations.

There are some areas that can be further explored for improvement. First, the limitation in the temporal availability of high quality snow-water equivalent (SWE) data limits the variation used in the econometric model. The number of years in which the average of SWE on April 1st is taken is not long enough for the plots whose inventory year is before 2013. The coefficient of the average SWE variable estimated by the linear probability model is negative and significant and the check using a Bayesian method also suggests it is robust. The results of a comparable probit model, however, showed that there is a lack of robustness in this variable. Since the SNODAS data used for this study is only available from 2004, an alternative dataset should be explored to cover the years required for taking 10-year average for all the plots. The second limitation is how to use projected figures of climate variables to estimate the probability of thinning under future climate change. This study used only mean temperature and precipitation in the growing season for the estimation. Effects of snow variables and fire risk variable are not used because projection of these variables at an appropriate scale for this study is not available. Further exploration on how to include projection of these variables can improve the estimation of the marginal change in the probability of thinning in response to climate change that affects multiple independent variables.

A forest landscape with a low risk of spreading wildfire is a public good. As fire risk increases due to climate change, how to prompt each forest owner to provide this public good should be sought. This study clarifies that the current fire management response to climate in private forests does not necessarily increase with fire risk, and that some stands are projected to be less likely to be thinned in response to a drier future climate despite the higher fire risk. The negative effect of a warmer and drier future climate on timber productivity and timber rents suggests that there is a smaller private economic benefit to landowners from fire management, and thus, there is a potential divergence between the private incentives to thin forests less in response to climate change and the social incentive to thin more due to higher risk of wildfire spread across large landscapes. These findings and implications can contribute to building a basis for future management plan to create a forest landscape at low risk of fire.

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