# Estimating the economic net returns of Oregon & Washington forests with regard to climate change

by
Zoe I. Johnson

A THESIS

submitted to

Oregon State University

University Honors College

in partial fulfillment of
the requirements for the
degree of

Honors Baccalaureate of Science in Agricultural Sciences
(Honors Scholar)

Presented May 26, 2016
Commencement June 2016

# AN ABSTRACT OF THE THESIS OF

Zoe Johnson for the degree of Honors Baccalaureate of Science in Agricultural Sciences presented on May 26, 2016. Title: Estimating the economic net returns of Oregon & Washington forests with regard to climate change .

Abstract approved:

______________________________________________________

David Lewis

Little work has been conducted regarding the net returns of forest lands. The Ricardian model is ripe with potential to estimate the effects of climate on net returns to forestry.

Multiple linear regression allows each climate variable to measure its effect of net returns with the assumption of all other factors being fixed. Independent variables of average temperature (°C), average temperature squared (°$C^2$), average precipitation (mm), average precipitation squared ($mm^2$), maximum August temperature (°C), and minimum December temperature (°C) were scaled by year using dummy variables to output the dependent variable of real net returns (USD 2010) per county of tree species.

This OLS linear regression showed annual precipitation, marginal precipitation, and maximum temperature experienced by forests to affect the net returns they produced. Increased precipitation is expected to increase net returns to forests while higher maximum temperatures will negatively impact net returns in Douglas Fir regions and positively affect pine regions. Precipitation is linearly related to forest net returns, while temperature is not linearly related. With this finding, various areas of Oregon and Washington that are expected to experience heavier precipitation due to climate change should expect more net returns from their forestlands.



Key Words: linear regression, econometrics, forest net returns



Corresponding e-mail address: johnsozo@oregonstate.edu

# Estimating the economic net returns of Oregon & Washington forests with regard to climate change

by
Zoe I. Johnson

A THESIS

submitted to

Oregon State University

University Honors College

in partial fulfillment of
the requirements for the
degree of

Honors Baccalaureate of Science in Agricultural Sciences
(Honors Scholar)

Presented May 26, 2016
Commencement June 2016

Honors Baccalaureate of Science in Agricultural Sciences project of Zoe Johnson presented on May 26, 2016.

APPROVED:

David Lewis, Mentor, representing Applied Economics

Christopher Mihiar, Committee Member, representing Applied Economics

Joe Kerkvliet, Committee Member, representing Applied Economics

Toni Doolen, Dean, University Honors College

I understand that my project will become part of the permanent collection of Oregon State University, University Honors College. My signature below authorizes release of my project to any reader upon request.

Zoe Johnson, Author

## Introduction

The USA has wide expanses of crop, pasture, forest, range, and urban land. In 2012, 19% of the 1,944 million acres that makes up the lower 48 states plus islands such as Hawaii, Puerto Rico, and the U.S. Virgin Islands was cropland; other percentages of the 1,944 acres consisted of 6% pasture, 21% forest, 21% range, 6% urban, and 21% federal lands (USDA.) Our history, economics, and culture is centered around this land and how it is utilized. Systemic climate change not only changes climatic patterns but also the purpose and utility of our resources.

Forests are iconic to the Pacific Northwest and provide wood products that go towards paper and building supplies. The research that has been done centering around Pacific Northwest forests explore the maximum potential mean annual increment (PMAI), comparative genetic responses, and gross primary productivity (GPP) relating to climate change. All of these topics are highly dependent on climate.

Drs. Latta, Temesgen, Adams, and Barrett found in 2009 that depending on the future climate scenario they ran, PMAI (calculated from site index) increased from 2% to 7% for the west side of the Cascades and increased 5% to 20% for the east side of the Cascades. Temperature, climate moisture index, precipitation, shade tolerance, and squared variations were the variables in their core OLS regression.

Similarly, Drs. Weiskittel, Crookston, and Radtke related site index (SI), GPP, and climate to past trends. GPP and SI had a small relationship with an average $R^2$ of 46%. GPP and climate had an average $R^2$ of 84%. SI and climate had an average $R^2$ of 73%. Weiskittel et al. used a nonparametric regression-- dropping variables with low fit statistics to result in a two variable model. These variables were typically the difference between mean temperature in the warmest and coldest months and growing season precipitation.

While SI and GPP are relevant and useful, net return is a metric that can relate economic trends, climate, and other factors to the dollar amount that an acre of land can produce. Once net returns for different land uses have been determined, hypothesizing future uses that landowners will choose to employ will be easier and more accurate. With the unpredictability and high variation in climatic trends, estimating net returns and land use will be useful to project future land use and economic results from those choices as a function of climate change.

In 1994 Drs. Mendelsohn, Nordhaus, and Shaw derived a new type of climate model to be used in the agricultural sector to find net returns: the Ricardian. Previous researchers had relied on the "production-function" approach which centered around empirical and experimental production functions to predict environmental damage. Variables such as historic temperature, precipitation, and carbon dioxide levels would be entered into a crop-yield model in order to hypothesize climate's impact on yield. Through years of production-function studies, the result of climate change always pointed to agricultural devastation-- overestimating the damage of the changing, unpredictable climate. This method was strict, rigid, and unsatisfying. Production-function models did not capture the scope of farming and land use. The "dumb-farmer scenario" that it introduced never allowed for theoretical growers to fully adjust to their changing environment in order to maximize the profits from their land. Changes in fertilizer, irrigation, or cultivars that previous models accounted for did not account for the potential scope of farmers introducing completely new crops, biotechnical changes, or a complete shift of land use.

Instead of predicting environmental damage to be entered in a crop model, the Ricardian approach examined how climate affected value of farmland. This captured the economic trends of different crop substitutions, input substitutions, and overall revenues from the farm. By analyzing value of the farm itself instead of the crops it generated, the dependent variable was in a general unit that could be easily switched in and out from the specific practices or crops. This shift acknowledges the dynamic nature of agriculture and land.

At the end of this first Ricardian study, Mendelsohn et al. hypothesized that climate change would be beneficial to Californian, Southeastern, and Midwestern agriculture while only harming mountainous regions. Accounting for specialty warm-weather crops such as citrus, cotton, and vegetables, while weighing commodities such as corn and cereals less, provides a "silver lining behind the climate-change cloud" (764.)

With innovation comes push-back. The field of mathematical climate modeling is no exception. In 2005 Drs. Schlenker, Hanemann, and Fisher challenged Mendelsohn's 1994 Ricardian model with the claim that one of the major inputs in agriculture cropland is water-- much of which humans (not the clouds directly) supply. Mendelsohn made the assumptions that 1) precipitation equates to the water supply used on farmland, and 2) production cost (including water supply) will be captured in the calculated land values like they have been historically. While growers choose what to grow based on their climate and geography, irrigation allows corn to be grown en masse in Nebraska and cotton to flourish in California. As climate change progresses, freshwater costs and availability will undoubtedly change, making irrigation more expensive for growers. Whether dryland or irrigated farming is being practiced, Schlenker et al. claim that multiple models should be constructed to capture the dynamic interplay between water and crops. For non-urban dryland areas, they found that climate change will cause an annual loss of around $5 billion.

Taking this critique in stride, Mendelsohn perfected his Ricardian method by performing a nationwide analysis of Mexican farming in 2009 with Drs. Arellano-Gonzalez and Christensen. This edition of the model included parameters not only on temperature and precipitation, but also of elevation, distance to nearest city, and soil. Separate models were constructed to examine large versus small farms and rainfed versus irrigated farms. Mendelsohn et al. admitted some faults in their analysis-- the model doesn't accurately show the complete transition cost a farmer would face by a new crop learning curve, the universal fertilization effect of all crops due to increased

$CO_2$ levels, and variance of input and output prices regionally. All four farm-types tested showed harmful impacts from climate change, with irrigated farms being the most sensitive. Average losses were estimated to be between 42% and 54%, varying on region. Lastly, Mendelsohn touches on the importance of policy; government should be an aide and help growers pursue property and land rights while being wary of not subsidizing farmers to stay on unproductive land.

In a constant attempt to perfect the Ricardian method, Drs. Fezzi and Bateman point to the facts that the model does not account for year-to-year shocks or the physiological need for plants to require more water at higher temperatures. Instead of treating temperature and precipitation as independent variables, Frezzi and Bateman interacted the terms to account for the crops' increased need for water during times of high temperature in their 2013 study. It follows that precipitation is more valuable when temperatures are high; if there is enough precipitation to prevent drought, temperature has a positive effect on land value. Their study was done on a smaller, farm-based scale due to the dense climate data available in Great Britain. The temperature-precipitation interaction was significant on the given scale, but became insignificant once zoomed out to the county level (a typical scale in US studies.)

Throughout the years, the Ricardian method has become the most popular approach in microeconomics, especially relating to climate and agriculture. While it is more adaptable, geographically precise, and easier to implement than the production-function approach, it still presents flaws. Mendelsohn's colleagues voice hopes about the the method becoming more dynamic to capturing the nature of climate and agriculture. The topic of irrigation has been thoroughly addressed but overall approach to climate change has not. Climate is constantly evolving and the effects of climate compound. These models typically see climate as a "snapshot" view of a single project trend rather than an unpredictable entity. Recently econometricians have been using net revenue from the farm instead of land value to judge the economic effect. While net revenue is a more robust measure, it is prone to fluctuations dependent of the year and by incorporating the entire gamut of economic forces. Lastly, it is difficult to get complete climate or economic data to runs these models with-- especially in developing nations (De Slavo).

Agricultural economists have honed the Ricardian analysis with regards to both domestic and international cropland. Little work has been conducted regarding the net returns of forest lands. The Ricardian model is ripe with potential to estimate the effects of climate on net returns to forestry. As mentioned before, much of the dispute about the Ricardian model centers around the concepts of irrigation and cultivation. Unlike agriculture, forests do not require extensive irrigation. Forest lands are a prominent part of Pacific Northwest industry and a valid land use for the region, both currently and looking ahead.

Fully exploring related trends between climate and economic net returns will assist ecological understanding, policy making, and adapting the forestry sector to be more successful.

## Methods

This model was constructed by running multiple linear OLS regressions with Stata 13.0 to estimate parameters. In the great tradition of the Ricardian analysis, various independent variables accounting for climate relate to the dependent variable of net returns. Multiple linear regression allows each climate variable to measure its effect of net returns with the assumption of all other factors being fixed. Independent variables of average temperature (°C), average temperature squared (°C$^2$), average precipitation (mm), average precipitation squared (mm$^2$), maximum August temperature (°C), and minimum December temperature (°C) were scaled by year using dummy variables to output the dependent variable of real net returns (USD 2010) per county of tree species. Counties in Oregon and Washington were the units of observation.

$$\begin{aligned} Net\ Returns \ = \ & \beta_0 + \beta_1 temp + \beta_2 temp^2 + \beta_3 prcp + \beta_4 prcp^2 + \\ & \beta_5 99 + \beta_6 00 + \beta_7 01 + \beta_8 02 + \beta_9 03 + \beta_{10} 04 + \beta_{11} 05 + \beta_{12} 06 + \beta_{13} 07 + \beta_{14} 08 + \beta_{15} 09 + \\ & \beta_{16} 10 + \beta_{17} 11 + \beta_{18} 12 + \beta_{20} 13 + \beta_{21} 14 + \beta_{22} tmaxAug + \beta_{23} tminDec + u \end{aligned}$$

## Data

**Net Returns**

Net return is a function of price and tree growth. Faustmann's formula is a common way of measuring net returns, or present value:

$$PV = \frac{pf(T)}{e^{rT}-1}$$

where r is a rate assumed at 0.05, p is a constant timber price, and f(T) is a function of timber growth at a certain time. T was previously solved for by Chris Mihiar to maximize present value. f(T) used in these calculations are from the Forest Inventory Analysis Database (FIADB). p was determined by using stumpage pricing from the Oregon Department of Forestry and Washington State Department of Revenue.

The timber industry in Oregon and Washington is dominated by Douglas Fir forests since they are the only tree that is typically replanted on cutover sites west of the Cascades. In an attempt to account for the more arid, eastern portion of the states, pines such as Ponderosa and Jeffrey were also modeled. Tree growth data was sourced from FIADB, which is produced by the USDA Forest Service. Net return values used were county averages of 2010 dollars per acre. Three models were produced: one with only Douglas Fir growth and returns, one with only Ponderosa Pine and Jeffrey pine growth and returns, and one with all species of trees growth and returns as weighted averages. These weighted averages are based off of the current composition of the forests. The current share of each county's net return was split based on the forest composition of each species.

**Time Dummies**

The years 1998-2014 of growth data was available. To capture this information, dummy variables (_99, _00, etc.) were made with 1998 being the base year. By regressing these sixteen qualitative variables, the resulting slope of the regression shifts vertically based on the economic climate of the given year in comparison to 1998. Economically speaking, any forces that shift demand or supply for wood products would have an effect on forest net return to a given county. Factors that alter demand include changes in consumer income, changes in the price of substitutes and the price of compliments. Similarly, factors that affect supply, such as changes in input costs including labor and raw materials, change the lumber or paper market as a whole. The time dummy variables account for these whole-market shifts by capturing all time-varying aspects that uniformly affect net returns across the region.

**Climate**

Data on average annual precipitation, average annual temperature, temperature maximums in August, and temperature minimums in December were gathered from the National Oceanic and Atmospheric Administration (NOAA.) Temperature and precipitation terms were squared and made into quadratic variables in the regression. This will allow for non-linear effects of annual precipitation and temperature on net returns to be represented.

## Results

Tables 1, 2, and 3 interpret the beta coefficients from the regressed climate variables for each model: all species, Douglas Fir, and Ponderosa and Jeffrey Pines. Marginal change in precipitation was the only regularly statistically significant parameter up the 99% confidence level with p-values of 0.000. Maximum temperature in August was also highly significant in all models. For the pines, marginal increase in temperature was highly significant.

For the maximum and minimum temperatures, the coefficient and statistical values were taken from Stata output. The marginal increases in precipitation and temperature were calculated by taking the derivative of the regression formula with respect to the variable of interest, evaluated at the sample mean of that variable. The following is the formula for marginal effect on net returns from temperature:

$$\frac{d\ temp}{d\ net\ returns} = \beta_1 + 2\beta_2 \overline{temp}$$

Table 1: Interpreted results of marginal effects from precipitation and temperature from OLS regression of all tree species, t-statistics and p-value included.
F(22,1116) = 62.76. n = 1139. Adjusted $R^2 = 0.5442$

| | | t | P>\|t\| |
|---|---|---|---|
| If average precipitation increases by 1mm → real net returns will change by | $1.94/acre | 16.69 | 0.000 |
| If average temperature increases by 1°C → real net returns will change by | -$4.53/acre | -0.89 | 0.373 |
| If maximum temperature increases by 1°C → real net returns will change by | -$2.89/acre | -3.16 | 0.002 |
| If minimum temperature increases by 1°C → real net returns will change by | -$0.71/acre | -0.66 | 0.511 |

Table 2: Interpreted results of marginal effects from precipitation and temperature from OLS regression of Douglas Fir trees, t-statistics and p-value included.
F(22,1082) = 56.98. n = 1105. Adjusted $R^2 = 0.5273$

| | | t | P>\|t\| |
|---|---|---|---|
| If average precipitation increases by 1mm → real net returns will change by | $1.94/acre | 16.66 | 0.000 |
| If average temperature increases by 1°C → real net returns will change by | -$4.45/acre | -1.05 | 0.296 |
| If maximum temperature increases by 1°C → real net returns will change by | -$4.48/acre | -3.64 | 0.000 |
| If minimum temperature increases by 1°C → real net returns will change by | -$1.81/acre | -1.25 | 0.212 |

Table 3: Interpreted results of marginal effects from precipitation and temperature from OLS regression of Ponderosa and Jeffrey Pine trees, t-statistics and p-value included. F(22,538) = 3.45. n = 561. Adjusted $R^2$ = 0.0877

| | | t | P>\|t\| |
|---|---|---|---|
| If average precipitation increases by 1mm → real net returns will change by | $2.32/acre | 13.35 | 0.000 |
| If average temperature increases by 1°C → real net returns will change by | -$3.71/acre | -2.70 | 0.007 |
| If maximum temperature increases by 1°C → real net returns will change by | $1.26/acre | 2.75 | 0.006 |
| If minimum temperature increases by 1°C → real net returns will change by | -$0.21/acre | -0.45 | 0.650 |

With the base year of 1998, the sixteen dummy variables accounting the year have beta coefficients displayed in Table 4. These values give the magnitudes of the shifts that the regression line experienced year to year. Shifts take into account all of the economic forces in play to change the supply or demand of the lumber or pulp industries. Negative coefficients mean a poorer economic year of the selected population of trees compared to 1998.

Table 4: Beta coefficients for the time dummy variables representing years 1999-2014. Base  years is 1998.

| | Douglas Fir | Ponderosa and Jeffrey Pine | All species |
|---|---|---|---|
| 1999 | 9.0 | 9.3 | 9.5 |
| 2000 | 29.8 | 7.9 | 28.4 |
| 2001 | 35.6 | 3.2 | 34.0 |
| 2002 | 28.0 | 8.3 | 22.5 |
| 2003 | -17.9 | -0.6 | -12.4 |
| 2004 | 30.9 | -1.0 | 17.8 |
| 2005 | 13.9 | -5.5 | 15.9 |
| 2006 | -24.9 | -1.5 | -13.8 |
| 2007 | 1.2 | -3.5 | 4.7 |
| 2008 | -25.8 | -10.1 | -5.8 |
| 2009 | -51.5 | -4.3 | -26.8 |
| 2010 | -63.7 | 5.2 | -38.4 |
| 2011 | -23.2 | -0.9 | -4.2 |
| 2012 | -41.5 | -14.6 | -20.5 |
| 2013 | 11.2 | -3.7 | 27.4 |
| 2014 | -29.0 | -7.9 | -6.3 |

Table 5 shows all of the output generated from all three populations: all species, Douglas Fir, and Ponderosa and Jeffrey Pines. The p-values of squared climate variables are bolded. Precipitation squared has a p-value close to zero, showing it does not have a linear relationship with net returns. The null hypothesis of $\beta_{climate} = \beta_1, \beta_2, \beta_3, \beta_4, \beta_{22}, \beta_{23} = 0$ is rejected for the variables of precipitation, precipitation squared, and maximum temperature in August assuming a significance level of 94%.

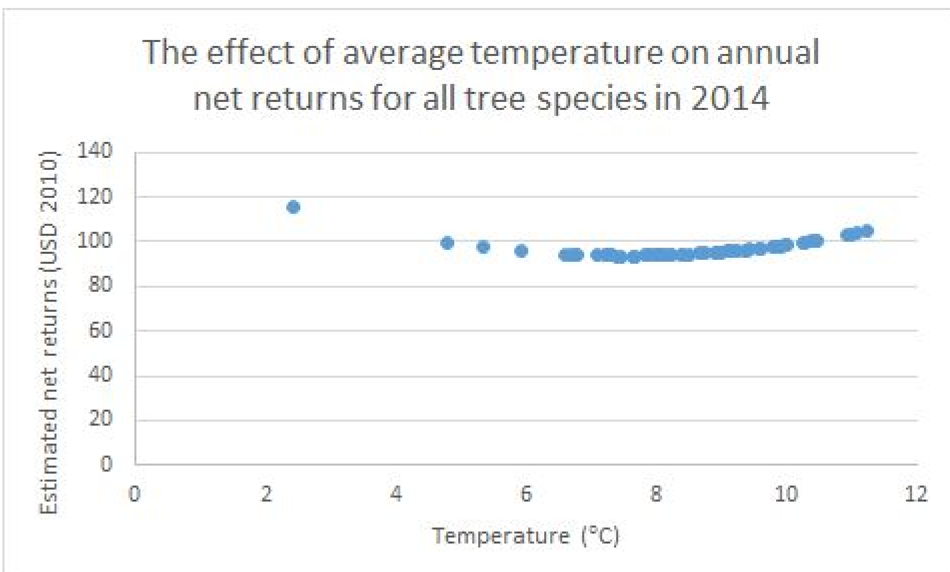
Table 5: Regression output for all tree species: coefficients, t-statistics, and p-value included.

| | Beta Coef. | t | P>\|t\| | Beta Coef. | t | P>\|t\| | Beta Coef. | t | P>\|t\| |
|---|---|---|---|---|---|---|---|---|---|
| | All | | | Doug | | | Pines | | |
| $Beta_0$ | 45.3 | 0.98 | 0.328 | -30.2 | -0.49 | 0.626 | 1.7 | 0.08 | 0.933 |
| Temp | -12.3 | -0.99 | 0.324 | 17.0 | 1.02 | 0.308 | -10.9 | -1.71 | 0.088 |
| $Temp^2$ | 0.8 | 1.11 | **0.266** | -1.2 | -1.22 | **0.223** | 0.4 | 1.10 | **0.272** |
| Prcp | 2.9 | 10.25 | 0.000 | 3.8 | 9.86 | 0.000 | 0.9 | 4.14 | 0.000 |
| $Prcp^2$ | 0.0 | -4.83 | **0.000** | -0.01 | -4.27 | **0.000** | -0.005 | -2.8 | **0.005** |
| 1999 | 9.5 | 0.58 | 0.559 | 9.0 | 0.41 | 0.683 | 9.3 | 1.17 | 0.241 |
| 2000 | 28.4 | 1.91 | 0.056 | 29.8 | 1.48 | 0.138 | 7.9 | 1.15 | 0.252 |
| 2001 | 34.0 | 1.99 | 0.047 | 35.6 | 1.54 | 0.124 | 3.3 | 0.42 | 0.678 |
| 2002 | 22.5 | 1.24 | 0.217 | 28.0 | 1.14 | 0.254 | 8.3 | 0.99 | 0.325 |
| 2003 | -12.4 | -0.89 | 0.371 | -17.9 | -0.96 | 0.337 | -0.6 | -0.09 | 0.927 |
| 2004 | 17.8 | 1.05 | 0.294 | 30.9 | 1.35 | 0.178 | -1.0 | -0.13 | 0.898 |
| 2005 | 15.9 | 1.14 | 0.253 | 13.9 | 0.74 | 0.461 | -5.5 | -0.84 | 0.399 |
| 2006 | -13.8 | -0.96 | 0.338 | -24.9 | -1.28 | 0.203 | -1.5 | -0.22 | 0.829 |
| 2007 | 4.7 | 0.30 | 0.765 | 1.2 | 0.06 | 0.956 | -3.5 | -0.47 | 0.636 |
| 2008 | -5.8 | -0.45 | 0.650 | -25.8 | -1.49 | 0.137 | -10.1 | -1.70 | 0.089 |
| 2009 | -26.8 | -2.19 | 0.028 | -51.5 | -3.13 | 0.002 | -4.3 | -0.74 | 0.461 |
| 2010 | -38.4 | -2.89 | 0.004 | -63.7 | -3.55 | 0.000 | 5.2 | 0.86 | 0.391 |
| 2011 | -4.2 | -0.28 | 0.780 | -23.2 | -1.14 | 0.255 | -0.9 | -0.13 | 0.898 |
| 2012 | -20.5 | -1.31 | 0.190 | -41.5 | -1.97 | 0.050 | -14.6 | -2.11 | 0.035 |
| 2013 | 27.4 | 2.07 | 0.038 | 11.2 | 0.63 | 0.529 | -3.7 | -0.59 | 0.556 |
| 2014 | -6.3 | -0.47 | 0.640 | -29.0 | -1.60 | 0.111 | -7.9 | -1.25 | 0.213 |
| tmax_Aug | -2.9 | -3.16 | 0.002 | -4.5 | -3.64 | 0.000 | 1.3 | 2.75 | 0.006 |
| tmin_Dec | -0.7 | -0.66 | 0.511 | -1.8 | -1.25 | 0.212 | -0.2 | -0.45 | 0.933 |

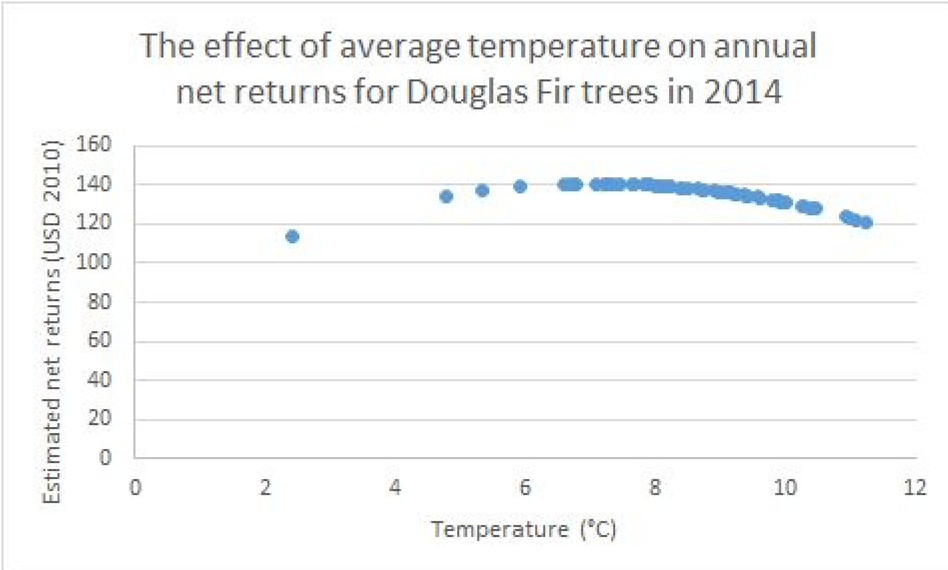
Graphs 1, 2, and 3 plot the predicted dependent variable and show the effect that temperature has on the estimated annual net returns to the respective tree populations: all species Douglas Fir, and Ponderosa and Jeffrey Pines.

For all species (Graph 1), net returns decrease as temperature increases until it reaches a minimum around 8°C. Past this minimum, net returns increase within the natural range.
For Douglas Fir trees (Graph 2), net returns increase as temperature increases until it reaches a maximum around 8°C. Past this maximum, net returns decrease within the natural range.
For Ponderosa and Jeffrey Pine trees (Graph 3), net returns continuously decrease as temperature increases while in the observed range of temperatures.
The range of net returns in the all species graph is closer to the Douglas Fir range, however the behavior reflects the shape of the Pines figure.

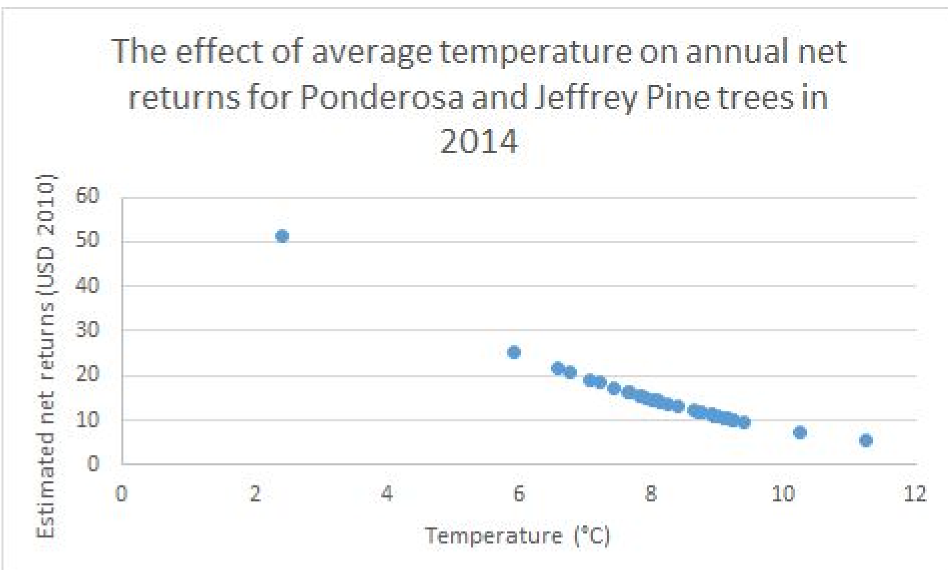
However, as discussed in Table 5, temperature parameters rejected the null hypothesis of $\beta_{climate} = \beta_1, \beta_2, \beta_3, \beta_4, \beta_{22}, \beta_{23} = 0$ at the 95% significance level. The relationship between temperature and net returns is linear due to P-values being greater than 0.1 for the squared terms.




Graph 1: The effect of average temperature on annual net returns for all tree species in 2014. All non-temperature values were evaluated at their mean.

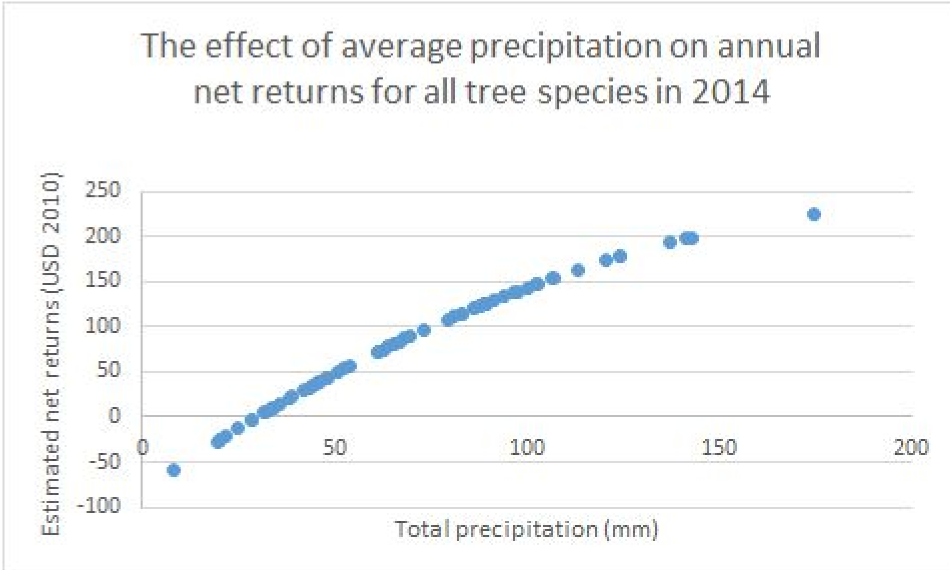



Graph 2: The effect of average temperature on annual net returns for Douglas Fir trees in 2014. All non-temperature values were evaluated at their mean.




Graph 3: The effect of average temperature on annual net returns for Ponderosa and Jeffrey Pine trees in 2014. All non-temperature values were evaluated at their mean.

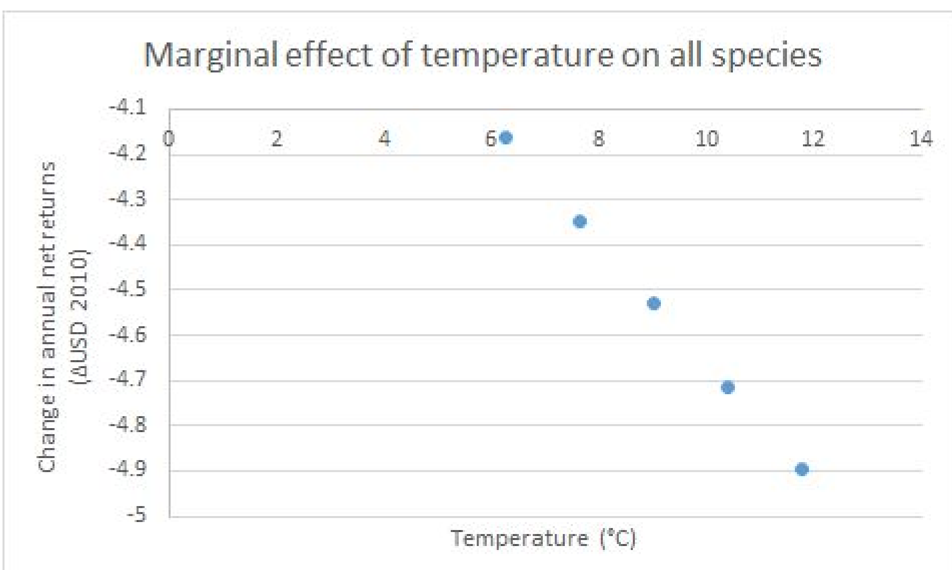
Graph 4 shows the effect that precipitation has on the estimated annual net returns to all tree species. In the precipitation range of the data, as precipitation increases, estimated annual net returns increase. As precipitation continues to increase, the rate of increase decreases. The precipitation v. net return trends for Douglas Fir and Ponderosa and Jeffrey Pines also showed similar behavior.
As discussed for Table 5, precipitation is a significant parameter showing a linear relationship to net returns at the 95% confidence interval.




Graph 4: The effect of average precipitation on annual net returns for all tree species in 2014. All non-precipitation values were evaluated at their mean.

The marginal effect of temperature on annual estimated net returns for all tree species is shown in Graph 5 and Table 6. With each additional degree of temperature increase, the resulting change in net return decreases at a constant rate (slope: -0.1327.) Table 6 has the coordinate of each point and the associated standard error with the change in net return, along with the associated t-statistics.

The t-statistics in Table 6 show that none of the selected temperatures are statistically significant on the 95% level due to large standard errors.



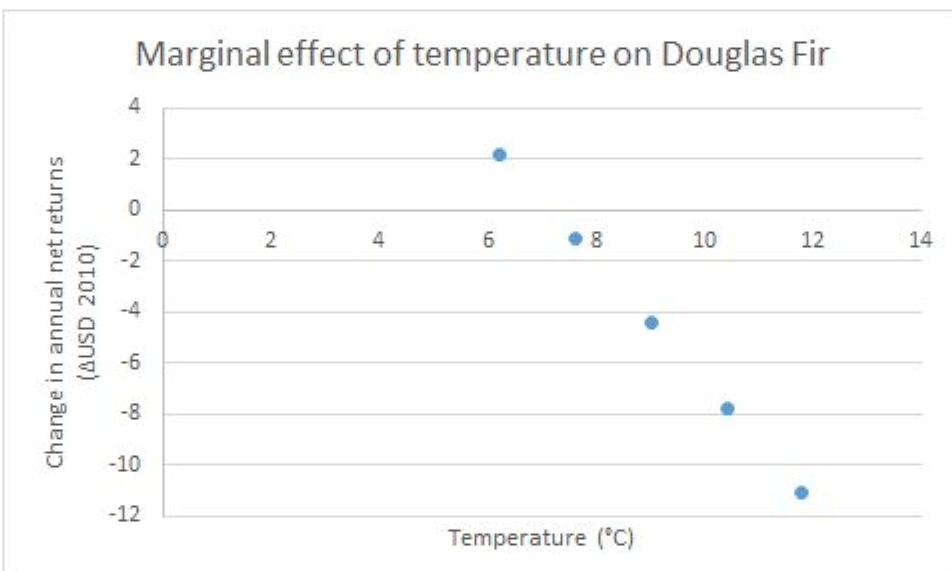

Graph 5: Marginal effect of temperature on annual net returns of all tree species

Table 6: Selected temperatures (-2SD, -SD, mean, +SD, +2SD) and calculated marginal effects on annual net returns for all tree species, standard errors and t-statistics included.
Mean temperature: 9.023°C, standard deviation: 1.381°C.

| Temperature (°C) | dNR/dTemp (ΔUSD 2010) | S.E. | \|t\| |
|---|---|---|---|
| 6.26 | -4.16 | 4.38 | 0.95 |
| 7.64 | -4.35 | 4.07 | 1.07 |
| 9.02 | -4.53 | 5.08 | 0.89 |
| 10.40 | -4.71 | 6.87 | 0.69 |
| 11.79 | -4.90 | 8.97 | 0.55 |

Similarly, the marginal effect of temperature on annual estimated net returns for Douglas Fir trees is shown in Graph 6 and Table 7. With each additional degree of temperature increase, the resulting change in net return decreases at a constant rate (slope: -2.3743.) Table 7 has the coordinate of each point and the associated standard error with the change in net return, along with the associated t-statistics.

The t-statistics in Table 7 show that none of the selected temperatures are statistically significant on the 95% level due to large standard errors.



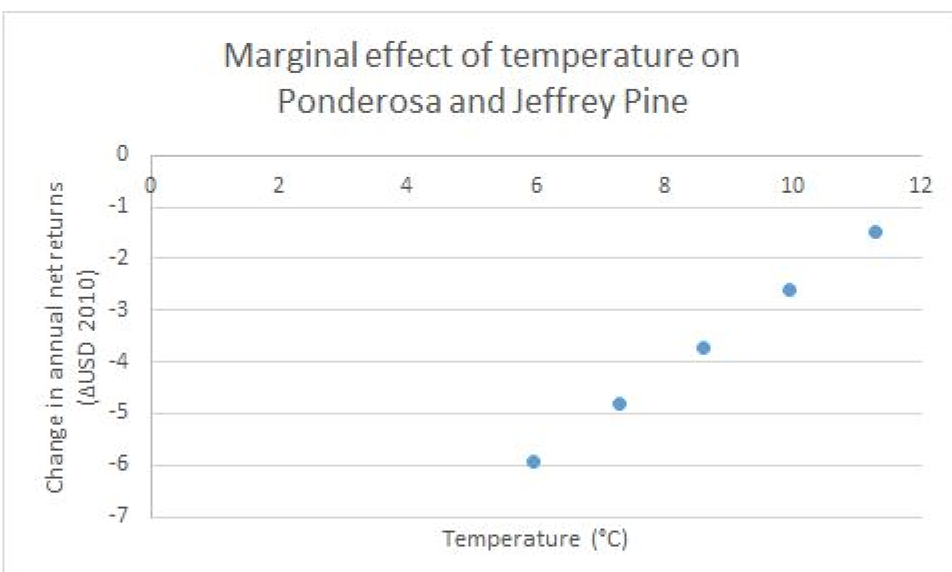

Graph 6: Marginal effect of temperature on annual net returns of Douglas Fir trees

Table 7: Selected temperatures (-2SD, -SD, mean, +SD, +2SD) and calculated marginal effects on annual net returns for Douglas Fir trees, standard errors and t-statistics included.
Mean temperature: 9.016°C, standard deviation: 1.393°C.

| Temperature (°C) | dNR/dTemp (ΔUSD 2010) | S.E. | \|t\| |
|---|---|---|---|
| 6.23 | 2.17 | 5.69 | 0.38 |
| 7.62 | -1.14 | 4.23 | 0.27 |
| 9.02 | -4.45 | 4.25 | 1.05 |
| 10.41 | -7.76 | 5.75 | 1.35 |
| 11.80 | -11.06 | 7.91 | 1.40 |

The marginal effect of temperature on annual estimated net returns for Ponderosa and Jeffrey pine trees is shown in Graph 7 and Table 8. With each additional degree of temperature increase, the resulting change in net return increases at a constant rate (slope: 0.8299.) Table 8 has the coordinate of each point and the associated standard error with the change in net return, along with the associated t-statistics.

The t-statistics in Table 8 show temperatures at the mean and lower are statistically significant on the 95% level.



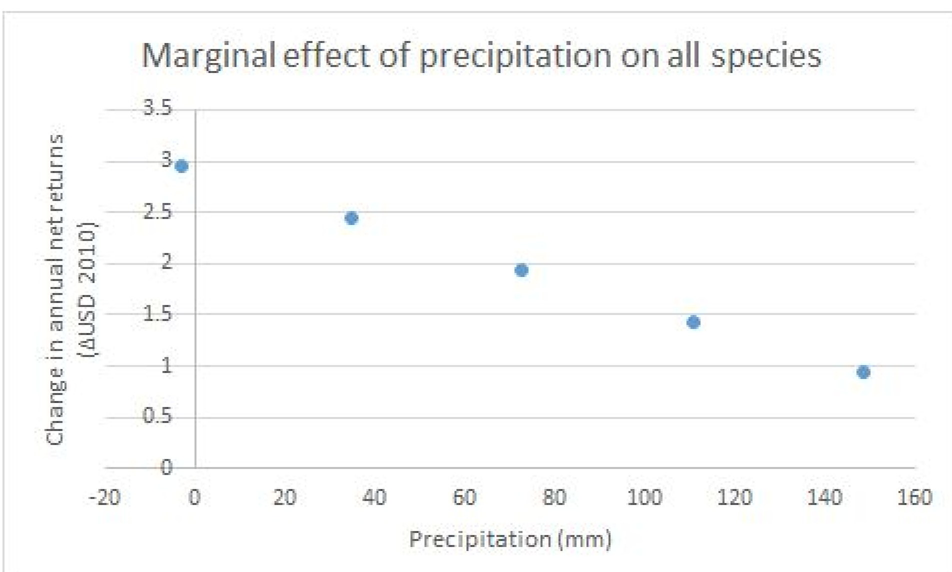

Graph 7: Marginal effect of temperature on annual net returns of Ponderosa and Jeffrey pine trees

Table 8: Selected temperatures (-2SD, -SD, mean, +SD, +2SD) and calculated marginal effects on annual net returns for Ponderosa and Jeffrey pine trees, standard errors and t-statistics included.
Mean temperature: 8.624°C, standard deviation: 1.333°C.

| Temperature (°C) | dNR/dTemp (ΔUSD 2010) | S.E. | \|t\| |
|---|---|---|---|
| 5.96 | -5.93 | 2.19 | 2.71 |
| 7.29 | -4.82 | 1.53 | 3.15 |
| 8.62 | -3.71 | 1.38 | 2.69 |
| 9.96 | -2.61 | 1.86 | 1.40 |
| 11.29 | -1.50 | 2.66 | 0.56 |

Lastly, the marginal effect of temperature on annual estimated net returns for all tree species is shown in Graph 8 and Table 9. With each additional millimeter of precipitation increase, the resulting change in net return decreases at a constant rate (slope: -0.0133.) Table 9 has the coordinate of each point and the associated standard error with the change in net return, along with the associated t-statistics. The trends of marginal precipitation v. change in net return for Douglas Fir and Ponderosa and Jeffrey Pines showed similar behavior as Graph 8.

The t-statistics in Table 9 show that all of the selected temperatures are statistically significant on the 95% level.




Graph 8: Marginal effect of precipitation on annual net returns of all tree species

Table 9: Selected precipitation levels (-2SD, -SD, mean, +SD, +2SD) and calculated marginal effects on annual net returns for all tree species, standard errors included. Mean temperature: 72.724 mm, standard deviation: 37.864 mm.

| Precipitation (mm) | dNR/dTemp (∆USD 2010) | S.E. | \|t\| |
|---|---|---|---|
| -3.00 | 2.95 | 0.29 | 10.17 |
| 34.86 | 2.44 | 0.20 | 12.2 |
| 72.72 | 1.94 | 0.12 | 16.17 |
| 110.59 | 1.44 | 0.10 | 14.4 |
| 148.45 | 0.94 | 0.17 | 5.53 |

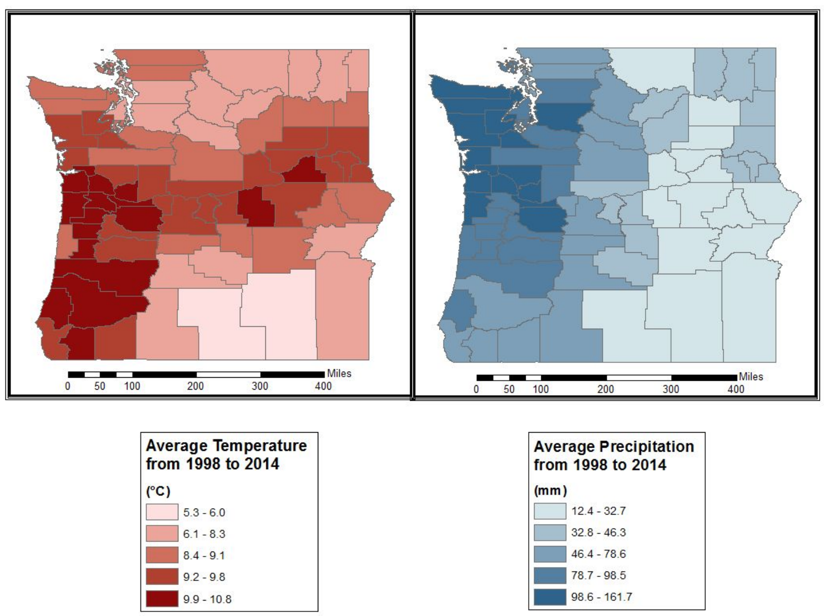



Figure 1: Maps of Oregon and Washington counties showing average temperature and precipitation from 1998 to 2014. Source of data: NOAA.

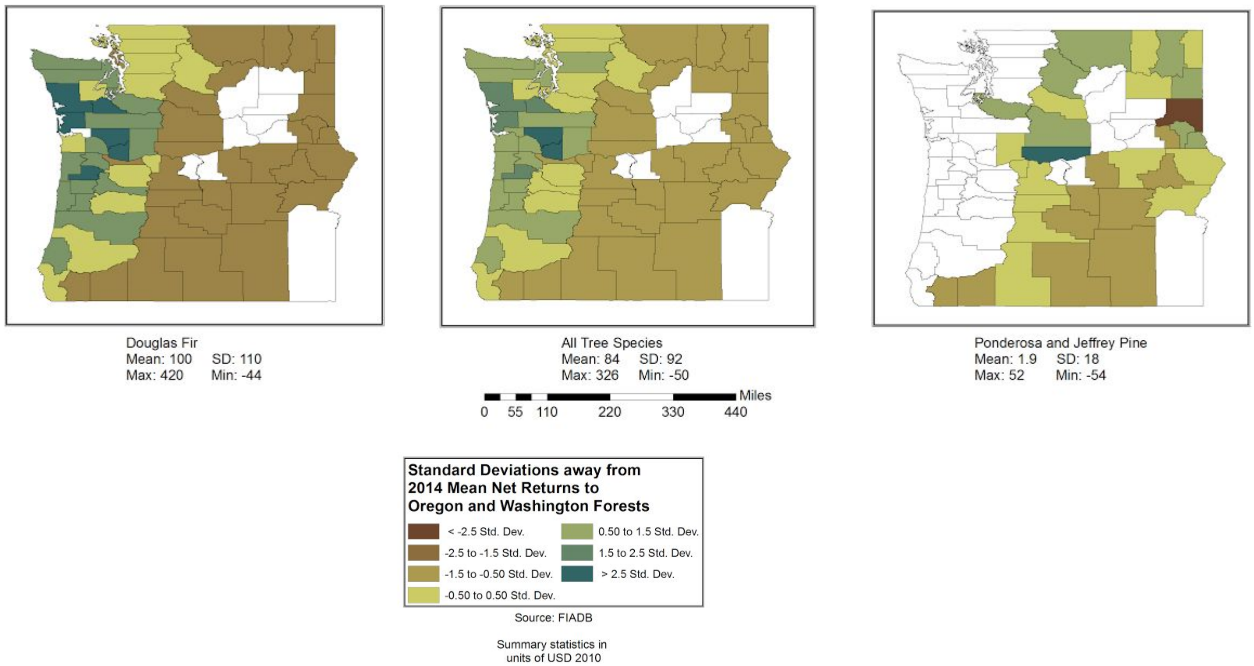



Figure 2: Maps of Oregon and Washington counties showing the standard deviations away from the 2014 mean of forest net returns. Source of data: FIADB

Figures 1 and 2 show a clear divide in both climate and net returns along the ridge of the Cascade mountain range. Temperatures are higher on the western side of the Cascades and in the Columbia River Gorge. West of the Cascades, and especially the Olympic Peninsula, are wetter than the rest of the states. The net returns of all species in 2014 heavily reflects the patterns of the Douglas Fir net returns since the strong majority of trees harvested in Oregon and Washington are Douglas Fir. Ponderosa and Jeffrey Pine trees are present in many of the counties east of the Cascades. Washington generally has higher net returns form pines compared to Oregon.

## Discussion

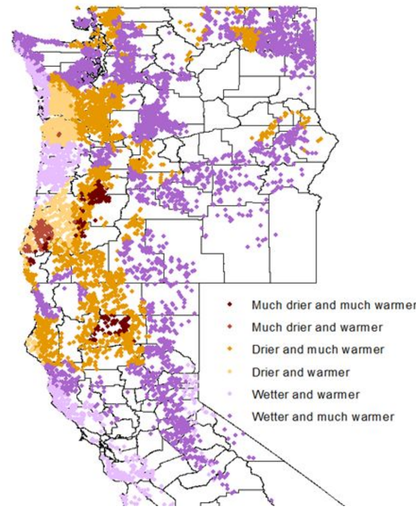



Figure 3: Projected climate in Washington, Oregon, and California by 2070. “Much drier”= >50mm decrease; “Much warmer”= >3°C increase. Source: AdaptWest Project. 2015.

As shown above, temperature (aside from the maximum temperature in August) is not linearly related to net returns. Precipitation, or “wetness”, seems to be the driving factor of net returns on forestland. Wetter areas are shown in Figure 3 as purple dots. Areas that are projected to have more precipitation are also projected to be more profitable from their forests in the coming years. These areas are the northeastern and northwestern corners of Washington, the northwest corner and mid-central region of Oregon. Areas that projected to be drier in the coming years are also projected to be less profitable from their forests. The southwestern corners of both Oregon and Washington, along with the Cascades are projected to have less forest net returns.

From running restricted and unrestricted regressions without and with climate parameters respectively, an F-stat of 213.767 was found. This value is much greater than the critical value of 2.10 at $\alpha = 0.05$, so the null hypothesis of $H_0 : \beta_{climate} = 0$ is rejected. Climate does have an impact on forest net returns.

One concession that is always made in linear regression is the bias-variance trade-off. As one adds more variables to the regression equation, more data that was previously captured in the *u* error term is expressed in an accounted for variable. This successfully decreases error in the regression and therefore also decreases the omitted variable bias of the *u* term. However, additional variables also begin to double-capture information from existing regression variables. This increases the multicollinearity of the regression matrix. Each regression must strike a balance of which information in a system should be represented in the selected regression variables to capture an appropriate amount of error without too much multicollinearity.

This model used counties and calendar years. They are arbitrary markers in space and time that are typically used. Weather on the east versus west sides of the county line or before or after the date January 1 is essentially the same, despite being labeled otherwise. While this method could not be avoided easily, this means the model's standard error values may be incorrect.

Lastly, the information for both net returns and climate used was only regarding the forests in the states Oregon and Washington. The trends and relationships found in this regression can not be extrapolated out to other regions of the nation or world.

## Conclusion

Climate significantly impacts forest net returns. This OLS linear regression showed annual precipitation, marginal precipitation, and maximum temperature experienced by forests to affect the net returns they produced. Increased precipitation is expected to increase net returns to forests while higher maximum temperatures will negatively impact net returns in Douglas Fir regions and positively affect pine regions. Precipitation is linearly related to forest net returns, while temperature is not linearly related. With this finding, various areas of Oregon and Washington that are expected to experience heavier precipitation due to climate change should expect more net returns from their forestlands.

With the certainty of climate change but the uncertainty of the exact climate patterns to be expected, managing and caring for the forests of Washington and Oregon is still a nuanced balance. Understanding the impact of changing temperature and precipitation in this region will hopefully allow economists and policy makers in the field to further understand the implications of global climate change, especially in regard to forest management.

## Works Cited

De Salvo, M., Begalli,D., and G. Signorello. 2014. The Ricardian analysis twenty years after the
original model: Evolution, unresolved issues and empirical problems. Journal of Development and Agricultural Economics, 6(3): 124-131.

Fezzi, C., and I. Bateman. 2015. The impact of climate change on agriculture: Nonlinear effects
and aggregation bias in Ricardian models of farmland value. Journal of the Association
of Environmental and Resource Economists, 2(1): 57-92.

Latta, G., Temesgen, H., Adams, D., and T. Barrett. 2009. Analysis of potential impacts of
climate change on forests of the United States Pacific Northwest. Forest Ecology and Management, 259: 720-729.

Mendelsohn, R., Nordhaus, W.D., and D. Shaw. 1994. The impact of global warming on agriculture: A Ricardian analysis. American Economic Review, 84(4): 753-771.

Mendelsohn, R., Chrstensen, P., and J. Arellano-Gonzalez. 2010. The impact of climate change on Mexican agriculture: A Ricardian analysis. Environmental and Development Economics, 15: 153-171.

Rehfeldt, G., Jaquish, B.C., Lopez-Upton, J., Saenz-Romero, C., St Clair, J.B., Leites, L.P., and D.G. Joyce. 2014. Comparative genetic responses to climate for the varieties of *Pinus ponderosa* and *Pseudotsuga menziesii*: Realized climate niches. Forest Ecology and Management, 324: 126-137.

Schlenker, W., Hanemann, M., and A. Fischer. 2005. Will U.S. agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach. American Economic Review, 95(1): 395-406.

U.S. Department of Agriculture. 2015. Summary Report: 2012 National Resources Inventory, Natural Resources Conservation Service, Washington, DC, and Center for Survey Statistics and Methodology, Iowa State University, Ames, Iowa.

Weiskittel, A.R., Crookston, N.L., and P.J. Radtke. 2011. Linking climate, gross primary productivity, and site index across forests of the western United States. Canadian Journal of Forest Research, 41: 1710-1721.

## Appendix

Stata Do-Files:

```
*Feb 7, 2016
*GOALS:
*Append Files to collapse months into years
*Creat table of [county, year, fips, temp, p]

*Started with "doug_fir" and "climate" files
*Manually made table/file (?) of "State,Fips,County" in Excel and then imported
```

**Collapse "climate" set
collapse (mean) avgtemp=tmean avgprcp=prcp, by(county year)
*Didn't save first file with all the failed attemps... Lesson learned.

collapse (mean) avgtemp=tmean avgprcp=prcp, by(county state year)
*^Got state to be included on climate file
*Saved as "2.8.16UPDATEDclimate"

*Had to change variable names to match between both files. Did manually in Data Editor
*Had to change "OR" to "Oregon", etc.
gen state1="OR" if state=="Oregon"
replace state1="WA" if state=="Washington"

*Changed variable names again-- kept both.
rename state statename
rename state1 state

**MERGE! "State,Fips,County" (master) with "UPDATEDclimate" (using)
merge m:m state county using "Z:\2.8.16UPDATEDclimate.dta"
*SUCCESS!

*Change typos in Fips file I created
replace county = "Okanogan" in 60
replace county = "Grays Harbor" in 50

*Merged again with 1350 matched, 0 not matched
*Clean up table by dropping "merge" variable
drop _merge
*Saved as "2.11.16fips,averageclimate"

*Change variable names in "doug_fir"
rename Fips fips
rename cntyfp fips

*Merge "2.11.16fips,averageclimate" (master) with doug_fir (using)
merge m:m fips using "Z:\doug_fir.dta"
*try this:
merge m:m year fips using "Z:\doug_fir.dta"

*"doug_fir" file doesn't have 2015 or Okanogan (fip 53047) data.
*Only items that didn't merge perfectly.

*Clean up by dropping "merge" variable
drop _merge
*Saved as "2.11.16fips,avgclimate,netreturn"

*Make plots!
scatter net_return avgtemp
scatter net_return avgprcp
scatter net_return year

*Feb 21, 2016
*GOAL: Collapse data to year and county averages.
*Produce plots of trends over "space and time"

collapse (mean) avgtemp2=avgtemp avgprcp2=avgprcp avgreturn=net_return, by(fips county)
*Saved as "2.21.16 temp,prcp,returns by fips"
*Checked average values for Benton

scatter fips avgreturn

scatter fips avgtemp2

scatter fips avgprcp2
*All saved as PDFs

collapse (mean) avgtemp2=avgtemp avgprcp2=avgprcp avgreturn=net_return, by(year)
*Saved as "2.21.16 temp,prcp,returns by year"
*Checked average vales for 1998

scatter year avgreturn

scatter year avgtemp2

scatter year avgprcp2
*All saved as PDFs

*Feb. 28, 2016
*GOAL: Make dummy variables of years '99-'14
*Run regression of NR of temp and dummies

*Make dummy variables for the years

```
gen _99=1 if year==1999
replace _99=0 if year!=1999

gen _00=1 if year==2000
replace _00=0 if year!=2000

gen _01=1 if year==2001
replace _01=0 if year!=2001

gen _02=1 if year==2002
replace _02=0 if year!=2002

gen _03=1 if year==2003
replace _03=0 if year!=2003

gen _04=1 if year==2004
replace _04=0 if year!=2004

gen _05=1 if year==2005
replace _05=0 if year!=2005

gen _06=1 if year==2006
replace _06=0 if year!=2006

gen _07=1 if year==2007
replace _07=0 if year!=2007

gen _08=1 if year==2008
replace _08=0 if year!=2008

gen _09=1 if year==2009
replace _09=0 if year!=2009

gen _10=1 if year==2010
replace _10=0 if year!=2010

gen _11=1 if year==2011
replace _11=0 if year!=2011

gen _12=1 if year==2012
replace _12=0 if year!=2012

gen _13=1 if year==2013
```

```
replace _13=0 if year!=2013

gen _14=1 if year==2014
replace _14=0 if year!=2014

*Part-way through this process, I realized some sort of loop would have been nice.
*I looked through the manual for a for-loop... It was rather confusing. While-loop
*doesn't really make intuitive sense for this situation. Below is a feeble example
*of what I thought it might be...
*while year==1999:2014 {
        *gen _00= 1 if year==2000
        *replace _00 if year !=2000
        * (don't know know to make _00+1 since _00 isn't a number.)
        *etc. etc. ??


*Run regression
reg net_return avgtemp _99 _00 _01 _02 _03 _04 _05 _06 _07 _08 _09 _10 _11 _12
_13 _14


*Mar. 7, 2016
*GOAL: CPI adjustments to get "real $" in NR column.
*http://www.usinflationcalculator.com/inflation/consumer-price-index-and-annual-percent-
changes-from-1913-to-2008/

*1998: 163 Annual Avg CPI w/ 1982 being 100.
*63% inflation since '82.

gen realNR=net_return*1.63 if year==1998

replace realNR=net_return*1.666 if year==1999

replace realNR=net_return*1.722 if year==2000
replace realNR=net_return*1.771 if year==2001
replace realNR=net_return*1.799 if year==2002
replace realNR=net_return*1.84 if year==2003
replace realNR=net_return*1.889 if year==2004
replace realNR=net_return*1.953 if year==2005
replace realNR=net_return*2.016 if year==2006
replace realNR=net_return*2.073 if year==2007
replace realNR=net_return*2.15303 if year==2008
replace realNR=net_return*2.14537 if year==2009
```

replace realNR=net_return*2.18056 if year==2010
replace realNR=net_return*2.24939 if year==2011
replace realNR=net_return*2.29594 if year==2012
replace realNR=net_return*2.32957 if year==2013
replace realNR=net_return*2.36736 if year==2014

*Saved as "3.6.16 fips,avgclimate,NR,dummies,realNR"

reg realNR avgtemp avgprcp _99 _00 _01 _02 _03 _04 _05 _06 _07 _08 _09 _10 _11 _12 _13 _14

*Mar. 14, 2016
*Just a few regressions

reg realNR avgtemp avgprcp _99 _00 _01 _02 _03 _04 _05 _06 _07 _08 _09 _10 _11 _12 _13 _14

reg realNR avgtemp _99 _00 _01 _02 _03 _04 _05 _06 _07 _08 _09 _10 _11 _12 _13 _14

reg realNR avgprcp _99 _00 _01 _02 _03 _04 _05 _06 _07 _08 _09 _10 _11 _12 _13 _14

reg net_return avgtemp avgprcp _99 _00 _01 _02 _03 _04 _05 _06 _07 _08 _09 _10 _11 _12 _13 _14

reg net_return avgtemp _99 _00 _01 _02 _03 _04 _05 _06 _07 _08 _09 _10 _11 _12 _13 _14

reg net_return avgprcp _99 _00 _01 _02 _03 _04 _05 _06 _07 _08 _09 _10 _11 _12 _13 _14

*April 11, 2016
*GOAL: Add NOAA data to master spreadsheet
*Run more regressions

*In NOAA data
rename state statename

label variable statename "statename"

*In realNR data
rename state stateid

label variable stateid "stateid"

*Merge!
merge m:m stateid county year using "Z:\4.11.16 states,county,year,NOAAclimate.dta"

*Drop 2015 due to no NR data
drop in 1276/1350

*Saved as new 4.11.16 data file

*Regression w/o NOAA
reg realNR avgtemp avgprcp _99 _00 _01 _02 _03 _04 _05 _06 _07 _08 _09 _10 _11 _12 _13 _14

*Regression w/ temp max/min extremes
reg realNR avgtemp avgprcp _99 _00 _01 _02 _03 _04 _05 _06 _07 _08 _09 _10 _11 _12 _13 _14 tmax_Aug tmin_Dec

*Clean up spreadsheet
drop _merge
*Saved again

*April 19, 2016
*GOAL: merge new NR data, run regressions

drop v1
label variable nr "Net Returns (2010 USD)"
label variable spgrpcd "doug, pond, all"
rename spgrpcd treegroup

*NR v. 2 in year and geoid
*Master in year and fips

rename geoid fips

```
label variable fips ""

save "Z:\NR v.2.dta", replace

*Merge!
merge m:m fips year using "Z:\NR v.2.dta"

*Seperated 10,11,99 groups into 3 spreadsheets
*Did the drops below on all 3 sheets
drop v1 net_return
drop realNR
drop treegroup _merge

*Regressions (run on all 3 sets)
 reg nr avgtemp avgprcp _99 _00 _01 _02 _03 _04 _05 _06 _07 _08 _09 _10 _11 _12
_13 _14 tmax_Aug tmin_Dec

 *Squared interactions (run on all 3 sets)
gen tempsq=avgtemp^2
gen prcpsq=avgprcp^2

 reg nr avgtemp tempsq avgprcp prcpsq _99 _00 _01 _02 _03 _04 _05 _06 _07 _08 _09
_10 _11 _12 _13 _14 tmax_Aug tmin_Dec

 *Restricted model w/o climate
 reg nr _99 _00 _01 _02 _03 _04 _05 _06 _07 _08 _09 _10 _11 _12 _13 _14


*April 29, 2016
*GOAL: average climate and NR data to get mapped (only 1 value for each year, county)

*Get climate data from All Species.dta
mean avgtemp, over(fips)

mean avgprcp, over(fips)
*"All Species" didn't include all counties

*Get NR averages for all 3 sets
mean nr, over(fips)
```