PREDICTING THE GROWTH RESPONSE OF SMALL PONDEROSA PINE TREES UNDER VARYING LEVELS OF OVERSTORY RETENTION, VEGETATIVE COMPETITION AND SITE QUALITY

By

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DEDICATION

BIOGRAPHY

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I would first like to extend appreciation to the INGY Cooperators, particularly those who participated in the Small Tree Competing Vegetation Study (STCV) for their commitment to this long term study. Their participation required that many stands not be harvested for the duration of the study and a substantial monitary cost over 15 years.

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TABLE OF CONTENTS

Contents

LIST OF APPENDICES

List of Tables

List of Figures

1 Introduction

Ponderosa pine is an important species both ecologically and commercially in the Inland Northwest. t is a key species in a range of silvicultural systems that vary widely by region and site conditions. Although a full array of silvicultural systems are found applied to ponderosa pine stands in the Northern Rocky Mountains, group selection, seed tree, or shelterwood systems are often recommended (Adams 1994). In the Pacific Northwest, multiple-entry management using either long-rotation even-aged systems or uneven-aged systems are suggested, with group selection being the most highly recommended (Tesch 1994). These groups provide openings with sufficient light to allow shade intoloerant species to germinate and be competitive in mixed species stands (O'Hara). The resultant multi-aged stand is suitable for achieving a variety of objectives including timber production, aesthetics, and restoring presettlement stands structures (O'Hara). Nearly all of the proposed systems include a retained overstory component which is achieved through variable retention harvesting.

Variable retention harvest allows for the removal of merchantable trees while retaining elements of the previous stand's overstory structure. Those trees provide both seed source for a new cohort, benefits for wildlife, and have even been proposed as an approach to emulate natural disturbances (Franklin et al. 1997). Powers et al.(2011) found that variable retention harvesting of pondersosa pine stands can result in improved seedling photosynthetic capacity, water relations and growth. The enhanced growth of the small trees on sites without much overstory may be perpetuated throughout the growth of the stand. However, there is limited work examining the factors that affect the developmental responses of the small trees released through variable retention harvests.

1.1 Ecology of Ponderosa Pine Regeneration and Growth

Natural regeneration of ponderosa pine is dependent upon the combination of adequate seed crop and favorable weather the subsequent growing season. Soil texture, plant competition, and seedbed conditions are other determinants of survival of young seedlings (Curtis). Germination and initial seedling survival and growth is also reduced by moisture stress. A study conducted in southwestern ponderosa pine stands found that seed germination, root penetration, root dry weight, and cotyledon length decreased as the moisture stress increased beyond 0.7 MPa (7 bars) (Schubert).

Following germination, the importance of competing vegetation as an impediment to early survival and development of young seedlings is well-established. In central Idaho, soil moisture remained above the wilting point at depths below 15 cm (6 in) on areas free of competing vegetation throughout the growing season but dropped to or below that critical point on the majority of vegetated plots (Curtis). Shrub competition also reduced the height and diameter growth of ponderosa pine planted in northern California (Oliver); similar growth reductions have been reported for stands in Oregon (Barrett). Busse et al. also found that the presence of understory vegetation adversely affected the growth of ponderosa pine for an estimated 20 years (Busse, Cochran, and Barrett 1996). In a central Oregon study, trees completely surrounded by understory shrubs grew only 9 cm (3.5 in) per decade. Those trees with no competitive ground cover averaged 12 cm (4.7 in) of growth per decade. The severity of understory effects on growth also varies by site, in California on a droughty soil, severe shrub competition reduced diameter growth to less than half that of competition-free trees(Oliver,1984).

The direct competition for light, water and nutrients is not the only way that ponderosa pine is affected by understory vegetation. Insect damage has also been found to be greater on the trees competing with shrubs, accounting for some of the growth depression (Oliver 1984). Despite the numerous examples of adversely affected growth attributed to competing vegetation, the presence of vegetation is not without some benefit to the stand. There is a long term carbon and nitrogen benefit to the upper soil horizon from maintaining understory vegetation (Busse, Cochran, and Barrett 1996). Understory vegetation also provides forage and habitat for a wide range of species, stabilizes soil, and captures nutrients after disturbance. Fireweed (*Chamerion angustifolium* (L.) Holub), for example, regenerates after fire and captures and recycles nitrogen (Cooper and others 1991, Daubenmire and Daubenmire 1968).

Understory non-arboreal vegetation is also not the only ecological competition for young ponderosa pine. Overstory trees and other small trees can effectively restrict growth. Stagnation in diameter, and often in height, represents a problem in densely stocked stands, but especially on poor sites (Oliver and Ryker). Just as juvenile trees must face this often severe competition from overstory trees, so must the understory vegetation. The productivity of ponderosa pine forest understory (in terms of total herbage production, perennial grass prouctiodn, and forage consumed in weight per unit area) has been found to be inversely related to the density of overstory trees, regardless of whether expressed in basal area, trees per acre, percent canopy cover, or stand density index (Ffolliott 1983, Moore and Dieter 1992). The species composition of forest understory is also controlled by overstory trees which filter light, moderate understory air and soil temperature, and directly compete for soil water and nutrients (Spurr and Barnes 1980). For example, conifer reforestation efforts are often hampered by the competitive ability of *Carex* and *Calamagrostis* because they respond positively to the removal of the overstory (Sloan et al. 1987).

Regardless of why ponderosa pine growth is suppressed and for how long, this species is remarkably resilient and is fully capable of growth when the suppressing factor is resolved. Ponderosa pine remains physiologically young perpetually and was found to respond to overstory release up to age 200 in Arizona (Barrett, 1979). Stagnated sapling stands in other regions have been found to respond to thinning at ages 70 to 100 years old and seem to grow as vigorously as unstagnated stands, when crowns grow to sufficient size to occupy the additional growing space (Barrett, Van-Deusen and Boldt 1974).

1.2 Small Tree Competing Vegetation Study

The Small Tree Competing Vegetation Study (STCV) was initiated by the Inland Northwest Growth and Yield Cooperative in 1999 to examine seedling and sapling growth response to the density of residual overstory cover and to the abundance of understory vegetation. Data from 29 installations distributed accross eastern Washington, Idaho and Western Montana included measurements of tagged small trees, understory vegetation and retained overstory over the course of 16 years.

Preliminary findings revealed an extrememly skewed distribution of height growth responses on the tagged trees. Specifically, many trees over many periods exhibited annualized height growth <x feet per year while a number of trees attained much more rapid growth. This pattern suggested a broad range of growing conditions had been captured by the STCV, ranging from those resulting in near stagnation of growth to those promoting rapid differentiation. It was also revealed that efforts to describe mean growth would be of limited utility.What was needed instead was a method of characterizing the full distribution of height growth rates and the factors associated with the levels and differentiation of those rates

1.3 Introduction to Quantile Regression

The desire to focus on the full distribution of growth rates naturally led to an investigation of quantile regression (Koenker, this technique allows for the characterization of multiple quantiles of the height growth responses of small trees. Quantile regression utilizes the simplex algorithm (as opposed to least-squares) to calibrate linear regression functions to describe a through specified or set of specified quantiles (τ) of the response distribution. Specifying the .90 quantile (τ=.90), for example, allows for the examination of the "maximum" or upper portion of the height growth response distribution and its relationship with stand and site factors. By contrast, τ=.50 would describe the median height growth response.

This characterization of the response distribution also allows for predictor variables to have entirely different effects accross quantiles. The quantile regression visualization shown below (Figure 1) compares three quantiles of the annual height growth response against overstory basal area and site index. In the example above, the τ=.10 quantile plane shows very little response for both overstory basal area and site index. However, the height growth in the τ=.90,.50 quantile planes change readily as site index and retained basal area respectively increase and decrease. Although not the case in this example, the factors that affect the growth of the slowest growing trees may not be significant predicting the growth of the fastest growing trees. In an extreme case, the factors may even have opposing signs between quantile planes.

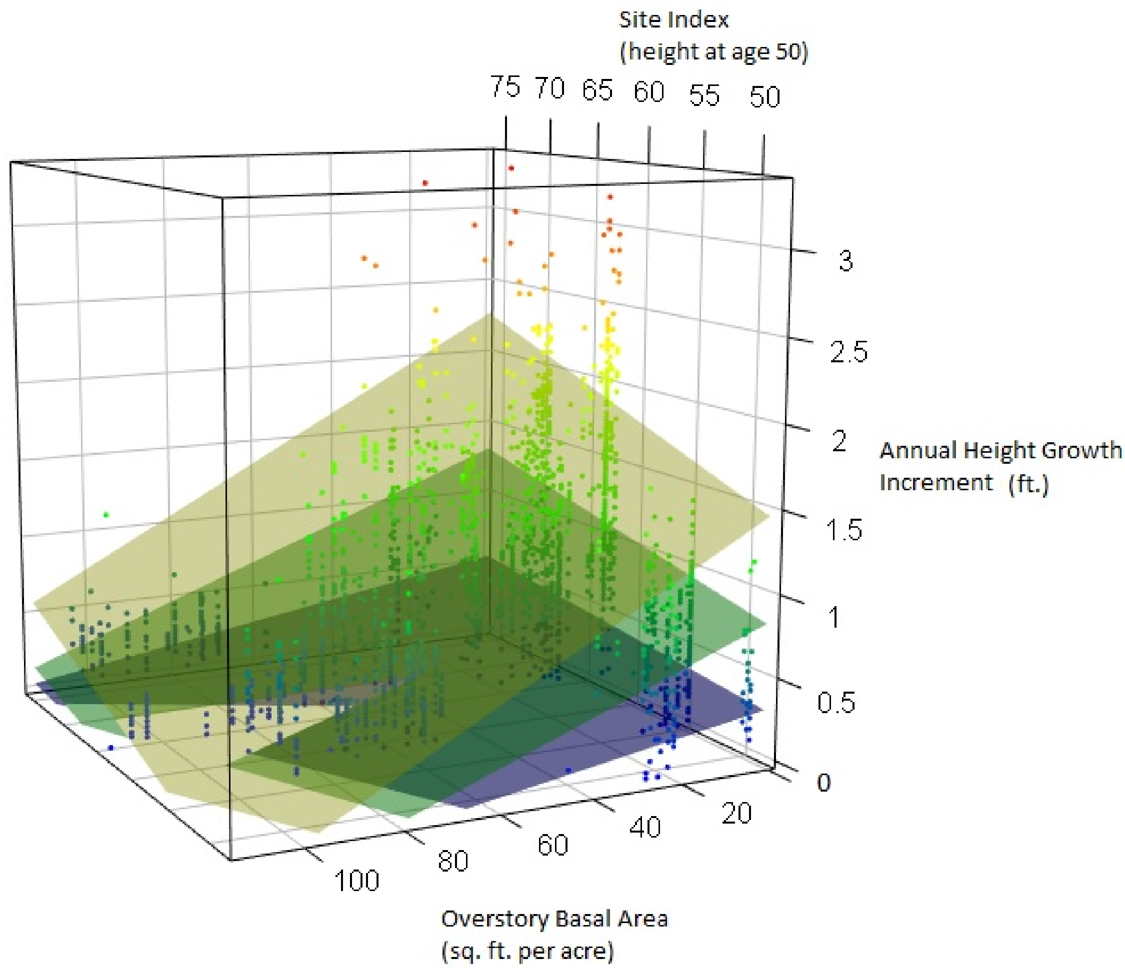

Figure 1: Quantile Regression Visualization.

Quantile regression allows for the description of the impact of both measured and unmeasured competitive factors that may be explaining much of the variance in height growth response. Two subject trees within the same 10 foot radius plot may experience vastly different growth rates despite having the same values of measured factors. For ponderosa pine small tree growth, unmeasured factors may relate to such things as genetic characteristics, micro-climate, micro-site suitability or other location specific factors such as distance from a retained overstory tree or competing vegetation. Vegetation is known to have a major effect on micro-climate, affecting light, temperature, precipitation and wind (Tappenier). However, most growth and yield field sampling methods attempt to maintain a degree of simplicity and reproducibility and therefore avoid sampling at a micro-resolution. This inevitably leads to variance since there are many unmeasured factors and is well-suited to quantile regression since the homogeneity of variance assumption does not apply to this semi-parametric approach.

The description of growth in terms of centiles has been used since the 19th century as a graphical method to monitor height-for-age and weight-for-age trajection of infants and children (Wei,Koenker). Although most of these charts were created through parametric methods (LMS, Cole), recognizing what may be considered out of the ordinary or what the maximum expected growth could be has undoubtedly provided medical practitioners with a useful tool in caring for patients. It has more recently been proven useful in evaluating and predicting other rates of change of biological growth functions near the upper boundary(Cade, 2003).

Applications of quantile regression in ecology are increasingly realized. Examples include pronghorn density by forage availability where least squares fails to recognize that pronghorn densities changed at different rates as a function of shrub cover in the higher and lower quantiles. Quantile regression has also been used to reveal the effects of density dependent self-thinning procceses of annual plants in the Southwestern US. This process was most evident in the upper quantiles, where competition for resources was greatest and other effects minimal (Cade and Guo). Just as growth charts have assisted doctors, ecologists are benefiting from an enhanced window into the entire distribution of the response variable.

There are few examples of quantile regression in applied forest growth modeling. However, Bohora and Cao have compared quantile regression models to mixed effect models in predicting the diameter growth of *Pinus taeda.* The authors concluded that the quantile regression predictions of diameter growth increment were adequate but that the mixed model had lower bias. Coomes and Allen (2007) used quantile regression to fit an upper boundary curve to a size-growth distribution to test similarity to the Enquist model of uninhibited growth (stem-diameter growth scales as the one-third power of stem diameter).

More recently, Araujo et al. utilized quantile regression to obtain localized site index curves in Eucalyptus plantation stands. The authors found that estimates made with quantile regression generate a more accurate family of height growth curves between the observed data than by the guide curve method, obtained using standard regression. These examples of successful use of quantile regression in forestry are encouraging and lend support to this effort to use it to describe the growth of ponderosa pine.

1.4 Modeling Small Tree Growth

Modeling of small trees is typically focused on height growth as it is a driving force in a tree's development as it competes for light and vertical growing space.

In the Inland Northwest, FVS is a distance independent growth model used to project stand level characteristics. The small-tree routine in FVS estimates individual height growth first. Factors used to estimate height growth include National Forest location code, habitat type, species dependent intercept, stand crown competition factor (CCF), basal area in trees larger than the subject tree, aspect, slope and initial height. The estimaterepresents the mean growth of a population of trees exposed tothose factors , it does not of course indicate if a particular tree will achive that mean or not. It does not provide any information about the likelihood of a tree achieving that mean or of achieving a heght growth of .5times the mean or1.5 times the mean. That is, no information on the probability distribution of potential growth rates for the tree. Although, there is a random error component included in the estimate.

The individual tree height growth increment model proposed in this thesis provides an idea of what the maximum growth of a given small ponderosa pine tree could be. However, it will not be able to predict with any certainty whether a particular tree will achieve its maximum growth. If enough information was available to predict this, it would negate the need for quantile regression. The utility of the model is in providing managers an idea of the growth rate of the fastest growing trees.

Having a better idea of the growth rate of the fastest trees has a number of potential applications. Forests managed under the Sustainable Forest Initiative (SFI) or Forest Stewardship Counsel (FSC) are required to achieve "green-up" whereby trees in clearcut areas are at least 3 years old or 5 meters high at a desired stocking level before adjacent units can be harvested. This could lead to better predicting when stands will reach green up.

Stand initiation is such a critical stage in stand development. Growth trajectory can be largely altered by suppressing forces during this stage. Moreover, it may be difficult to diagnose issues early enough to implement treatments to help facilitate growth if managers are focusing on the mean growth response. For instance, they may be overlooking the fact that the fastest growing trees are not thriving. After all, these are the trees which will likely occupy space in the canopy and ultimately become commercially viable. Just as medical practitioners use growth charts to monitor indicators of health in children, forest managers in the Inland Northwest could use this model to evaluate whether sufficent numbers of trees are young ponderosa pine stands are achieving optimal growth.

2 Methods

2.1 Sampling Strategy

Twenty-six study sites were established on a variety of cooperative member ownership ranging from the eastern slopes of the Cascade Mountains to western Montana (see Figure 2). Installations were established in stands with various forest cover (e.g., mixed ponderosa pine, Douglas-fir, and grand fir types), with each stand exhibiting relatively homogeneous levels of site quality, overstory tree density, and understory competition. Installations were located in recently harvested stands that were either clearcut or harvested with one of the aforementioned variable retention harvest systems: shelterwood, seed tree or heavy thinning.

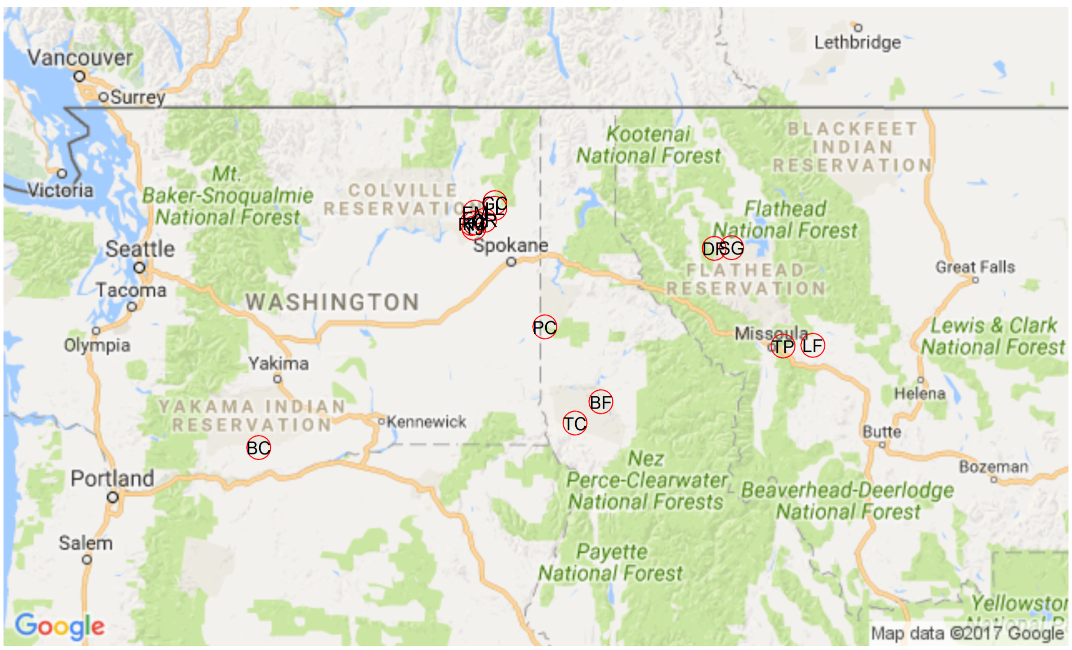

Figure 2: Map of STCV Installations

The year of initiation of installations varied with most being established in the last years of the 1990s and early 2000s. Three check plots were also installed to audit the quality of the data collection efforts. Treatments were randomly assigned to seven plots within each installation (see Figure 3). Three plots received multiple applications of regionally effective herbicide. The remaining four plots were split between the one-time treatment group (just one application of herbicide) and control plots which received no herbicide treatment.

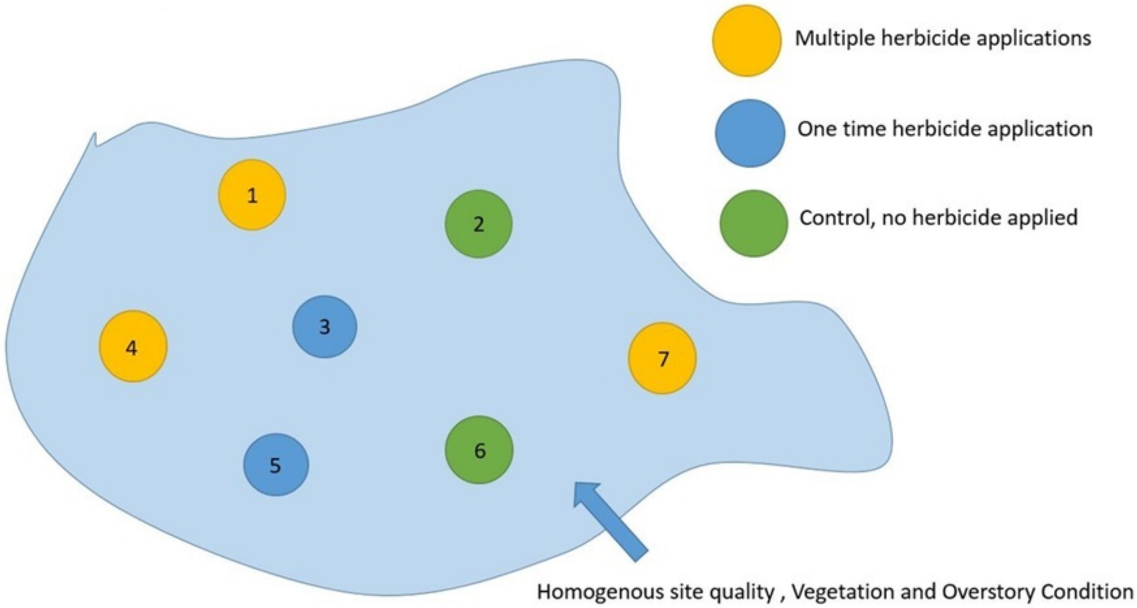

Figure 3: Illustration of an STCV installation and herbicide assignments

The primary objective of the herbicide treatments was to decouple the site quality and vegetative effects. It has been reported that like tree growth increases in good sites, levels of understory increase as well (Stage and Boyd 1987, Walstad and Kuch 1987). The herbicide treatments reveals how small trees grow under varying levels of site quality without the presence of a corresponding increase non-arboreal vegetation. Because the objective of the herbicide treatments was to simply provide a range of non-arboral vegetation levels, the herbicide application regimes varied greatly and not all installations recieved treatment.

Figure 4 shows the temporal scope of the data collection as well as herbicide applications and overstory measurements. An attempt to capture growth at each installation at four year intervals was successful for many installations but in some cases the intervals were somewhat irregular (i.e., 3-5 years in length). The schedule of measurements was based on twelve-year projection cycles that were used by participating cooperative members.

A point of concern is that some measurements were taken at times that would not have allowed for the herbicide applications to take full effect. That is, several measurement years were concurrent with or followed too quickly after the first herbicide application. This necessitated careful selection of the appropriate measurement years on an installation by installation basis. The"first interval years" were selected such that one to three years following the initial herbicide application were included to allow

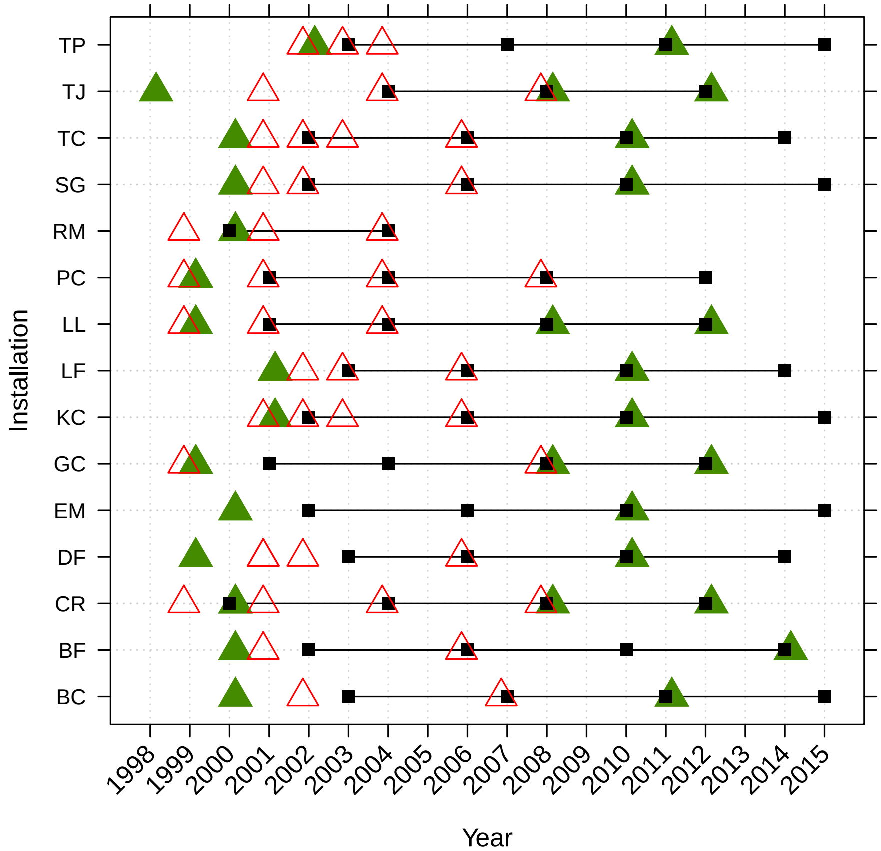

Figure 4: Timeline of Installation Measurements and Treatments.Green and red triangles represent years of overstory measurements and herbicide treatment, respectively. The black squares represent the years of the selected growth intervals.

for the herbicide to take effect. Ultimately, the height growth increments were standardized to the same temporal scale of periodic annual increment regardless of whether they were collected on a 3, 4 or 5-year interval.

When comparing the vegetation depths between the control and the herbicide plots in the first year of the selected measuremnt intervals, it is apparent that there is a large drop in vegetation levels within installations with large amounts of understory vegetation in the control plots(see Figure 5). This indicates some success in establishing a wide range of non-arboreal vegetative conditions on installations. However, the herbicide applications failed to contribute to a marked difference in depth in installations of little vegetative volume in control plots.

Each plot contained a series of nested plots that decrease in area with physiologically smaller

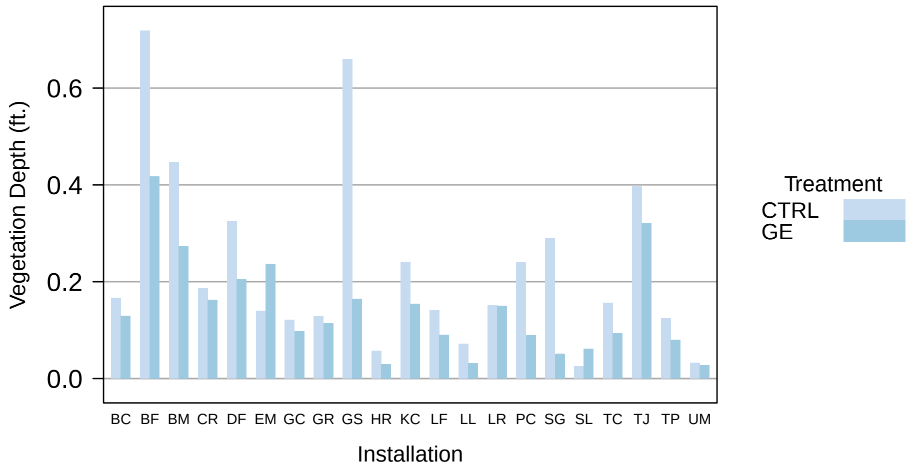

Figure 5: Control and Herbicide Plot Vegetation Volume

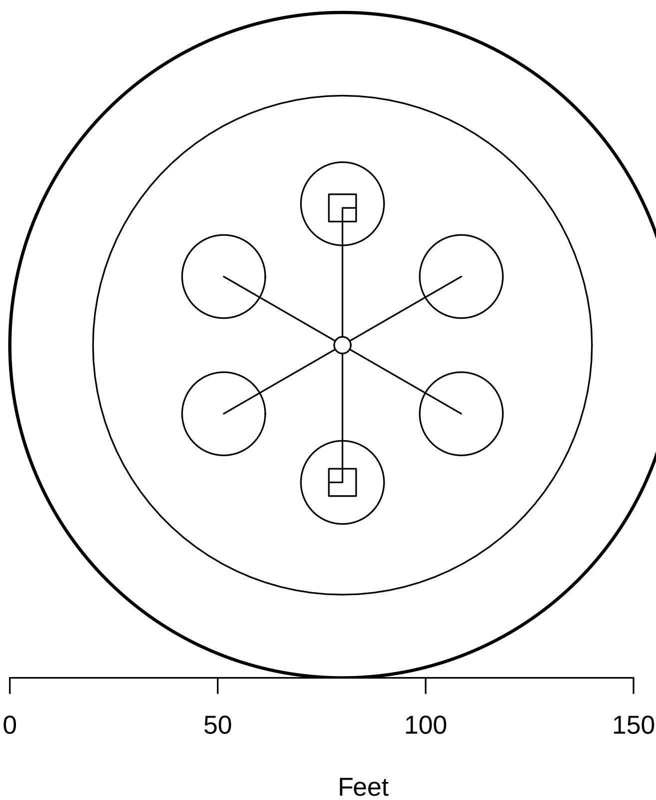

Figure 6: Design of STCV Sampling Plot. Note that vegetation quadrants exist for all six small tree plots although only illustrated on two.

vegetation units (see Figure 6). Starting with the full extent of the plot, overstory trees (> 10.5 in DBH) were measured on an approximately half acre. Medium trees, with DBH greater than 3.5 in but less than 10.5 in were measured on a smaller nested plot of roughly a quarter acre.

Small trees were defined as those that have a DBH less than 3.5 in yet are greater than .5 ft in height for shade tolerant species or 1 ft for shade intolerant at the time of initial measurements. Small trees were measured on six .007 acre plots 60 degrees apart from plot center at a distance of approximately 30 feet.

There were two sampling methods used to measure vegetative competition. The first was transect based where point measurements of vegetation were obtained at one foot intervals along a 40 ft transect. We also took vegetation measurements in the middle of the small tree plots in the form of both $1m^2$ and $4m^2$ grids. These vegetation measurements quantified separately the amounts of forbs, grasses and shrubs to the species level. This is an example of how the resolution of the data goes beyond the scope of this analysis though will undoubtedly be of use in future research efforts.

2.2 Model Construction

The objective was to obtain a parsimonious model that is easily understood and informed by our understanding of the factors surrounding small tree growth. The variable selection process for each individual quantile will be guided by the ecological framework behind small tree growth. The quantile regression model was constructed in a forward stepwise selection that proceeded from one of the four previously mentioned categories of ecological competition that affect tree growth (see Figure **??** on page **??**). These categories are understory tree competition, understory non-tree vegetative competition, retained overstory competition, and site productivity.

Only the installations with greater than 60 ponderosa pine tagged small trees at initiation were included in the model (see Figure 9). At these installations, the response variable; annual height increment, was calculated by finding the appropriate measurement intervals according to the timeline in Figure4 on page 11, then subtracting earlier height increments from the latter and then dividing by the difference between measurement years.

The site productivity of the installations was measured according to the dominate site tree which varied between ponderosa pine, douglas fir and western larch. Selecting only stands with greater than 60 small tagged ponderosa for this analysis effectively removed nearly all stands that measured site index with a species other than ponderosa pine.

There appears to be a group of six installations with similarly low overstory retention levels and high site index values (see red colored installations in Figure 7). It makes sense from a forest management perspective, that relatively little residual overstory would be left on highly productive sites. These installations were used to develop the understory model since they were so alike in overstory and site productivity. There are many other installations that were brought in later to expand the model to other levels of productivity and overstory retention.

It was also during this stage of preparation that damage codes were addressed. Over the years many of the small tagged trees endured some kind of damage (see figure 8) including mortality, broken tops, forked tops, sweep or animal damage. Dead trees and those with dead tops were removed from analysis since these trees typically experienced a decrease in height growth from the previous measurement year. See ***appendix for the complete list of damage codes recorded.

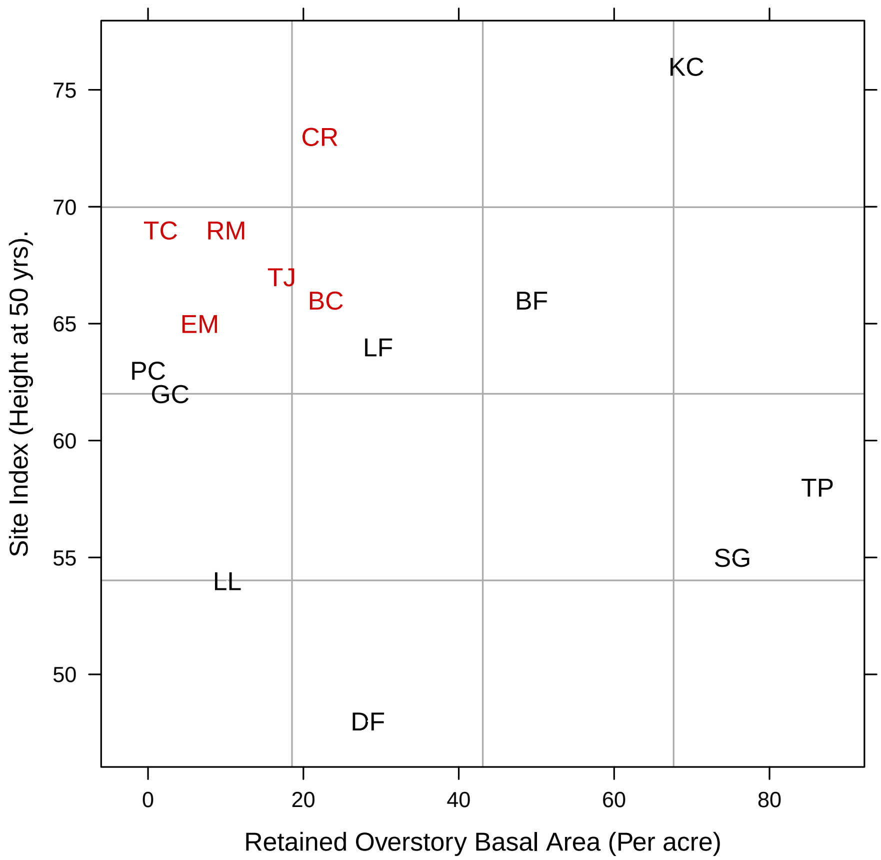

Figure 7: Site Index and Overstory Basal Area at Initiation

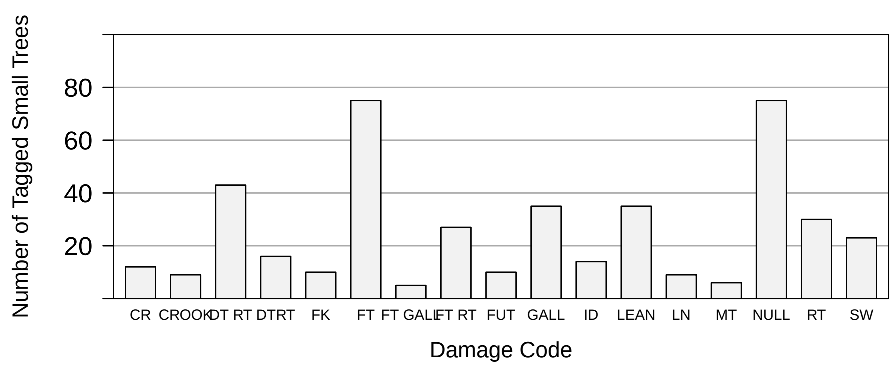

Figure 8: Number of Small Tagged Ponderosa Pine Trees by Damage Code

Within each plot, one of the six small tree plots was randomly selected as validation data. The randomness was necessary to account for the uphill orientation of the first STP on each plot and clockwise layout of the subsequent STPs. The check plots and installations that have sustained a post-initiation harvest were also excluded from analysis.

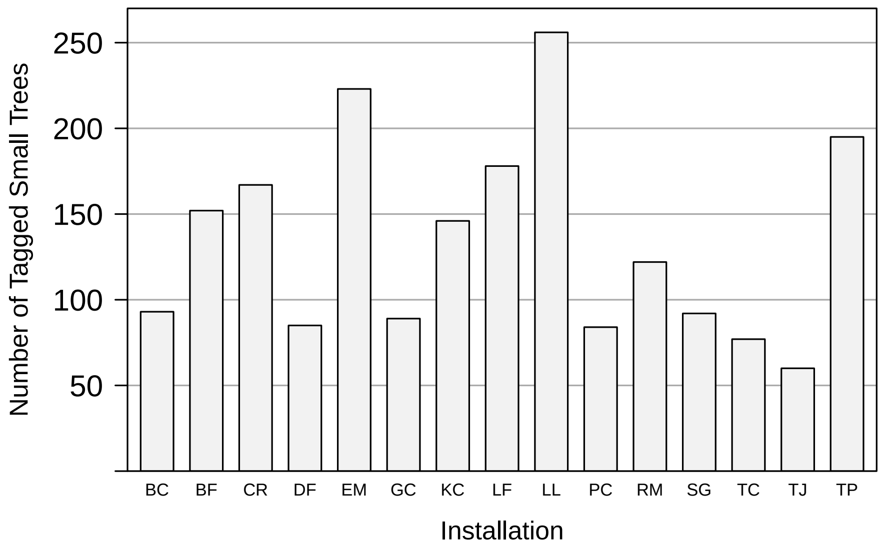

Figure 9: Number of Small Tagged Ponderosa Pine Trees

Within each category of ecological factor, a subset of relevant predictor variables were considered that also evaluated the utility of higher-order polynomial expressions using generalized additive models (GAM) with smoothers of first-order predictors. If inclusion of a higher-order predictor was justified by the partial residual plot from a GAM then it was considered alongside all other predictors and as an interaction term. Variable selection from within these categories was made with respect to their importance in describing trends in the median (τ=.5) quantile regression using the `quantreg` package by Roger Koenker Koenker 2015. The square root of initial height (height at the beginning of measurement period) explains much of the variability in height growth increment and was included as a predictor in the base model.

Aikekes Information Criterion (AIC) was used to compare model fit between variables within each category. The predictor with the lowest AIC was selected to represent that category in the model. If two predictors had similarly low AIC values, then they were both carried forward into the subsequent categories until a clear advantage could be discerned. If a category was unable to produce a predictor with a meaningfully low AIC or the predictor was deemed impractical, no predictor was selected from that category. Refer to appendix **??** for a step-by-step guide to model construction.

2.3 Variable Acquisition

Under story Tree Competition: For this category of ecological competition, only stands of similar overstory basal area and site productivity were selected to compare predictor variables within. This was done to isolate the effects of inter-small tree competition. Ranges of retained basal area and site productivity undoubtedly have influence on small tree growth rates and will be accounted for in subsequent categories.

The tallies of small trees from each small tree plot (STP) were summed by height class and then multiplied by 138.73 to obtain per acre estimates. The number of trees greater than the subject trees was found by summing all height class tallies with class midpoints greater than the height of the subject tree. Crown length was found by subtracting the crown base from the total height. Crown width was found as an average of the two perpendicular measurements of crown width obtained in the field. Crown ratio was obtained by dividing the crown length by the total tree height. Basal diameter and diameter at breast height required no further refinement.

Understory Vegetation Competition:

All stands with greater than 60 tagged small ponderosa pine trees were brought into consideration for the three remaining categories. Although measurements were recorded to 4m vegetation plots in the later years or the study, only the 1m vegetation plots were utilized in this analysis since they were used for the entire duration of the study.

Average differences at the STP level between base and top height measurements were found separately for forbs,low shrubs, high shrubs and grasses. Ocular estimates of percentage cover were obtained for poly-vegetation, forbs, low shrubs, high shrubs and grasses. Average height differences for low shrubs, high shrubs, forbs were calculated for the 30 or 40 transect points corresponding to each small tree plot. Percentage cover of grass obtained ocularly through a 6in by 6in grid and through measurement of the top height of grasses averaged over the length of the transect. Two relative measures of competition were created by subtracting the tallest understory vegetation height from that of the subject tree for both 1m and transect vegetation.

Retained Overstory Tree Competition:

Dead overstory tree records were removed from the analysis. Basal area was calculated for each overstory tree was aggregated from both the .26ac and .46ac overstory plots to provide a per acre estimate of basal area. Zero basal area per acre (BAPA) were assigned to installations without an overstory record due to clearcut. Basal area per acre was linearly interpolated between measurement years to provide estimates for years of small tree and understory measurement. The initial and final years of overstory measurement provided limits of the interpolation meaning that a vegetation measurement year preceding or following the overstory measurements would be assigned the BAPA calculated for the initial or final Overstory measurement year, respectively. Crown competition factor (CCF) was obtained by calculating crown width as an average between the two perpendicular measurements of width and then converting crown width to crown area in square feet. Crown area was then computed in terms of percent of an acre (taking into account the plot size that each overstory tree was sampled in). Linearly interpolated estimates of plot level CCF were obtained in the manner described previously for BAPA. Trees per acre (TPA) is calculated from the plot level aggregation of the two overstory tree plots.

Site Quality: Slope, elevation and aspect were calculated using Google Earth Engine (*Google Earth Engine: A planetary-scale geo-spatial analysis platform*) for each plot's GPS recorded decimal degree coordinates. Slope is in units percentage and elevation in meters. Aspect was transformed by taking cos((aspect*π)/180) and sin((aspect*π)/180). Interacting effects of elevation, slope and aspect were considered according to a linear model proposed by Salas and Stage(Stage and Salas 2007). This model allows for the aspect effects to involve slope and varying elevation.

$$y = b_0 + s[b_1 + b_2\cos(\alpha) + b_3\sin(\alpha)] + \ln(el + 1) * s[b_4 + b_5\cos + b_6\sin(\alpha)]$$
$$+(el^2) * s[b_7 + b_8\cos(\alpha) + b_9\sin(\alpha)] + b_{10}el + b_{11}el^2, \tag{1}$$

where y is the growth response,s is the slope in percent, el is elevation in feet, a is aspect in radians

Site index was included from STCV records of each installation's initiation. An open grown dominate site tree was identified at the initiation of the site and site index calculated from standard site index curves. Site index species was ponderosa pine for the installations included in analysis although many other species were used at other installations.

2.4 Model Validation

The fact that quantile regression attempts to characterize the entire distribution of heights makes it more difficult to test and validate than an ordinary least squares regression. The regression estimates at the selected quantile provide predictions for that specific quantile and it is likely that the predictive ability of the model changes at different quantiles. For example, the model may better predict the median than the upper quantile.

To evaluate the model, three quantiles of the height growth response distribution (τ=.10,.50 and .90) were calculated for each individual tree in the validation data set. The actual recorded annualized height growth increments were then binned according which of the four quantile intervals they fell (i.e. less than .10, .10 to .50, etc.). To add further evaluate the model, the validation trees were also classified into initial height classes of "less than 3 feet", "3-5 feet" and "greater than five feet".

A chi-squared test for homogeneity was then conducted to compare the actual and expected frequencies of annual tree height growth increments within each interval.

Hypotheses tested:

H_0 : The distribution of responses is .10,.40,.40,.10 for each height class

H_A : At least one of the proportions is not .10,.40,.40,.10 for each height class

3 Results and Evaluation

Table 1: Akaike Information Criterion (AIC) for .5 Quantile Regression by Category of Small Tree Competition

Small Tree	n	AIC	Vegetation	n	AIC	Overstory	n	AIC
Nothing	683	1267.72	Nothing	2155	1952.73	Nothing	2155	1952.73
SmallTPA	683	1128.73	POLV.cov	2155	1917.27	BAPA	2155	1878.24
Trees15+	680	1211.25	F.cov	2155	1936.24	CCF	2155	1799.89
TGT	680	1164.91	LS.cov	2155	1947.57	TPA	2155	1753.38
BD	682	928.5	HS.cov	2155	1946.06	Site	n	AIC
DBH	596	928.2	G.cov	2155	1943.72	TPA	2155	1753.38
CrownWidth	680	1126.07	LS.diff	2155	1872	SI	2155	1590.61
CrownLength	680	1014.34	HS.diff	2155	1862.7	Slope	2155	1735.13
CrownRatio	680	934.79	LS.tran	2155	1875.83	Elevation	2155	1752.72
			HS.tran	2155	1912.21	Aspect	2155	1696.07
			G.tran.diff	2155	1863.14	SEA Int	2155	1518.36
			G.tran.cov	2153	1953.86			
			mx.vg.diff1m	2155	1925.21			
			mx.vg.diff.tr	2155	1925.21			

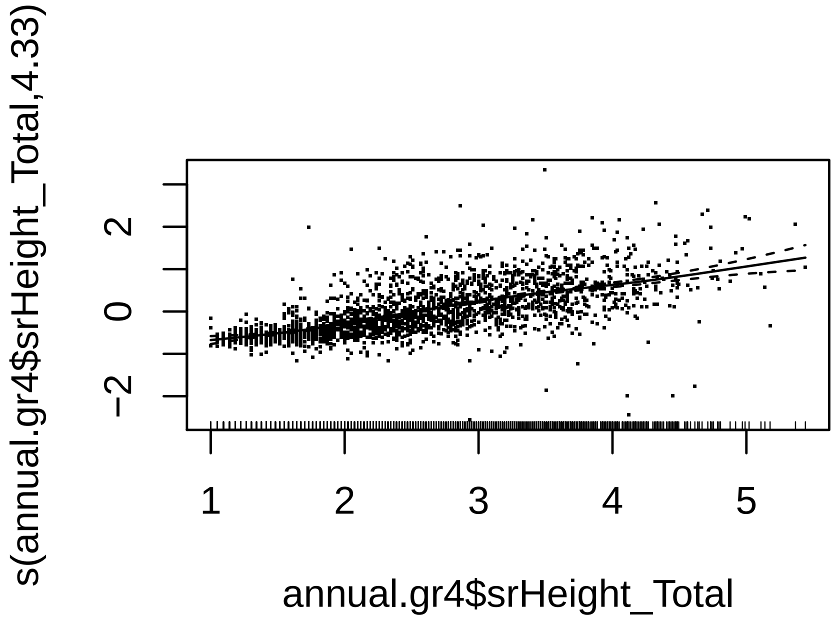

Figure 10: Timeline of Installation Measurements and Treatments

Zhang et al. found that the importance of shrub control on growth increment was not evident in the final years of their study, as tree-shrub competition likely switched to tree-tree compitition. However, shrub control is critical for stand development on low quality sites.

A number of reports on Ponderosa Pine Level-of-Growing Stock Study found that regardless of stand age, ponderosa pine responded to thinning immediately and that average dbh and crown length and width increased with decreasing residual stand densities.(Barrett 1983; Ronco et al. 1985; Cochran and Barrett 1995, 1999; Oliver 1979, 1997, 2005)

Table 2: Engel's Law

Quantiles	(Intercept)	srHeight$_{T}otal$	CrownLength	treeminus	TPA.OS	slopePercent	aspect	elevation
0.1	−0.270	0.049	0.074	−0.022	−0.003	0.027	0.000	0.001
	(0.120)	(0.032)	(0.007)	(0.008)	(0.000)	(0.011)	(0.000)	(0.000)
0.2	−0.261	0.107	0.077	−0.024	−0.003	0.025	0.000	0.001
	(0.085)	(0.022)	(0.005)	(0.005)	(0.000)	(0.008)	(0.000)	(0.000)
0.3	−0.310	0.111	0.076	−0.021	−0.004	0.039	0.001	0.001
	(0.081)	(0.018)	(0.004)	(0.004)	(0.000)	(0.008)	(0.000)	(0.000)
0.4	−0.279	0.107	0.085	−0.026	−0.005	0.040	0.001	0.001
	(0.082)	(0.021)	(0.004)	(0.005)	(0.000)	(0.008)	(0.000)	(0.000)
0.5	−0.231	0.122	0.096	−0.035	−0.005	0.040	0.001	0.001
	(0.097)	(0.021)	(0.005)	(0.005)	(0.000)	(0.009)	(0.000)	(0.000)
0.6	−0.191	0.121	0.110	−0.036	−0.006	0.036	0.001	0.001
	(0.101)	(0.023)	(0.006)	(0.005)	(0.000)	(0.009)	(0.000)	(0.000)
0.7	−0.051	0.116	0.117	−0.038	−0.006	0.038	0.001	0.001
	(0.098)	(0.024)	(0.006)	(0.006)	(0.000)	(0.008)	(0.000)	(0.000)
0.8	−0.004	0.096	0.125	−0.036	−0.007	0.033	0.001	0.001
	(0.146)	(0.033)	(0.008)	(0.007)	(0.000)	(0.011)	(0.001)	(0.000)
0.9	0.187	0.108	0.129	−0.040	−0.009	0.050	0.001	0.001
	(0.206)	(0.053)	(0.011)	(0.012)	(0.000)	(0.022)	(0.001)	(0.000)

A. Bibliography

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uA3ugsjLxIen8cfz3BRuoHqUfzOR2uTWtHJVpFt-ylBIy7ZPD0cwBu15Wqy4vvYaUGCS6rbKIxtVFTLKC32FusI2sIR9HJ
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All analyses were performed using the R statistical software R version 3.3.0 (2016-05-03). This thesis was compiled using the document preparation program LaTeX.

B. Variable Selection Steps

1. Select intallations with >60 *P. Ponderosa* small tagged trees at initiation
2. Select installations of similar overstory basal area and site productivity
3. Retain the sixth small tree plot of each installation for validation
4. Create a list of the practical predictor variables within each category:
   - Understory Tree (UT)
   - Understory Non-tree (UV)
   - Overstory Tree (OT)
   - Site Productivity (SP)
5. For each candidate variable in UT generate a generalized additive model (GAM) using the base model and only the control plots (no herbicide):

$$\Delta \text{ height annual} = \sqrt{\text{initial height}} + \text{ candidate small tree variable} \tag{2}$$

6. Visually examine the results and the partial residual plots of the models produced in 5
7. Include quadratic terms of variables in the list of candidate variables if warranted
8. Fit a quantile regression model with each candidate variable for $\tau = .5$ using the quantreg package

$$Q_{.50}\Delta \text{ height annual} = \sqrt{\text{initial height}} + \text{ candidate small tree variable} \tag{3}$$

9. Calculate the AIC for each model within the UT category
10. Select the variable from the model with the lowest AIC to be carried forward into UV category
11. Repeat steps 5-10 for the UV variables
12. Select variables from the overstory and site productivity categories using the process outlined in steps 5-11 using all installations selected in step 1 (and all plots)
13. Using the variables selected for the τ=.5, fit quantile regressions for τ=.1,.9. This will estimate different bτ for each specified quantile.

    Final Models:

$$\Delta_\tau = \mathrm{b}_{0,\tau}\sqrt{\mathrm{h}} + \mathrm{b}_{UT,\tau}\mathrm{UT} + \mathrm{b}_{UV,\tau}\mathrm{UV} + \mathrm{b}_{OT,\tau}\mathrm{OT} + \mathrm{b}_{SP,\tau}\mathrm{SP} \tag{4}$$

List of Equations