ESTIMATING THE EFFECTS OF OVERSTORY RETENTION, VEGETATIVE COMPETITION AND SITE QUALITY ON THE GROWTH RESPONSE OF SMALL PONDEROSA PINE TREES USING REGRESSION QUANTILES

By

Colin Patrick Kirkmire

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Approved by:

Scott Whittenburg, Dean of the Graduate School
Graduate School

Dr. David L.R. Affleck, Co-Chair
Forest Management

Dr. John Goodburn, Co-Chair
Forest Management

Dr. David Patterson
Statistics

Dr. Peter Kolb
Forestry Extension

Kirkmire, Colin, M.SC, May 2017 Forestry

Estimating the Effects of Overstory Retention, Vegetative Competitions and Site Quality on the Growth Response of Small Ponderosa Pine Trees using Regression Quantiles

Dr. David L.R. Affleck, Co-Chair
Dr. John Goodburn, Co-Chair

Variable retention harvesting is an increasingly viable option in multiple objective silviculture. As a shade-intolerant, fire-adapted species, ponderosa pine is especially well-suited to the simulated disturbance represented by variable retention harvests. Stand initiation following harvest is a critical stage in stand development yet little is known about how small ponderosa pine trees in the understory respond to competitive factors. To assess these sources of competition, we examined post-harvest understory non-arboreal vegetation, overstory trees, and a subsample of tagged small trees over a period of 16 years on 29 sites throughout the Inland Northwest.

Modeling difficulties including a skewed response distribution and longitudinal data led to an examination of quantile regression models. Initial height, crown ratio, overstory trees per acre and slope/elevation/aspect were found to be significant predictors of height growth across all predicted quantiles (τ= .1, .5 and .9). However, the effects of these predictors were found to be different between quantiles which suggests that the predictors influence the fastest growing trees in a different way than the slowest and median trees. We found that quantile regression models could be used to provide an empirically based distribution of height growth under a retained overstory.

ACKNOWLEDGEMENTS

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1 Introduction

Variable retention harvesting is an increasingly common and viable option in multiple objective silviculture. Variable retention harvest allows for the removal of merchantable trees while retaining elements of the previous stand's overstory structure. The benefits of the retained trees include improved aesthetic, provision of seed for a new cohort and improved habitat for wildlife. Variable retention harvest has even been proposed as an approach to emulate natural disturbances (Franklin et al. 1997). As a shade-intolerant, fire-adapted species, ponderosa pine (*Pinus ponderosa*) is especially well-suited to the simulated disturbance represented by variable retention harvests. However, the modeling of small ponderosa pine growth dynamics following variable retention harvest requires consideration of complex competitive effects from both the retained overstory and the understory vegetation.

1.1 Ponderosa Pine Silviculture Systems

Ponderosa pine is an important species both ecologically and commercially in the Inland Northwest. It is a key species in a range of silvicultural systems that vary widely by region and site conditions. Although a broad array of silvicultural systems are 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 of retained trees provide openings with sufficient light to allow shade intolerant species to germinate and be competitive in mixed species stands (O'Hara 2005). The resultant multi-aged stand is suitable for achieving a variety of objectives including timber production, aesthetics, and restoring presettlement stand structures (O'Hara 2005). Nearly all of the aforementioned systems include a retained overstory component which is achieved through variable retention harvest.

Ponderosa pine exists in two typical stand structures: even-aged and uneven-aged. An even aged stand consists of a cohort of trees of a single age class where most trees cluster near an average diameter. Growth in young even-aged ponderosa pine stands is governed primarily by size-density relationships and the site quality. Therefore, density management diagrams (Drew and Flewelling 1979) that incorporate fundamental assumptions about density dependent behavior of populations can be used used to guide management (Long and Shaw 2012).

Uneven-aged aged stands have high variation in height resulting in an irregular stand profile in the vertical dimension (Peng 2000). The difficulty of modelling forest growth in uneven-aged stands stems from a lack of experimental data, a lack of a temporal reference system and a lack of a canonical way to describe the structure of such stands (Peng 2000). Stand age and tree age lose meaning in uneven-aged stands because an individual ponderosa pine may remain physiologically young perpetually or at least for many decades- they have been 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 (Van-Deusen and Boldt 1974). Regardless of why ponderosa pine growth is suppressed and for how long, this species is remarkably resilient and is capable of growth when the suppressing factor is resolved.

1.2 Factors that Affect Small Ponderosa Pine Germination 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 and Lynch 2007). 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 1974).

Powers et al.(2011) found that variable retention harvesting can result in improved seedling photosynthetic capacity, water relations and growth compared to unharvested stands. Moreover, 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.

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

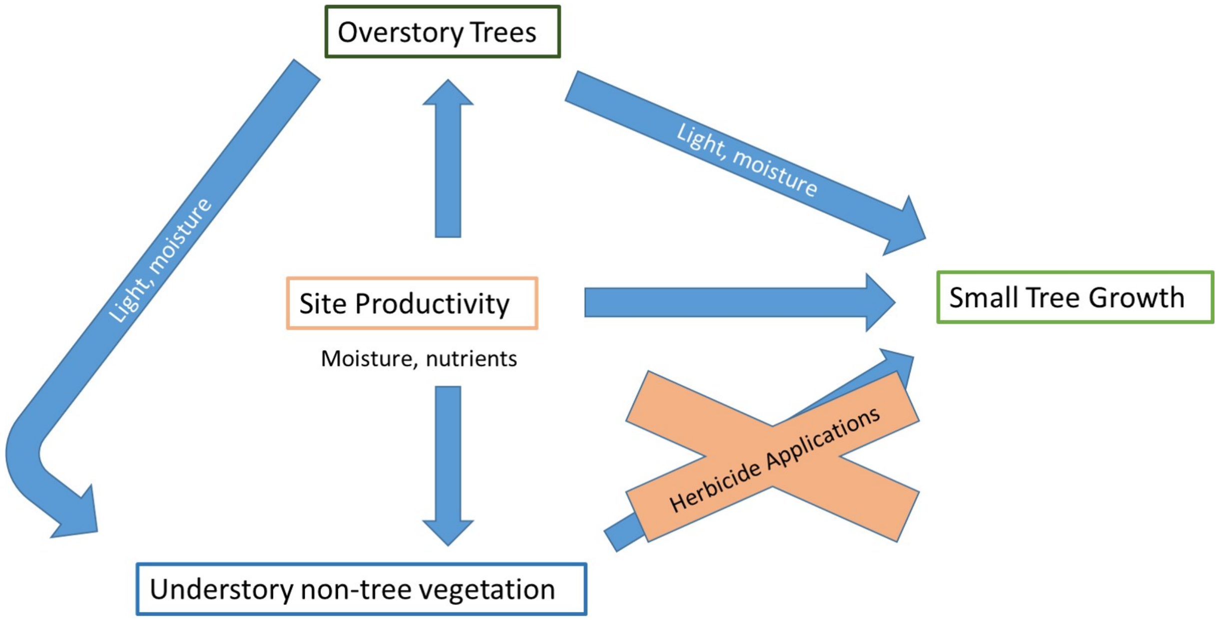

Figure 1: Biological framework of small tree growth. Small trees are defined as those that have a DBH less than 3.5 inches.

growing season but dropped to or below that critical point on the majority of vegetated plots (Curtis and Lynch 2007). Shrub competition also reduced the height and diameter growth of ponderosa pine planted in northern California (Oliver 1979); similar growth reductions have been reported for stands in Oregon (Barrett 1979).

Busse et al.(1996) also found that the presence of understory vegetation adversely affected the growth of ponderosa pine for an estimated 20 years. In a central Oregon study, trees completely surrounded by understory shrubs grew in height 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 1984b). 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 trees competing with shrubs, accounting for some of the growth depression (Oliver 1984b).

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 (Daubenmire and Daubenmire 1968).

Overstory trees and other small trees can also effectively restrict growth. Stagnation in diameter, and often in height, represents a problem in densely stocked stands, but especially on poor sites (Oliver 1984a). 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 production, 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 and Clary 1982, Moore M.M 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 (*Forest Ecology*). For example, conifer reforestation efforts are often hampered by the competitive ability of *Carex* and *Calamagrostis* because these shrub species respond positively to the removal of the overstory (Sloan et al. 1987). These competitive interactions are represented in Figure 1 and constitute a proposed theoretical framework of factors affecting small tree growth.

1.3 Modeling Small Tree Growth following Variable Retention Harvest

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 across 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 from the STCV study revealed an extremely skewed distribution of height growth responses on the tagged trees. Specifically, many trees measured over many periods, exhibited annualized height growth <1 foot 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 experimental manipulations, 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.

1.4 Applications of Quantile Regression

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 trajectory of infants and children (Wei et al. 2004,Koenker). Although most of these charts were created through parametric methods (Cole and Green 1992), 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 and Noon 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 processes 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 2000). 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 (2014) 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. (2016) 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.

With this in mind, the objectives of this research were to

1. Investigate quantile regression as a methodology to describe the competitive effects of overstory and understory factors on the height growth increments of small ponderosa pine
2. Assess the effects of these competitive factors across the distribution of height growth responses
3. Relate findings to the standard regional modeling methodology for small tree growth

The subsequent chapter describes the STCV study in detail and the modeling techniques developed. This is followed by a presentation of results, which include overarching descriptive results as well as those relating to model specification and validation. The final chapter is a discussion of the results and possible further applications.

2 Methods

2.1 Study Design

Twenty-nine STCV study sites were established on private, public and tribal forestlands 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), but 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 according to a shelterwood, seed tree or heavy thinning variable retention harvest.

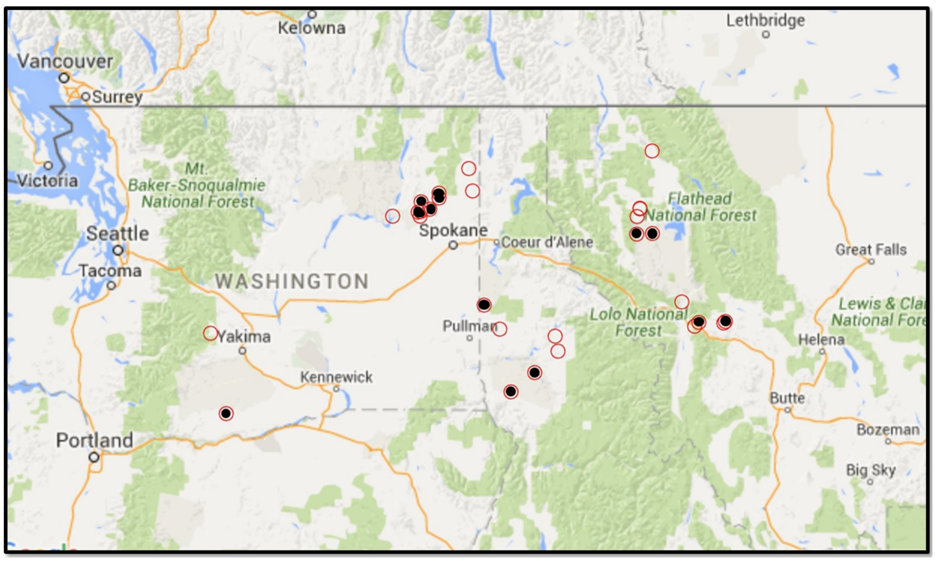

Figure 2: Map of STCV Installations, those included in this study labeled with a black circle.

The year of initiation varied across installations with most being established in the late 1990s and early 2000s. Treatments were randomly assigned to seven plots within each installation (see Figure 3). Three plots received multiple applications of regionally effective herbicide (e.g. Pronone). 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.

Each plot contained a series of nested subplots that decrease in area with physiologically smaller vegetation units (see Figure 4). Starting with the full extent of the plot, overstory trees with greater than 10.5 in diameter at breast height (DBH, 4.5 ft), were measured over approximately half an acre.

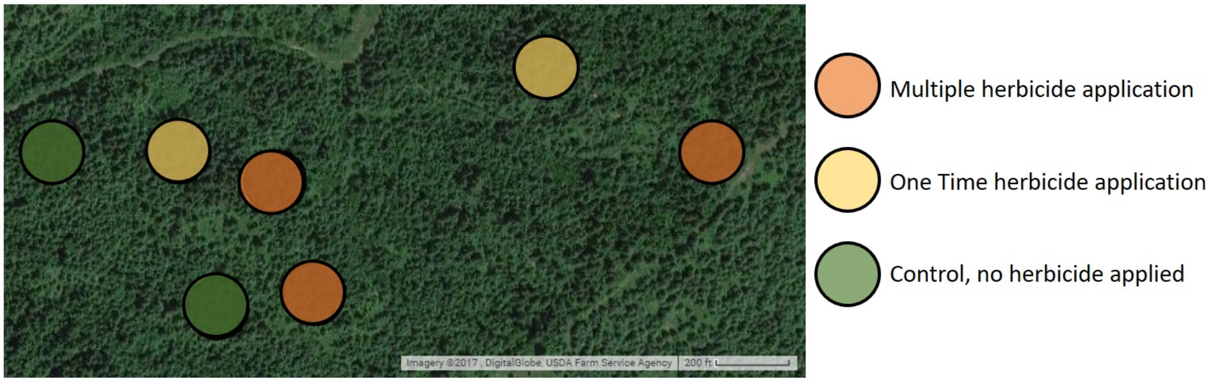

Figure 3: Griner Saddle (GS) installation in northern Idaho and associated plot treatments.

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[1] ID         Species   Lifeform  Lifeform2
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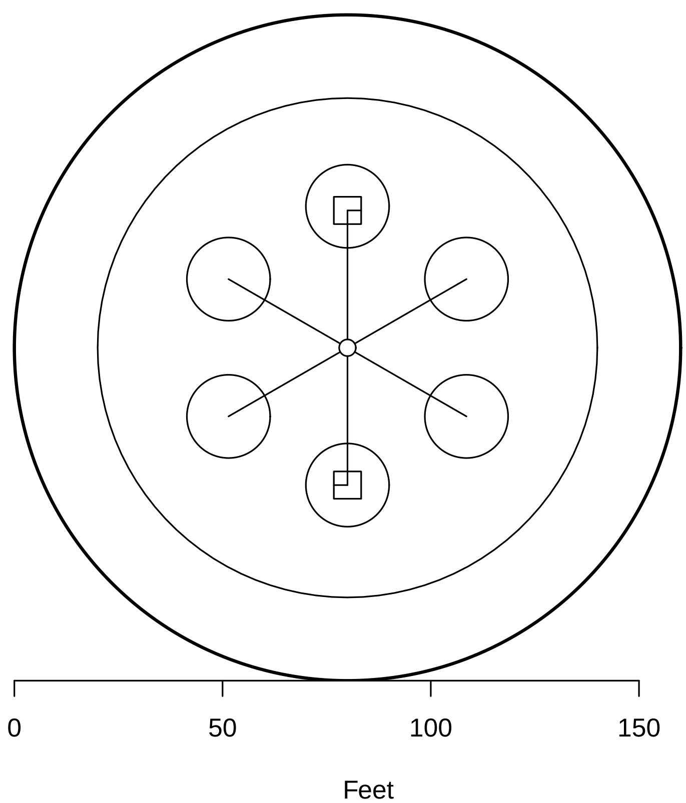


Figure 4: Design of STCV Sampling Plot. Note that vegetation quadrants exist for all six small tree plots although only illustrated on two.

Overstory trees with DBH greater than 3.5 in but less than 10.5 in were measured on a smaller nested subplot of roughly a quarter acre.

The small trees, whose growth responses are the subject of this research, were defined as those that have a DBH less than 3.5 in yet a height greater than .5 ft for shade tolerant species, or 1 ft for shade intolerant species at the time of initial measurements. Small trees were measured on the six .007 ac subplots 60 degrees apart from plot center at a distance of approximately 30 ft. All small trees on the .007 ac subplot were tallied by 2 ft height class and species.

A sub-sample of the small trees was tagged, mapped and measured repeatedly over the course of the study. Height classes for each subplot were determined by dividing the range in heights by four. Two trees per height class and species were then selected when possible. Ultimately, the number of tagged trees should be between 4 and 8 trees per species per small tree subplot.

There were two sampling methods used to estimate vegetative competition. The first was transect based where point measurements of vegetation were obtained at one foot intervals along a 30 or 40 ft transect (initially, transects ran from plot center to small tree subplot center but were extended an additional 10 ft later in the study). We also took vegetation measurements at the centers of the small tree plots using both 1 m^2 and 4 m^2 quadrats. These vegetation measurements quantified separately the amounts of forbs, grasses and shrubs and identified the dominant species for each lifeform. 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.

The primary objective of the herbicide treatments was to decouple the harvesting and understory vegetation effects on small tree growth. It has been reported that, like tree growth, levels of understory increase with site productivity (Stage and Boyd 1987). The herbicide treatments revealed how small trees grow under varying levels of site quality (looking across installations) 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-arboreal vegetation levels, the herbicide application regimes varied greatly in form, timing and level, and not all installations received treatment.

Figure 5 shows the temporal scope of the data collection as well as of the herbicide applications and overstory measurements. An attempt to capture small tree growth at four year intervals was successful

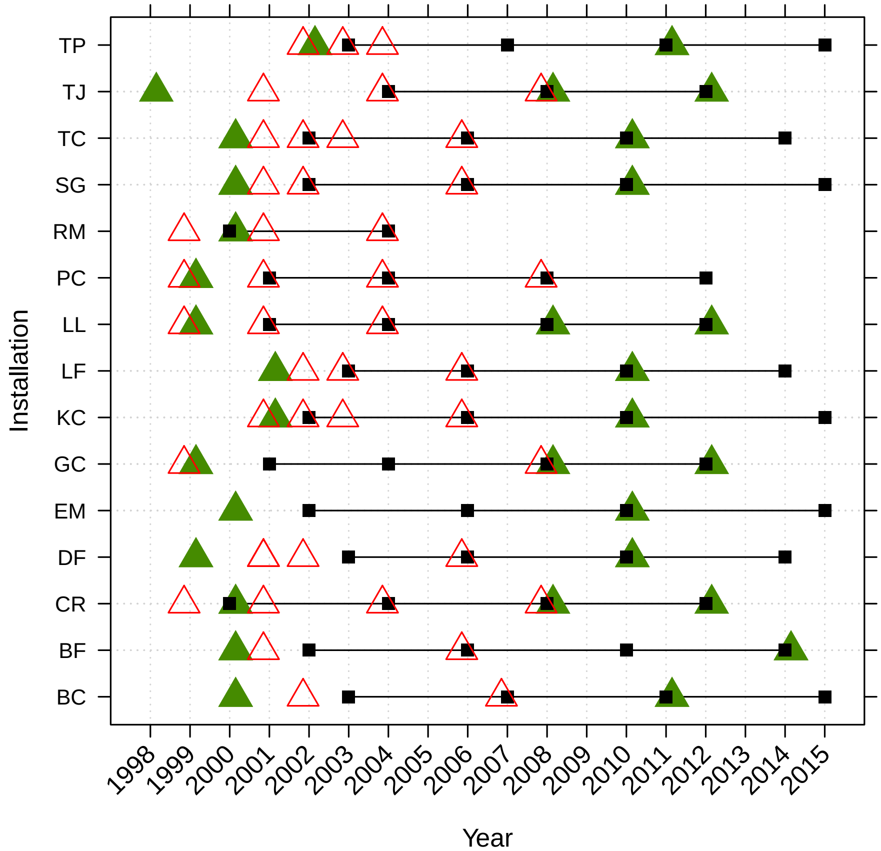


Figure 5: Timeline of Installation Measurements and Treatments.Green and red triangles represent years of overstory measurements and herbicide treatment, respectively. The black squares represent the years of the selected growth intervals.

for many installations but in some cases the intervals were somewhat irregular (i.e., 3-5 years in length). Ultimately, the height growth increments were standardized to a common periodic annual increment regardless of whether they were collected on a 3, 4 or 5-year interval.

A point of concern is that some measurements were taken at times that may not have allowed herbicide applications to take full effect. That is, several measurement years were concurrent with or followed soon after the first herbicide application. For example, the TJ installation was measured in 2001, concurrent with the first measurement year. 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 had elapsed since the initial herbicide application to allow for the herbicide to take effect.

2.2 Variable Acquisition

Understory Tree Competition:

The small trees in each small tree subplot (STP) were tallied by height class and then multiplied by 138.73 to obtain per acre estimates. The number of trees taller than the subject tree was also found by summing all small tree tallies with height class midpoints greater than the height of the subject tree. Crown length was found by subtracting the crown base from the total height (crown base is considered the height of the lowest contiguous branch). 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 (dbh) were measured at 1 in above root collar and at 4.5 ft, respectively.

Understory Vegetation Competition:

Although measurements of understory vegetation and height were recorded in 4 m^2 quadrats in the later years of the study, only the 1 m^2 quadrats were utilized in this analysis since they were used for the entire duration of the study.

Average differences (depth) at the quadrat 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 forbs, low shrubs, high shrubs and grasses. The ocular estimates of percentage cover also included an overall estimate of vegetation cover combined in the quadrat. A volume measurement combined the two measures of vegetation by multiplying the percentage cover by the average depth of the associated cover.

Average height depths for low shrubs, high shrubs, forbs were calculated for the 30 or 40 transect points corresponding to each small tree plot. The original sampling design called for a 30 foot transect that would extend from plot center to the center of each STP (30 transect points), however, in subsequent years 10 ft were added to the length of the transect to extend it through the STP (40 transect points). Percentage cover of grass obtained ocularly through a 6 in by 6 in 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 1 m^2 and transect vegetation.

Retained Overstory Tree Competition:

Basal area was calculated for each live overstory tree and aggregated over each plot to provide an estimate of stand basal area (ft^2/ac, BAPA). Crown area was obtained for each overstory tree from the average of the two perpendicular measurements of width. Total crown area was then computed in terms of percent of an acre (CAPA). Trees per acre (TPA) is calculated from the plot level aggregation of the two overstory tree plots. Stand density index (SDI) was calculated in the following equation:

$$SDI = \sqrt{(BAPA/TPA)/.005454154} \quad , \tag{1}$$

where SDI is the Stand density index, $BAPA$ is the basal area per acre, and TPA is trees per acre.

All retained overstory variables were linearly interpolated between overstory measurement years to provide estimates for intervening years of small tree and understory measurement. The initial and final years of overstory measurement provided limits of the interpolation meaning that a measurement year preceding the first overstory measurement (or following the last) would be assigned the overstory variable value calculated for the initial (or final) overstory measurement year.

Site Quality: Slope (%), elevation (m) and aspect (degrees from North) were calculated using Google Earth Engine (*Google Earth Engine: A planetary-scale geo-spatial analysis platform*) based on each plot's GPS coordinates. 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 the model proposed by Salas and Stage (2007):

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

where y is the growth response, s is the slope in percent, el is elevation in feet, α is aspect and the b are coefficients estimated from the data.

Site trees were identified at the initiation of the study as one or more open grown, undamaged, dominant ponderosa pine. However, there was a single installation (Grouse Creek) that utilized Douglas-fir as the site tree. Site index was calculated from standard site index curves for the Inland Northwest (Milner 1992) with a base age of 50 years at breast height.

2.3 Quantile Regression Modelling Framework

The desire to focus on the full distribution of growth rates naturally led to an investigation of quantile regression (Koenker 2009). 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 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 10th percentile 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 different effects across quantiles. The quantile regression visualization shown in Figure 6 compares three quantiles of the annual height growth response against overstory basal area and site index. In this example, 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 and τ=.50 quantile planes change readily as site index and retained basal area respectively increase and decrease. The factors that affect the growth of the trees in the lower portion of height growth responses may not influence the growth observed in the upper portion of the response distribution or vice versa. In an extreme case, the factors may even have opposing signs between quantile planes.

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 small tree height growth. 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 (Tappeiner, 2007). 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 unexplained variation since there are many unmeasured factors. Quantile regression allows for an explicit (though semi-parametric) description of patterns in this unexplained variation.

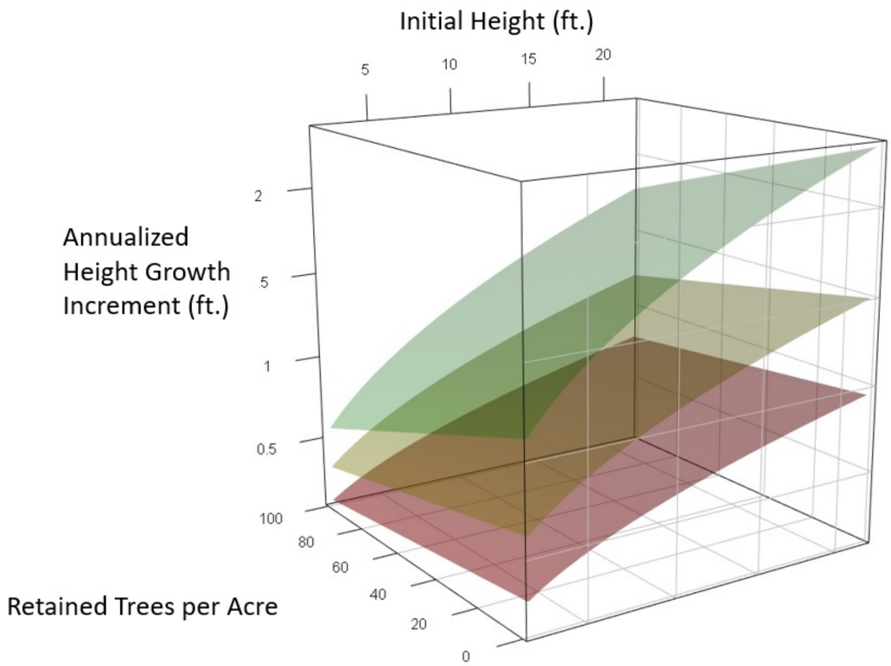


Figure 6: Hypothetical separation of the distribution of annual height increments according to 3 quantile regression surfaces as a function of trees per acre and initial tree height. The red, yellow and green surfaces represent the τ= .1, .5 and .9 quantiles, respectively.

2.4 Model Specification

The objective was to obtain a parsimonious system of quantile regression models informed by our understanding of the factors surrounding small tree growth (see Figure 1). These quantile regression models were constructed in a forward stepwise process that proceeded from one of the four categories of ecological factors that affect tree growth (see Appendix 4).

Only the installations with greater than 60 ponderosa pine tagged small trees at initiation were used for model development. This minimum number of trees ensured that installations included in model building would have a sufficient number of tagged small trees to contribute to model development. The installations that sustained a post-initiation harvest were also excluded from analysis. At these installations annual height increment was calculated by finding the appropriate measurement intervals according to the timeline in Figure 5, then subtracting earlier height measurements from the later oner and dividing by the difference between measurement years.

$$y_{i,j} = (h_{i,j+1} - h_{i,j})/(t_{i,j+1} - t_{i,j}) \quad , \tag{3}$$

where y is the annualized growth response in feet, h is the height in feet, i is the unique tree, t is year, j is the measurement period.

It was also during this stage of preparation that small tree damage codes were screened. Over the years, many of the small tagged trees endured some kind of damage, including, but not limited to, mortality, broken tops, forked tops, sweep or animal damage. See Appendix 3 for the complete list of damage codes recorded. Dead trees and those with dead tops were removed from analysis since these trees typically exhibited a decrease in height growth from the previous measurement year. All tree records that exhibited a negative height growth increment were also removed from consideration since this indicated either a measurement error or some mis-recorded damage to the top.

Within each plot, one of the six small tree subplots was randomly selected to serve as validation data. The randomness was necessary to account for the systematic uphill orientation of the first STP on each plot and the clockwise layout of the subsequent STPs (Figure 4).

Within each category of ecological factor, a subset of relevant predictor variables were considered. Their effects on annual height growth were initially assessed using generalized additive models (GAM). If the partial residual plot of a GAM suggested the inclusion of quadratic terms, then these were considered alongside all other predictors and as interaction terms. Variable selection within these categories was made with respect to their importance in describing trends in the median (τ=.5) quantile regression surface using the `quantreg` package (Koenker 2015). The square root of initial height (height at the beginning of measurement period) was included as a predictor in the base model.

Akaike's Information Criterion (AIC) was used for model comparison within each category. The predictor effecting the largest drop in AIC was selected to represent that category in the model going forward. 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 supply a predictor that lowered AIC or if the predictor was deemed impractical for field measurement, no predictor was selected from that category. For a step-by-step outline of the stepwise regression, see Appendix 2.

In the first category (understory tree competition), only plots that received multiple applications of herbicide within installations of similar site index and overstory stocking were used. This was done to minimize difference in non-arboreal vegetation levels, overstory competition, and site productivity, and to focus on small-tree competitive effects. Plots of all levels of vegetation treatment (control, one time herbicide treatment and multiple herbicide treatment), were brought into the modeling for the understory vegetation variable selection. Finally, all installations in Figure 8 were considered for the site level variable selection steps of overstory competition and site quality.

2.5 Model Validation

To evaluate the performance of the selected model, three quantiles of the height growth response distribution (τ= .10, .50 and .90) were estimated for each individual tree in the witheld validation data set. The recorded annualized height growth increments were then classified according to where they occurred among the four interquantile intervals (i.e. $<$.1, .1-.5, .5-.9, $>$.9). The validation records were also classified into initial height classes of 1-5 feet, 5-10 feet and greater than 10 feet.

Chi-squared tests for homogeneity were then conducted to compare the actual and expected frequencies of annual tree height growth increments across the four interquantile intervals and height classes.

3 Results

3.1 Installation Characteristics

Figure 7 describes the elevation and directional distributions of plots by installation. All plots range in elevation between 600 and 1200 m. Plots within the same installation have generally similar values of elevation and aspect. The Loon Lake (LL) and Cemetery Ridge (CR) installation are notable exceptions where the topography was fairly flat and thus aspect varied within the installation's plots. There is a broad range of aspects and elevations as plots are well-distributed among the regions of the polar plot.

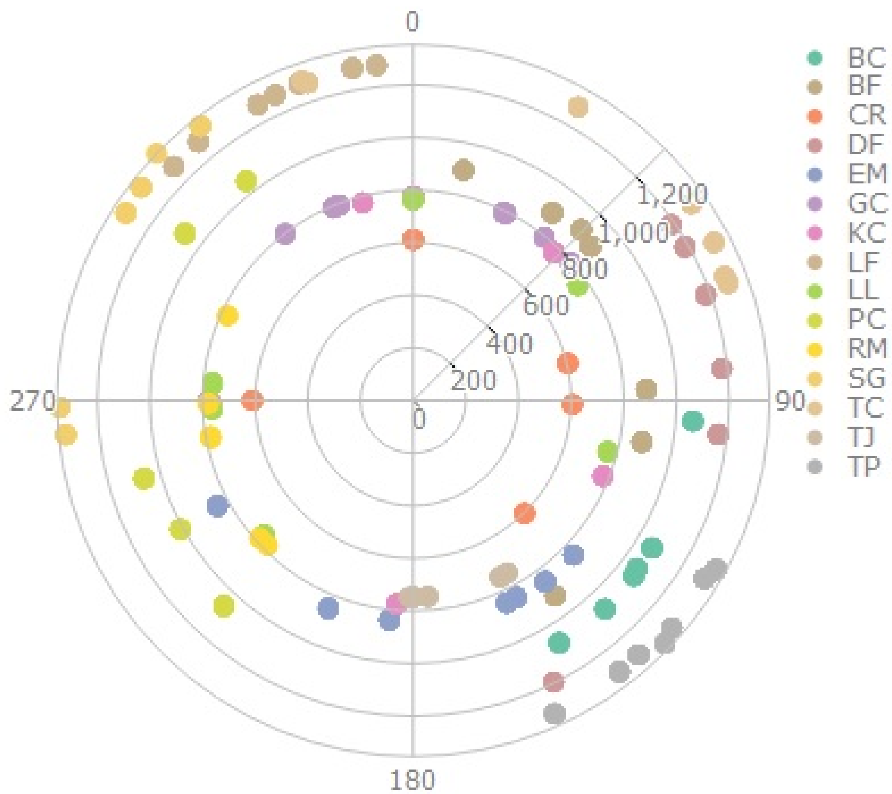


Figure 7: Aspect and elevation by plot and installation.

The study captured a wide range of productivity and overstory retention levels from low site and low retention to high site and high retention (Figure 8). However, there is a distinct concentration of installations with similarly low overstory retention levels and high site index values. These six installations (colored red) were selected to develop the understory model since they were so alike in overstory and site characteristics. In the following figures, these installations will be identified by a * preceding the name

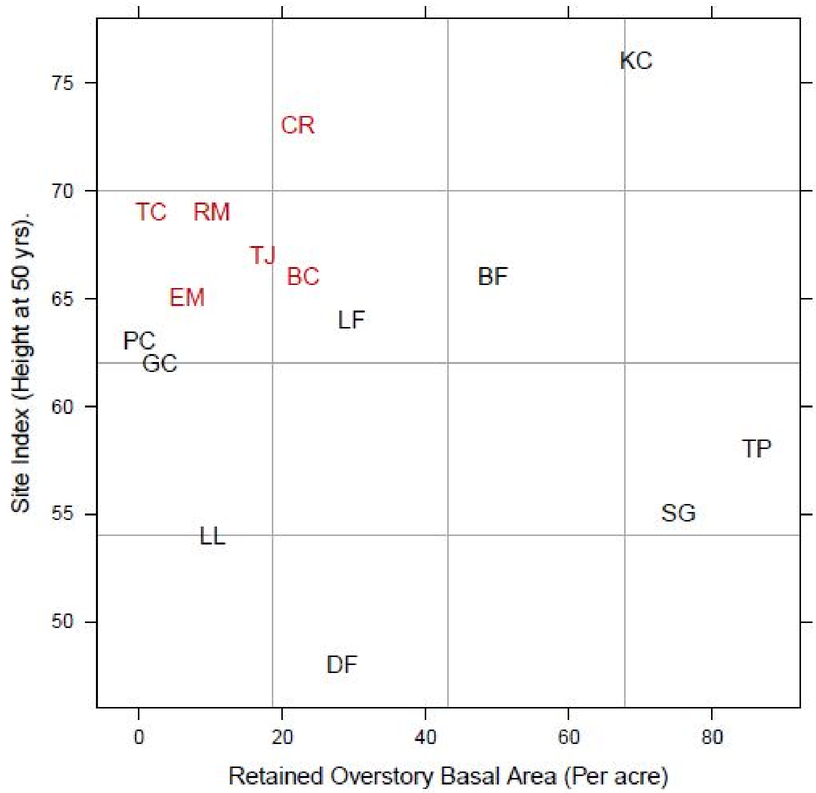


Figure 8: Site index and initial basal area per acre (ft^2/ac).

of the installation (ex: *EM). There is also a noticeable gap where there are no intermediate retained overstory sites (20-60 (ft^2/ac)) that have a low site index.

Figure 9 shows the plot-level interpolations of overstory trees per acre. Most plots stayed constant in the number of overstory trees per acre. However, due to mortality, there may be slight differences. For most installations the overstory retention levels are similar. Within several installations, there is noticeable variation in overstory trees per acre between plots. Installations LF (Lubrecht Forest) and EM (Empey Mountain) show considerible differences in overtory TPA between plots.

Figure 10 shows the positive correlation between the SEA value and the site index. Since both of these variables relate to the inherent productivity of the site they should be positively correlated. The lack of a strong correlation can be attributed in part to a difference in resolution. One site index was obtained for each installation and the SEA value relates productivity to the slope, aspect and elevation at the plot level.

The number of tagged ponderosa pine trees at initiation is not ultimately reflective of how

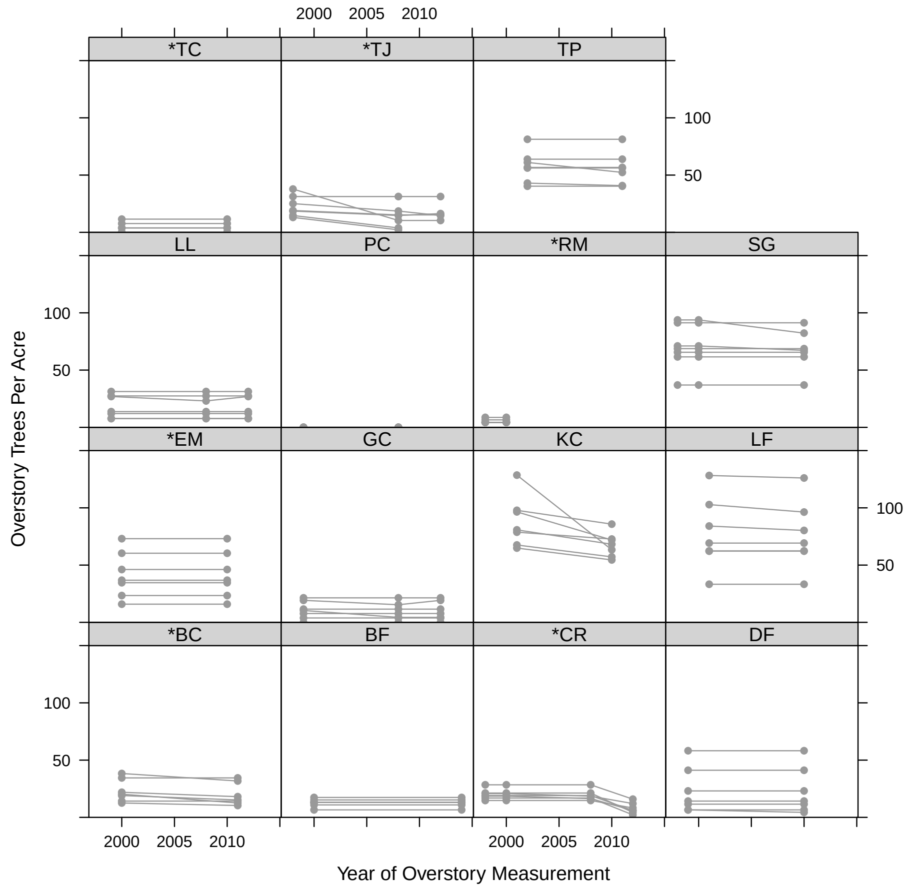


Figure 9: Interpolated overstory TPA by study site, plot and year.

many tree records each installation represents. The number of measurement intervals included from each installation as well as an account of tree records excluded due to mortality/damage/missing are necessary considerations to express the relative contribution of each installation to the model. Figure 11 shows that when these factors are accounted for, many installations contribute over 150 tree records to the model, while installations with only a single measurement interval included Round Mountain (RM) and TJ's Installation (TJ) actually contributed less than 60 tree records. There were five installations that had tagged ponderosa pine tree records in excess of 200 and two that had over 300: Emphey Mountain (EM) and Lubrecht Forest (LF).

Table 1 is related to Figure 11 in that it reveals the number of times a unique tree contributed to the model. A nearly equal amount of trees contributed to the model over either one, two or three measurement intervals. Ultimately, the majority of the tree records were from trees that were included over three intervals.

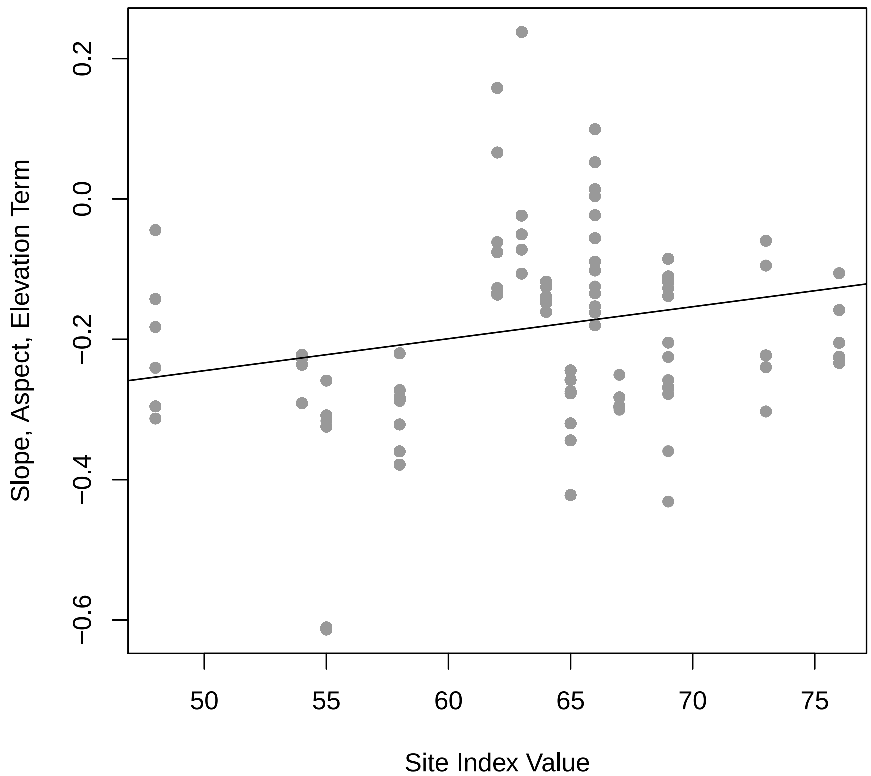


Figure 10: Examination of relationship between the slope, elevation and aspect interaction term and site index

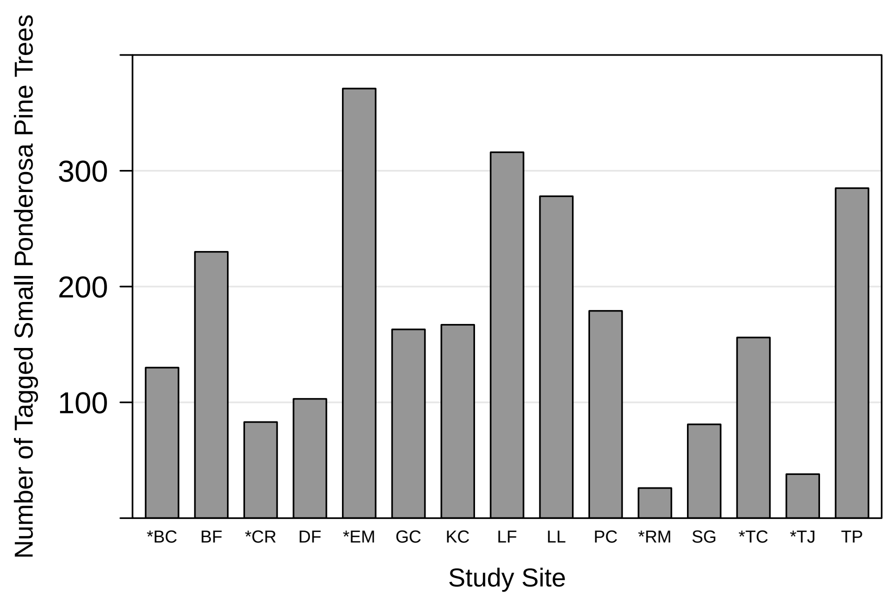


Figure 11: Number of small tagged ponderosa pine tree records by STCV study site.

Table 1: Number of tree records from each unique tree.

Number of Observations	Number of Trees	Number of Tree Records
1	425	425
2	475	950
3	411	1233

The dead, dead top or animal damaged trees were removed from the model whether the damage was recorded at the beginning or end of a given interval (see Figure 12). Other damage codes were recorded for subject trees (see Appendix 3) but only trees with the specified damage relating directly to top damage or mortality were removed. Most installations exhibited similarly low levels of mortality or other specified damage. The number of tree records removed generally does not exceed 20 trees. However, some installations such as KC, RM and CR showed high levels of mortality and damage, especially in the later years of the study. Unique trees may appear across multiple years. Any reductions in the number of tree records removed across measurement years is attributed to an improvement in tree health or an inability to locate and categorize the tree as dead or damaged.

The threshold number of tagged ponderosa pine limits the analysis to installations with a significant ponderosa pine understory component. However, to obtain a clear description of the inter-species understory tree competition between installations, it is necessary to look beyond the tagged subject trees to the tallied trees at initiation (Figure 13). Based on the frequencies of small trees by species and installation in, the selected installations are not dominated by Douglas-fir regeneration although there are number of installations that are very closely split between the two species.

When comparing the vegetation depths between the control and the herbicide plots in the first year of the selected measurement 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 14). 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.

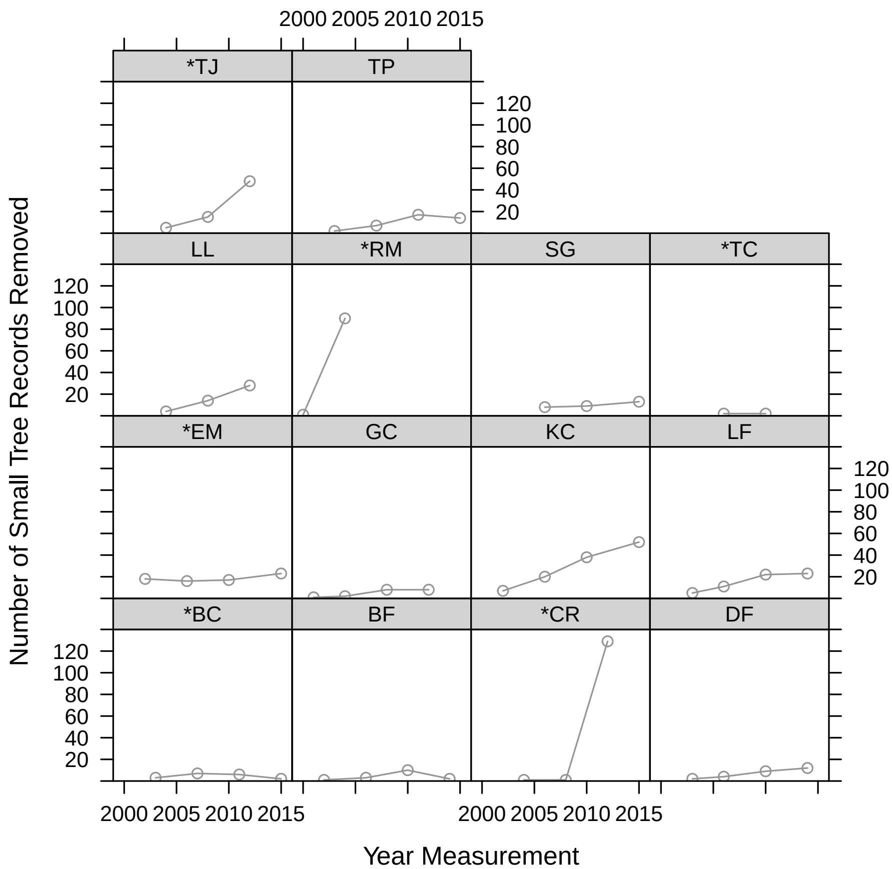


Figure 12: Small tree records removed due to top damage or mortality over time.

3.2 Subject Tree Characteristics

The initial height of small ponderosa pine trees at the beginning of measurement intervals ranges between 1 foot (the minimum height to be included in the sample) to just under 30 feet with the majority of tagged trees are between 1 and 15 feet in initial height (Figure 16). KC and TP have especially narrow distributions of initial height. These installations have very dense, vertically homogeneous ponderosa pine regeneration that are slowly growing. These conditions are not typically found in a natural ponderosa pine stand and these installations may benefit from an understory treatment such as a prescribed burn or non-commercial thinning that promotes differentiation among understory ponderosa pine so they can emerge into the canopy. Although, these stands may not represent optimum management, they are important to include to estimate the effects of small tree competition in extremely dense conditions.

Ponderosa pine vary in annual height growth according to which installation they are located

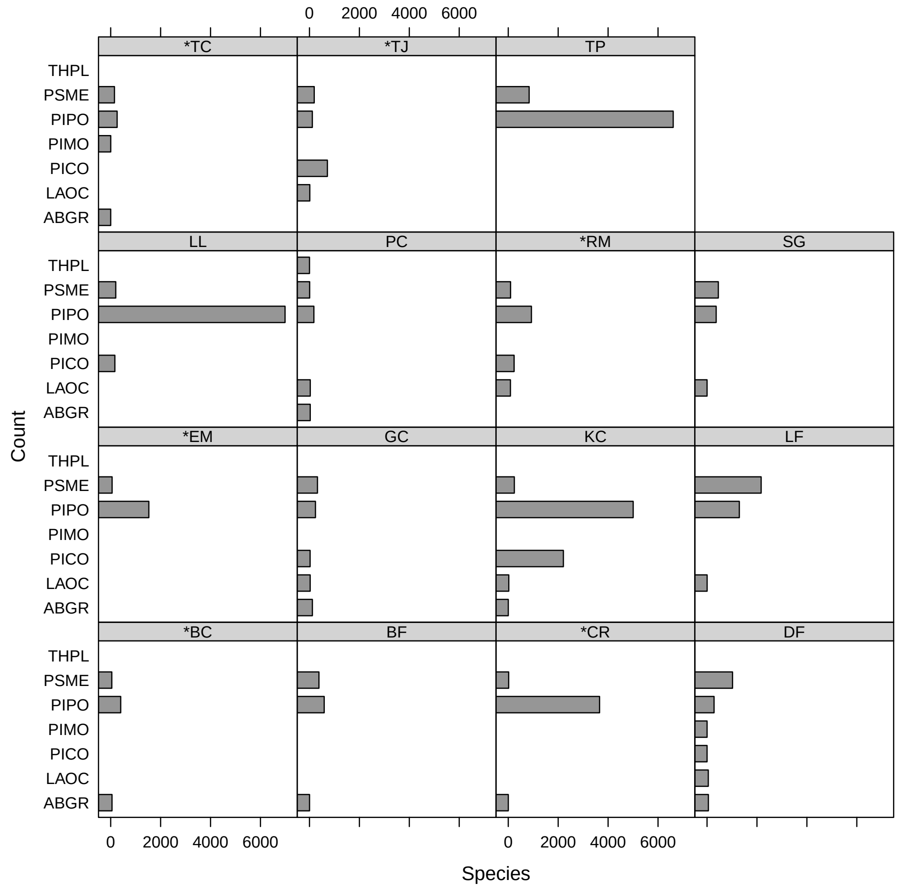


Figure 13: Species composition of small tree plots in installations with more than 60 tagged ponderosa pine at initiation. PSME= *Psuedotsuga menziesii*, PIPO= *Pinus ponderosa*, ABGR= *Abies grandis*, THPL= *Thuja plicata*, PIMO= *Pinus monticola*, PICO= *Pinus contorta*, LAOC= *Larix occidentalis.*

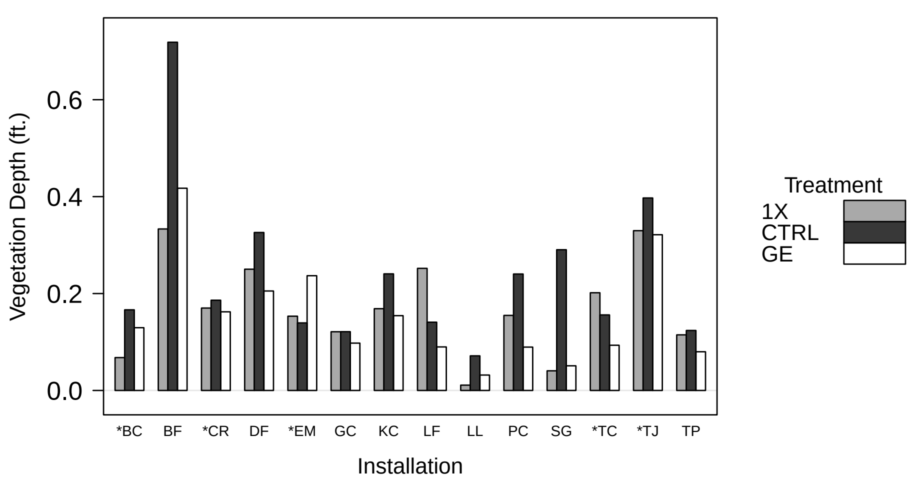


Figure 14: Plot vegetation volumes by herbicide treatment at the start of the measurement period (GE = multiple applications, 1X = one time application, CTRL = no herbicide).

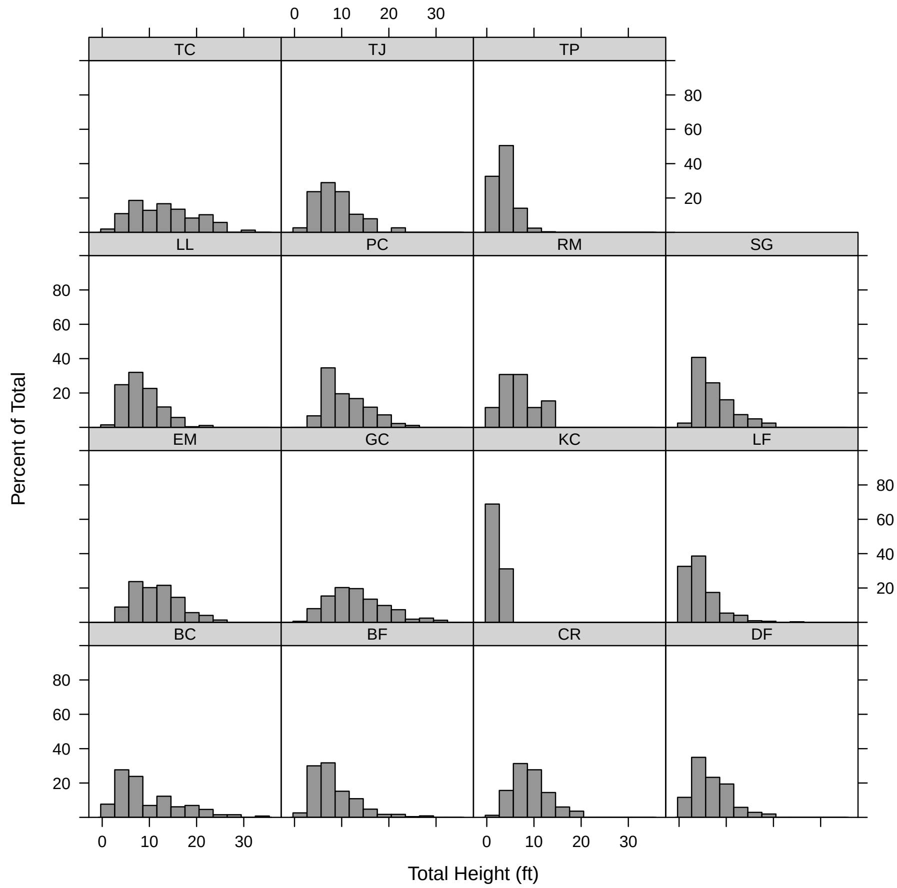


Figure 15: Initial height of small tagged trees by installation.

within (Figure 15). The asymmetric, right skewed distributions reveal that most subject trees experience annual height growth between 0 and 2 ft with very few trees exceeding 2 ft. Note that the distribution itself changes between installations. Some installations such as TP and KC have a vary narrow distribution of annualized height growth which indicates that most trees are experiencing similar levels of growth. In these stands, this can likely be attributed to their dense understory regeneration in which trees struggle similarly for resources. In contrast, installations such as GC and BC have fairly even distributions of annual height which indicates differentiation in competition and a corresponding wide range of initial heights.

Annual height growth increment tends to increase with initial height (Figure 17). This relationship was positive although weak and increasing in variance with points fanning out from the origin in decreasing density. This reveals that most of the tree records used for this model represent shorter in stature trees that exhibit only modest increases in height growth increment. Despite this concentration

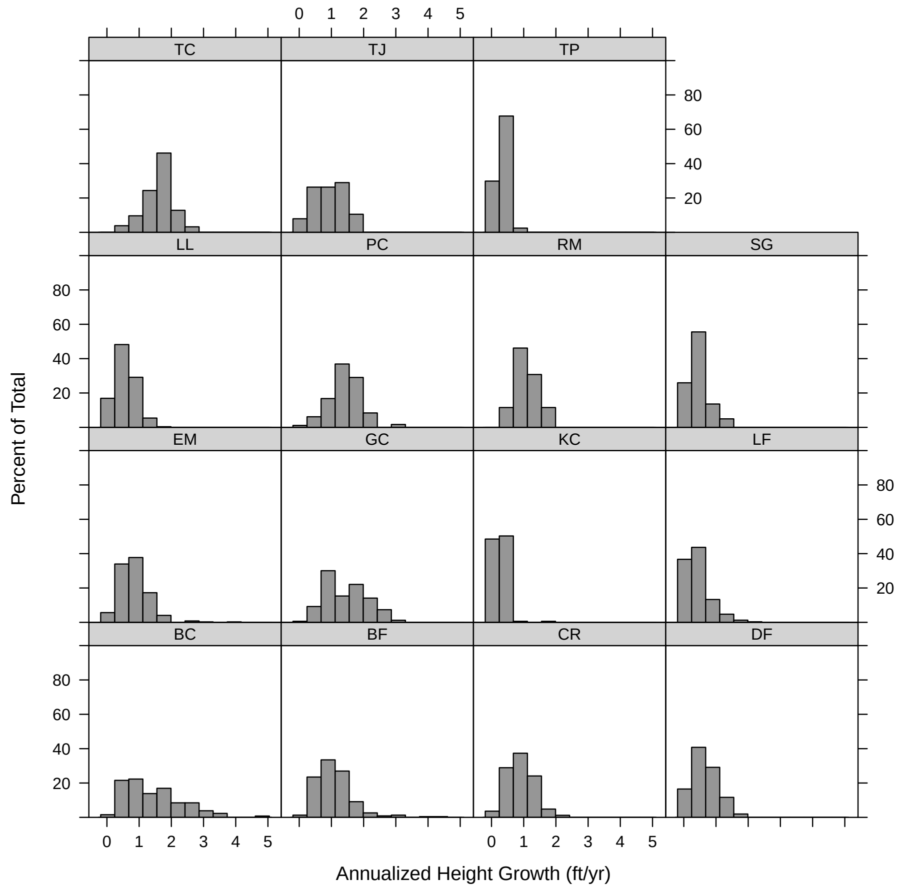


Figure 16: Annualized height growth of small tagged trees by installation.

of shorter subject trees, there is a wide range of both initial height values and annualized height growth that includes trees greater than 25 ft tall and trees that experience approximately 3 feet of annual growth. While taller trees tend to exhibit greater annual height growth, the variability in height growth also increases with initial height (non-homogeneous variance).

Crown ratio (crown length/total height) appears to act as an upper limit to annual height growth (Figure 18a). Small trees with very little crown exhibit height growth responses that are correspondingly small. As crown ratio increases the upper values of the height growth response distribution also increase. However, variance in annual height growth also increases for increasing values of crown ratio. Trees with larger crown ratios exhibit greater variability in height growth. For trees with the fullest crowns (>.8), annual height growth tends to exceed .5 ft.

As initial height increases, the lower extent of crown ratio response increases. As subject tree height increases, the variability of the response distribution of crown ratio also decreases. Trees that are

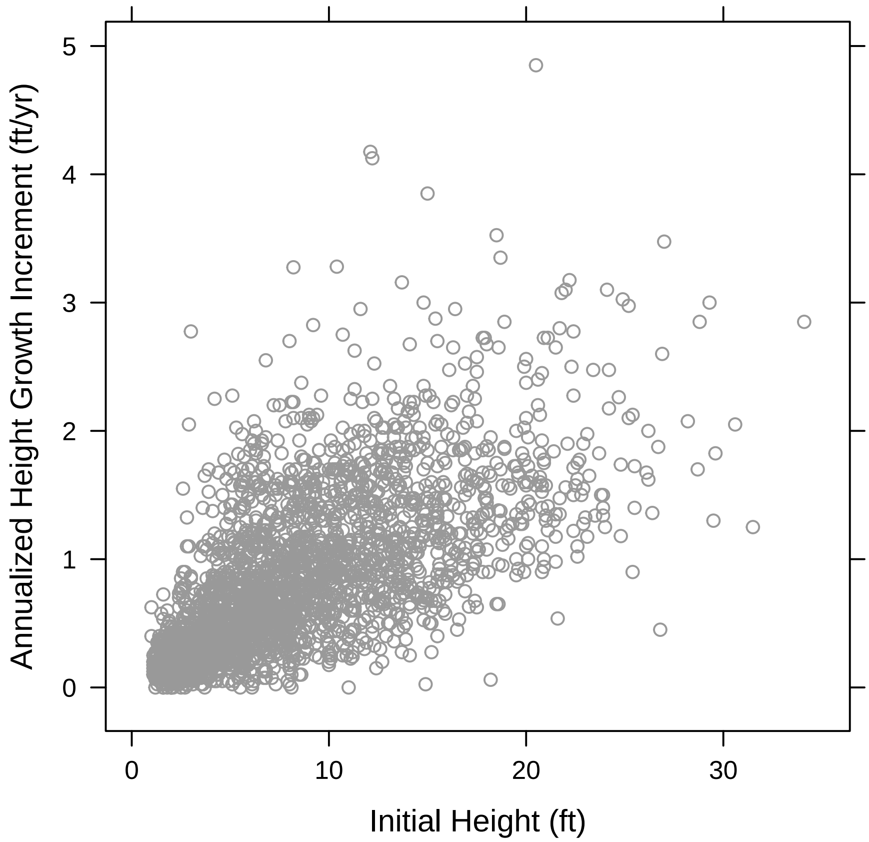
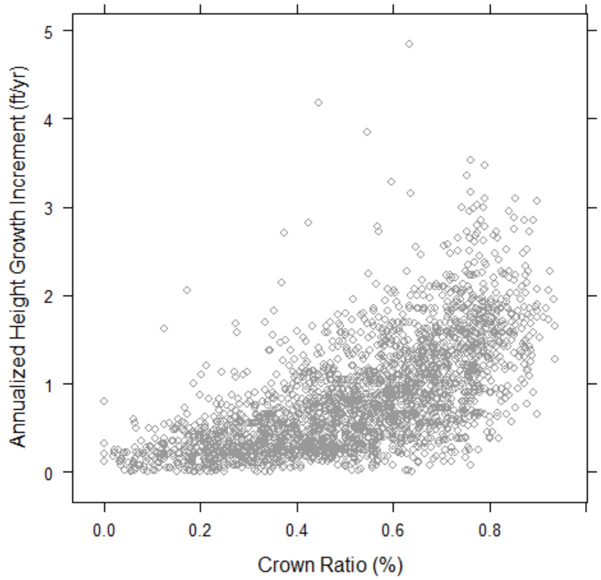
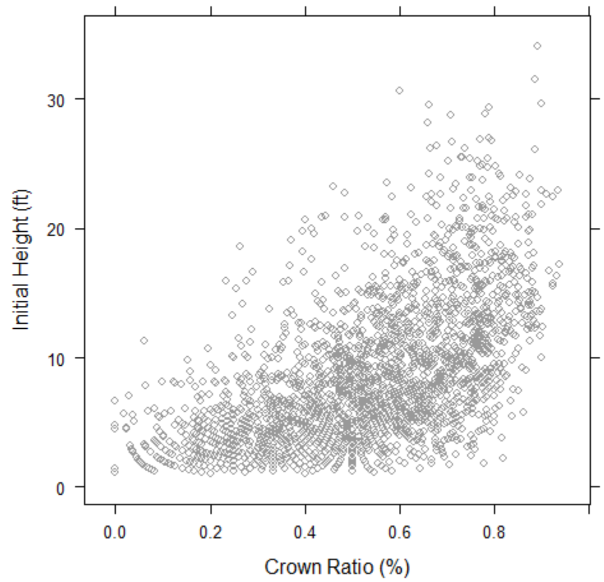


Figure 17: Annualized height growth increment vs. initial height.

exceedingly tall nearly always have high crown ratios. In contrast, the range of variability in the shorter trees corresponds to a wide range of crown ratios. These findings relate physiologically to the relationship between the crown as a driver of growth and tree height; a full crown is necessary to achieve such stature.



(a) Annualized height growth increment (ft/yr) vs. crown ratio.



(b) Crown ratio vs. initial height (ft).

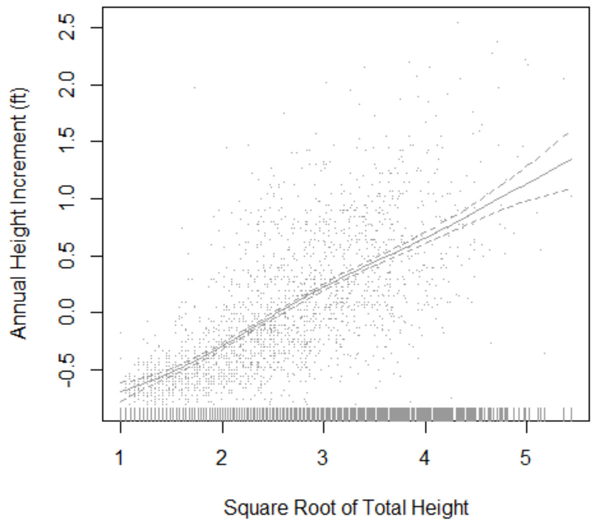
Figure 18: Scatterplots of small tree growth characteristics.

Table 2: Candidate variables and associated sample size (n) and AIC.

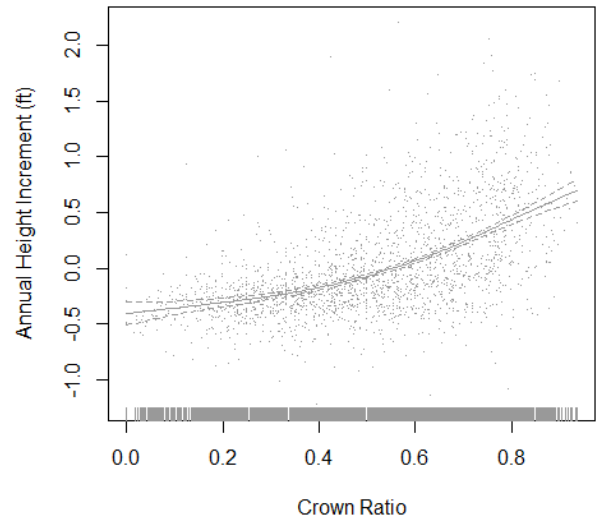
Variable	n	AIC	Variable	n	AIC	Variable	n	AIC
Nothing	423	839.7	Nothing	721	1011	Nothing	2608	2552.1
SmallTPA	423	708.7	POLV.cov	721	1004	BAPA	2608	2490.5
Trees15+	422	771	F.cov	721	1012.9	CAPA	2608	2417
TGT	423	760.9	LS.cov	721	1012.8	TPA	2608	2346.2
BD	422	610.7	HS.cov	721	1011.9	SDI	2608	2454
DBH	389	603.2	F.depth	721	1011.6	Site	n	AIC
CrownWidth	423	713.4	LS.depth	721	1012.5	SI	2608	2051.7
CrownLength	423	674.8	HS.depth	721	1005.1	Slope	2608	2340.7
CrownRatio	423	585.4	F.vol	721	1012.4	Elevation	2608	2348.1
			LS.vol	721	1012.5	Aspect	2608	2347.5
			HS.vol	721	1012.5	SEA Int	2608	1986.5
			F.tran	721	1012.4			
			LS.tran	721	1010.9			
			HS.tran	721	1012.9			
			G.tran.depth	721	1005.8			
			G.tran.cov	721	1009.1			
			mx.vg.diff.1m	721	1009.8			
			mx.vg.diff.tr	721	1012.4			

3.3 Variable Selection

The primary form of the model included the square root of initial height, since it was found to be have a strong, positive, linear relationship with height growth increment (Figure 19a). The generalized



(a) GAM of annualized height growth increment vs. initial height.



(b) GAM of annualized height growth increment vs. crown ratio.

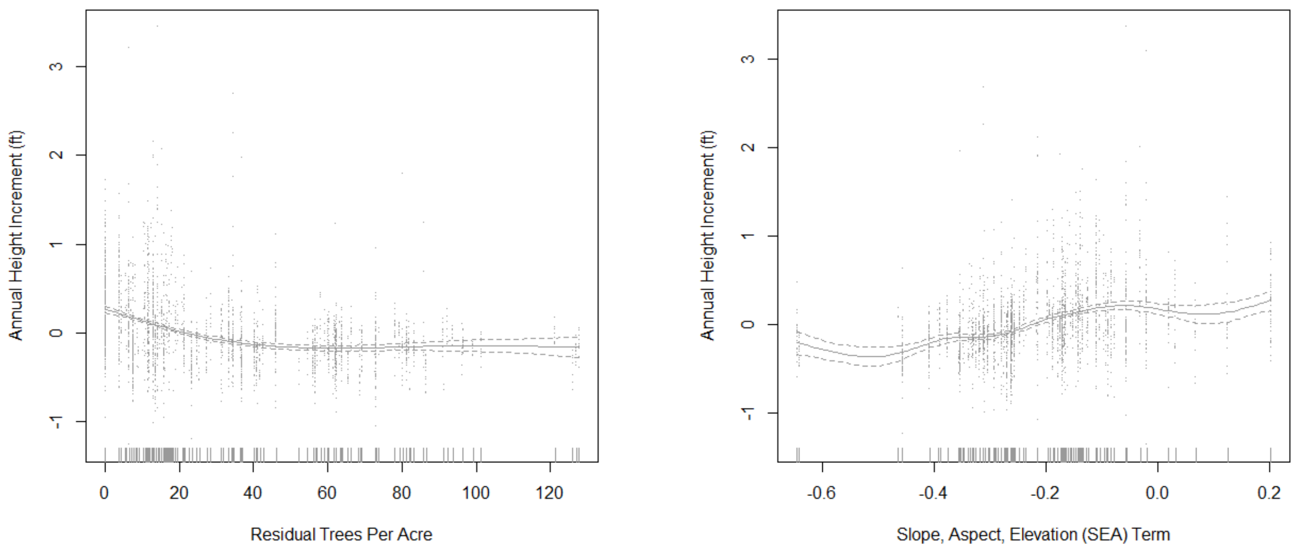
Figure 19: Generalized additive models of annualized height growth vs. initial height and crown ratio.

additive model (GAM) in this figure shows the predicted value of height increment as a function of initial height. Generally, the taller the tree at the beginning of the period, the greater the height growth increment.

Proceeding forward from the primary model to the small tree category of competition, the AIC of the crown ratio variable was found to be much lower than the other candidate variables (see Table 2) for τ=.5. This variable was therefore selected to represent competition from other small trees. The GAM created to visualize crown ratio includes square root of initial height as a linear term and is smoothed for crown ratio (Figure 19b). The relationship for this variable is less linear than that of the primary model yet predicted height growth increment is shown to increase as crown ratio increases. Small trees with larger crown lengths relative to total height are predicted to have greater height growth increments.

The understory non-arboreal vegetation candidate variables failed to provide an AIC significantly less than that of including only the two previously selected variables. The only variables that offered even marginal improvement over the previous iteration of the model were the 1m^2 % cover of all non-arboreal vegetation (POLV.cov) and transect measured grass depth (G.tran.depth). However, the inclusion of these variables is hardly justified considering the modest improvement they provide and the impracticality of measuring either in the field. Therefore, no candidate variable was selected from this category of competition.

The overstory candidate variable with the lowest AIC was trees per acre (TPA). The measure of crown area per acre (CAPA) provided a close second and basal area per acre (BAPA) was also much lower than the previous iteration of the model. The GAM of TPA shows that predicted height increment decreases steeply between 0 and 40 TPA but appears to flatten past 40 TPA (Figure 20a). As a predictor of height growth increment, TPA is important to distinguish between clearcut (0 TPA) and modest overstory retention levels. However, beyond 40 TPA, it fails to relate to predicted height growth increment.



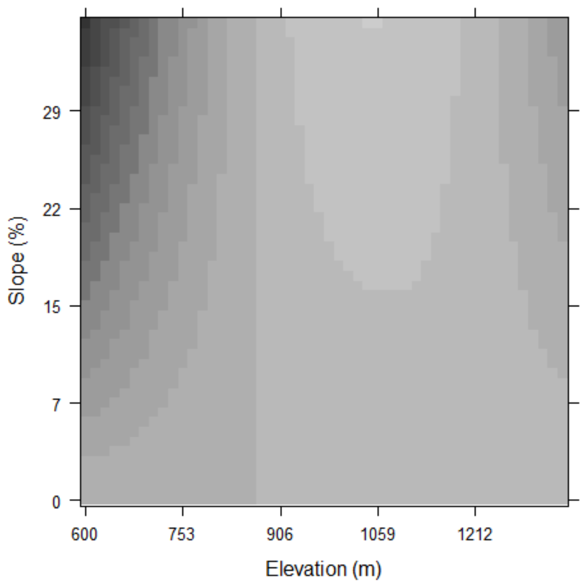
(a) GAM of annual height growth vs. TPA.

(b) GAM of annual height growth vs SEA.

Figure 20: Generalized additive models of annualized height growth vs. TPA and SEA.

Site metrics of slope, aspect and elevation failed to provide an improvement over the null model. However, when considered together in the slope, aspect and elevation (SEA) interaction model (Stage and Salas 2007, see Equation (2)), these terms provided the lowest AIC by a wide margin. The AIC of the site index metric was also quite low but failed to surpass that of the SEA term. The values for the SEA interaction were obtained though fitting only the SEA related coefficients of the τ=.5 model to all small tree records. The GAM for this term shows that an increase in the slope, aspect and elevation term is related to general increase in predicted height increment for most SEA values (and most plots). However, the smooth function shows that for the outer values of SEA, this trend is not linear.

Figure 21 illustrates the relative effects of the slope and elevation on estimated height growth for two different aspects. For the south-east aspect, a negative effect of increasing slope is apparent at the lowest elevations. Small trees growth on steep south-facing slopes is reduced at low elevations. The opposite is observed on north-west facing slopes where small trees are estimated to grow the most on steeper slopes at low elevations. Both aspects show that there is a moderate reduction in height growth at high elevations and steep slopes.



(a) South-east aspect (135°)

slope_elevation_NW.png

(b) North-west aspect (315°)

Figure 21: Standardized τ=.5 predicted growth increment by slope (%) and elevation (m). Lighter shades indicate a greater predicted height growth increment. Initial height= 1ft, crown ratio=.5, overstory TPA=40.

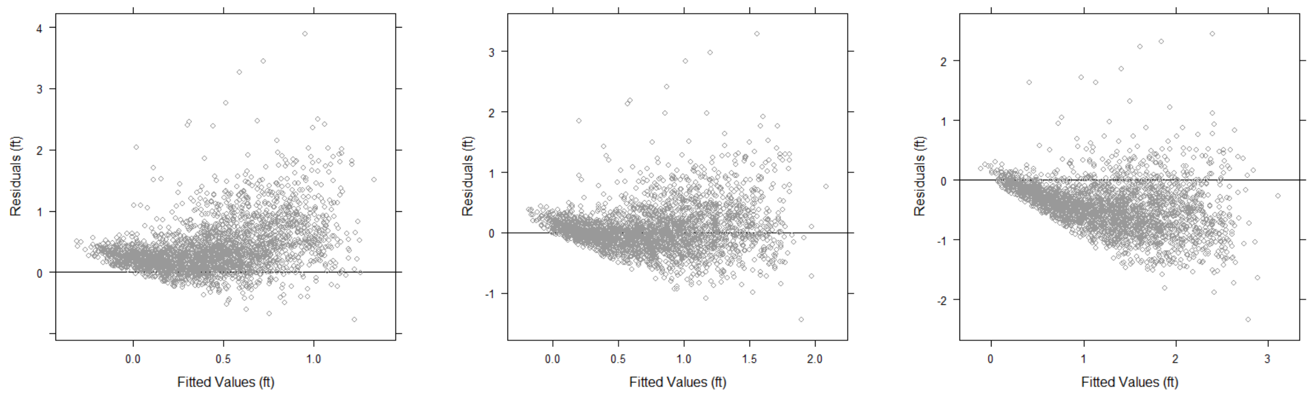
The resultant model is specified as follows:

$$h_\tau = b_{0,\tau}\sqrt{i} + b_{cr,\tau}cr + b_{TPA,\tau}TPA + b_{S,\tau}S \qquad , \tag{4}$$

where h is the predicted growth response, i is the initial height in feet, cr is the crown ratio, TPA is the overstory trees per acre and S is the slope, aspect and elevation term

3.4 Fitted Quantile Models

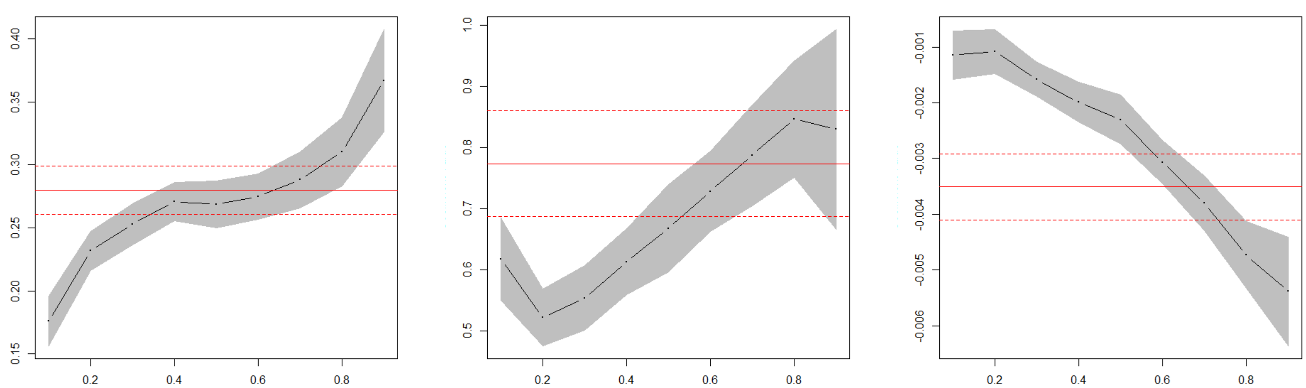
The middle residual plot above (Figure 22b) shows that the variance of the residuals is split roughy proportionally above and below zero. This result is expected as the median (τ=.5) quantile



(a) τ=.1 residuals. (b) τ=.5 residuals. (c) τ=.9 residuals.

Figure 22: Residual plots of predicted height growth increment (ft) from τ=1,5 and 9 regression surfaces.

regression is specified to describe the linear trends in the central portion of the response distribution. The model seems to do this well as the residuals appear to be evenly distributed above and below zero. Figure (22a) reveals that most residuals are greater than zero for the τ=.1 quantile that describes the lower portion of the response distribution. However, for all positive values of predicted height, there are a number of number of negative residuals. In the τ=.9 quantile, most residuals are found to be negative but there is a modest number of positive residuals across all predicted height increments. Collectively, these residual plots show that the three fitted quantile regression models describe a broad range of the annual height growth response distribution.



(a) Coefficient plot of initial height. (b) Coefficient plot of crown ratio. (c) Coefficient plot of TPA.

Figure 23: Quantile regression coefficient estimates and 95% confidence intervals accross τ=1-9.

The coefficient plot (Figure 23a) shows that the effect of initial height increases as the specified quantile increases. For the middle range of quantile values (τ=.3-.7), the effect remains within the bounds of the 95% confidence interval (CI) of the least squares regression estimate (red dotted lines). However, for the two lowest τ values, the estimate is below the 95% CI while it is above the CI for the two highest quantiles. This means that the effect of initial height is estimated to be greater for the trees in the upper portion of the response distribution (i.e. the fastest growing trees). This is in opposition to the least squares estimate which would maintain a moderate, constant effect of initial height for all trees.

Similarly, the effect of crown ratio increases as the τ value increases. The estimated effect for the lower half of the response distribution fall below that of the 95% CI for the mean regression. Given that all other predictors are held constant, the slowest growing trees exhibit an effect of crown ratio that is far less than that of the mean regression. The mean regression estimate of crown ratio does appear to describe the effect of crown ratio well for the faster growing trees as the estimates for the τ=7-9 surfaces fall within the 95% CI.

As we saw earlier, overstory trees per acre (TPA) in the range of (0-40 TPA) was negatively correlated to annual height growth (Figure 20a). Here we see that estimates for the effect of overstory TPA are negative for all values of τ and steadily decrease as τ increases (Figure 23c). The negative effect of TPA is least pronounced for the trees in the lower portion of the response distribution. In contrast, the fastest growing trees (in the upper portion of the response distribution), exhibit the most negative effects of overstory competition. This result is especially practical since the level of overstory tree retention is one of the primary means of manipulating stand structure.

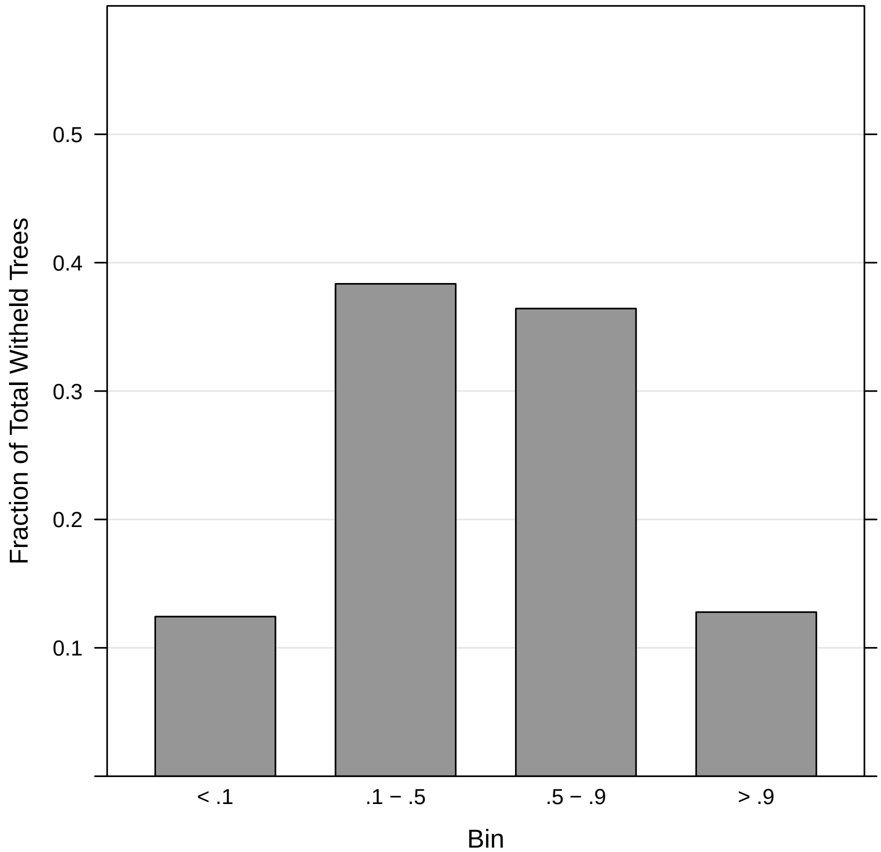


Figure 24: Witheld tree height growth increments sorted by predicted height growth increment quantiles.

3.5 Model Validation Results

Predicted annual height growth increments for τ= .1, .5 and .9 were generated for the witheld data (1 randomly selected small tree plot at each plot). The actual height growth increment was then binned according to where it fell among the quantile regression predicted height growth increments (<.10, .1-.5, .5-.9 or >.9). Visually, the actual height growth increment are distributed approximately as expected with .4 falling between the .1-.5 and, 5-.9 τ predictions and .1 falling below the .1 τ and above the .9 τ predicted height (Figure 24).

In order to provide higher resolution to the validation, we classified the trees within the validation dataset by initial height (1-5, 5-10, 10+ ft). For the less than 5 ft initial height class, the distribution of annual height growth increments match our expected distribution within the central portion of the response distribution (Figure 25a). However, very few height growth increments were below their τ=.1

lessthan5.png

(a) Initial Height less than 5 ft.

between5and10.png

(b) Initial Height between 5 and 10 ft.

greaterthan10.png

(c) Initial Height > 10 ft.

Figure 25: Witheld tree height growth increments sorted by predicted height growth increment quantiles intervals and initial height classes.

predicted height increments. In contrast, far more responses exceeded the τ=9 predicted value than expected. For the shorter trees in the data set (< 5 ft), many more than expected exhibited growth surpassing their τ=.9 prediction and none exhibited growth below their $\tau = .1$ prediction.

Trees in the intermediate height class (5-10 ft initial ht) appear to disproportionately frequently exhibit height growth within the τ=<.1 predicted height growth interval (Figure 25b). An approximately equally number of trees appear to be absent from the τ=.5.-.9 quantile interval. A similar pattern is observed between the extremes of the predicted height growth intervals; more trees grew below their .10 prediction and fewer grew above their .90 prediction. In the 5-10 ft height class, trees generally grew less than their median prediction of height growth.

The trees within the tallest initial height class (10+ ft) appear to have a distribution of height growth increments within inter-quantile bins that conforms very nearly to the expected distribution. Slightly more trees appear in the extremes of the height growth quantile intervals than in the center of the distribution.

The results from the chi-squared analysis below (Table 3) provide a statistical comparison between the actual and expected distribution of height growth increments across the inter-quantile intervals. The p-value for the overall chi-squared test (all height classes) was .039 which provides sufficient evidence to reject the null hypothesis (that the distributions are equal) at the α=.05 significance level. The p-values were also below α=.05 for the chi-squared tests by initial height classification. In the less than

Table 3: Chi-squared analysis expected counts, actual counts and p-values by initial height class.

Initial.Height.Class	Interquantile Interval	Expected	Observed	P-value
<5 ft	<.10	16.6	7	0.003
	0.10-.50	66.4	62	
	0.50-.90	66.4	69	
	>.90	16.6	28	
5-10 ft	<.10	20.1	39	0.000
	0.10-.50	80.4	81	
	0.50-.90	80.4	63	
	>.90	20.1	18	
>10 ft	<.10	19.5	21	0.442
	0.10-.50	78.0	74	
	0.50-.90	78.0	74	
	>.90	19.5	26	
All Height Classes	<.10	56.2	67	0.039
	0.10-.50	224.8	217	
	0.50-.90	224.8	206	
	>.90	56.2	72	

five feet initial height class, the p-value was .003. The chi-squared test for the intermediate initial height class (5-10 ft) produced a p-value of <.001 which fails to reject the null hypothesis. The tallest height class (10+ feet) had a p-value= .442 which rejects the null hypothesis at the α=.05 significance level but is the closest to having an actual distribution accross interquantile intervals that matches the expected distribution.

Whether viewed by height class or combined, the actual height growth increments visually conform to our expectations provided by the quantile regression predictions but fail to provide a distribution that is statistically equal to our expectations.

4 Discussion

4.1 Design

The study encompassed a wide range of overstory retention and site index values, however; there was a concentration of sites that were characterized as high site index and low overstory retention. This effect means that most of the tree records used to build the model are from these sites and that their growth is reflective of these conditions. This may result in a model that is most relevant to predicting small tree growth on similar sites.

It may be the case that these high site index/low overstory conditions are common following variable retention harvest in the Inland Northwest; it may be a more economical practice to leave fewer trees on high site quality sites. If this is the case, it would be an advantage to have an abundance of data from the regions of the site index and overstory basal area matrix that are more frequently observed in practice. Otherwise, the model could improve by incorporating a wider range of site conditions.

The herbicide applications were relatively inconsistent in both frequency and interval. These applications were accomplished on an "as-needed" basis without a consistent gauge of herbicide effectiveness used to reassess application. The comparison of vegetation depth by site revealed that differences in vegetation depth within the STPs was not pronounced although the control (no herbicide) plots generally had the highest depths followed by the one time herbicide application plots. The differences should have been especially obvious at this point of the study since these depths are from the beginning of each installation's measurement period and after at least one application of herbicide. Although the study certainly created some differences in vegetation levels at most installations, the effects of the herbicide applications did not create the wide range that was intended.

The sites used to develop the understory model generally exhibited the expected effects of the herbicide, although there are several where the herbicide application plots exceeded that of the control plots. Since it has been shown that understory vegetation increases with increases in site productivity, it was crucial that the herbicide create a range of conditions on these sites. If the herbicide applications truly failed to create a wide range of vegetative conditions, we would expect that the effect of site productivity on height growth increment was underestimated since it may have represented an increase in vegetative competition that detracted from the height growth of small trees.

The herbicide applications themselves may have been have been detrimental to small tree health especially for certain species. Douglas fir and western larch were reported to have exhibited herbicide-induced mortality although ponderosa pine appears resilient to the effects of herbicide. On the site with mixed Douglas-fir and ponderosa pine understory, it is possible that the ponderosa pine in the herbicide treated plots gained an additional height growth advantage through the herbicide-induced mortality of other competing understory tree species.

A side-effect of the sampling design was that the herbicide was most effective towards the center of the plot. In the later years of the study, vegetation was observed to colonize within the bounds of the plots and may have presented some competition within even the multiple application plots. The location of the STPs near the edge of the plots may mean that the tagged small trees experienced higher levels of vegetative competition than experienced towards the center of the plot. This has a direct implication on the utility of the transect vegetation measurements to describe the growing conditions within the small tree plot. However, the $1m^2$ plots would still be able to describe the colonizing vegetation within the small tree plots.

The repeated measures study design may introduce some underestimation of the standard errors of the parameter estimates, since the calculation of standard error assumes that each observation is unique. This could be especially important if model building criteria was based on standard error of the candidate variables, rather than AIC. Table 1 shows the majority of the tree records used for the study came from trees that were measured two or three times which means that most of the tree records used in this study were not independent observations.

To address this issue in the future, Linear Quantile Mixed Models (LQMMs, Geraci and Bottai 2014) could be pursued as a way to account for lack of independent observations and extend quantile regression framework to the analysis of longitudinal data. This method estimates the conditional quantile functions with subject-specific location-shift random effects (Geraci and Bottai 2007). The likelihood is based on the asymmetric Laplace density (ALD), which provides an optimum level of penalization.

4.2 Subject Tree Growth

The tagged trees in the study ranged from 1-30 ft in initial height. Trees in the upper range of height are no longer "small" and have typically entered into the canopy and are competing against the overstory trees. Although they may seem inappropriate for a small tree growth model, it is valuable to have these trees contribute to the model because they represent the greatest capactity for height growth as well as the greatest variability in height growth. It is also important to include the trees that are just barely over the lower limit for selection (1 ft). These smallest of the small trees were very commonly observed in the study and exhibited height growth increments that vary widely relative to size. Desire to describe the range of growth of these very short trees was one motivation for quantile regression.

The relationship between initial height and annual height was not surprising; taller trees generally had greater annual height growth. What was surprising was how great the variance in height growth is. Trees as short as 15 feet exhibited variance in annual height growth rates of approximately 4 ft. It is commonly said that "the rich get richer" in regard to small tree growth and competition, however, considering this high degree of variance, some of "the rich" are not. Incorporating this increasing variability into the model is important and a quantile regression technique that describes the full distribution of this relationship is one way to do so.

Initial height and annual height related to crown ratio in similar ways. Crown ratio provided a biological upper limit to both initial height and annual height growth. The small trees that exhibited growth greater than 1 ft annually had crown ratios greater than 50%. This emphasizes the importance of the crown ratio to annual height growth. Small trees without sufficient crown are simply unable to produce enough photosynthate to accrue a substantial annual height growth. Small trees that were greater than 10 ft at initial measurement had crown ratios greater than 50%.

Having a full crown does not necessarily mean that a given tree will be gain more than a foot of height growth a year or be at least 10 ft in height; rather, trees that are greater than 10 ft tall or gain more than a foot of height annually will more likely possess a high crown ratio (>50%). Once again, quantile regression provides a technique to describe growth along this upper limit imposed by crown ratio (by specifying τ=.9). The central and lower regions of this distribution are also described by the quantile regression (τ=.5 and .1, respectively).

4.3 Model Form

There were several counterintuitive results from the variable selection process. The most striking of these was that no candidate variable was selected from the understory vegetation category. None of the candidate variables provided an improvement over the null model (with only initial height and crown ratio). There are two explanations that may provide an answer to why this occurred. First, the previously selected variable, crown ratio may not only represent competition from other small trees but may also be reflecting competition from non-tree vegetation. As vegetation competition increases, it likely contributes to a reduction in crown ratio and possibly even in initial height. Introducing other measures of vegetation once crown ratio is accounted for is possibly redundant.

Another explanation for lack of predictor of annual height growth from non-tree vegetation may be that the vegetation sampling design simply failed to characterize the relevant levels of vegetation to the subject trees. The transect method is especially suspect since most of the transect (20 out of 30 or 40 feet) lies outside the STPs and towards the center of the plot. The levels of vegetative competition faced by the small trees may have dramatically differed from that of the interior of the plot in cases where herbicide was applied and vegetation colonized the outer boundary.

The alternative measure of vegetation, the 1m^2 plots may have also failed to adequately capture the vegetative competition despite being within the STPs. This issue was recognized a few years into the study, leading to the introduction of the 4m^2 vegetation plots. Only the smaller size plots were maintained throughout all measurement intervals in the model, so it was used instead of the larger ones. The 1m^2 plots cover such a small proportion of the STPs (3.4%) that they may be unable to adequately characterize the vegetation. Although the location of the 1m^2 in the center of the STP means that it is spatially tied to the STP, this may also be a source of bias. The tagged tree mapping is referenced to STP center and unless carefully delineated, these plots may have become an area of high impact from researchers. However, protocol stipulated that the vegetation measurements occur before STP measurements.

The other unanticipated result of the variable selection process was that the overstory trees per acre variable (TPA) provided a superior model fit than all other overstory candidate variables. Crown area per acre (CAPA) had the second lowest AIC, but basal area per acre (BAPA) and stand density index (SDI) were expected to best describe the overstory retention since they provide information about the density of the retained overstory trees. However, there is a disadvantage to BAPA metric; the basal area contributed by many trees of a small diameter is considered to be equivalent to the basal area of few large diameter trees. The TPA metric may be better at capturing the competitive effects of these smaller overstory trees since it can differentiate between many and few overstory trees.

The signs of the effects of the selected variables fell in line with expectations. Increases in initial height and crown ratio contribute to increases in predicted height increment. Overstory TPA is associated with a decrease in the height growth rate that is intuitive considering the response of understory trees to the enhancement in light level provided by the canopy openings. Although it is difficult to interpret the interaction terms, increases in slope and elevation detracted from predicted tree height.

In terms of magnitude, the crown ratio and initial height effect provided the greatest marginal contribution to predicted annual height growth. High levels of TPA can have a large negative effect on the height growth. The SEA term effect is much more difficult to interpret because of the interaction terms. However, on north-west facing slopes, the greatest predicted height growth is estimated for low elevation/high slope plots. This may relate to the increases in soil moisture since these plots are sheltered from intense solar radiation. On the south-east aspects, the greatest reductions in growth are estimated for low elevation/high slope plots. These plots likely receive intense solar radiation during the growing season that limits available soil moisture. Both aspects show reductions in growth associated with high elevations and steep slopes. This most likely is due to greater snowpack and shorter growing season at these higher elevations.

When the effects were mapped across τ values, the effects produced some unexpected patterns (Figure 23). The effect of initial height is positive and increases across quantiles, meaning that the effect is estimated to become larger in the upper quantiles. Crown ratio effect is also positive and increases across quantiles. TPA has a negative effect on annual height growth and becomes more negative in the upper quantiles. It was unanticipated that the effect of TPA would change so much across quantiles, as all trees within a plot are subjected to the same level of overstory retention. Apparently, the negative effect of TPA is much more pronounced for trees in the upper quantiles (the fastest growing trees, all other variables held constant). This could be an important consideration in management as overstory retention is one of the primary ways to influence the understory development.

One unanticipated result of using quantile regression to examine all part of the response distribution was that 49 validation trees were predicted to have slightly negative τ=.1 growth rates. These few trees were very short (μ= 2 ft), exhibited poor crowns (μ= 19%) and were found on sites with very dense small tree competition (KC, TP, LF).

These negative estimates of growth likely occurred as a consequence of fitting quantile surfaces to predictors that had large effects on the predicted height growth. These surfaces had to be "angled" in such a way that they described the growth of the specified τ across all values. For the .10 quantile prediction, this meant that the surface dropped below zero for some combination of predictors. This explains why so few trees in the 1-4 ft height class exhibited height below their .10 quantile prediction-they would have had to decrease in height over the measurement interval.

By selection, none of the trees used to develop the model had a height growth increment less than zero. Despite this, the effects are so pronounced in higher values that the hyperplane drops below zero for others. The model was not very far off from the actual annual growth of these trees (avg. ht = .26 ft) and perhaps if a "floor" for predictions were incorporated (i.e. .2 ft) the validation of the model would improve.

Visually the results of the other initial height categories matched the expected distribution. The 10+ ft height class and the "all trees" validation appeared particularly ideal and it was surprising that the distributions were statistically different than the expected distribution. Although the model failed to fully statistically demonstrate that it is capable of producing distributions of height growth increment that were observed in the validation data, the model still produces a range of height increments that describes the height growth distribution for the intermediate height class. A lower limit for predicted height would likely improve the outcome of validation.

4.4 Comparison of results to related studies

Although there have been no other studies that predict height growth of small ponderosa pine trees with quantile regression, we can qualitatively compare our results to that of other empirical models. We can also compare the effects of our selected predictors to studies that examine specific competitive effects on small ponderosa pine growth.

A study of ponderosa pine regeneration on the Nez Perce and Spokane Tribal lands found that height growth increased with increasing initial tree size and larger crown ratios (Ferguson et al. 2011).

However, this study focused on growth response of the regeneration following pre-commercial thinning. The authors also found that trees with small crown ratios; slower 5-yr pre-thinning height growth and higher height to diameter ratios had a higher probability of mortality. These characteristics of low crown ratio and little height growth were also found in trees that had were predicted to have very low (or even negative) τ=.1 height growth increments. Our model does not account for mortality, but it is likely that many of the trees with very low τ=.1 predicted height growth increments are succumbing to competition induced mortality.

Salas and Stage used STCV data to develop the small tree component of their individual-tree height growth model for Inland Northwest douglas-fir height growth ("Modeling Effects of Overstory Density and Competing Vegetation on Tree Height Growth"). The authors also used "attained height" (initial height) as a predictor variable that avoids the problems associated with tree age. They represented overstory and understory competition with basal area in larger trees and ocularly estimated understory cover, respectively.

It was surprising that no predictors relating to crown or small tree competition were included in their model and that vegetation cover was. These differences in model form may relate to species differences between ponderosa pine and Douglas fir since ponderosa pine is considered to be a more shade intolerant species and thus crown ratio may better relate to height growth. As ponderosa pine grows in drier conditions that are less conducive to dense vegetation, the overwhelming vegetation competition sometimes observed on doug-fir sites may be more important to early height growth.

Similar to the model presented in this thesis, site productivity is represented by factors other than site index (slope, elevation, aspect and ecological habitat type). As an endnote to their paper, the authors stated that they tested the inclusion of the number of small trees but found no improvement and speculate that even though the correlation between site productivity and greater understory was reduced, it was still a problem for small conifers because they were not thinned.

The following section will compare the proposed model to that of the current standard in forest growth modeling; the Forest Vegetation Simulator (FVS, (Dixon 2013). FVS is a distance independent growth model used to project stand level characteristics and has regional variants that cover most of the United States. The Inland Empire Variant covers most of the study sites used in this analysis (eastern Washington, north-central Idaho and Western Montana) and was originally the Prognosis model developed under the direction of Stage (Stage 1973).

4.5 Qualitative Comparison to the Inland Empire Variant FVS Small-Tree Height Increment Model

The small-tree routine in the Inland Empire Variant of FVS provides a 5-year estimate of individual height growth first and then estimates diameter growth from height growth (Keyser 2008). The FVS small tree growth routine for the Inland Empire Variant utilizes the following equation to predict the height growth of small trees (less than 3 in DBH):

$$
\begin{aligned}
HTG &= exp(X) \\
X &= [LOC + HAB + SPP +_{C_1} lnHT +_{C_2} *CCF + \\
&\quad _{C_3} * BAL/100 + .22157 * SL * cos(ASP) - 0.12432 * SL \\
&\quad * sin(ASP - .10987 * SL)] \qquad ,
\end{aligned}
$$

where $HTG =$ the estimated height growth for the cycle,

$LOC =$ is a location-specific coefficient,

$HAB =$ habitat type dependent intercept,

$SPP =$ species dependent intercept,

$CCF =$ crown competition factor,

$BAL =$ total basal area in trees larger than the subject tree,

$ASP =$ stand aspect,

$SL =$ the stand slope,

$HT =$ initial tree height,

$_{C_1} - _{C_3} =$ species specific coefficients.

(5)

Height growth estimates from the small-tree model are weighted with the height growth estimates from the large tree model over a range of diameters in order to smooth the transition between the two models.

The FVS small growth equation is quite similar to the model proposed in this thesis. The height growth in the FVS small tree growth equation is estimated from initial height, site quality (in terms of location, habitat type, slope and aspect), CCF and BAL. Although the FVS equation utilizes crown competition factor instead of crown ratio, both terms relate to the crown competition. However, CCF relates strictly to competition from arboreal competition whereas crown ratio may be a reflection of all competition including non-tree vegetation. Similarly, the FVS model uses basal area of trees larger than the subject tree to quantify competition from the larger trees whereas our model uses trees per acre.

The FVS height growth estimate represents the mean growth of a sample of small trees that have similar characteristics and growing conditions to the modeled subject tree. Alternatively, the proposed model considers the entire range of height growth increments a given tree may be capable of. As we saw earlier, modeling the mean height growth is not appropriate because the effects of the predictors changes across quantiles of the response distribution.

However, FVS does accommodate multiple trajectories of the same tree record to provide some degree of variation from the mean estimate. When there are many small trees, a small random error is then added to the height growth estimate. When relatively few samples represent the stand, two additional tree records are created that triplicate the characteristics of the tree except the predicted height growth and the number of trees per acre represented by the source tree. The two new records are given 15 and 25 percent of the original value. Each of the records correspond to a portion of the error distribution of deviations about the predicted height.

It is within this "tripling" framework that our quantile regression model may find its greatest utility. Instead of drawing random increments from within the normal distribution, the three tree records could be assigned predicted quantile values for $\tau=$ .25, .50 and .75. These quantile derivations of height provide a more empirically based distribution of possible height values for a given set of predictors.

The individual tree height growth increment model proposed in this thesis provides an estimate of what the entire range of possible 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 primary utility of the model is in providing managers an idea of the growth rate of the fastest growing trees and how post-harvest stand conditions such as retained overstory can be expected to effect these specific trees.

4.6 Potential Applications

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 prediction of when stands will reach green-up.

Another example of a possible application is an improved idea of which ponderosa pine stands may benefit from an understory thinning or herbicide application. Within similar site conditions and initial tree heights, the stand with lower predicted height growth increments is presumably experiencing more competition from understory vegetation or other small trees. However, one disadvantage of failing to disintangle the sources of understory competition that it becomes difficult to know which understory component to manipulate as a forest manager. This is where adequate knowledge of the stand understory is neccesary to guide management.

Accurate modeling of the development of recruited and juvenile trees following removal of overstory is crucial for simulation models to achieve a consistent simulation output (Golser and Hasenauer 1997). When combined with a large-tree growth model such as in FVS, the proposed model could contribute to an improvement in modeling long-term stand development and enable managers to make better informed decisions regarding overstory retention and understory vegetation following variable retention harvest.

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A. 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):

$$\Delta \text{ height annual} = \sqrt{\text{initial height}} + \text{ candidate small tree variable} \tag{6}$$

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

$$Q_{.50}\Delta \text{ height annual} = \sqrt{\text{initial height}} + \text{ candidate small tree variable} \tag{7}$$

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 b_τ for each specified quantile.

Final Models:

$$\Delta_\tau = \mathrm{b}_{0,\tau}\sqrt{\mathrm{h}} + \mathrm{b}_{UT,\tau}\mathrm{UT} + \mathrm{b}_{UV,\tau}\mathrm{UV} + \mathrm{b}_{OT,\tau}\mathrm{OT} + \mathrm{b}_{SP,\tau}\mathrm{SP} \tag{8}$$

B. Tagged Tree Damage Codes

	Code	Explanations
1	AD	Animal Damage
2	BR	Blister rust
3	BT	Broken top
4	CK	Check
5	CO	Commandra Rust
6	CR	Crook
7	Dead	NULL
8	DT	Dead Top
9	FK	Fork
10	FT	Forked top
11	FUT	Multiple damages, too many to list
12	Gall	NULL
13	ID	Insect damage
14	Lean	NULL
15	MIA	Unable to locate tree, no evidence of death
16	Mistle	Mistletoe
17	MT	Mistletoe
18	PD	Pronone (herbicide) damage
19	RT	Reestablished Top
20	Small Broom	NULL
21	SW	Sweep

C. Predictor Variable Definitions and Symbols

Predictor	Unit	Resolution	Symbol
Small Tree			
Initial height	ft	tree x interval	h
Crown length	ft	tree x interval	cl
Crown width	ft	tree x interval	cw
Crown ratio	%	tree x interval	cr
Basal diameter	in	tree x interval	BD
DBH	in	tree x interval	DBH
Trees per acre overall	trees/ac	tree x interval	SmallTPA
Trees per acre >15 ft in ht	trees/ac	STP x interval	Trees15+
Trees per acre above subject tree	trees/ac	tree x interval	TGT
Non-tree Vegetation			
Forb depth in $1m^2$ q	ft	STP x interval	F.depth
Low shrub depth in $1m^2$ q	ft	STP x interval	LS.depth
High shrub depth in $1m^2$ q	ft	STP x interval	HS.depth
Forb volume in 1m2 q	m^2*ft	STP x interval	F.vol
Low shrub volume in $1m^2$ q	m2*ft	STP x interval	LS.vol
High shrub volume in $1m^2$ q	m2*ft	STP x interval	HS.vol
% Cover forb	%	STP x interval	F.cov
% Cover low shrub	%	STP x interval	LS.cov
% Cover high shrub	%	STP x interval	HS.cov
% Cover combined veg	%	STP x interval	POLV.cov
Transect grass depth	ft	transect x interval	G.tran.depth
Transect forb depth	ft	transect x interval	F.tran.depth
Transect low shrub depth	ft	transect x interval	LS.tran.depth
Transect high shrub depth	ft	transect x interval	HS.tran.depth
Grass transect cover	%	transect x interval	G.tran.cov
Tallest veg - subject tree (1m2)	ft	tree x interval	max.vg.diff.1m
Tallest veg - subject tree (transect)	ft	tree x interval	max.vg.diff.tr
Overstory Tree			
Trees per acre	trees/ac	plot x interval	tpa
Basal area per acre	ft^2/ac	plot x interval	bapa
Crown area per acre	%	plot x interval	capa
Stand Density Index		plot x interval	SDI
Site Quaility			
Slope	%	plot	s
Elevation	m	plot	el
Aspect	N°	plot	asp
Site index	ft	installation	SI
Slope, aspect, elevation term	X	plot	SEA, S

D. Parameter Estimates for Final Models

Table 4: Parameter Estimates for the τ=.1 Quantile

qr.SI.1.sum	Value	Std. Error	t value	Pr(>|t|)
(Intercept)	$2.91e-01$	$2.63e-01$	1.11	$2.68e-01$
srHeight.Total	$1.69e-01$	$1.28e-02$	13.20	$0.00e+00$
cratio	$6.24e-01$	$4.80e-02$	13.00	$0.00e+00$
TPA.OS	$-1.44e-03$	$3.08e-04$	-4.68	$2.97e-06$
slopePercent	$-7.15e-01$	$2.29e-01$	-3.13	$1.77e-03$
elevation	$-1.59e-03$	$5.72e-04$	-2.78	$5.47e-03$
I(elevation^2)	$9.46e-07$	$2.98e-07$	3.17	$1.52e-03$
slopePercent:cos.rad.asp	$2.08e+00$	$3.67e-01$	5.68	$1.53e-08$
slopePercent:sin.rad.asp	$9.36e-01$	$2.53e-01$	3.69	$2.25e-04$
slopePercent:log(elevation + 1)	$1.16e-01$	$3.55e-02$	3.26	$1.14e-03$
slopePercent:I(elevation^2)	$-7.26e-08$	$1.56e-08$	-4.65	$3.46e-06$
slopePercent:cos.rad.asp:log(elevation + 1)	$-3.21e-01$	$5.69e-02$	-5.65	$1.82e-08$
slopePercent:sin.rad.asp:log(elevation + 1)	$-1.45e-01$	$3.94e-02$	-3.69	$2.29e-04$
slopePercent:cos.rad.asp:I(elevation^2)	$1.33e-07$	$2.47e-08$	5.37	$8.58e-08$
slopePercent:sin.rad.asp:I(elevation^2)	$6.41e-08$	$1.75e-08$	3.66	$2.57e-04$

Table 5: Parameter Estimates for the τ=.5 Quantile

qr.SI.5.sum	Value	Std. Error	t value	Pr(>|t|)
(Intercept)	$-7.36e-03$	$3.23e-01$	-0.0228	$9.82e-01$
srHeight.Total	$2.73e-01$	$1.14e-02$	23.9000	$0.00e+00$
cratio	$6.62e-01$	$4.34e-02$	15.2000	$0.00e+00$
TPA.OS	$-2.40e-03$	$2.61e-04$	-9.2100	$0.00e+00$
slopePercent	$-9.64e-01$	$2.24e-01$	-4.3100	$1.69e-05$
elevation	$-7.25e-04$	$6.96e-04$	-1.0400	$2.98e-01$
I(elevation^2)	$5.02e-07$	$3.54e-07$	1.4200	$1.56e-01$
slopePercent:cos.rad.asp	$3.33e+00$	$3.38e-01$	9.8400	$0.00e+00$
slopePercent:sin.rad.asp	$1.36e+00$	$2.25e-01$	6.0400	$1.73e-09$
slopePercent:log(elevation + 1)	$1.53e-01$	$3.47e-02$	4.4000	$1.10e-05$
slopePercent:I(elevation^2)	$-8.39e-08$	$1.54e-08$	-5.4500	$5.37e-08$
slopePercent:cos.rad.asp:log(elevation + 1)	$-5.14e-01$	$5.24e-02$	-9.8100	$0.00e+00$
slopePercent:sin.rad.asp:log(elevation + 1)	$-2.11e-01$	$3.48e-02$	-6.0600	$1.56e-09$
slopePercent:cos.rad.asp:I(elevation^2)	$2.15e-07$	$2.26e-08$	9.5400	$0.00e+00$
slopePercent:sin.rad.asp:I(elevation^2)	$9.30e-08$	$1.48e-08$	6.3000	$3.45e-10$

Table 6: Parameter Estimates for the τ=.9 Quantile

qr.SI.9.sum	Value	Std. Error	t value	Pr(>|t|)
(Intercept)	$-2.11e+00$	$5.07e-01$	-4.15	$3.38e-05$
srHeight.Total	$3.80e-01$	$2.37e-02$	16.00	$0.00e+00$
cratio	$8.53e-01$	$9.32e-02$	9.16	$0.00e+00$
TPA.OS	$-5.04e-03$	$5.64e-04$	-8.93	$0.00e+00$
slopePercent	$-1.08e+00$	$4.62e-01$	-2.34	$1.95e-02$
elevation	$4.32e-03$	$1.10e-03$	3.92	$8.95e-05$
I(elevation^2)	$-2.05e-06$	$5.74e-07$	-3.56	$3.76e-04$
slopePercent:cos.rad.asp	$3.66e+00$	$6.65e-01$	5.50	$4.08e-08$
slopePercent:sin.rad.asp	$1.23e+00$	$4.93e-01$	2.50	$1.23e-02$
slopePercent:log(elevation + 1)	$1.66e-01$	$7.12e-02$	2.33	$2.00e-02$
slopePercent:I(elevation^2)	$-7.03e-08$	$3.05e-08$	-2.30	$2.14e-02$
slopePercent:cos.rad.asp:log(elevation + 1)	$-5.64e-01$	$1.03e-01$	-5.48	$4.62e-08$
slopePercent:sin.rad.asp:log(elevation + 1)	$-1.92e-01$	$7.64e-02$	-2.51	$1.22e-02$
slopePercent:cos.rad.asp:I(elevation^2)	$2.31e-07$	$4.39e-08$	5.26	$1.58e-07$
slopePercent:sin.rad.asp:I(elevation^2)	$8.50e-08$	$3.32e-08$	2.56	$1.05e-02$