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

By

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B.Sc. Forest Management, University of Washington, Seattle, Washington, 2015

Thesis

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Estimating the Effects of Overstory Retention, Vegetative Competition, and Site Quality on the Height Growth of Small Ponderosa Pine Trees Using Regression Quantiles

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

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Ponderosa pine (*Pinus ponderosa* C. Lawson) forests in the Inland Northwestern region of the US are increasingly managed under multi-aged silvicultural systems that provide stand structure for wildlife habitat, timber production, enhanced aesthetic, or restoration of presettlement conditions (O'Hara 2005). Partial retention harvest, where an element of the previous stand's overstory structure is retained, is commonly used to achieve a multi-aged stand structure. However, little is known about how ponderosa pine trees in the understory respond to overstory and understory competitive factors following partial retention harvest. The height growth of small trees was hypothesized to be influenced by site quality, competition from the retained overstory, understory non-tree vegetation, and other small trees.

To assess the impacts of 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 17 years on 15 sites throughout the Inland Northwest. A novel approach was taken in describing the distribution of height growth responses through quantile regression (Koenker and Bassett 1978). This technique allows for the characterization of multiple quantiles of the height growth response for a given set of covariates.

Initial height, crown ratio, number of overstory trees per acre, slope, elevation, and aspect were found to be significant predictors of height growth across all modeled quantiles (.1, .5 and .9). The effects of initial height and crown ratio were positive and the effect of overstory trees per acre was negative. However, the effects of these predictors were found to be different among quantiles which suggests that the predictors influence the upper limits to growth in a different way than the lower limits and median growth rates. Examining the effects of the selected variables showed that the positive effects of initial height and crown ratio increase as the quantiles increased from .1 to .9. The negative effect of retained overstory trees per acre on small tree height growth became more pronounced in the upper quantiles. No effect of understory non-arboreal vegetation was incorporated into the models because there was no appreciable improvement, possibly because the effects of crown ratio and initial height were included.

We found that quantile regression models could be used to provide an empirically-based estimate of the distribution of height growth under a retained overstory. Quantile regression estimated height growth increments introduce variability in small tree height growth increment that could improve long-term projections of multi-aged stand growth.

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1 Introduction

Managing forests as multi-aged structures with more than a single canopy layer has become increasingly common, particularly in ponderosa pine (*Pinus ponderosa* C. Lawson) forests at lower elevations where ownerships often have multiple objectives. Partial retention harvesting allows for the removal of merchantable trees while retaining elements of the previous stand's overstory structure whether to meet objectives of improved aesthetic, enhanced wildlife habitat or the provision of seed or shelter for new trees (Franklin et al. 1997). Partial retention harvest is commonly used in ponderosa pine stands to facilitate a complex multi-aged stand structure, in part because such structures were historically created through a natural disturbance regime of relatively frequent but low severity surface fires (Arno, Scott, and Hartwell 1995).

Increased overstory density is associated with a greater survival potential for recruited germinates, however, growth is reduced following establishment (Keyes and Maguire 2005). Understory non-tree vegetation provides conflicting facilitating and competitive effects on ponderosa pine regeneration growth and survival (Keyes and Maguire 2005). The shading provided by the understory vegetation helps prevent desiccation within the microenvironment in the summer months. However, these relationships may transition from facilitation to competition between the seedling and sapling stages (Keyes and Maguire 2005). Partial retention harvests may provide a balance of the overstory retention and understory vegetation effects, as ponderosa pine regeneration responds positively to openings in the canopy, particularly on moisture limited sites (Harrod et al. 2009, Aubry, Halpern, and Peterson 2009).

Predictive modeling of small ponderosa pine growth dynamics following partial retention harvest treatments can be very challenging however, particularly relative to even-aged stands, as it 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 region of North America. Ponderosa pine stands have been managed by a broad array of silvicultural systems in the Northern Rocky Mountains, including group selection, seed tree, or shelterwood systems (Adams 1994). 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). 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 partial 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 site quality. Therefore, density management diagrams (Drew and Flewelling 1979) that incorporate fundamental assumptions about density dependent behavior of populations can be 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 are poor predictors of growth in uneven-aged stands. An individual ponderosa pine may remain physiologically young for many decades. Ponderosa pine 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, once 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 Ponderosa Pine Germination and Growth

Natural regeneration of ponderosa pine is dependent upon the combination of factors including adequate seed crop and favorable weather the subsequent growing season. Germination and initial seedling survival and growth is reduced by moisture stress, which can be driven by soil texture, plant competition, and seedbed conditions (Curtis and Lynch 2007). For example, a study conducted in southwestern pon-

derosa 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 partial 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 partial retention harvests, particularly addressing variability in individual sapling growth within microsites.

Following germination, the importance of competing vegetation as an impediment to early survival and development of young seedlings is well-established. In a central Idaho study, soil moisture at depths below 15 cm (6 in) dropped below the wilting point on the majority of vegetative plots but remained above that critical point for areas free of competing vegetation throughout the growing season (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) 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 droughty soil, severe shrub competition reduced diameter growth to less than half that of competition-free trees (Oliver 1984). The direct competition for light, water and nutrients is not the only way that ponderosa pine is affected by understory vegetation. Insect damage has also been found to be greater on trees competing with shrubs, accounting for some of the growth depression (Oliver 1984).

Despite the numerous examples of adversely affected growth attributed to competing vegetation, the presence of vegetation is not without some benefit to the stand. There is a long term carbon and nitrogen benefit to the upper soil horizon from maintaining understory vegetation (Busse, Cochran, and Barrett 1996). Understory vegetation also provides ecosystem services such as 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 soil nitrogen

(Daubenmire and Daubenmire 1968).

Overstory trees and other small trees can also effectively restrict growth of regenerating ponderosa pine. Stagnation in diameter, and often in height, is common in densely stocked stands, but especially on poor sites (Oliver 1984). Just as juvenile trees must face the 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 1992). The species composition of forest understory is also controlled by overstory trees which filter light, moderate understory air and soil temperature, and directly compete for soil water and nutrients (Spurr and Barnes 1998). For example, conifer reforestation efforts in the Intermountain West are often hampered by the competitive ability of *Carex* and *Calamagrostis* because these sedge and grass 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.

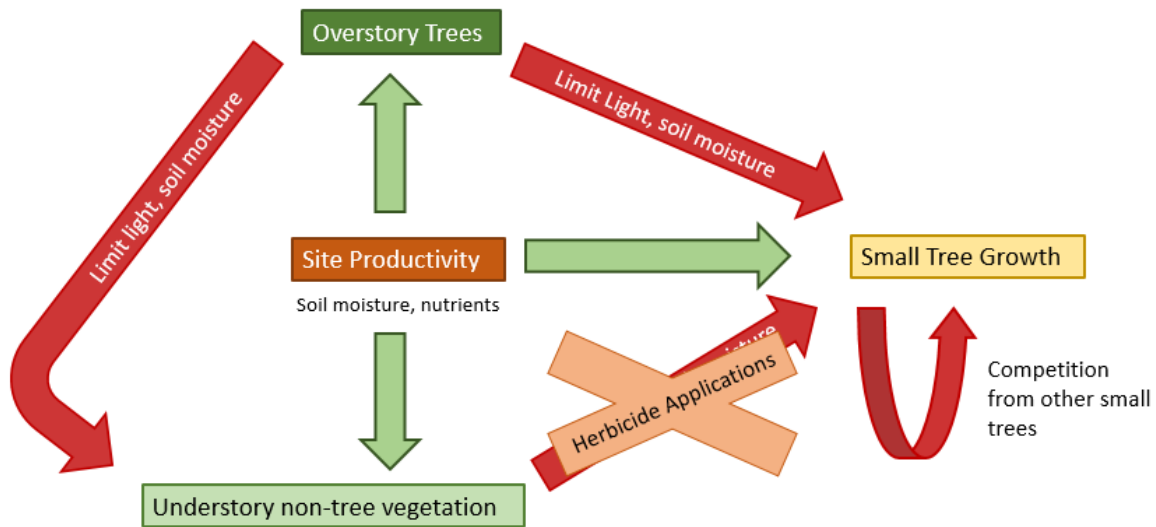


Figure 1: Biological framework of small tree growth. Red arrows indicate hypothesized growth limiting, competitive relationships and green arrows indicate hypothesized growth facilitating relationships. The study used in this research employed herbicide treatments to inhibit competitive effects of understory vegetation on small tree growth.

1.3 Modeling Small Tree Growth following Partial 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 17 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 small 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 also suggested 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 Quantile Regression

The description of the distribution 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). 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 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).

Quantile regression (Koenker and Bassett 1978) provides a statistical technique for estimating families of response curves corresponding to different quantiles of interest. Each of these quantile surfaces can be conditioned by covariates- either a common set or a set unique to each surface. This technique has only recently begun to see applications in ecology and forestry. Examples include pronghorn density by forage availability where standard mean regression fails to recognize that pronghorn (*Antilocapra*

americana) densities changed at different rates as a function of shrub cover in the higher and lower quantiles. The highest densities of pronghorn changed rapidly with shrub cover, but the lower extent of pronghorn density did not.

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 factors 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 loblolly pine (*Pinus taeda*). The authors concluded that the quantile regression predictions of diameter growth increment were adequate but that the mixed model had lower bias in terms of mean difference. 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 those 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.

In the Inland Northwest, the Forest Vegetation Simulator (Dixon 2013), is commonly used to project trees' growth. This model introduces within-tree variability in height growth increment through assigning deviations from average growth using an assumed normal distribution. However, considering the oftentimes skewed response distribution of small tree growth, estimating the mean height increment from the covariates may not be as informative as estimating the median, and a normal distribution may be inadequate for capturing the full distribution of responses.

1.5 Objectives

Looking beyond the impacts of competitive and site factors on the mean height growth of ponderosa pine, 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 Forest Vegetation Simulator methodology for projecting 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 descriptive characteristics of the study as well as results 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 installations 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 treated according to a shelterwood, seed tree or heavy thinning partial retention harvest.

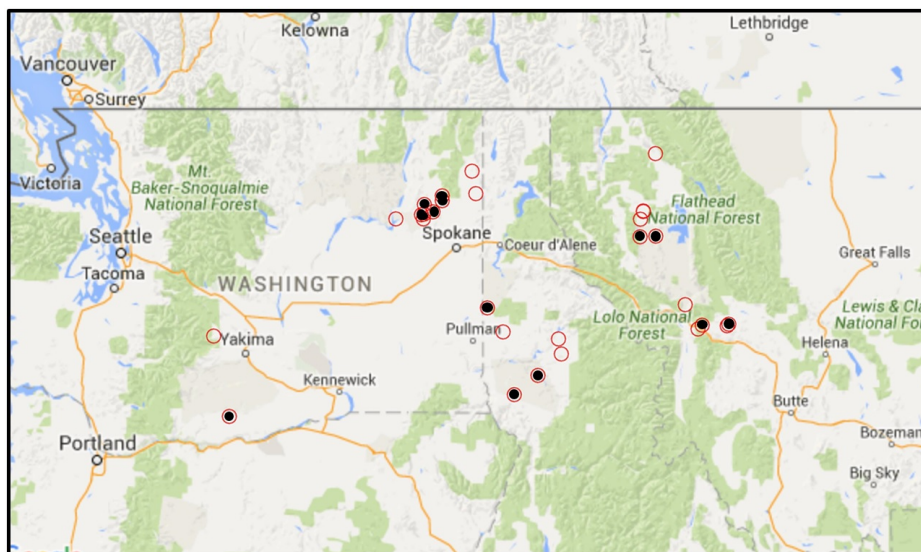


Figure 2: Map of STCV installations. Installations included in this study denoted with a black circle.

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 the control group 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 (radius

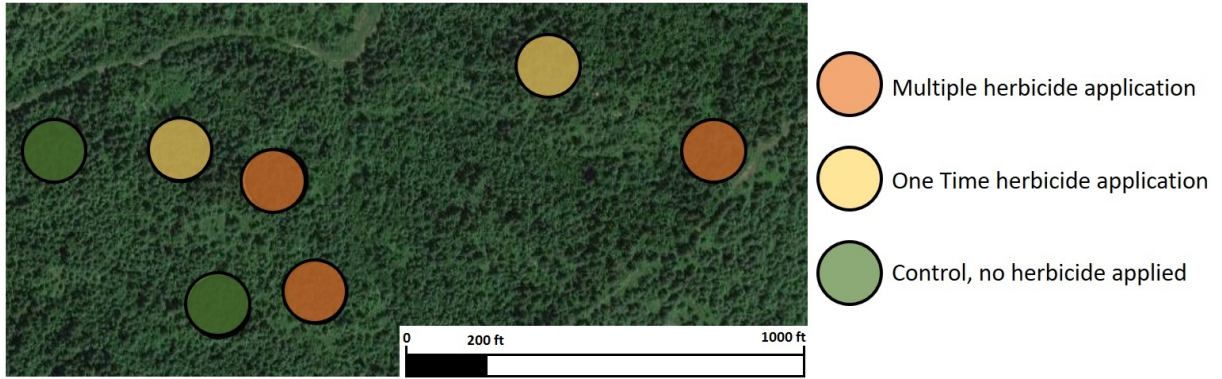


Figure 3: Griner Saddle (GS) installation in northern Idaho and associated plot treatments.

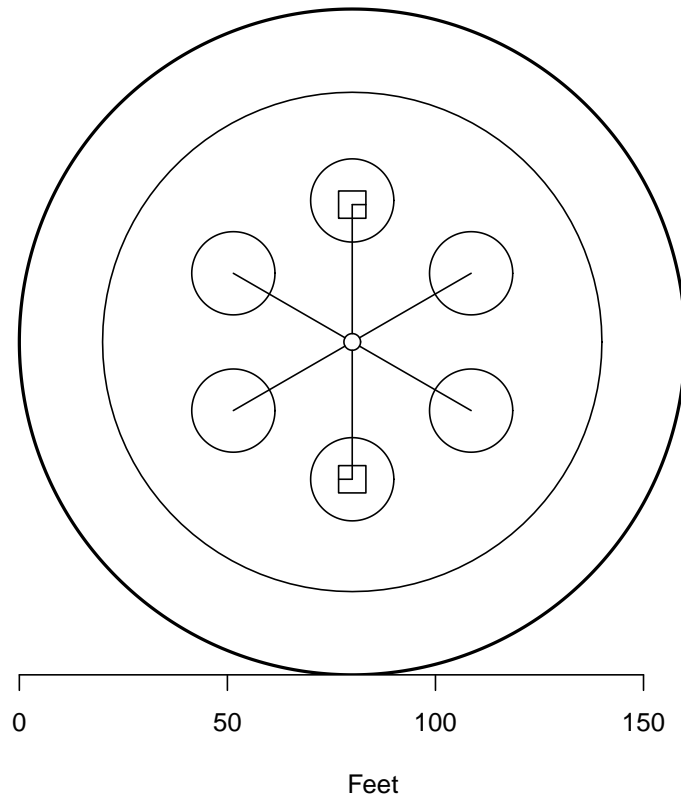


Figure 4: Design of STCV sampling plot. Note that vegetation quadrants exist for all six small tree plots although only illustrated on two.

80 ft). Overstory trees with DBH greater than 3.5 in but less than 10.5 in were measured on a smaller nested subplot of approximately a quarter acre (radius 60 ft).

The small trees, whose growth responses are the subject of this research, were defined as those that had a DBH less than 3.5 in yet a height greater than 1 ft for shade intolerant species or .5 ft for shade tolerant species at the time of initial measurements. Small trees were measured on six .007 ac small tree plots (abbrv. STP, radius 10 ft) 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 observed heights by four. Two trees per height class and species were then selected when possible. Ultimately, the number of tagged trees fell 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 two 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 m² (10.76 ft²) and 4 m² (43.06 ft²) quadrats. These vegetation measurements quantified separately the cover 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.

The objective of the herbicide treatments was to decouple the harvesting and site productivity related impacts on the understory vegetation from the latter's effects on small tree growth. It has been reported that, like tree growth, levels of understory increase with site productivity (Stage and Boyd 1987) and with decreases in overstory trees (Ffolliott and Clary 1982, Moore 1992). The herbicide treatments revealed how small trees grow under varying levels of site quality and overstory retention (looking across installations) without the presence of a corresponding increase non-arboreal vegetation (cf. Figure 1). 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

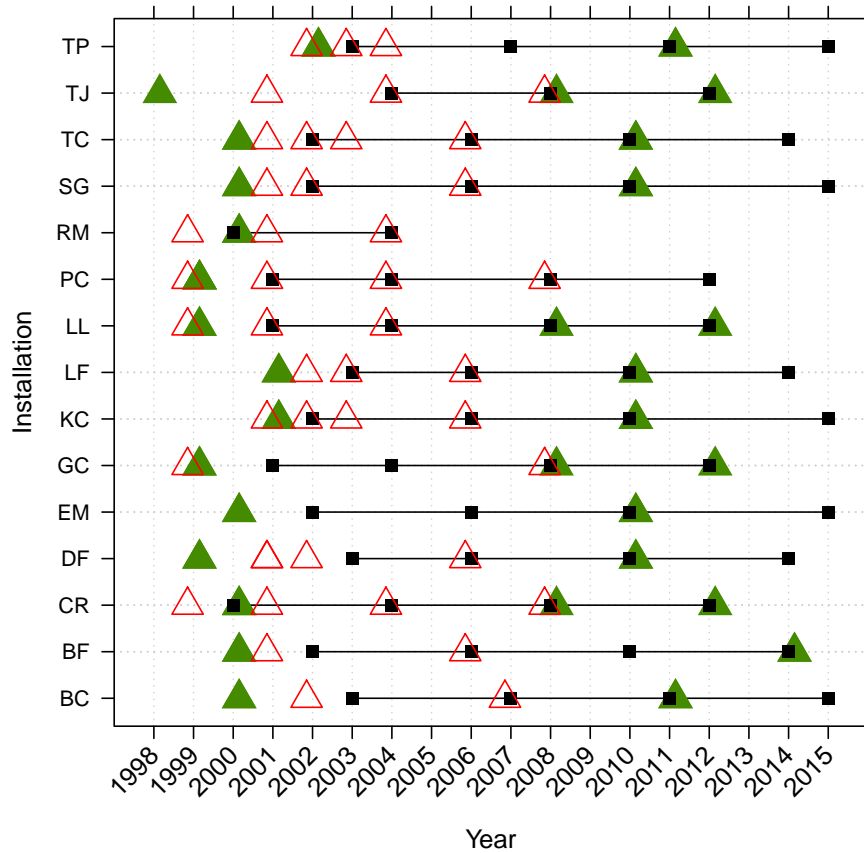


Figure 5: STCV installation treatment and measurement schedule. Green and red triangles represent years of overstory measurements and herbicide treatment, respectively. The black squares represent the years bounding the selected growth intervals.

and overstory measurements for a subset of the installations. An attempt to capture small tree growth at four year intervals was successful for many installations but in some cases the intervals were somewhat irregular (i.e., 3-5 years in length). 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 herbicide application. Thus the measurements taken in 2001 would not well represent the vegetation levels experienced by the small trees from 2001 to 2004. This necessitated careful selection of measurement interval 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.

2.2 Variable Acquisition

The variables can be divided into four categories; understory tree competition, understory vegetation competition, retained overstory competition, and site quality. The resolutions and symbols for these variables are summarized in Appendix A.

Understory Tree Competition:

The small trees in each small tree subplot (STP) were tallied by height class and then divided by .007 ac 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 live branch on a whorl contiguous with the main crown). Crown ratio was obtained by dividing the crown length by the total tree height. Crown width was found as an average of the two perpendicular measurements of crown diameter obtained in the field. 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 m² quadrats in the later years of the study, only the 1 m² quadrats were utilized in this analysis since they were used for the entire duration of the study.

Average differences (depths) 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 in the quadrat. A volume per area measurement combined the two measures of vegetation by multiplying the percentage cover by the depth of the associated cover:

$$v = \frac{cover}{100} \times (top - base) \tag{1}$$

where v is the volume of vegetation per unit area, $cover$ is the ocularly estimated percentage cover of vegetation, top is the vegetation top height in feet and $base$ is the vegetation base height in feet.

Average depths for low shrubs, high shrubs, and forbs were also calculated for the 30 or 40 transect points reaching out from plot center to each STP. The original sampling design called for a 30 foot transect that would extend from plot center to the center of each STP (15 transect points). However, in subsequent years 10 ft were added to the length of the transect to extend it through the STP (20 transect points). At each point a 6 in x 6 in quadrat was used to measure grass height and percentage cover.

Relative measures of competition were created by subtracting the tallest understory vegetation height from that of the subject tree. A negative value reflects a subject tree that is potentially overtopped by proximal vegetation. A positive value describes how much taller the subject tree is than the tallest recorded 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 (*BAPA*, ft²/ac). Crown area was obtained for each overstory tree from the average of the two perpendicular measurements of crown 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 using the following equations:

$$\begin{aligned}
 QMD &= \sqrt{(BAPA/TPA)/(\pi/4/144)} \quad , \\
 SDI &= TPA \times \left(\frac{QMD}{10} \right)^{1.605} \quad ,
 \end{aligned}
 \tag{2}$$

where *QMD* is the Quadratic Mean Diameter (in.), *BAPA* is the basal area per acre, and *TPA* is trees per acre. Stand Density Index represents the equivalent number of trees per acre in a stand with a *QMD* of 10 in (Reineke 1933).

All retained overstory variables were linearly interpolated between overstory measurement years to provide estimates for intervening small tree and understory measurements. 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, and aspect 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 into two variables expressing northerly and easterly exposure by applying the cosine and sine functions. Interacting effects of elevation, slope and aspect were considered according to the model proposed by Salas and Stage (2007):

$$S = sl[b_1 + b_2\cos(\alpha) + b_3\sin(\alpha)] + sl \ln(el + 1)[b_4 + b_5\cos + b_6\sin(\alpha)] + (el^2)sl[b_7 + b_8\cos(\alpha) + b_9\sin(\alpha)] + b_{10}el + b_{11}el^2 \quad , \quad (3)$$

where S is the relative site quality, sl is the slope in percent, el is elevation in feet, α is aspect and the b are coefficients estimated from the data.

One or more open-grown, undamaged, dominant ponderosa pine were identified at the initiation of the study. However, there was one installation (Grouse Creek) that recorded only Douglas-fir as the site tree. Site index was calculated from these trees’ heights and ages using 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 a set of specified, quantiles (τ) of the response distribution. Specifying the .90 quantile ($\tau=.90$), 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, $\tau=.50$ would describe the median height growth response conditional on the predictors.

This characterization of the response distribution 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 retained trees per acre and initial height. In this example,

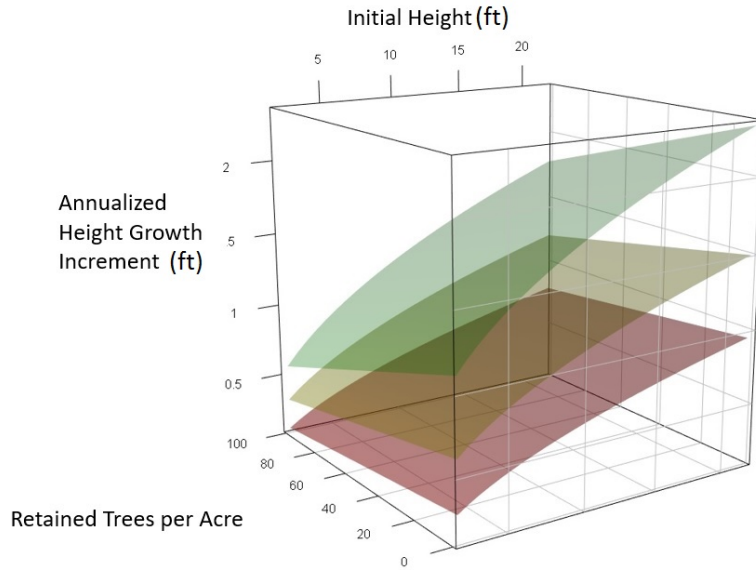


Figure 6: Hypothetical separation of the distribution of annual height increments according to 3 quantile regression surfaces as a function of trees per acre and initial tree height. The red, yellow and green surfaces represent the $\tau = .1$, $.5$ and $.9$ quantiles, respectively.

the $\tau = .10$ quantile plane shows very little change as a function of both overstory trees per acre and initial height. However, the $\tau = .90$ and $\tau = .50$ quantile planes change readily as initial height increases and as retained trees per acre decreases. Thus, the factors that affect the growth of the trees in the lower portion of height growth responses may not influence the upper portion of the response distribution or vice versa. In extreme cases, the factors may even have opposing signs between quantile planes.

Quantile regression allows for the description of the impact of both measured and unmeasured factors that may be responsible for variance in small tree height growth. Two subject trees within the same 10 ft radius plot may experience vastly different growth rates despite having the same values of measured factors. For small ponderosa pine tree growth, measured factors may relate to genetic characteristics, micro-climate, micro-site suitability or other location specific factors such as distance from a retained overstory tree. 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. Quantile regression allows for an explicit (though semi-parametric) description of patterns in this unexplained variation as illustrated by the diverging planes in Figure 6.

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 through the four categories of ecological factors presumed to drive tree growth (Figure 1).

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 the retained 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 ones and dividing by the difference between measurement years.

$$y_{i,j} = (h_{i,j+1} - h_{i,j}) / (t_{i,j+1} - t_{i,j}) \quad , \quad (4)$$

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 B 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 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 mean 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 with previously selected terms. Variable selection within categories was made with respect to their importance in describing trends in the median ($\tau=.5$) 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 C.

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 differences 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 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 ($\tau= .10, .50$ and $.90$) were estimated for each individual tree in the withheld 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 separated into initial height classes of 1-5 feet, 5-10 feet and greater than 10 feet.

χ^2 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 orientation of plots by installation. All plots range in elevation between 2000 and 4500 ft. There is a broad range of aspects and elevations as plots are well-distributed among the regions of the polar plot. Plots within the same installation have generally similar values of elevation and aspect. The Loon Lake (LL) and Cemetery Ridge (CR) installations are notable exceptions where the topography was fairly flat and thus aspect varied widely among the installations' plots.

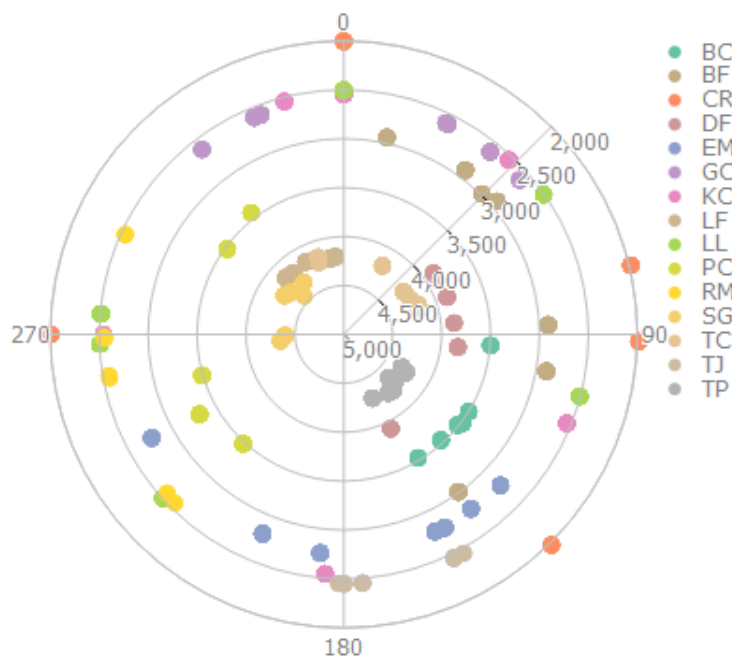


Figure 7: Aspect ($^{\circ}$) and elevation (ft) of STCV plot by installation. Only installations with >60 ponderosa pine are shown.

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 concentration of installations with similarly low overstory retention levels and high site index values. These six installations (colored red in Figure 8) were selected to develop the understory model since they were relatively homogeneous in overstory and site characteristics. In the following figures, these installations will be identified by an

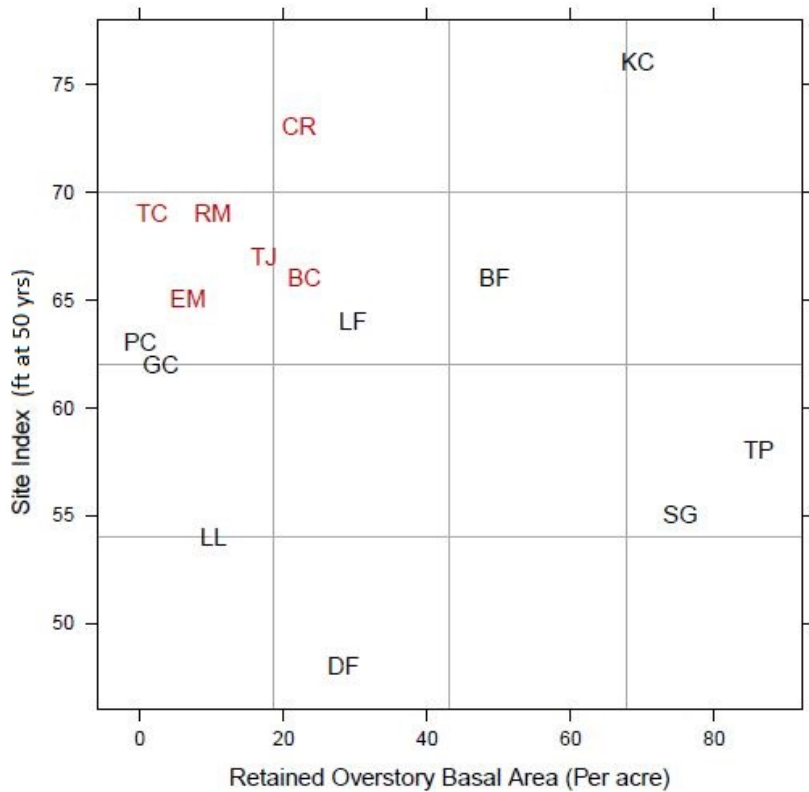


Figure 8: Site index and initial basal area per acre of the STCV installations with >60 ponderosa pine.

asterisk preceding the name of the installation (ex: *EM). There is also a noticeable gap where there are no intermediate retained overstory installations (20-60 ft²/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 across plots, though there is noticeable variation in LF (Lubrecht Forest) and EM (Empey Mountain).

The total number of small tagged ponderosa pine trees provided by each installation varied substantially (Figure 10). When multiple growth intervals and the number of tree records excluded due to mortality or damage are accounted for, 9 installations contribute over 150 tree records to the model, while installations with only a single measurement interval (RM and TJ) contribute fewer than 60 records. There were five installations that had tagged ponderosa pine tree records in excess of 200 and two that had over 300 (EM and LF).

Table 1 is related to Figure 10 in that it reveals the number of times a unique tree can contribute

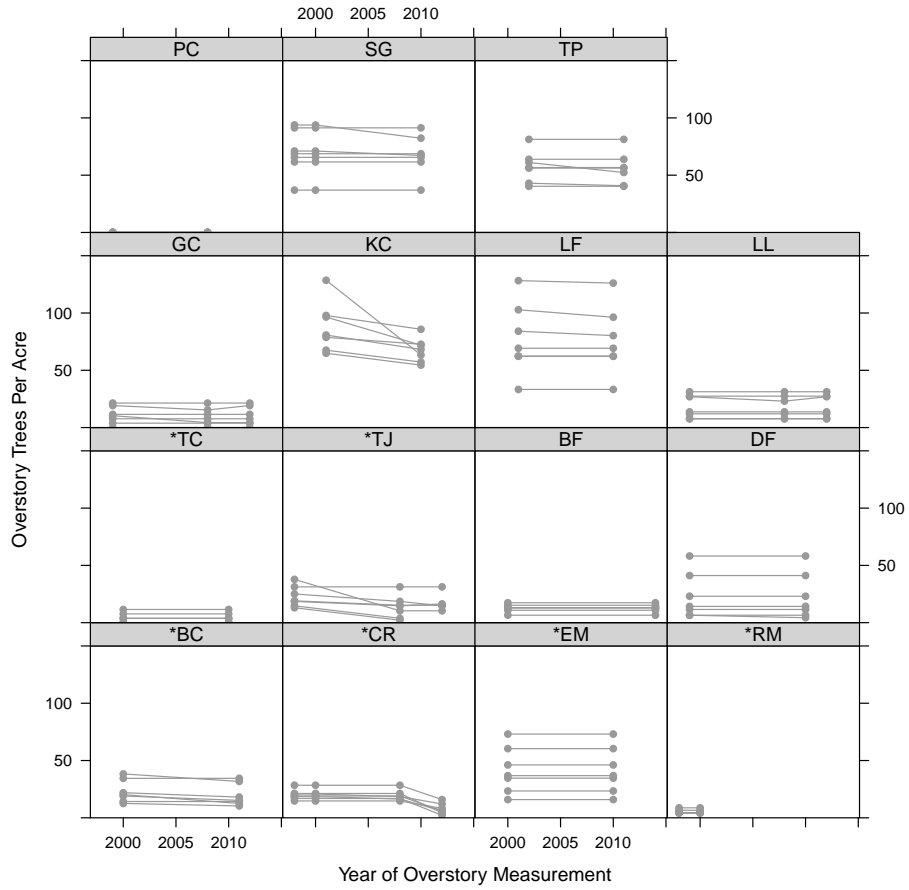


Figure 9: Overstory trees per acre by installation, plot and year.

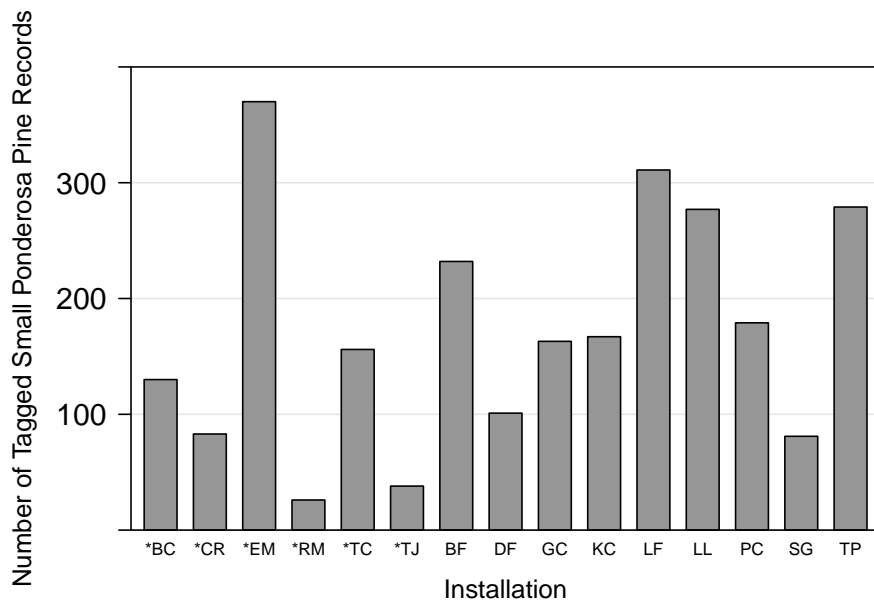


Figure 10: Total number of small tagged ponderosa pine tree records by STCV installation.

Table 1: Distribution of the number of height growth records from each unique tree.

Number of Observations	Number of Trees	Number of Growth Measurements
2	425	425
3	475	950
4	411	1233

to the models. A nearly equal number of unique trees contributed to the model over either one, two or three measurement intervals. Yet ultimately, the most common class of tree records were those from trees that were included over three intervals (4 observations).

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. For example, if damage occurred at the beginning or end of a measurement interval, the tree would be removed and there would be no record of growth over the interval for that tree (although other growth intervals for the tree without associated damage may be included). Other damage codes were recorded for subject trees (see Appendix B) 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 (see Figure 11). The number of tree records removed generally does not exceed 20 per installation and per interval. However, some installations such as KC, RM and CR showed high levels of mortality and damage, especially in the later years of the study. 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 the tree.

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 among installations, it is necessary to look beyond the tagged subject trees to the full set of tallied trees at initiation (Figure 12). Based on the frequencies of small trees by species and installation, the selected installations are not dominated by Douglas-fir (*Pseudotsuga menziesii*) or grand fir (*Abies grandis*) regeneration although there are a number of installations that are very closely split between the three species.

When comparing the vegetation cover 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 13).

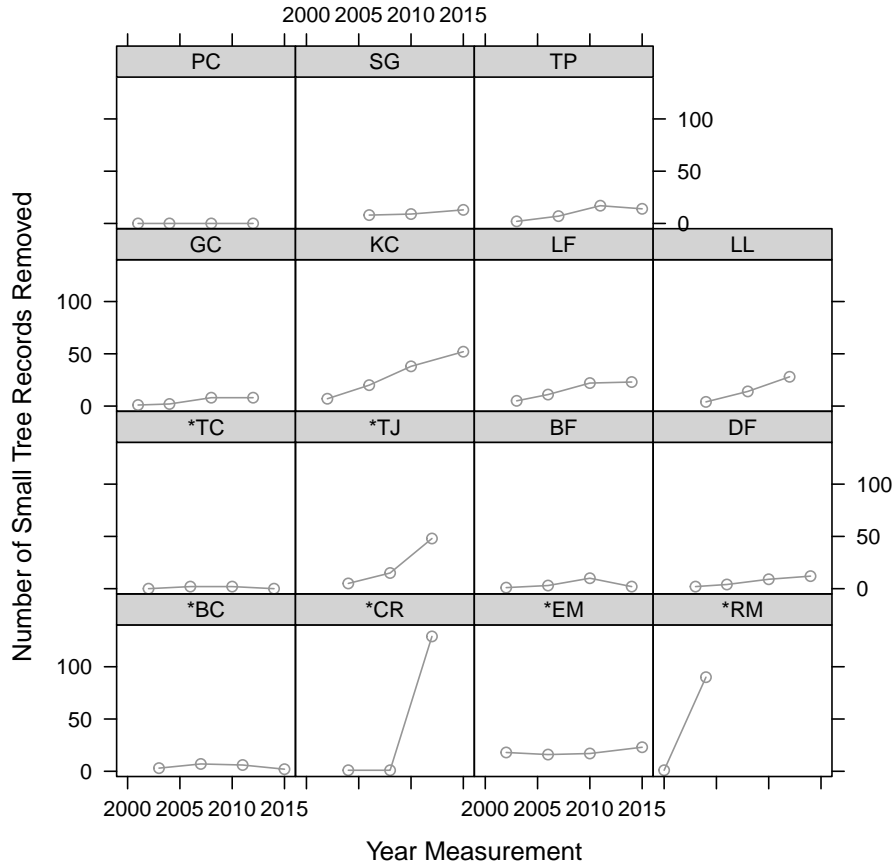


Figure 11: Small tree records removed due to top damage or mortality over time.. Installation PC (Pine Creek) had no records removed over the measurement periods.

This indicates some success in establishing a wide range of non-arboreal vegetative conditions on these installations. However, the herbicide applications failed to contribute to a marked difference in depth in installations with little vegetative volume in control plots.

Figure 14 shows that the crown area per acre (CAPA) and trees per acre (TPA) variables are closely correlated ($r=.92$). Variation in trees per acre within plots is attributed solely to mortality therefore any change in trees per acre across measurement years is negative. Crown area per acre may increase or decrease depending on the growth of crowns in overstory trees and the loss of crown area due to tree mortality. Many plots in the intermediate TPA range (40-70 TPA) show a lack of overstory mortality and an increase in crown area per acre. However, plots with higher residual overstory TPA tend to exhibit higher levels of mortality and a corresponding decrease in crown area per acre.

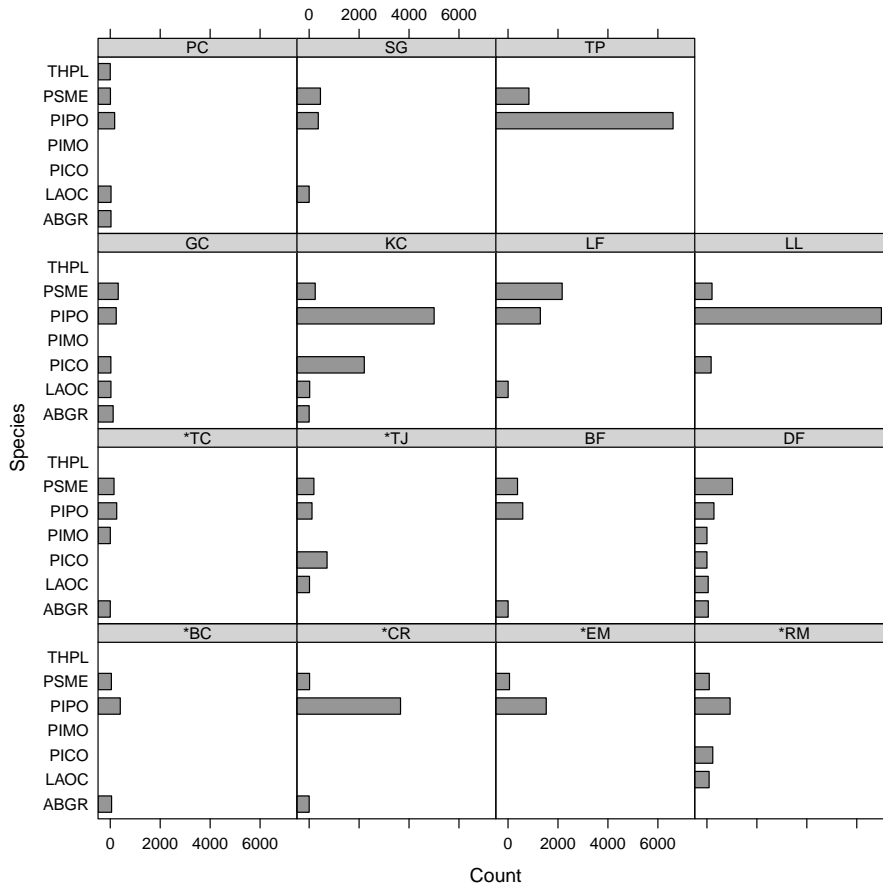


Figure 12: Species composition of small tree plots in installations with more than 60 tagged ponderosa pine at initiation. Species represented are *Pseudotsuga menziesii* (PSME), *Pinus ponderosa* (PIPO), *Abies grandis* ABGR, *Thuja plicata* (THPL), *Pinus monticola* (PIMO), *Pinus contorta* (PICO), and *Larix occidentalis* (LAOC).

3.2 Tagged Tree Characteristics

The heights of tagged ponderosa pine trees at the beginning of the selected 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 between 1 and 15 feet (Figure 15). KC and TP have especially narrow distributions of initial height despite having 3 measurement periods each. These installations have very dense, vertically homogeneous ponderosa pine regeneration.

The distribution of ponderosa annual height growth varied by installation (Figure 16). The asymmetric, commonly right-skewed distributions reveal that most subject trees experience annual height growth between 0 and 2 ft with very few trees exceeding 2 ft. Some installations such as TP and KC

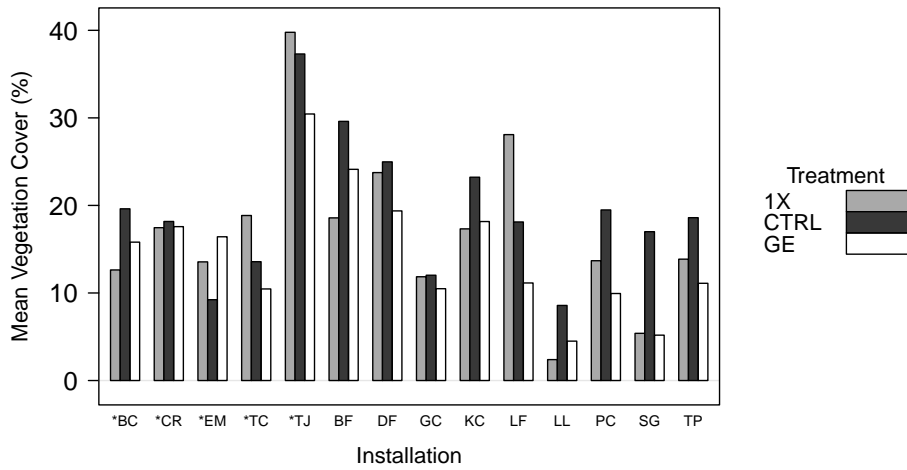


Figure 13: Average percentage cover by herbicide treatment at the start of the measurement period (GE = multiple applications, 1X = one time application, CTRL = no herbicide).

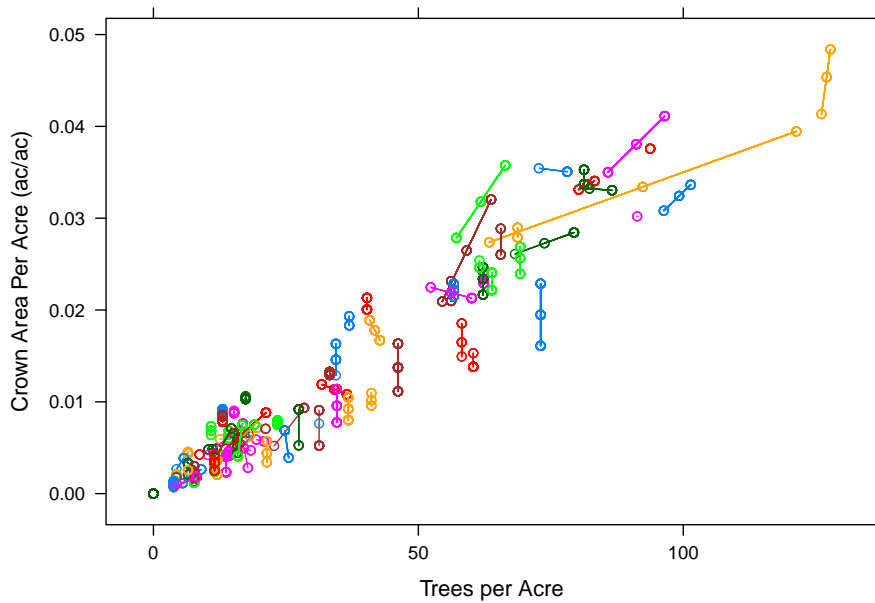


Figure 14: Crown area per acre vs. trees per acre by plot. The values for each plot across overstory measurement years are connected by line and drawn in the same color.

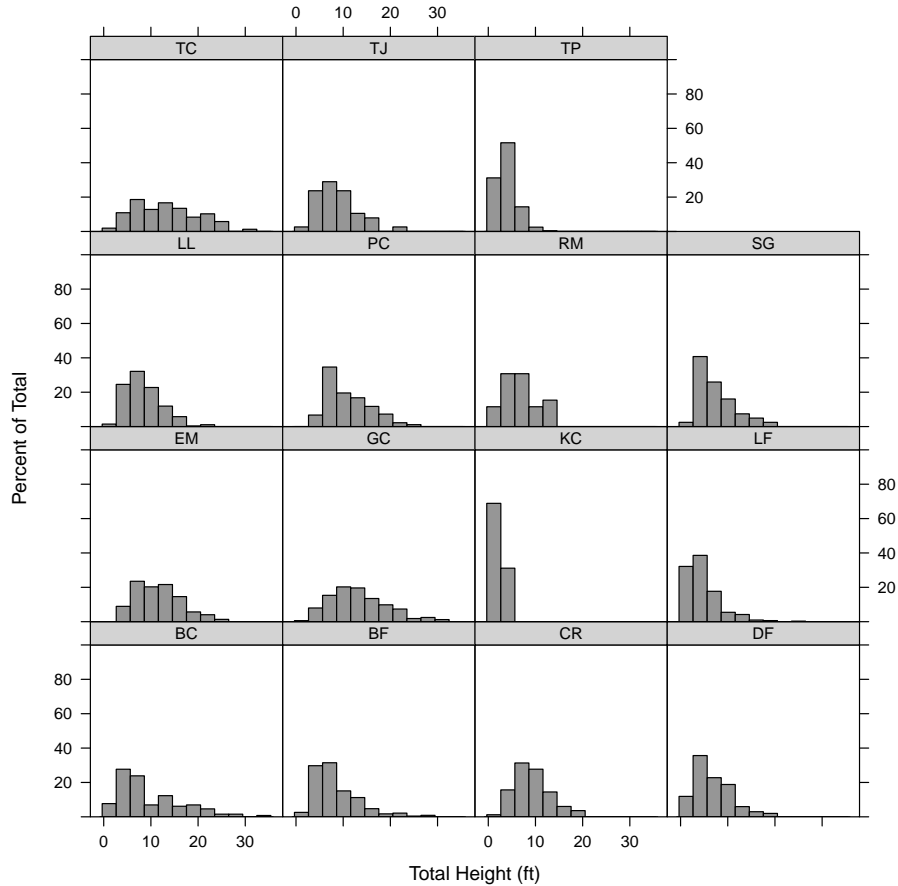


Figure 15: Distribution of initial heights of small tagged trees by installation.

have a very narrow distribution of annualized height growth. In contrast, installations such as GC and BC have fairly broad distributions of annual height which suggests 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 ($r \approx .65$) and increasing in variance with points fanning out from the origin in decreasing density. This reveals that most of the tree records represent shorter-in-stature trees that exhibit only modest increases in height growth increment. Despite this concentration 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.

Crown ratio appears to impose an upper limit on annual height growth (Figure 18a). Trees with very little live 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

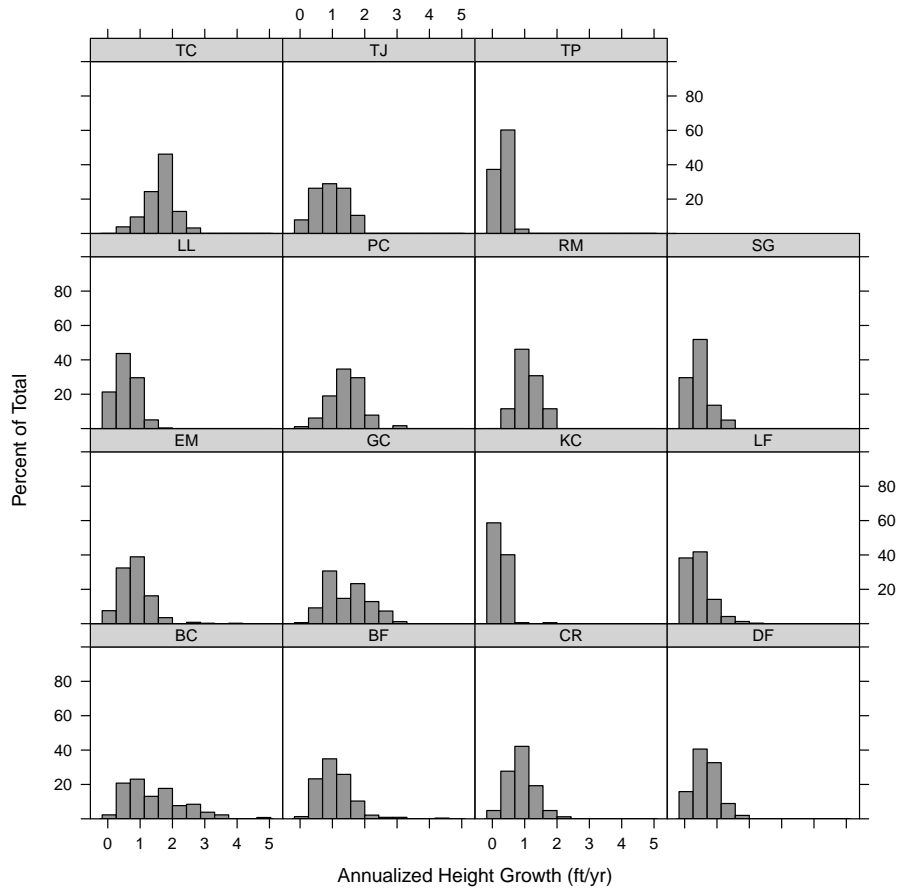


Figure 16: Distribution of annualized height growth of small tagged trees by installation.

annual height growth also increases for increasing values of crown ratio. For trees with the fullest crowns (>.8), annual height growth tends to exceed .5 ft but be limited to under 3 ft.

As initial height increases, crown ratio increases and the variability of crown ratio decreases (Figure 18b). 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.

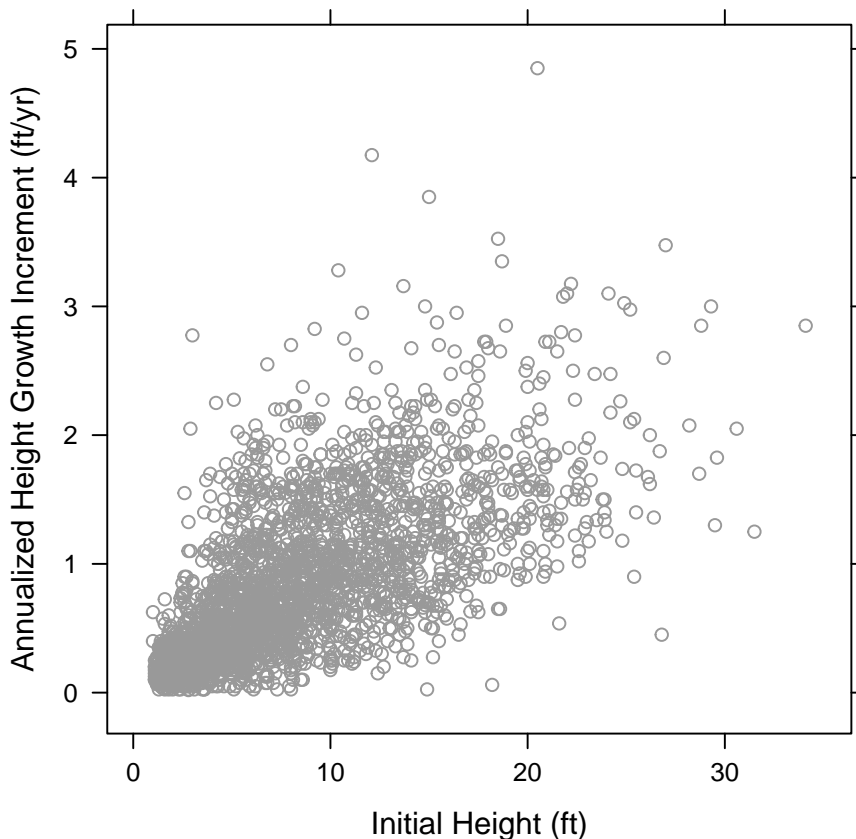
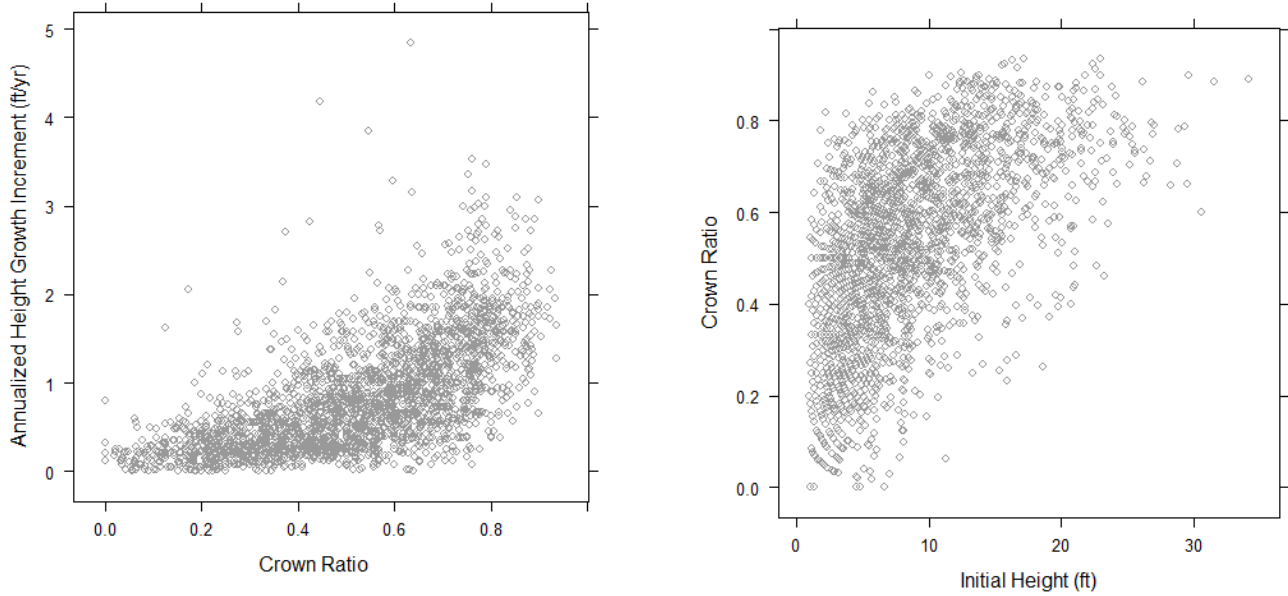


Figure 17: Annualized height growth increment vs. initial height.

3.3 Variable Selection

The primary form of the model included the square root of initial height, since it was found to have a strong, positive, linear relationship with height growth increment (Figure 19a). The partial residual plot of the base model shows the partial effect of the square root of initial height and error across the square root of initial height.

Proceeding forward from the base model to the small tree category of competition, the AIC value for the $\tau=0.5$ QR model with the crown ratio variable was found to be much lower than those for the models incorporating other candidate variables (see Table 2). This variable was therefore selected to represent competition from other small trees. The partial residual plot created to visualize the crown ratio effect includes square root of initial height as a linear term and is smoothed for crown ratio (Figure 19b). The relationship for this variable is non-linear yet estimated height growth increment is shown to



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

(b) Initial height (ft) vs. crown ratio.

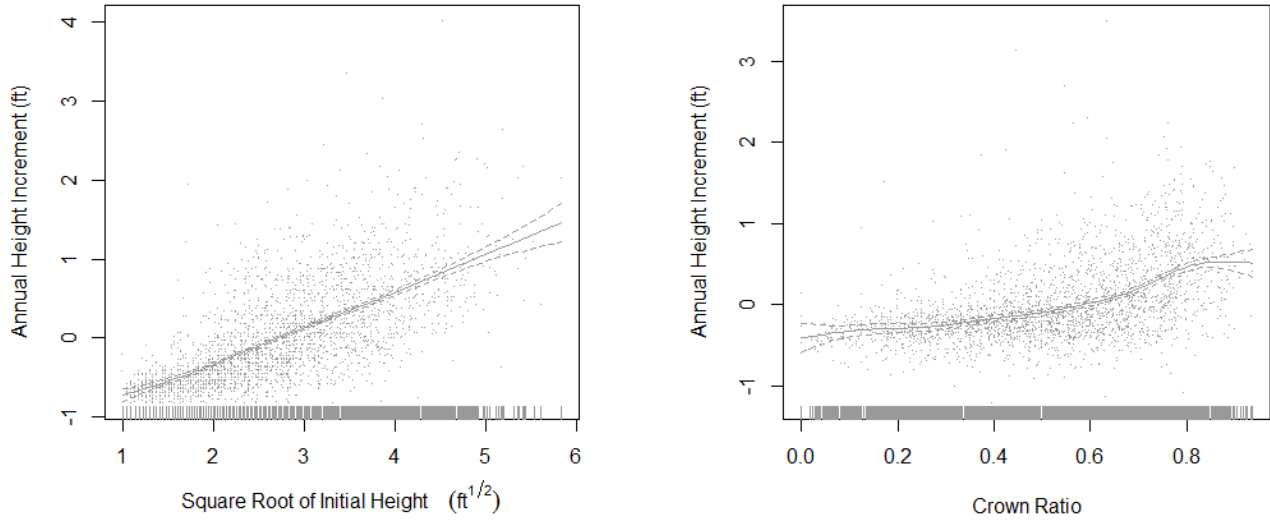
Figure 18: Scatterplots of small tree growth characteristics.

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

UT Var.	n	AIC	UV Var.	n	AIC	OS Var.	n	AIC	SQ Var.	n	AIC
cr	420	580	d_{hs}	721	1005	TPA	2608	2346	S	2608	1987
dbh	386	593	\tilde{v}_g	721	1006	CAPA	2608	2417	SI	2608	2052
dgl	419	600	c_g	721	1009	SDI	2608	2454	sl	2608	2341
cl	420	667	mx.vg.diff.1m	721	1010	BAPA	2608	2491	α	2608	2348
STPA	420	700	\tilde{v}_{ls}	721	1011	\sqrt{h} and cr	2608	2552	el	2608	2348
cw	420	702	\sqrt{h} and cr only	721	1011						
\sqrt{h} only	420	828	f	721	1012						
STPA ₊	420	757	d_f	721	1012						
STPA ₁₅	419	759	c_{hs}	721	1012						
			v_f	721	1012						
			mx.vg.diff.tr	721	1012						
			d_{ls}	721	1013						
			v_{hs}	721	1013						
			v_{ls}	721	1013						
			c_{ls}	721	1013						
			\tilde{v}_{hs}	721	1013						
			comb	721	1013						
			c_f	721	1013						

increase as crown ratio increases. Quadratic terms were evaluated to improve this relationship to no avail.

Small trees with larger crown ratios are estimated to have greater height growth increments.



(a) Partial residuals of annualized height growth increment vs. initial height.

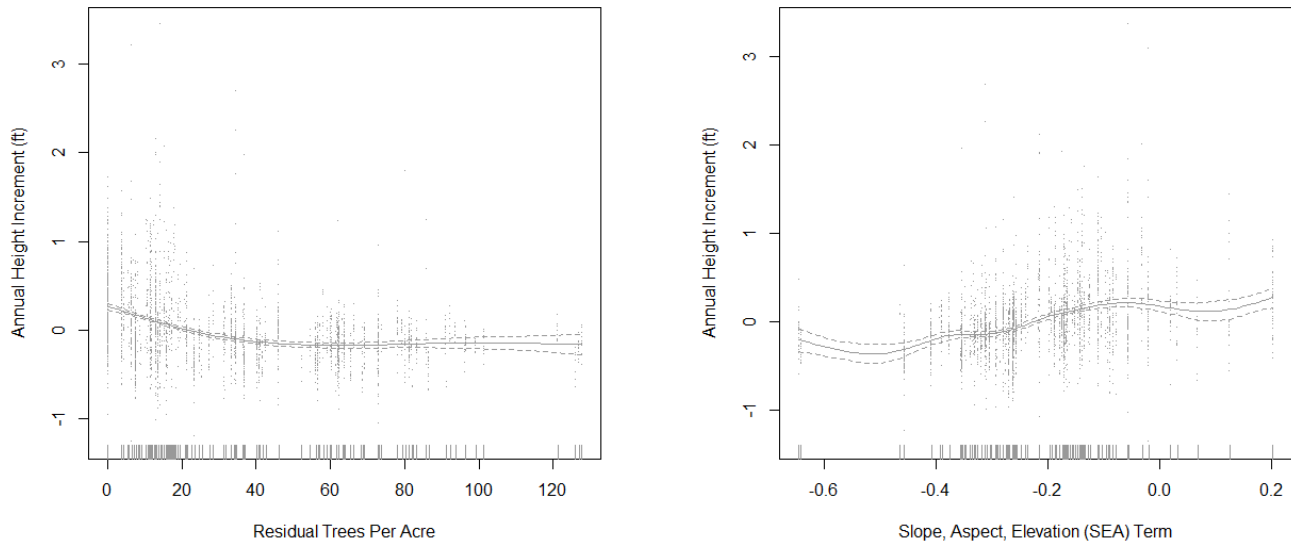
(b) Partial residuals of annualized height growth increment vs. crown ratio.

Figure 19: Partial residual plots of annualized height growth vs. initial height and crown ratio.

The understory non-arboreal vegetation candidate variables failed to provide a model with an AIC appreciably less than that of the model with \sqrt{h} and crown ratio. The variables that offered marginal improvement over the previous iteration of the model were high shrub depth (d_{hs}), transect measured grass depth (\tilde{v}_g) and grass cover (c_g). However, the inclusion of these variables is hardly justified considering the modest improvement they provide and the expense of measuring either in the field. Therefore, no candidate variable was selected from this category of competition.

The overstory candidate variable that lowered model AIC the most was trees per acre (TPA). The measure of crown area per acre (CAPA) provided a close second and the model adding basal area per acre (BAPA) also resulted in an AIC much lower than the previous iteration of the model. The partial residual plot of TPA shows that 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 may not relate to height growth increment.

Individually, the plot metrics of slope, aspect and elevation failed to provide an improvement over the model with \sqrt{h} , crown ratio, and TPA. However, when considered together in the slope, aspect and elevation (S) interaction model (Stage and Salas 2007, see Equation 3), these terms lowered AIC by



(a) Partial residuals of annual height growth vs. TPA. (b) Partial residuals of annual height growth vs S.

Figure 20: Partial residual plots of annualized height growth vs. trees per acre and S.

a wide margin. The AIC of the model with site index was also quite low but failed to surpass that using the S term. The partial residual for this term shows that an increase in the slope, aspect and elevation term is related to a general increase in height increment for most S values (and most plots).

Figure 21 shows the positive association between the partial contribution of the SEA terms and 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 value of site index was obtained for each installation whereas the S value relates productivity to the slope, aspect and elevation at the plot level.

Figure 22 illustrates the relative effects of 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. Growth of small trees 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 reduction in height growth at the highest elevations and steepest slopes, although the south-east aspect shows higher growth at high elevations.

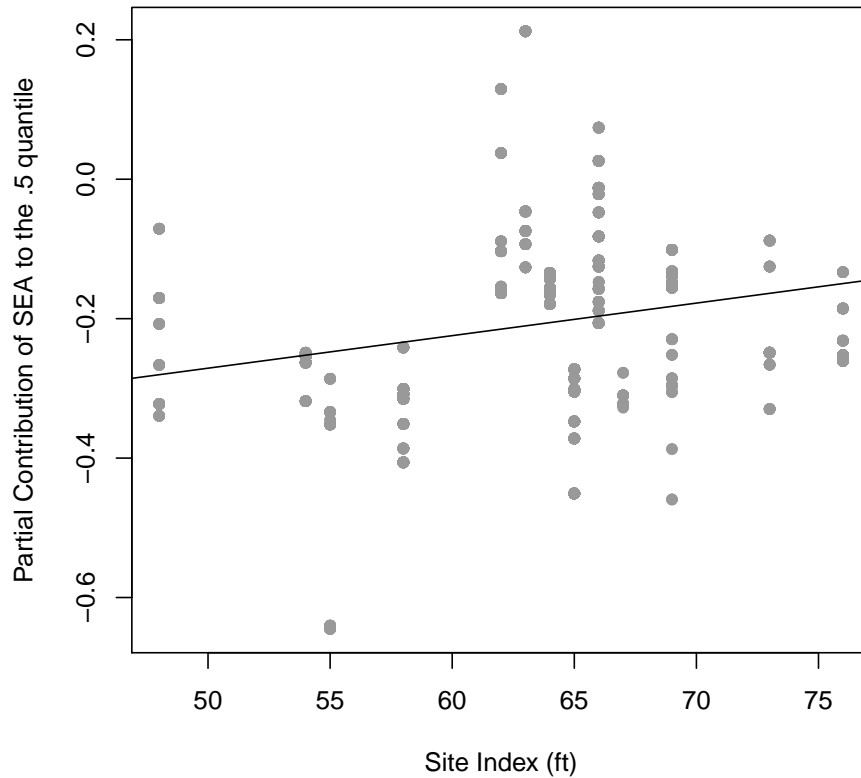


Figure 21: Partial contribution of slope, elevation and aspect interaction (SEA) to the $\tau=.5$ estimated annual height growth model and site index (ft at base age of 50 yrs)

After the 4 variable selection steps, the resultant model is specified as follows:

$$Q_{\tau}[\Delta h] = b_{0,\tau}\sqrt{h} + b_{cr,\tau}cr + b_{TPA,\tau}TPA + S(b) \quad , \quad (5)$$

where Δh is the estimated growth response, h is the initial height in feet, τ is the specified portion of the response distribution, cr is crown ratio, TPA is the overstory trees per acre and S is the complex of slope, aspect and elevation terms and estimated coefficients (b , Equation 3). Coefficients and their bootstrap-estimated standard errors are given in Table 3.

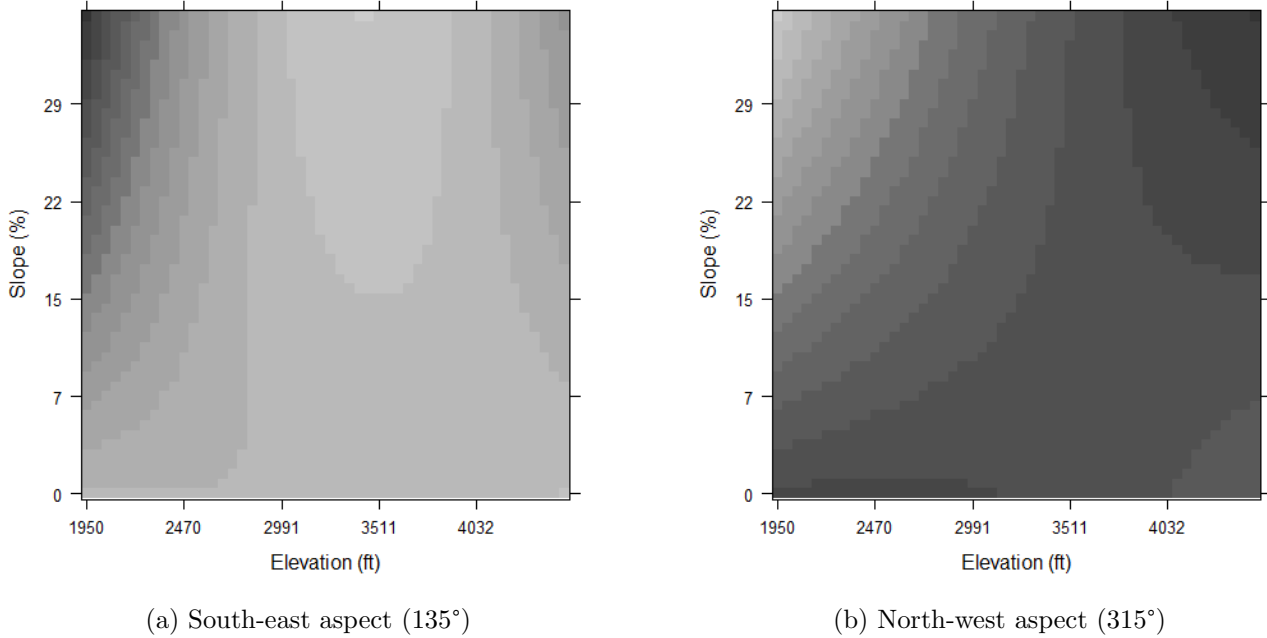


Figure 22: Standardized median growth increment by slope (%) and elevation (ft). The minimum growth was subtracted from the projected growth and divided by the range of growth, thus standardizing the growth increments between 0 and 1. Lighter shades indicate a greater estimated height growth increment.

Table 3: Quantile regression parameter estimates. Coefficient estimates for S terms are not shown.

	Q _{.1} (Δh)		Q _{.5} (Δh)		Q _{.9} (Δh)	
	b	SE(b)	b	SE(b)	b	SE(b)
(Intercept)	2.91E-01	2.63E-01	-7.36E-03	3.23E-01	-2.11E+00	5.07E-01
\sqrt{h}	1.69E-01	1.28E-02	2.73E-01	1.14E-02	3.80E-01	2.37E-02
cr	6.24E-01	4.80E-02	6.62E-01	4.34E-02	8.53E-01	9.32E-02
TPA	-1.44E-03	3.08E-04	-2.40E-03	2.61E-04	-5.04E-03	5.64E-04

3.4 Fitted Quantile Models

The quantile regression coefficient plot (Figure 23a) shows that the estimated effect of initial height increases as the specified quantile increases. For the middle range of quantile values ($\tau=.3-.7$), the effect remains within the bounds of the 95% confidence interval (CI) of the least squares regression effect estimate (red dotted lines). However, for the $\tau \leq .2$ values, the estimate is below that CI while it is above the CI for the $\tau \geq .8$ quantiles. This means that the maximum or upper-quantiles of the growth distribution increase more rapidly with initial height than does the median and much more rapidly than do the lower quantiles. The effect of initial height on median growth is about the same as would be estimated by standard linear regression.

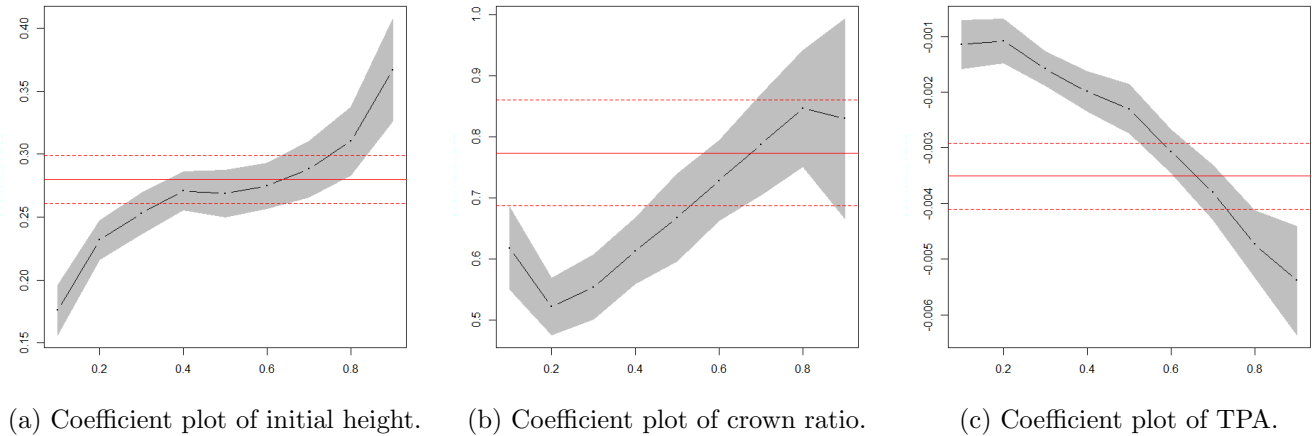


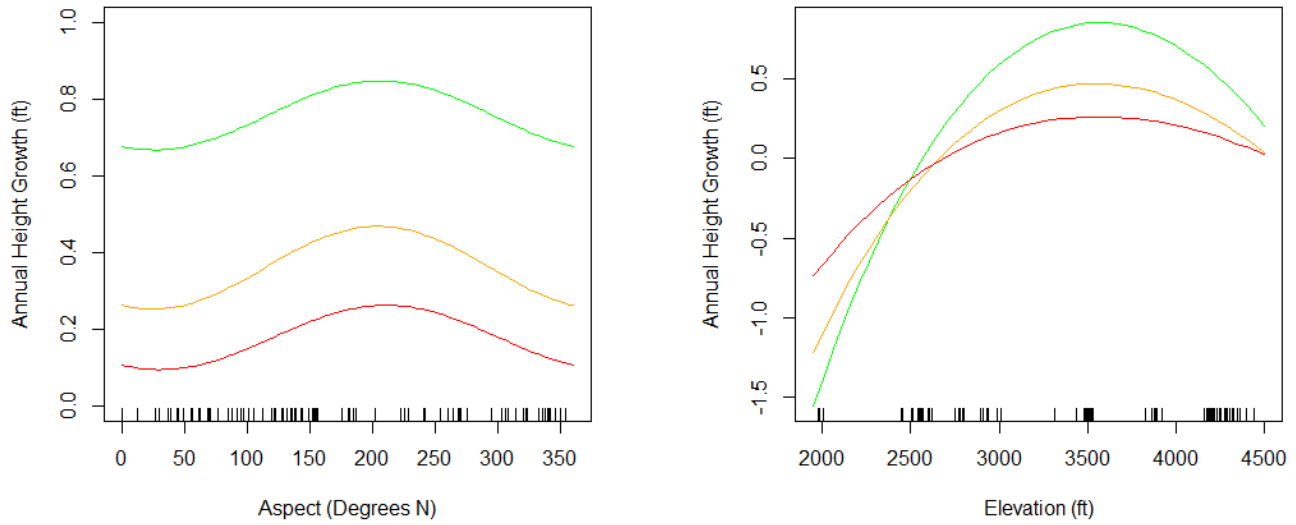
Figure 23: Quantile regression coefficient estimates and 95% confidence intervals across $\tau=1-9$.

Similarly, the effect of crown ratio generally increases as the τ value increases (Figure 23b). There are some inconsistencies with this trend at the extreme τ values (.1 and .9) where there are also considerably wider confidence intervals around the estimates. Given that all other predictors are held constant, the slowest growing trees reveal an effect of crown ratio that is far less than that of trees that exhibit higher annual growth.

As we saw earlier, overstory trees per acre (TPA) in the range of (0-40 TPA) was negatively correlated with annual height growth (Figure 20a). In terms of quantile regression 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 quantiles of the growth distribution. In contrast, the fastest growing trees (in the upper quantiles of the growth distribution), experience the most negative effects of overstory competition, although with a slightly larger confidence interval around the estimate.

Figures 24a and 24b show the effects of slope and elevation among quantile estimates of annual height growth when all other variables are held constant. In Figure 24a, the effect of aspect increases as the τ value increases. However, the differences in height growth estimates among quantiles by aspect may change at different elevations or slopes due the interaction between these terms. Aspect is shown to increase annual height growth at an optimum of approximately 200° when the slope is 10% and the elevation is 3,500 ft.

Figure 24b shows that elevation is estimated to have a positive effect on annual height growth

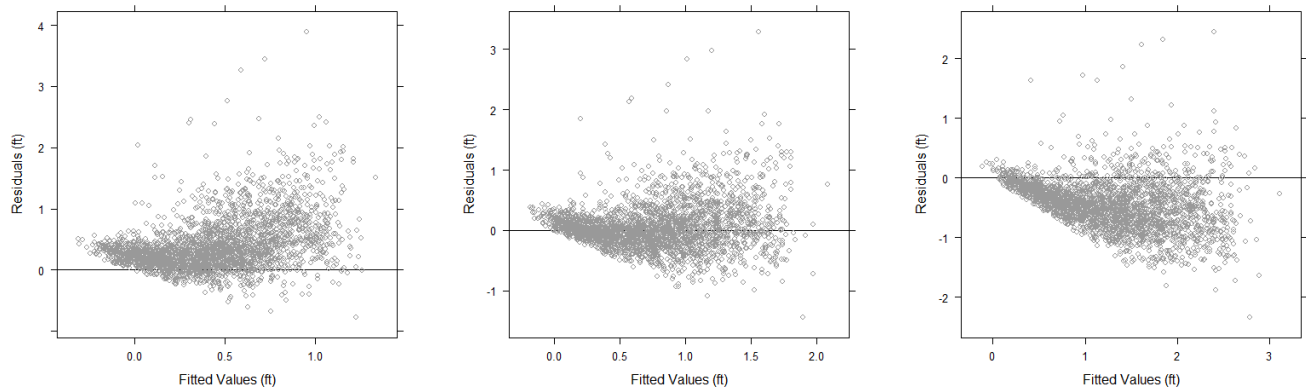


(a) Annual height growth by aspect, elevation set to 3500 ft

(b) Annual height growth by elevation, aspect set to 180°

Figure 24: Estimated annual height growth by aspect and elevation. Red, yellow and green lines represent the .9, .5 and .1 regression quantiles, respectively. Slope = 10%.

for most elevations, although, for lower elevations where there is sparse data, elevation is estimated to have a negative contribution to annual growth. The magnitude of the elevation effect increases across quantile τ values for commonly observed elevation conditions. This means that the effect of elevation is greater for the fastest growing trees. However, as in Figure 24a, the effect of elevation may change for different slope and aspect values due to the interaction between these predictors. The optimum elevation appears to be around 3500 ft for all τ values when the aspect is 200° and the slope is 10%.



(a) $\tau=.1$ residuals.

(b) $\tau=.5$ residuals.

(c) $\tau=.9$ residuals.

Figure 25: Residual plots of height growth increment (ft) from $\tau=1, 5$ and 9 regression surfaces.

The middle residual plot (Figure 25b) shows that the residuals for the $\tau=.5$ model are split roughly proportionally above and below zero. This result is expected as the median ($\tau=.5$) quantile regression is specified to describe the linear trends in the central portion of the response distribution. Figure (25a) reveals that most residuals are greater than zero for the $\tau=.1$ quantile model that describes the lower portion of the response distribution. In the $\tau=.9$ quantile, most residuals are found to be negative but there is a modest number of positive residuals across all estimated height increments. The .1 and .5 models appear to understate growth at low estimates because the models negative height increments. Thus the residuals of the lowest fitted values are exclusively positive. Collectively, these residual plots suggest that models are working well for where estimates of height increment are positive, but are not constrained to be positive.

3.5 Model Validation Results

Estimated annual height growth increments for $\tau = .1, .5$ and $.9$ were generated for the withheld data (1 randomly selected STP at each plot). The actual height growth increment was then binned according to where it fell among the estimated height growth quantiles ($<.10, .1-.5, .5-.9$ or $>.9$). Visually, the actual height growth increments are distributed approximately as expected with 40% falling between the $.1-.5$ and $.5-.9$ τ quantiles and 10% falling below the $.1$ quantile and above the $.9$ quantile (Figure 26).

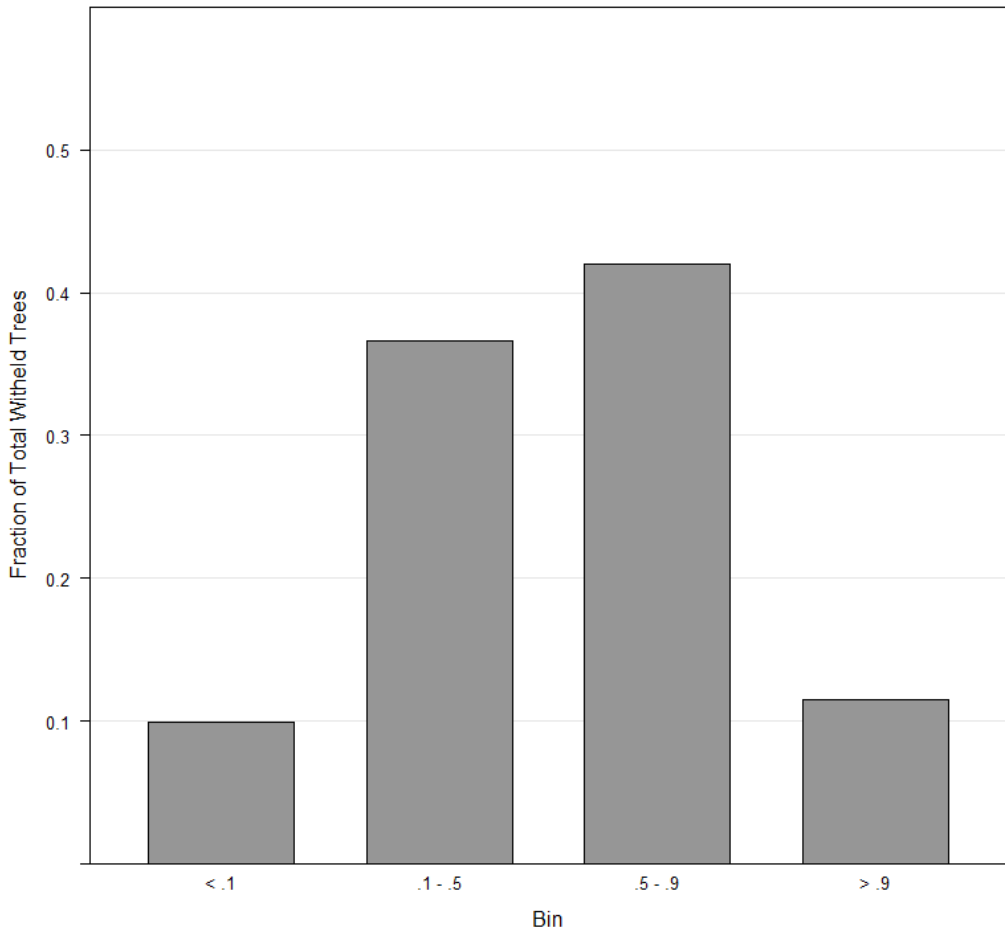


Figure 26: Withheld tree height growth increments sorted by estimated height growth increment quantiles.

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 27a). However, very few height growth increments were below their $\tau=.1$ estimated height increments. In contrast, far more responses exceeded the $\tau=.9$ estimated value than

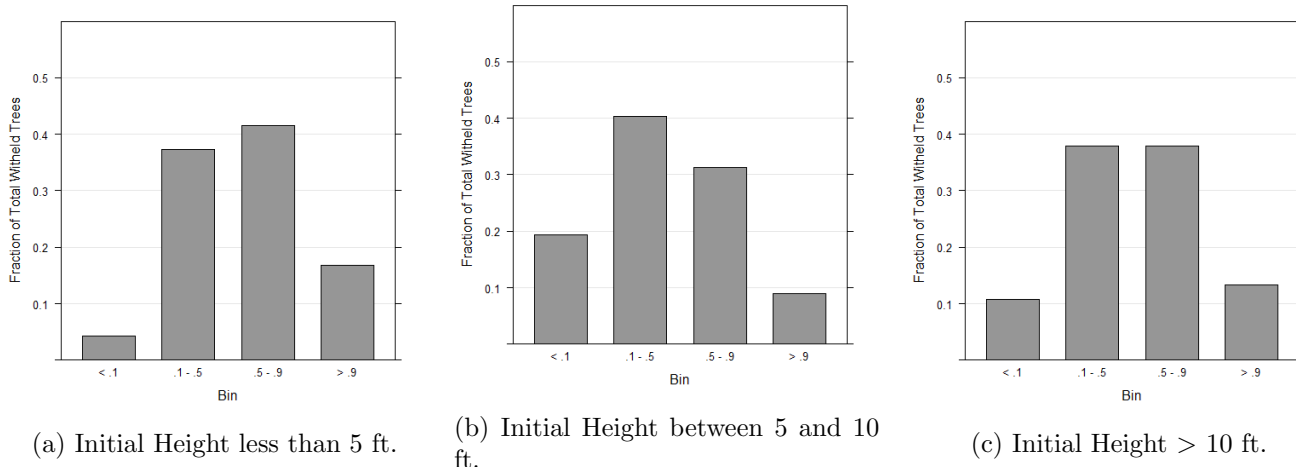


Figure 27: Withheld tree height growth increments sorted by estimated height growth increment quantiles intervals and initial height classes.

expected.

Trees in the intermediate height class (5-10 ft initial ht) appear to disproportionately exhibit height growth below the .1 estimated quantile (Figure 27b). An approximately equally number of trees appear to be absent from the $\tau=.5-.9$ quantile interval. In the 5-10 ft height class, trees generally grew less than their median estimates 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 χ^2 analysis (Table 4) 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 χ^2 test (all height classes) was .039 which provides sufficient evidence to reject the null hypothesis (that the observed and expected distributions are equal) at the $\alpha=.05$ significance level. The large difference between the expected number of height growth increments (56) below their $\tau=.1$ estimates and the observed (96) contributed greatly to the statistical difference between the distributions.

The p-values were also below $\alpha=.05$ for two of the χ^2 tests by initial height classification. In the less than five feet initial height class, the p-value was .003. The χ^2 test for the intermediate initial height class (5-10 ft) produced a p-value of $<.001$ which provides sufficient evidence to reject the null hypothesis.

Table 4: χ^2 analyses 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	

The tallest height class (10+ feet) had a p-value= .442 which fails to reject the null hypothesis at the $\alpha=.05$ significance level.

4 Discussion

4.1 Study Design

The STCV study provides an extraordinary amount of information on the growth of small trees in the Inland Northwest. The temporal scope, geographic range and resolution are unparalleled. The original dataset contains over 40,000 tree records obtained over 17 years with detailed information on competing vegetation to the species level. The study also encompassed a wide range of retention levels and site qualities. Among the installations selected for this analysis, there was a concentration of installations with high site index (62-72 ft at age 50) and low overstory retention (0-30 BAPA, Figure 8). Figure 10 shows that although many of the installations are characterized by high site/low retention (with asterisk), most of the tree records are from other installations. This means that many of the tree records used to build the model are from a broad range of installations and that modeled growth is not only reflective of high site/low retention conditions.

It may be the case that these high site index/low retention conditions are common following variable retention harvest in the Inland Northwest. Alternatively, it may be a more economical practice to leave fewer trees on high site quality sites. If the modeling goal is to make estimates for common conditions rather than test a theoretical framework, 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.

The herbicide applications were inconsistent in both frequency and interval. These applications were carried out on an “as-needed” basis without a consistent gauge of herbicide effectiveness used to reassess application. The comparison of vegetation cover by installation revealed that differences among STPs was not pronounced although the control (no herbicide) plots generally had the lowest coverage followed by the one time herbicide application plots. The differences should have been apparent at this point of the study since these coverages 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 installations used to develop the understory model generally exhibited the expected effects

of the herbicide, although there are several where the herbicide application plots had higher levels of vegetation than the control plots. Since it has been shown that understory vegetation increases with decreases in residual TPA (Ffolliott and Clary 1982, Moore 1992), it was crucial that the herbicide create a range of conditions on these installations. If the herbicide applications truly failed to create a wide range of vegetative conditions, we would expect the effect of site productivity on height growth increment to be underestimated since increases in site productivity contribute to increase in vegetative competition that detract from the height growth of small trees (Figure 1). Similarly, we might expect that the negative effect of residual TPA is underestimated since decreases in TPA also contribute to increases in understory non-arboreal vegetation.

Added to this, the herbicide applications themselves may 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 (Goodburn 2017). On the installations 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 at the edges 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 quadrats would still be able to describe the colonizing vegetation within the small tree plots.

An analysis that fails to consider dependence among repeated measures of the same tree may introduce some underestimation of the standard errors of the parameter estimates, since the calculation of standard error assumes that all observations are independent. This could be especially important to model building criteria such as AIC, which likewise presumes that observations are independent. Table 1 shows the majority of the tree records used for the study came from trees that were measured 3 or 4 times which means that most of the tree records used in this study were not independent observations.

To address this issue in the future, quantile mixed models (LQMMs, Geraci and Bottai 2014) could be pursued as a way to account for lack of independent observations. This method estimates the conditional quantile functions with subject-specific location-shift random effects (Geraci and Bottai 2007).

4.2 Subject Tree Growth

The tagged trees in the study ranged from 1-30 ft in initial height (Figure 15). Trees in the upper portion of that range are no longer “small”, have typically entered into the canopy, and their growth dynamics are likely determined by other factors. Although they may seem less informative for calibrating a small tree growth model, it is valuable to have these trees contribute to the model because they represent the greatest capacity for height growth as well as the greatest variability in height growth. It is also important to include the trees that are at 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. A desire to describe the range of growth of these very short trees was one motivation for applying 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 was. Trees above 15 ft exhibited a standard deviation of approximately 41% of mean growth. 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” do not. Incorporating this increasing variability into the model is important and a quantile regression technique that describes the impact of height on the full distribution of growth is one way to do so.

Initial height and annual height growth related to crown ratio in similar ways. Crown ratio imposed a biological upper limit to 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. Nearly all small trees that were taller than 15 ft had crown ratios greater than 50% (Figure 18b).

Higher rates of growth are observed in trees that have greater crown ratios and heights. Once

again, quantile regression provides a technique to describe the maximum growth for a given crown ratio and height (by specifying $\tau=.9$). The central and lower regions of this distribution are also described by the quantile regression models ($\tau=.5$ and $.1$, respectively).

4.3 Model Form

The selected models describe the distribution of ponderosa pine annual height growth as a function of initial height, crown ratio, TPA and site quality. The theoretical framework for small tree growth in Figure 1 is well-represented by the selected variables with the exception of an understory non-tree vegetation variable.

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. Only four of the seventeen candidate variables provided a marginal improvement over the model with only initial height and crown ratio. There are two explanations that may provide an answer as to why this occurred. First, 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 through shading and crown recession. Introducing other measures of vegetation once crown ratio is accounted for is possibly redundant. Another explanation 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 a transect (20 out of 30 or 40 feet) lies outside the STP 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 quadrats, 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 quadrats. Only the smaller size plots were maintained throughout all measurement intervals in the model, so they were used instead of the larger ones. Yet, the 1m^2 quadrats 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 were to be taken 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 was expected to best describe competition from the overstory because it directly relates to ability of the overstory trees to shade the small trees in the understory and compete for belowground resources such as water. Basal area per acre (BAPA) and stand density index (SDI) were also expected to provide a superior model fit than TPA since they provide information about the size and number of the retained overstory.

The selection of the slope, aspect and elevation interaction terms were expected given that these site attributes are known to be useful surrogates for the factors that influence productivity such as radiation, precipitation and temperature (Stage and Salas 2007). The interaction term also provides plot-level information rather than installation-level.

As another candidate variable for site productivity, site index may have been influenced by the lack of ideal open-grown dominate specimen trees. Site index curves are based on the growth of open-grown and dominate trees. Despite the lack of ideal conditions for site index, it provided a greatly improved model fit over the previous iteration of the model (without a descriptor of site productivity).

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 estimated height increment at all quantiles. Overstory TPA is associated with a decrease in the height growth rate at all quantiles. That is intuitive considering the response of understory trees to the enhancement in light level and reductions in water use associated with the canopy openings and decreases in belowground competition, respectively.

Crown ratio and initial height effect contribute to estimated annual height growth but especially at the higher quantiles (Figures 23a and 23b). High levels of TPA can have a large negative effect on height growth, especially on the the higher quantiles (Figure 23c). On north-west facing slopes, the greatest height growth is estimated for low elevation/high slope plots (Figure 22b). 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, although it is much more pronounced for the north-west aspect. This most likely is due to greater snowpack and shorter growing seasons at these higher elevations and lower temperatures.

When the effects were mapped across τ values, the effects produced some expected and 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. This could be an important consideration in management as overstory retention is one of the primary ways to influence the development of small trees in the understory.

One unanticipated result of using quantile regression to examine all parts of the response distribution was that 49 validation trees were estimated to have slightly negative $\tau=.1$ growth because the estimated height growth was not constrained to be strictly positive. The few trees that were estimated to have a negative height growth were very short (average initial height of 2 ft) and exhibited short crowns (average crown ratio of 19%). These negative estimates of growth likely occurred as a consequence of fitting linear quantile surfaces to predictors that had nonlinear effects on height growth near the lower limit. These surfaces had to be parameterized in such a way that they described the growth of the specified τ across all values. For the .10 quantile estimates, this meant that the surface dropped below zero for some combination of predictors. This explains why so few trees in the 1-5 ft height class exhibited height below their .10 quantile estimates.

Visually the results of the other initial height categories matched the expected distribution, particularly the 10+ ft height class. 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 approximately describe the height growth distribution for certain ranges of the predictor variables.

4.4 Comparison of Results to Related Studies

Although there have been no other studies that describe height growth of small ponderosa pine trees with quantile regression, we can qualitatively compare our results to those 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.

Although several authors mentioned in the introduction found that vegetative competition reduced the height and diameter growth of ponderosa pine (Barrett 1979, Curtis and Lynch 2007, Busse, Cochran, and Barrett 1996, Oliver 1979), we found no suitable measure of vegetative competition that relates to height growth. However, the competitive effect of overstory trees described by Oliver (1984), Ffolliott and Clary (1982), and Moore (1992) was observed in all overstory measures and most pronounced in the measure of trees per acre.

Salas and Stage (2008) used a subset of the STCV data to develop an individual-tree height growth model for Inland Northwest Douglas-fir 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 deep rooted, 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 Douglas-fir habitat types may be more important to early height growth.

Similar to the model presented in this thesis, Salas and Stage (2008) represented site productivity with 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 as a predictor of height growth. They found no improvement and speculate that even though the correlation between site productivity and greater understory vegetation cover was reduced due to the herbicide treatments, the correlation between small tree density and site productivity was still a problem for small conifers because they were not thinned. Referencing Figure 1, this implies that the effects of site productivity on subject

tree growth may be confounded by corresponding increases in competition from other small trees.

4.5 Qualitative Comparison to the Forest Vegetation Simulator Inland Empire Variant Small-Tree Height Increment Model

The Forest Vegetation Simulator (FVS, Dixon 2013) 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 installations used in this analysis (eastern Washington, north-central Idaho and Western Montana) and was originally the Prognosis model developed by Stage (1973).

The small-tree routine in the Inland Empire Variant of FVS provides a 5-year estimate of individual height growth (Keyser 2008). It utilizes the following equation to estimate the height growth of small trees (less than 3 in DBH):

$$\Delta h \propto h^{B_1} e^{B_2 CCF} e^{B_3 BAL} f(HAB, LOC, sl, \alpha) \quad , \quad (6)$$

where CCF is crown competition factor (Krajicek, Brinkman, and Gingrich 1961), BAL is total basal area in trees larger than the subject tree, HAB is habitat type, LOC is a geographic location modifier, α is the stand aspect, and the parameters B_i and a function $f()$ are species-specific.

The FVS small tree height growth equation is quite similar to the model proposed in this thesis. The height growth is estimated from initial height, site quality (in terms of location, habitat type, slope and aspect), CCF and BAL. The main difference between the FVS equation and the one proposed in this model is that the FVS model relies more on stand-level metrics than tree-level metrics. Crown competition factor (CCF) is the percent of area that would be covered by crown projections if all trees had maximum crown widths for their diameter. Basal area in trees larger (BAL) than the subject tree is a relative measure of stand density that sums the cross-sectional area of the stems at breast height in trees greater in diameter than the subject tree. Both of these variables relate characteristics of the stand to small tree growth, whereas the proposed model captures the competitive effects of the stand with trees per acre (TPA) and at the tree-level via crown ratio.

The FVS height growth estimate represents the mean growth of small trees facing the given

conditions. The proposed models estimate the entire distribution of height growth increments these trees may achieve. As seen in Figure 23, modeling the mean height growth is not adequate because the effects of the predictors changes across quantiles of the response distribution.

FVS does accommodate multiple trajectories of tree records to provide some degree of variation from the mean. When relatively few samples represent the stand, two additional tree records are created that triplicate the characteristics of the tree except the number of trees per acre represented. The two new records represent 15 and 25 percent of the trees per acre and the original record represents 60 percent of trees per acre. A normally distributed random error (bounded between -1.5 and 1.0 size-dependent standard deviations) is then added to each of the triplicated tree records.

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

5 Conclusions

The individual tree height growth increment model proposed in this thesis provides an estimate of the range of possible growth of a given small ponderosa pine tree through multiple quantile regression functions ($\tau=.1, .5$ and $.9$). Predictors were selected from within categories of ecologically important factors (Figure 1). The model introduces empirically supported variation in small tree height growth estimates. The empirical evidence for the model was obtained through the most comprehensive and long-standing study of small tree growth in the Inland Northwest undertaken to date.

Statistical validation failed to demonstrate that the model described quantiles of height growth consistent with the height growth observed in withheld data. However, this is primarily due to negative estimates of the lower quantile ($\tau=.1$) of height increments under low growth conditions. Imposing a lower limit of $.2$ ft on estimated height growth would likely resolve the issue of negative estimates of height growth. Future work should consider mixed models (Geraci and Bottai 2007) and/or nonlinear quantile regression as these are quantile methods that accommodate longitudinal data and nonlinear relationships, respectively.

A compelling application of the proposed model is in providing managers an idea of the growth rates of the fastest growing understory trees and how post-harvest stand conditions such as retained overstory can be expected to affect these rates. Having a better estimate 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 estimates of when stands will reach green-up under alternative partial retention levels.

Another application of improved estimation of the maximum growth of small trees relates to growth into the retained canopy. Since the small trees that emerge into the canopy first may eventually compose the (co-)dominant crown class, it is especially important know how factors such as retained overstory and understory vegetation affect growth in these trees. The small trees that emerge first into the canopy may also eventually be of greater commercial interest or merchantable value.

As alluded to in the previous paragraph, improvement in the estimates of small tree growth has

implications beyond simply improving our knowledge of understory tree growth and related competitive factors. Improvements in small tree height growth estimates can be carried forward to improvements in modeling the later stages of stand development. 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 partial retention harvest.

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A. 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	dgl
Diameter at breast height	in	tree x interval	dbh
Trees per acre >3.5"	ac ⁻¹	tree x interval	STPA
Trees per acre >15 ft in ht	ac ⁻¹	STP x interval	STPA ₁₅
Trees per acre above subject tree	ac ⁻¹	tree x interval	STPA ₊
Non-tree Vegetation			
Forb depth in 1m ² q	ft	STP x interval	d_f
Low shrub depth in 1m ² q	ft	STP x interval	d_{ls}
High shrub depth in 1m ² q	ft	STP x interval	d_{hs}
Forb volume in 1m ² q	ft ³ /ft ²	STP x interval	v_f
Low shrub volume in 1m ² q	ft ³ /ft ²	STP x interval	v_{ls}
High shrub volume in 1m ² q	ft ³ /ft ²	STP x interval	v_{hs}
% Cover forb	%	STP x interval	c_f
% Cover low shrub	%	STP x interval	c_{ls}
% Cover high shrub	%	STP x interval	c_{hs}
% Cover combined veg	%	STP x interval	c_{comb}
Transect grass depth	ft	transect x interval	\tilde{v}_g
Transect forb depth	ft	transect x interval	\tilde{v}_f
Transect low shrub depth	ft	transect x interval	\tilde{v}_{ls}
Transect high shrub depth	ft	transect x interval	\tilde{v}_{hs}
Grass transect cover	%	transect x interval	c_g
Tallest veg - subject tree (1m ²)	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	ac ⁻¹	plot x interval	SDI
Site Quality			
Slope	%	plot	sl
Elevation	ft	plot	el
Aspect	N°	plot	α
Site index	ft	installation	SI
Slope, aspect, elevation term		plot	SEA

B. Tagged Tree Damage Codes

Code	Definition
AD	Animal Damage
BR	Blister rust
BT	Broken top
CK	Check
CO	Commandra Rust
CR	Crook
Dead	Evidence of death
DT	Dead Top
FK	Fork
FT	Forked top
FUT	Multiple damages, too many to list
Gall	Western Gall Rust infection
ID	Insect damage
Lean	Stem not growing straight
MIA	Unable to locate tree, no evidence of death
Mistle	Mistletoe
MT	Mistletoe
PD	Pronone (herbicide) damage
RT	Reestablished Top
Small Broom	Mistletoe induced broom
SW	Sweep

C. Variable Selection Steps

1. Select installations with >60 *P. ponderosa* tagged trees at initiation.
2. Retain one randomly selected STP of the six STPs within each plot for validation.
3. Create a list of the predictor variables within each category:
 - Understory Tree (UT)
 - Understory Non-tree (UV)
 - Overstory Tree (OT)
 - Site Productivity (SP)
4. Select installations of similar overstory basal area and site productivity.
5. For each candidate variable in the UT set generate a generalized additive model (GAM) using the base model and only the plots with multiple applications of herbicide:

$$E[\Delta h] = b_0 + b_1\sqrt{h} + b_2(\text{candidate}) \quad , \tag{7}$$

where h is the tree height in feet and Δh is annual ht growth.

6. Visually examine the results and the partial residual plots of the GAM models produced.
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

$$Q_{.5}[\Delta h] = b_0 + b_1\sqrt{h} + b_2(\text{candidate}) \quad ,$$

where h is the tree height in feet and Q is the quantile function (for $\tau=.5$).

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 but with the addition of control and 1 time herbicide treated plots.
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 $\tau=.5$, fit quantile regressions for $\tau=.1, .9$.

Final Models:

$$Q_{\tau}[\Delta h] = b_0 + b_{1,\tau}\sqrt{h} + b_{2,\tau}\text{UT} + b_{3,\tau}\text{UV} + b_{4,\tau}\text{OT} + b_{5,\tau}\text{SP} \quad ,$$

where h is the tree height in feet, Q is the specified quantile, and b are the fitted coefficients.