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A regional coastal Douglas-fir index of site quality for young stands in western Washington, USA

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ABSTRACT

Site index is frequently used for deciding how to manage stands, however, it often omits or fails to accurately characterize the site-dependent growth of young (ages ≤8 years) trees. This early stage of development is a critical period in a rotation during which important management decisions with the potential to influence all future growth are made. To address this, we developed a new index of site quality for young, coastal Douglas-fir (*Pseudotsuga menziesii (Mirb.) Franco var. menziesii*) stands in western Washington, USA. We used high-density light detection and ranging (LiDAR) scans for 161 stands between 3 and 8 years old, in conjunction with Soil Survey Geographic Database information to identify site characteristics that were associated with productivity in young Douglas-fir sites. We utilized individual-tree detection algorithms to measure tree heights and developed a linear model for correcting LiDAR-derived heights in young Douglas-fir stands based on field-measured heights. Our findings indicated that Douglas-fir growth tended to be greatest on sites that were low in elevation, high in precipitation, and had fine-textured soils. We provide an index of site quality for young Douglas-fir based on elevation, precipitation, and soil textural classes to guide early stand management.

1. Introduction

Forest productivity is closely tied to site characteristics such as local climate and soils (Carmean, 1975; Splechtna, 2001). Measures of site quality are essential for informing management decisions, especially in deciding where to deploy intensive management (Carmean, 1975, 1996). The most utilized measure of site quality is site index which is based on the relationship between tree age and height (Skovsgaard and Vanclay, 2008). Assessing forests through this dendrocentric approach is efficient for forestry purposes as an index based on height is closely tied to volume production and relatively independent of factors such as spacing when trees are planted within the normal range of plantation densities (Skovsgaard and Vanclay, 2008). The simplicity of these dendrocentric approaches is advantageous for modeling mature forest productivity but may not accurately reflect young stages of growth. In fact, most site index curves start at age five and few if any indices exist to assess site quality during the early stage of stand development.

Early silvicultural interventions in young forests can result in significant growth and survival benefits over the rotation (Wagner et al., 2006, Westfall et al., 2004). Van Eck and Whiteside (1963) stressed that the evaluation of site index in stands younger than five years was important as this early growth affected growth over a fixed rotation considerably in *Pinus resinosa* plantations. Assessments of early tree growth and their ability to predict site index has been studied previously. Warrack and Fraser (1960) found tree ages of three years could be used in the "growth intercept" method (Wakeley, 1954) to predict site index for Douglas-fir (*Pseudotsuga menziesii (Mirb.) Franco var. menziesii*) plantations. Age two height was found to be predictive of base-age 25 site index in *P. taeda* plantations (Beasley et al., 2024). Early studies investigating the use of "the number of years to reach breast height" (1.37 m) to predict Douglas-fir site index in British Colombia found this measurement to be indicative of site quality in naturally regenerated stands (Smith and Ker, 1956). More recently, Ferguson and Carlson (2010), used naturally regenerating Douglas-fir as young as age 3 to investigate height-age relationships. As intensive silvicultural practices have evolved, the improvements to growing stock, planting methods, and vegetation control early in stand development may have considerably shortened rotation lengths since the growth intercept method and

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many site index curves were first created. Intensive management may have alleviated some of the issues associated with accurately predicting site quality at young ages while also necessitating an index to evaluate the effectiveness of early treatments in young stands. Despite this, most site index curves do not provide site index values for stands younger than five years old, nor do contemporary regional indices exist which could be used to evaluate early stand development based on site characteristics. This is partially due to the potential of non-site factors causing erratic growth patterns in early stand development, like weather and animal damage (Carmean, 1975). Moreover, in some cases, young growth patterns have been shown to fail to accurately predict later growth patterns, suggesting that factors influencing early-term growth differ from those impacting late-term growth (Carmean et al., 2006). Previous research has largely avoided developing site quality metrics for young stands due to their perceived low predictability of future growth, small tree-size differences among stands at young ages, and growth rates which may vary due to reasons other than site quality.

Light detection and ranging (LiDAR) may be useful to overcome issues associated with developing site indices for young stands. LiDAR enables the measurement of tree height across large areas with relatively high accuracy (Gatziolis, 2007), providing suitable sample sizes to address issues arising from small and erratic growth differences among sites. Furthermore, the development of individual-tree detection (ITD) algorithms allows for more accurate measurements of young trees with heights between 1 and 5 m than traditional canopy height model approaches (Rodriguez-Puerta et al., 2022). Some studies have used LiDAR in combination with management data to develop site indices for young stands on a regional scale (Gopalakrishnan et al., 2019) and to inform management decisions in young stands (Watt et al., 2013). While field measurements of height would provide the most accurate and precise data, LiDAR can estimate heights for potentially all planted trees in a stand and sample hundreds of stands in a single operational flight. Such logistical efficiencies may facilitate the rapid development of early site indices.

Douglas-fir is a globally important timber species that is intensively managed across its native range in North America and as an exotic in Europe, South America, Australia, and New Zealand (Hermann and Lavender, 1999). Studies that have examined young growth in Douglas-fir stands have mostly focused on the early stem exclusion stage of stand development, i.e. shortly after the crowns have escaped the threat of being overtopped by competing vegetation (Stoate and Crossin, 1959; Curt et al., 2001). This provides a challenge for managers as there is limited information to guide management decisions and characterize a stand's developmental progress during an important stage of stand development (i.e., stand initiation). Silvicultural interventions made during this period, such as whether to control competing vegetation, will have long-term effects on the development of the stand (Harrington et al., 2013).

Douglas-fir site quality is influenced by a variety of different factors in the Pacific Northwest. Growing season soil water availability is expected to be a common limiting resource in the region; therefore, increased water-stress, elevation, soil gravel content, and soil compaction are all associated with low-quality sites (Carmean, 1954). This has been found to be especially true in young Douglas-fir stands (Gonzalez-Benecke and Dinger, 2018; Carter et al., 2022). The importance of water stress makes competition control important for young Douglas- fir stands, and even more so on sites with high susceptibility to drought (Gonzalez-Benecke and Dinger, 2018; Devine and Harrington, 2006). Soil texture has a large influence on soil water retention and has been found to be a strong predictor of soil moisture at the small (<100 m^2) and intermediate (1–100 km) spatial scales (Dong and Ochsner, 2018). In addition, factors such as slope and geomorphic positions have been shown to have strong impacts on soil fertility and subsequent forest growth due to influence on water and nutrient accumulations (Scholten et al., 2017). The effects of geomorphic position have been shown to be greatest in the top 50 cm of soil (Scholten et al., 2017) which is the depth of soil that contains the largest volume of roots for planted Douglas-fir up until age 10 (Sundström and Keane 1999). Soil temperature regimes can also significantly alter a tree's ability to uptake water with cold temperature regimes resulting in low water uptake (Lopushinsky and Kaufmann, 1984). In the Pacific Northwest, Douglas-fir on cold, high-elevation sites typically also face negative impacts from reduced growing season length due to late snowmelts. The exhibited importance of soil moisture on Douglas-fir growth results in a suite of variables that all potentially influence Douglas-fir growth due to their modification of a site's soil moisture.

We examined site-level factors related to soil, climate, and topographic position that may be responsible for differing patterns of young growth among Douglas-fir stands between the ages of 3–8 years old at the time of laser scanning. Our objectives were to (1) assess the association of site variables with young Douglas-fir height growth using management histories and LiDAR coverage in combination with SSURGO (Soil Survey Geographic Database) data in western Washington, USA (n = 161 sites); and (2) to develop an early-term (age 3–8) index of site quality for Douglas-fir plantations. This age range corresponds to the window of time it takes most stands to reach 3 m in height, or "free to grow" status. We hypothesized that (*i*) coarse-textured soils would have less Douglas-fir height growth than that measured on fine-textured soils; (*ii*) Douglas-fir height growth would decrease with increasing elevation, (*iii*) that fine-textured, low-elevation sites would have the greatest young-stand index of site quality of all elevation and soil texture combinations tested and (iv) that there would be only modest disagreement between early heights and base age 50 site index values among stands.

2. Materials and methods

2.1. Study area

Western Washington primarily has a Mediterranean climate with warm dry summers and cool wet winters (Waring and Franklin, 1979). The volcanic and glacial history of the region leads to a prevalence of andisols and inceptisols in the lowlands while higher elevations feature sandy spodosols and inceptisols (Southard et al., 2017). Within the coastal range and the western Cascade Range, the 161 Douglas-fir plantations used in this study were selected based on (1) availability of LiDAR coverage, (2) requisite age ranges of 3–8 years old, (3) geographic distribution within the state of Washington, (4) similar management histories, and (5) greater than 5 ha of contiguous area to minimize edge effects of mature trees. Stands were located primarily in the Willapa Hills and southern Cascades descending into the Puget lowlands (Fig. 1).

For each site, soil data were acquired from the Soil Survey Geographic Database (SSURGO 2022) using the ESRI ArcGIS.com SSURGO downloader. The characteristics of the soil unit that covered the greatest proportion of the stand were used in this analysis. In most instances, a majority of the site was associated with only one soil map unit, but some sites had two map units where the minor unit encompassed less than 20 % of the stand area. This is likely due to many stand boundaries being developed utilizing soil maps provided by SSURGO. Sites occurred on four soil orders (alfisols, andisols, spodosols, and inceptisols), five soil map unit textural classes (clay loam, silt loam, loam, loamy sand, sandy loam), and over a range of elevations from 15 to 1319 m (Table 1).

SSURGO particle size variables (percent sand, silt, and clay) were converted into 0–30 cm and 30–60 cm increments for each map unit using a weighted average of the horizon values based on their depths. SSURGO categorical variables of texture major, texture minor, and taxonomic order were also extracted for each map unit. Climate variables were extracted for a center point in each stand from Climate NA (Wang et al., 2016). Monthly data were extracted for each site from the year of planting to the year of LiDAR data collection. From these data, an

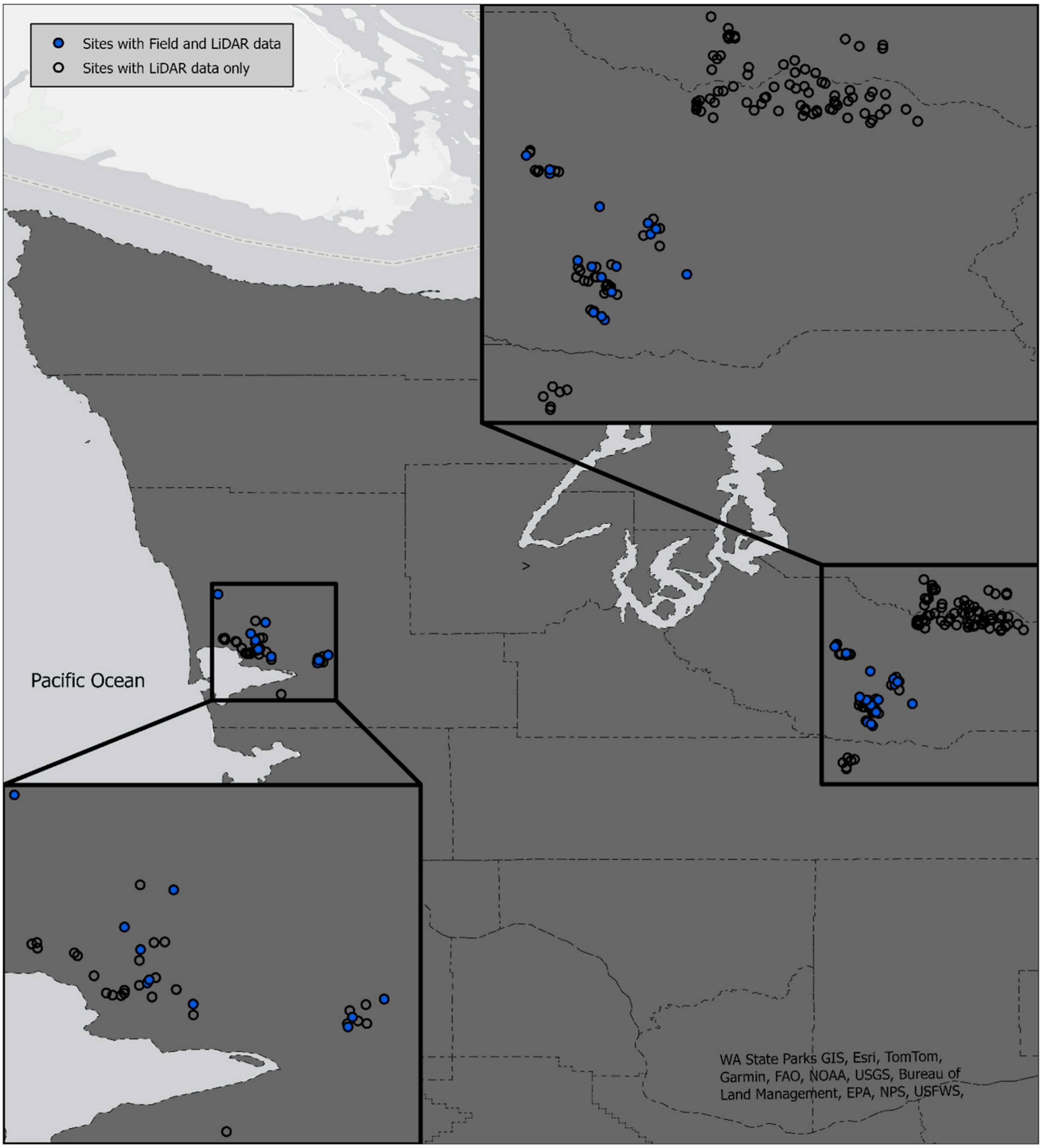

Fig. 1. The young Douglas-fir (*Pseudotsuga menziesii (Mirb.) Franco var. menziesii*) stands (ages 3–8) located across western Washington State, USA, with industrial LiDAR coverage (18–20 pulses per m^2) used in this study (n = 161). Blue dots are those sites that were used to validate LiDAR-derived heights.

average yearly and growing season (May-October) value was calculated for total precipitation, mean monthly temperature, mean maximum temperature, and mean minimum temperature for each site.

2.2. LiDAR data and height validation

Two separate aerial LiDAR acquisitions were utilized in this analysis: one from 2020 and one from 2021. The 2020 scan was performed using a Riegl VQ-1560I attached to a fixed wing aircraft at an average altitude of 1464 m, while the 2021 scan was performed using Riegl VQ-1560II between 2000 and 2500 m in altitude.

Lastools (Isenburg, 2014) was used to merge LiDAR tiles before clipping to stand boundaries using the R package LidR (Roussel et al., 2020). Digital terrain models for each stand were created using the Rasterize Terrain tool to create a 1 m triangulated irregular network of each stand. These digital terrain models were then used to normalize each stand using the normalize_height tool.

In the spring of 2022, 28 field sites were selected to generate a height validation dataset. The sites were selected to represent all age classes and soil characteristics captured in the LiDAR acquisition (Table 2). At each site, two, 5 m radius plots were installed on areas characteristic of the two extremes of stand's growing conditions. Usually, this presented itself as one upslope and one downslope location per site. At each plot, the heights of each Douglas-fir were collected with a height pole measuring to the nearest half centimeter. Heights were measured to the internode that would indicate growth at the end of the 2020, or 2021 growing seasons, corresponding to which year LiDAR scanning had been performed on that plot. Plot centers were recorded with a Javad Triumph-2 GNSS with sub-meter accuracy.

LiDAR height validation was performed using the R lidR package (Roussel et al., 2020) and plot-level data. GPS-coordinate plot-centers were buffered by 5 m to create a polygon plot shapefile. These plots were

Table 1
Site characteristics summary for all 161 sites with LiDAR data, including the mean and standard error for elevation (meters above sea level), age, and Douglas-fir (*Pseudotsuga menziesii (Mirb.) Franco var. menziesii*) height growth rates, total growing season precipitation (Wang et al. 2016), and mean annual temperature (MAT) (Wang et al. 2016). N indicates number of sites within each of the major soil order and texture characteristics from the Soil Survey Geographic Database (SSURGO), and the subsequent variables indicate the average and standard error of sites within each category (+/- indicates standard error).

Order	Texture	N	Elevation (m)		Age (Years)		Growth rate (cm•yr^{-1})		Total Growing Season PPT (mm•yr^{-1})		MAT (°C)	
			Mean	+/-	Mean	+/-	Mean	+/-	Mean	+/-	Mean	+/-
Alfisols		3	601.9	164.3	3.8	0.6	55.6	5.6	628.3	5.1	7.2	0.3
	Clay Loam	1	789.3	-	3.5	-	55.7	-	624.1	-	6.6	-
	Sandy Loam	1	533.8	-	3.5	-	61.1	-	638.3	-	7.0	-
	Silt Loam	1	482.6	-	4.5	-	49.9	-	622.3	-	7.8	-
Andisols		79	408.0	339.3	4.8	1.3	60.1	12.9	599.3	6.4	7.8	0.1
	Loam	24	655.8	161.8	4.6	1.2	54.4	7.4	598.9	9.8	7.0	0.1
	Loamy Sand	1	777.5	-	4.5	-	38.9	-	572.2	-	6.2	-
	Sandy Loam	5	489.3	314.8	4.5	1.0	52.4	7.3	474.7	40.8	7.7	0.8
	Silt Loam	49	270.8	335.9	4.8	1.3	64.1	13.8	612.7	5.7	8.3	0.2
Inceptisols		19	619.9	231.1	4.9	1.0	51.8	7.6	575.9	18.9	7.3	0.2
	Loam	15	576.4	229.4	4.9	1.0	51.6	7.4	561.1	22.4	7.5	0.3
	Silt Loam	4	783.1	173.1	5.0	1.3	52.5	9.4	631.4	10.6	6.6	0.3
Spodosols		60	838.5	200.3	5.4	1.0	51.3	11.4	582.8	13.1	5.9	0.1
	Loam	3	1116.5	191.5	5.8	0.6	41.1	10.9	594.9	29.0	4.6	0.4
	Loamy Sand	27	945.3	159.2	5.4	1.0	47.7	10.6	574.8	13.1	5.6	0.1
	Sandy Loam	30	714.5	147.9	5.3	0.9	55.5	10.7	588.8	23.4	6.4	0.1

Table 2
Field data summary of the validation sites' elevations (meters above sea level), ages, and Douglas-fir (*Pseudotsuga menziesii (Mirb.) Franco var. menziesii*) height growth rates for each of the major soil order and texture characteristics from the Soil Survey Geographic Database SSURGO (+/- indicates standard error).

Order	Texture	N	Elevation (m)		Age (Years)		Growth rate (cm•yr^{-1})	
			Mean	+/-	Mean	+/-	Mean	+/-
Andisols		20	**413.3**	**359.7**	**4.7**	**1.1**	**55.8**	**12.1**
Loam		5	805.6	97.1	4.7	0.8	48.5	4.5
Loamy Sand		1	799.5	-	6.5	-	59.3	-
Sandy Loam		1	231.3	-	5.5	-	66.6	-
Silt Loam		13	246.7	305.6	4.5	1.2	57.6	13.6
Inceptisols		4	**740.6**	**223.3**	**5**	**1.2**	**55.1**	**14.4**
Loam		3	682.3	231.2	4.8	1.4	60.7	11.7
Silt Loam		1	915.6	-	5.5	-	38.1	-
Spodosols		4	**718.5**	**234.1**	**5.7**	**0.9**	**60.7**	**12.2**
Loamy Sand		4	718.5	234.1	5.7	0.9	60.7	12.2

clipped from the normalized point clouds using the clip_roi tool. An individual-tree detection (ITD) function, locate_trees, was used to detect trees using a local maximum filter with a height minimum of 0.5 m and an adjustable window size defined by the following function:

$$f = (x * 0.1) + 3$$

Where f is the adjustable window size, x refers to the height above the ground of a point within the point cloud. The local maximum window size function was derived through parameter testing to minimize mean square error of height for each plot while ensuring tree counts always matched field values. Individual tree heights for each plot were output to lists where they were used to generate plot height averages. These plot averages were subsequently utilized with field plot averages to create a correction factor for LiDAR heights using linear regression. To create stand-level averages of height for all stands, the ITD algorithm and LiDAR correction factors established during the validation process were used on all stands. Stand-level tree lists of heights were generated using the locate_trees ITD algorithm. Tree heights greater than two standard deviations of the mean were removed to eliminate retained mature trees and buffer regions in the stand. This trimmed tree list was then related to field heights in a simple linear regression which produced an equation to correct the height underestimation bias from the LiDAR dataset. Stands were then averaged to generate a stand-level mean height. Mean heights were then turned into growth rates using stand establishment dates provided by industry partners. When recorded in management plan metadata, all planted growing stock was 2–0 (two years old) and were reportedly uniform in height when planted, 20–40 cm tall. Calculations of growth rates reflect the mean total height of the stand at scan date divided by years since planting.

2.3. Analysis

To examine the individual effects of soil texture, elevation, soil order, and slope on Douglas-fir growth, linear mixed effects models and analyses of covariance (ANCOVAs) were used to identify variables that were associated with Douglas-fir height and height growth rates (cm•yr^{-1}; total height divided by age). Douglas-fir annual height growth rates were calculated based on the LiDAR measured heights for each stand and the stand establishment year based on management records. For model response variables, age was used as a covariate while stand ownership was used as a random effect. Tukey's post-hoc tests were utilized to test for differences in slopes among groups.

Linear mixed effects models were performed using lmer from the R package lme4 (Bates et al., 2015; R Core Team 2023). When developing models for predicting Douglas-fir growth rate from all identified predictors, a best-subset selection was performed using the regsubsets function from the R package Leaps (Miller and Lumley, 2020) to identify best performing models. This function produced models with one to five variables included and selected the top five models of each size such that 25 models were selected. Each selected model was then run as a linear mixed effects model with age as a random effect. These models were then examined for collinearity using a variance inflation factor (VIF) from the package regclass (Petrie, 2023) and all models that included variables with a VIF greater than five were removed from consideration. The models with the best marginal r-squared values using r.squaredGLMM from the MuMIn package (Bartoń, 2023) were selected and where similar r-squared values occurred the model that minimized the Akaike Information Criterion (AIC) was selected. The alpha value for all tests was set at $p \leq 0.05$.

The models with the highest marginal r-squared values were then used to develop an index of site quality for young Douglas-fir stands using Python Version 3.9.3 (Python Software Foundation, 2021) and ArcGIS Pro Version 3.0.3 (ESRI Inc. 2022). Site-level height growth rates of young Douglas-fir were rasterized by combining three products: (1) 10 m digital elevation model from the US Geologic Surveys' 3D Elevation Program (3DEP), (2) a 30-year mean growing season precipitation (MGSPPT) raster layer which was produced using May-October precipitation data from Oregon States' Parameter-Elevation Regressions on Independent Slopes Model (PRISM), and (3) SSURGO soil maps. Maps were trimmed to areas within the range of elevations, precipitation rates, and soil orders represented in the dataset. The final product of this was a 10 m raster of young Douglas-fir height growth rates in centimeters per year within Washington State.

The young Douglas-fir growth rates product and existing site index data from SSURGO maps (i.e., King, 1966 and Monserud, 1984) were grouped into bins. Growth rate bins were based on the growth rate needed to outgrow most competing vegetation commonly found in young stands in western Washington (Carter et al., 2022). As such, the predicted growth rates were classified into five bins based on the number of years it would be expected to achieve a 3 m height (an approximate height at which trees can be assumed to be free to grow) based on the modeled growth rate. For comparison, site index values were extracted from SSURGO. This generated a shapefile of all map polygons that corresponded to soil orders represented in this study (spodosols, inceptisols, and andisols), with a site index value that was based on coastal Douglas-fir within Washington State. These polygons were then used to generate a 10 m raster product where each raster tile was given the value of the site index of the polygon that covered most of the created tile. The Douglas-fir SSURGO site index raster was divided into five growth classes based on even quintiles The growth-classes for both the young Douglas-fir growth raster and the Douglas-fir SSURGO site index raster were both ranked from 1 to 5 with 1 being the slowest growing (lowest quality site; ≥8 years to reach 3 m in height) and 5 being the fastest growing (highest quality site; ≤5 years to reach 3 m in height). These rasters were then subtracted from each other to examine areas where the young Douglas-fir index of site quality and the Douglas-fir SSURGO site index differed in ranking of site quality.

3. Results

3.1. LiDAR correction

LiDAR predicted heights underpredicted field heights by approximately 20 % (Fig. 2). Regressing field height with LiDAR height provided a correction with a high R^2 value of 0.91. The correction equation was:

$$48 + 1.2 * x$$

where x is the height in cm derived from LiDAR.

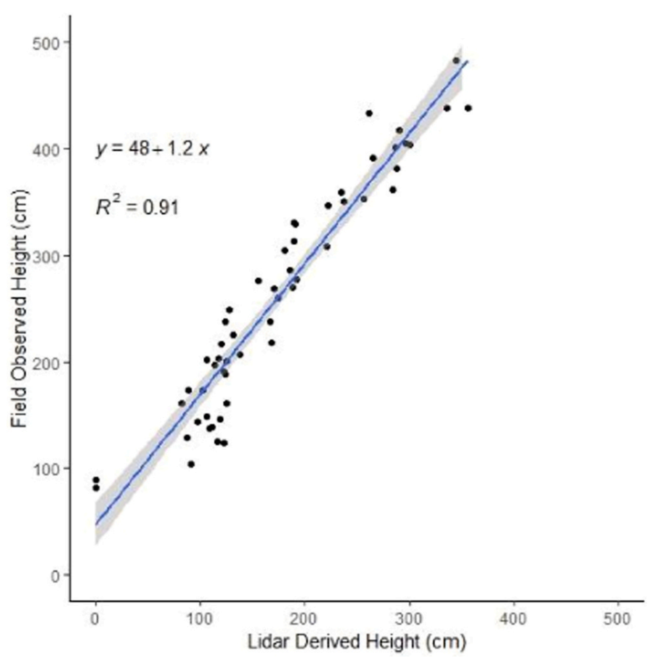

Fig. 2. Comparison of LiDAR-derived Douglas-fir (*Pseudotsuga menziesii (Mirb.) Franco var. menziesii*) height measurements and field height measurements for 56 validation plots across 28 sites in western Washington State, USA. The linear model y = 48 + 1.2x represents the equation to correct LiDAR-derived heights to align with field-measured heights.

3.2. Soil and growth rate

Major textural classes showed significant interactions with age to predict Douglas-fir height ($F = 18.0$, $p < 0.01$). Douglas-fir total height growth accumulation in years 3–8 was greater in fine-textured soils, such as silt-loams and loams, than coarse texture soils, such as sandy loams and loamy sands (Fig. 3). Douglas-fir growing on silt loams ($\beta_1 = 85.6 \pm 7.6$ cm•yr^{-1}) tended to grow more rapidly than both sandy loams ($\beta_1 = 42.8 \pm 9.2$ cm•yr^{-1}, $p < 0.01$), and loamy sands ($\beta_1 = 20.4 \pm 8.5$ cm•yr^{-1}, $p < 0.01$). Despite these significant relationships with soil texture, particle size variables by depth were not significant predictors for Douglas-fir growth rates (Table 3).

While soil order was not a significant predictor of growth rate, young Douglas-fir grown on andic soils tended to have greater height for a given age than other soil orders (Fig. 4) and were approximately 50 cm greater in height by age five than the next closest soil order's height.

The slope of heights on andic soil in relationship to age was significantly greater than that of the spodic soils ($p < 0.01$)

Elevation displayed strong relationships with Douglas-fir growth rate (Table 3) and, correspondingly, a strong relationship existed with site temperature as both growing season and mean annual temperatures showed significance ($p < 0.01$). Mean stand elevation had the highest R^2 (0.42) of any single variable predicting Douglas- fir growth rates. Growth rates decreased with increasing elevations (Fig. 5; $\beta_1 = -0.023 \pm 0.003$; $p < 0.01$).

Of the many permutations of models examined, three had moderately strong R^2 values for predicting young Douglas-fir growth rates. Mean annual temperature produced the highest marginal R^2 and one model utilizing taxonomic order, mean elevation and mean growing season precipitation had the highest conditional R^2 and lowest AIC (Table 4).

Similar to the pattern demonstrated in Fig. 4, we found that the model that utilized soil taxonomic order as a predictor showed andisols had the highest intercept (Table 5). The parameters for spodosols had the lowest intercepts of the three orders but significant slope coefficients for both elevation and mean growing season precipitation parameters.

The greatest growth rates were found in the low elevation sites along the coast (Fig. 6). Additionally, this model demonstrated that there are reduced growth rates as elevation increases and precipitation decreases.

When comparing SSURGO site index value rankings and the new, modeled young Douglas-fir index of site quality ranking spatially, 35.3 % of tiles showed no difference in ranking and 50.3 % showed only a difference of one (Fig. 7). Differences greater than one index value ranking occurred at high elevations (Fig. 7).

4. Discussion

Modeling early growth of Douglas-fir is essential for management planning as intervention, especially in regard to competition control, early in a stand's development can have a significant impact on survival and growth patterns of seedlings (Wagner et al., 2006). While traditional site index models have largely ignored younger growth due to its perceived unpredictability, models in this study demonstrated agreement with base age 50 site index values. As suggested in Carmean (1975), elevation and mean annual temperature served as primary predictors of young Douglas-fir growth rates while factors such as precipitation, soil order, and slope provided differentiation within areas of similar elevation. Fine-textured soil and low elevations were overall associated with greater growth rates within the western Washington region.

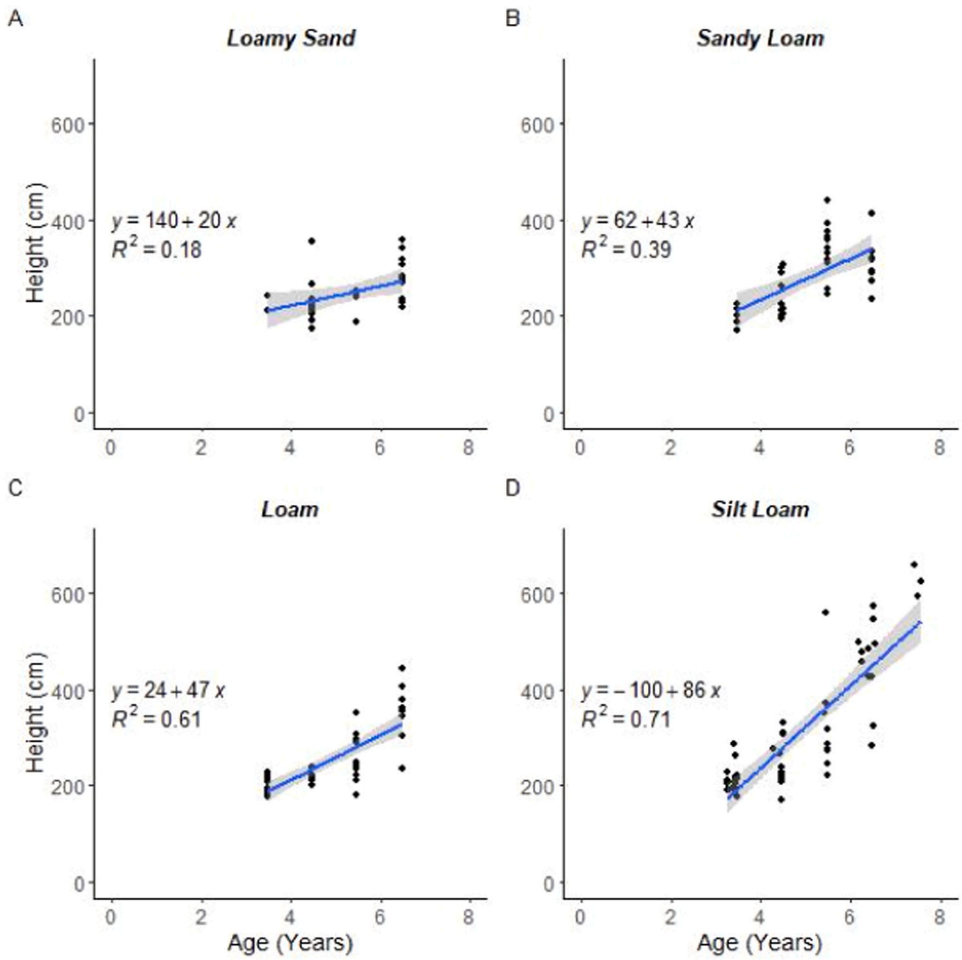

Fig. 3. Douglas-fir (*Pseudotsuga menziesii (Mirb.) Franco var. menziesii*) LiDAR corrected heights plotted by age for Soil Survey Geographic Database major textural classes in western Washington State, USA.

Table 3
The linear model and analysis of variance results for Douglas-fir (*Pseudotsuga menziesii (Mirb.) Franco var. menziesii*) growth rate and variables extracted from the Soil Survey Geographic Database and average stand elevation (m) extracted from LiDAR scans. Results are for models that include age as a covariate and ownership as a random effect.

Variable	Growth Rate (cm•yr^{-1})		Height (cm)	
	Test Statistic	*p*	*F*	*p*
% Sand 0–30 cm	t = 0.49	0.49	39.09	< 0.01
% Sand 30–60 cm	t = 0.63	0.43	31.67	< 0.01
% Silt 0–30 cm	t = 0.05	0.82	35.79	< 0.01
% Silt 30–60 cm	t = 1.58	0.21	31.86	< 0.01
% Clay 0–30 cm	t = 2.37	0.13	45.53	< 0.01
% Clay 30–60 cm	t = 3.03	0.08	40.02	< 0.01
Elevation (m)	t = 78.49	< 0.01	92.84	< 0.01
% Slope	t = 0.17	0.68	15.85	< 0.01
Texture Minor	*F* = 5.55	0.16	8.08	< 0.01
Texture Major	*F* = 2.35	0.06	18.03	< 0.01
Taxonomic Order	*F* = 0.49	0.69	11.57	< 0.01

We hypothesized that fine-textured, low-elevation sites would be associated with the greatest growth rates in young Douglas-fir. Our findings partially support the hypothesis as fine textured soils produced greater growth at lower elevations; however, there was not a significant continuous trend. These results align with previous studies (i.e., McArdle and Meyer, 1930; Carmean, 1954). The trend of increasing growth rates with increasing fine soil fractions met our expectations. The results were very similar to growth rate patterns of young Douglas-fir from Carter et al. (2022), where increasing percent sand in the top 30 cm of soil depth resulted in decreasing growth rates, increasing silt percent resulted in an increased growth rate, and increasing clay percent resulted in an even greater increase in growth rate than silt. These results were consistent with the results of the major textural classes where classes that shifted towards the silt and clay end of the texture spectrum exhibited greater growth rates than those with higher proportions of sand. As in Carter et al. (2022), the results here are likely to indicate an influence of soil texture on soil water content as the fine-textured soils, especially silt loams, have larger volumes of plant-available water compared to coarser textured soils.

On its own, precipitation was a rather weak predictor but, when combined with elevation, it contributed to significant model improvements. Our findings reflect that when elevations are constant, sites with greater precipitation and hence greater water availability will produce greater growth. This finding, combined with the greater growth rates on sites with fine-textured soils, indicates that greater soil water availability is an important factor for height growth for young, coastal Douglas-fir, behind the growing season length impacts of elevation.

Elevation and mean annual temperature were found to be the strongest predictors of height growth in this study. The two variables were correlated, however, with mean annual temperature being the marginally stronger predictor of the two. Elevation was able to be combined with other factors to provide a better overall model fit than mean annual temperature alone. However, mean annual temperature exhibited covariance issues with other useful variables, such as mean total growing season precipitation, that elevation did not. This allowed

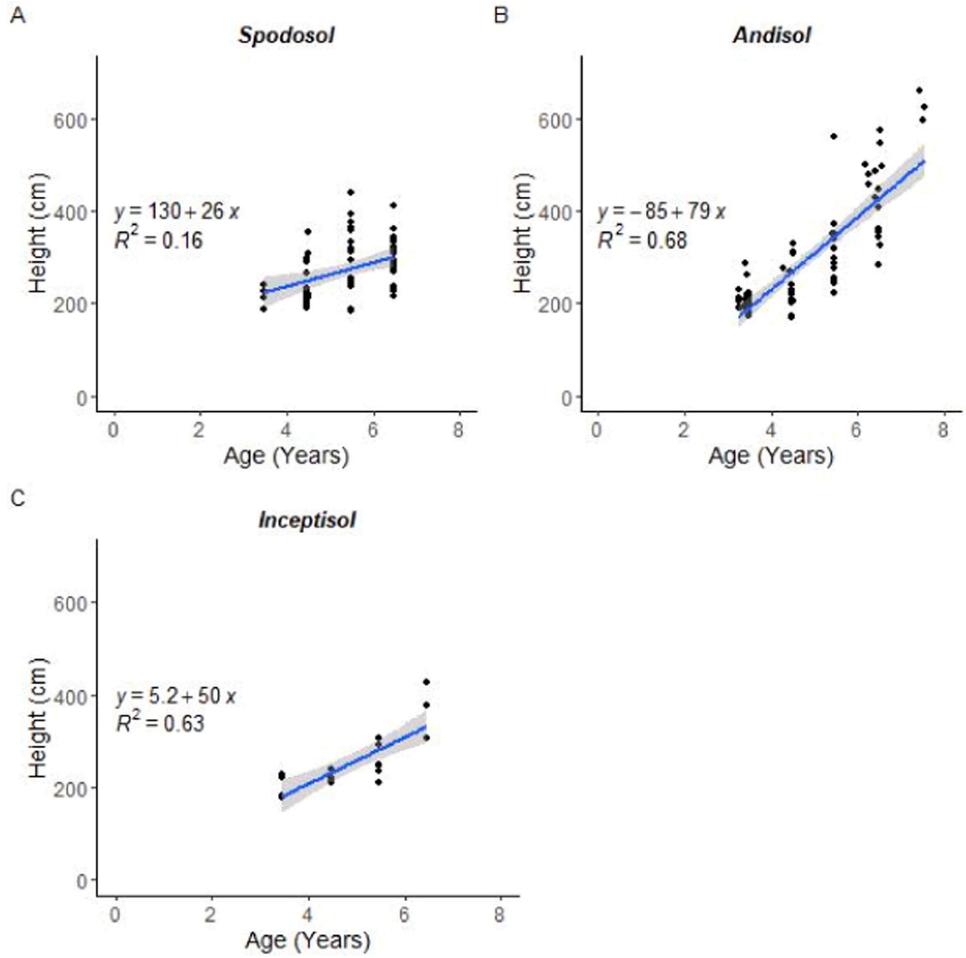

Fig. 4. Douglas-fir (*Pseudotsuga menziesii (Mirb.) Franco var.* menziesii) LiDAR-corrected heights plotted by age (ranging from 3 to 8 years old) among soil orders in western Washington.

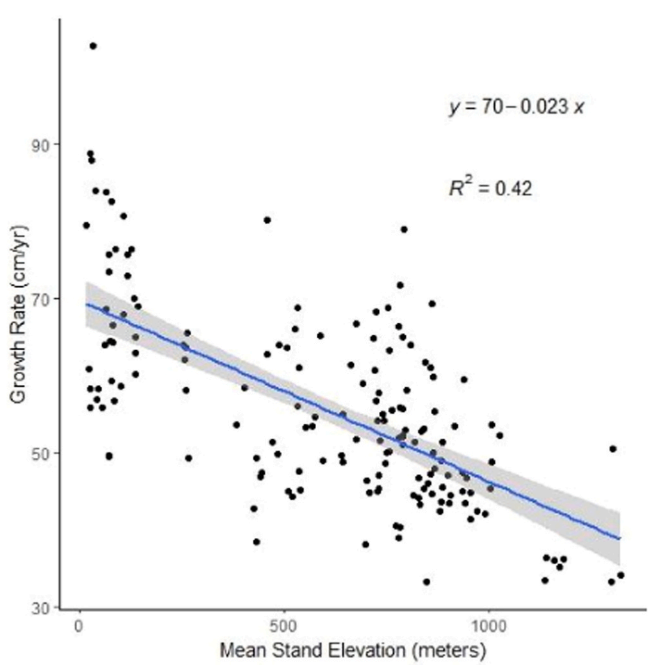

Fig. 5. Relationship between western Washington Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco var. *menziesii*) stand-average height growth rate in years 3–8 derived using LiDAR-derived heights and planting dates.

Table 4
Summary of models predicting young Douglas-fir (*Pseudotsuga menziesii (Mirb.) Franco var. menziesii*) height growth rate (cm•yr-1); **ORDER**: Taxonomic Order (Andisol, Inceptisol, Spodosol), **ELEV**: mean stand elevation (m), **MUS**: mean map unit slope (%), **GSP**: mean growing season precipitation (mm), **MAP**: mean annual precipitation (mm), and **MAT**: mean annual temperature (°C). Coefficients for each level of "ORDER" are provided in Table 5.

Response Variable	Model (+/- indicates direction of relationship)	AIC	Marginal R^2	Conditional R^2
Growth Rate (cm•year^{-1})	ORDER – 0.024 ELEV + 0.033 GSP	1178	0.37	0.56
Growth Rate (cm•year^{-1})	56.46–0.024 ELEV + 0.11 MUS + 0.01 MAP	1197	0.39	0.55
Growth Rate (cm•year^{-1})	31.32 + 4.042 MAT	1187	0.47	0.48

elevation to feature more frequently in high-ranking models with multiple predictors than the mean annual temperature. Our study exhibited a persistent decreasing pattern in growth with increasing elevations from 15 to 1300 m across a range of soil textures. This agrees with the site quality findings for Douglas-fir by Carmean (1954) who described a decreasing site index across a gradient of elevations from 0 to 1500 m. The pattern shows that Douglas-fir growth can be limited by low temperatures at high elevations (Case and Peterson, 2005). The lower temperatures and heavy snowpacks at high elevations delay the beginning of the growing season for these trees, allowing lower elevation trees

Table 5
Parameters and standard errors (SE) for individual soil orders from the selected model for predicting Douglas-fir (*Pseudotsuga menziesii (Mirb.) Franco var. menziesii*) growth rate in western Washington State of the model *Growth Rate = Taxonomic Order - Mean Elevation + Mean Growing Season Precipitation (GS PPT)*.

Soil Order	Response Variable	Intercept (Coefficient +/- SE)	Mean Elevation (Coefficient +/- SE)	Mean GS PPT (Coefficient +/- SE)
Andisol		60.864 + /- 11.740	−0.020 + /- 0.005	0.015 + /- 0.020
Inceptisol	Growth Rate	56.261 + /- 19.207	−0.009 + /- 0.016	0.004 + /- 0.048
Spodosol		55.517 + / −7.809	−0.030 + /- 0.006	0.037 + /- 0.011

to take advantage of this longer season and produce greater growth (Carmean, 1954). However, while our findings align with previously assumed concepts about Douglas-fir site quality, existing site indexes for Douglas-fir in this region are usually calibrated to either low elevation sites (King, 1966; Bruce, 1981) or to high elevations (Curtis et al., 1970; Monserud, 1984). Comparisons made between these site indexes have shown that there is little overlap in site qualities covered, with most of the high elevation site indices having height predictions at age 50 well below any measured in low site index studies (Monserud, 1985). The differences based on elevation are apparent, as we saw increasing disagreement between the young Douglas-fir model growth class ranks and the SSURGO site index growth class ranks at higher elevations. The higher frequency agreement in rank across the lower elevations, especially in the Puget lowlands, may show that the site index values are more effective at predicting young growth rates in areas where changes in elevation are not a significant factor. The young Douglas-fir model's basis in elevation allows it to cover a larger range of coast Douglas-fir than most Douglas-fir site quality models that are elevation constricted. Our model's increased range coverage and accuracy in predicting the growth rates of young stands compared to traditional site index provides a unique tool manager can utilize when assessing young stands.

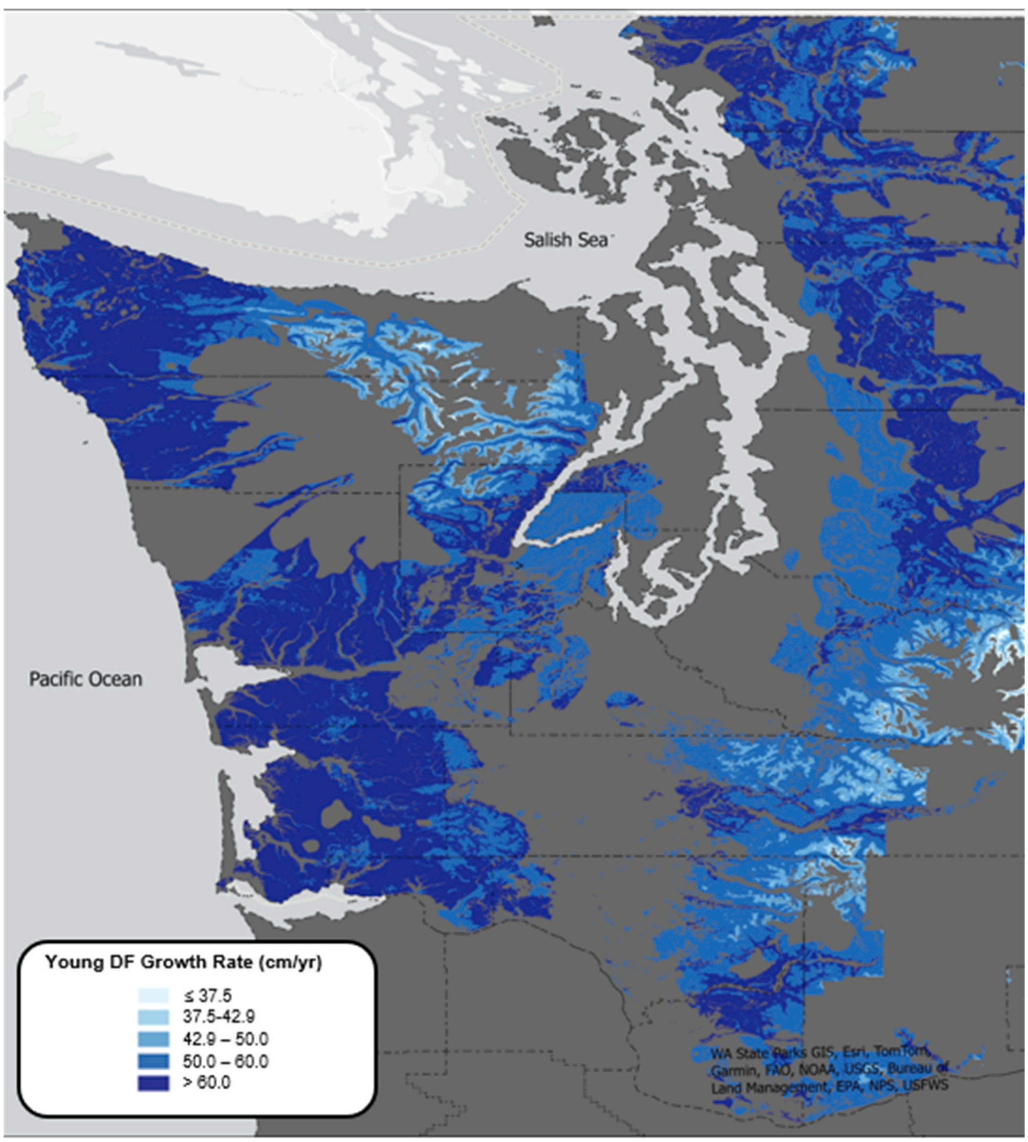

Fig. 6. Map of Douglas-fir (*Pseudotsuga menziesii (Mirb.) Franco var. menziesii*), ages 3–8 years, growth rates predicted by the model Growth Rate = Taxonomic Order - Mean Elevation + Mean Growing Season Precipitation. Symbology class ranges indicate the number of years a tree would be expected to take to grow to 3 m of height on a given site, when one can assume Douglas-fir has established dominance over competing vegetation and claimed the site (i.e. "free to grow"). The fastest growth class will reach 3 m in approximately 5 years while the slowest growth class will reach 3 m in more than 8 years.

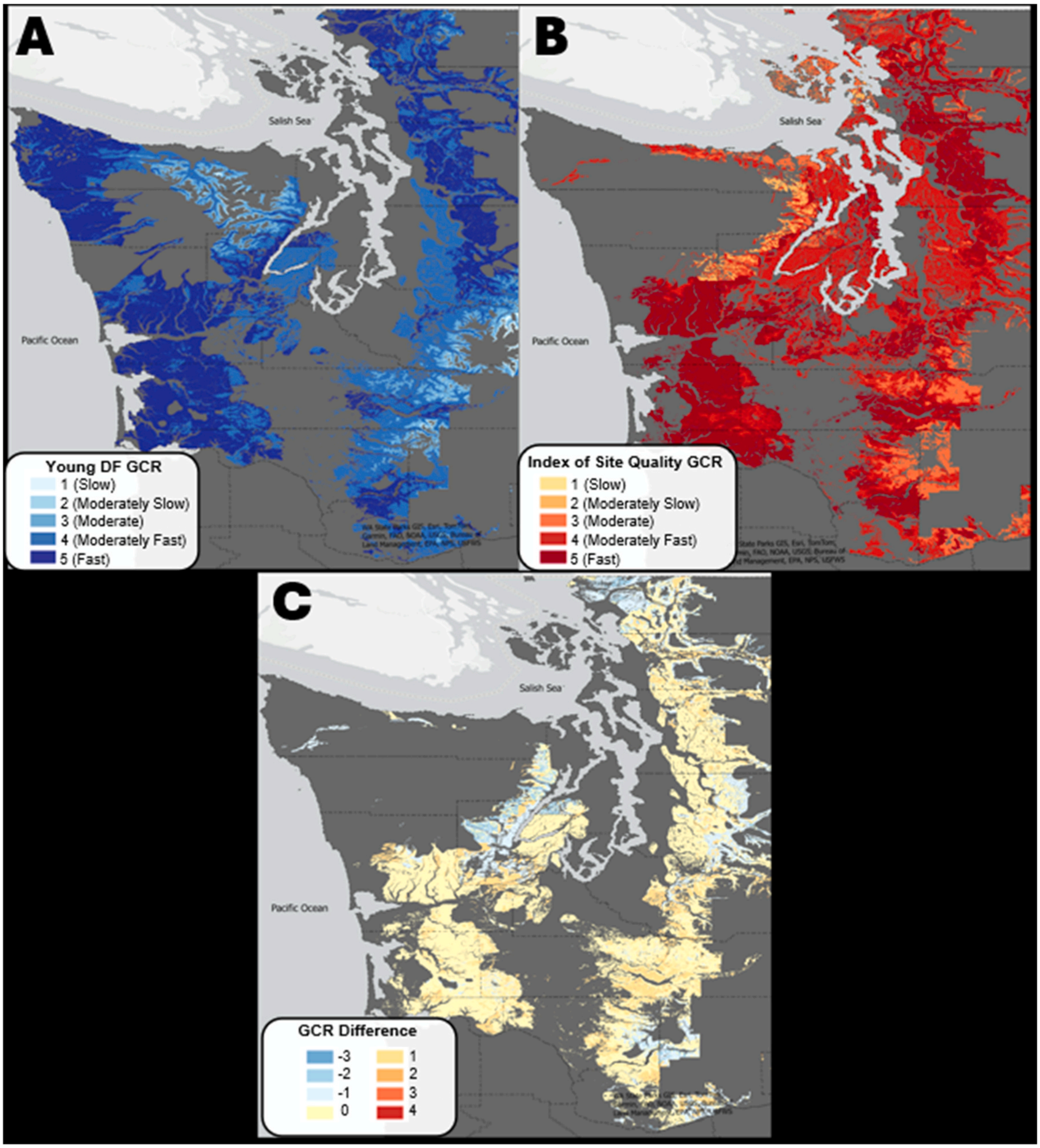

Fig. 7. Map of young (ages 3–8 years) Douglas-fir (*Pseudotsuga menziesii (Mirb.) Franco var. menziesii*; DF) growth class rankings (GCR) predicted by the model Growth Rate = Taxonomic Order - Mean Elevation + Mean Growing Season Precipitation (A), Compared with USDA Soil Survey Mapped Site index GCRs (B). The difference between the two systems GCR (C) is shown as the Index of Site Quality GCR - Young Douglas-Fir GCR where values represent the tendency of the models to agree or disagree on the quality of a site. Young DF GCR: 1 ($\leq$37.5 cm·yr^{-1}),2 (37.5–42.9 cm·yr^{-1}), 3 (42.9–50.0 cm·yr^{-1}), 4 (50.0–60.0 cm·yr^{-1}), 5 (>60.0 cm·yr^{-1})); (Site Index GCR: 1 ($\leq$56.9 ft),2 (56.9–76.9 ft), 3 (76.9–100.4 ft), 4 (100.4–122.2 ft), 5 (>122.2 ft)). GCRs are based on the number of years required to reach 3 m in height or "free to grow" status: GCR 1 $\geq$ 8 years, GCR 2 = 7 years, GCR 3 = 6 years, GCR 4 = 5 years, GCR 5 = < 5 years.

Dominant and co-dominant stems were not selected from the LiDAR data per stand. While there could be advantages to this in the form of generating greater correlation to base age 50 site index values, we argue that valuable data exist in evaluating virtually all heights in a stand. Not constrained by the need to physically measure stems in the field, LiDAR and photogrammetric point clouds (Ritz et al., 2022) provide the benefit of having nearly complete spatial coverage of a stand. Therefore, sub-stand variation in site quality can be captured using these methods (Raigosa-García et al., 2024). These values may provide a more robust estimate of stand-wide site quality rather than potentially over-estimating site index based on what could be locally favorable growing environments for relatively few stems exhibiting dominant or co-dominant status. With vegetation typically sufficiently controlled in intensively managed stands, any confounding in estimates due to suppression by competing vegetation ought to be low and young, planted trees are exhibiting little if any competition on each other during stand establishment at typical planting densities of Douglas-fir in western Washington. Therefore, the heights of each individual tree may be providing data on the quality of the site and, in aggregate, may be expressing a more realistic stand-level estimate of site index. Importantly, this argument would not hold in poorly managed, young stands with abundant competing vegetation or old stands with inter-tree competition. Due to limited information on growing stock and genetics, this study was unable to consider differences that may have occurred as a result of planting stock as opposed to site quality. Personal communications with managers indicated it was likely all stock planted was two years old and genetically suited for the elevations of the sites. Depending on the vendor, percent gains listed for growing stock suited for a given locality can vary by 10 % or more. Seedlings of different ages or genetics may diverge from the patterns we found, but we believe our 161 sites captured the majority of the range in variability one could encounter at present.

5. Conclusion

In western Washington State, elevation, average precipitation and soil texture are dominant factors in determining site quality in young Douglas-fir (ages 3–8 years) plantations. Our data suggest young Douglas-fir grow better on sites at low elevation and in fine-textured soils. This study demonstrated the use of LiDAR and individual tree detection algorithms for the measurement of young trees and the potential to capture regional variability that was previously sample-size prohibitive using traditional field methods. The method outlined in this study can be applied to other systems to develop indices of site quality for ages existing site quality metrics fail to describe well. While the R^2 values measured in this study (0.37–0.56) can be improved upon, the index we generated fill a knowledge gap where no previous index existed. Future work should include validating the models created against newly collected field data. The importance of having site quality metrics for this age range is critical as early interventions can increase site index or shorten rotation length. Conversely, early growth lost to improper management cannot be fully recovered without extending the rotation (Westfall et al., 2004).

CRediT authorship contribution statement

David R. Carter: Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Robert Slesak:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Valerie Thomas:** Supervision, Formal analysis, Conceptualization. **Brian Strahm:** Supervision, Investigation, Formal analysis. **Grady Boyle:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Robert Slesak reports financial support was provided by USDA Forest Service Pacific Northwest Region. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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