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Title: Forest Soils and Topography: Decoding the Influence of Physical Site Characteristics on Soil Water and Forest Productivity in Oregon's Coast Ranges

Abstract approved: ____

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Forest soils and topography have long been known to influence forest productivity in complex terrain such as Oregon's Coast Ranges. Incorporating physical site characteristics into predictions of forest growth and yield, however, has been problematic because of the high spatial variability of soil properties and the challenges associated with representing topography and soil properties at the stand level. We assessed the efficacy of using a combination of a spatially intensive surface soil sample and terrain indices derived from a digital elevation model for explaining local variability in forest productivity across a forested watershed in northwestern Oregon. Analysis of correlations between several textural characteristics of the surface soil horizon and the average values for the top 100 cm showed that surface soil samples could provide an index of deeper-soil water holding capacity. Analysis of a time series of soil moisture observations from 34 locations in the Panther Creek

Watershed revealed that surface soil texture, topographic wetness index, and slope can be used to predict relative soil moisture availability near the end of the growing season.

We integrated the findings of the first two analyses to assess the influence of surface soil texture, hydrology, and topography on fine-scale variability of basal area periodic annual increment, height increment, and site index across five intensively-managed Douglas-fir plantations within the Panther Creek Watershed. Basal area periodic annual increment was maximized on sites that slope approximately to the south-southwest on the shoulder of ridges, and did not appear to depend on any surface soil characteristics. In contrast, site index was maximized in north-facing draws and increased with clay content of the surface soil.

Forest Soils and Topography: Decoding the Influence of Physical Site Characteristics on Soil Water and Forest Productivity in Oregon's Coast Ranges

by

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

Henry Rodman, Author

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The two years I spent in Corvallis have passed more rapidly than I thought

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Chapter 1 General Introduction

In western Oregon, the climate is characterized by mild, wet winters and warm, dry summers. It follows that forest growth in this region is often limited by soil water availability during the growing season. It has been demonstrated that Douglas-fir (*Pseudotsuga menzesii*) productivity is heavily regulated by a combination of water availability and high vapor pressure deficits during the growing season (Emmingham and Waring, 1977; Waring et al., 2008); however, applying this principle in forest growth and yield predictions is not common due in part to the difficulty of attaining reliable stand-level estimates of soil characteristics. Available water holding capacity of the soil is approximately equivalent to the amount of water available to vegetation during the growing season in the absence of inputs from growing season precipitation and subsurface flow, but estimating this characteristic using established methods is too cumbersome to be applied operationally for high-resolution stand-level estimates. The development of a sampling method that can provide reliable estimates of available water holding capacity of the soil will be a foundational step towards the greater goal of explaining observed differences in forest productivity among sites and predicting seasonal and annual variation in growth.

While relatively few soil parameters are probably adequate to significantly enhance the use of soil factors to understand patterns in forest productivity across the landscape, soil survey protocols traditionally entail digging deep soil pits so that the entire soil profile can be characterized in great detail. This procedure tends to be very labor-intensive and, especially in topographically heterogeneous regions such as western Oregon's Coast Ranges, subsequent efforts at mapping soil characteristics from widely dispersed soil pits do not yield a great deal of information that can be applied to understanding growing conditions within a forested stand (Moore et al., 1993).

Available water holding capacity (AWHC) is defined as the volume of water stored in the soil between its field capacity and wilting point and is used to describe the amount of water available to plants during the growing season, assuming soils enter the growing season at field capacity and receive no recharge by precipitation or lateral flow (Hendrickson and Veihmeyer, 1945). Controlled by the soil depth, texture, organic material, bulk density (weight per unit volume), and coarse fragment content, AWHC can be measured directly by laboratory analysis, or estimated using pedotransfer functions that can calculate the soil's field capacity and wilting point from previously established empirical relationships (Pachepsky et al., 2006; Saxton et al., 1986). Laboratory analysis provides the most precise estimates of soil properties, but it is resource intensive (Rawls et al., 1982; Ryan et al., 2000). Furthermore, it is not clear that, at the spatial frequency of samples typical of soil survey, the added precision can provide keener insight into forest productivity responses than faster, more cursory methods focused strictly on textural assessment with subsequent application of pedotransfer functions for parameters of interest.

1.1 Limitations of soil survey information in forestry

Upon collection and analysis of soil samples, mapping soil attributes requires interpolation between sample locations. The Natural Resources Conservation Service (NRCS) maps soils across a large portion of the U.S. using interpolation guided by auxiliary information like topography and vegetation. However, the spatial variability in soil attributes across topographically complex areas like the Coast Ranges of Oregon must be known at a finer resolution to inform stand-level silvicultural decisions. Despite the limitations of the NRCS maps, the descriptions of soil series across the region provide a baseline for further investigation of specific topographic features that correlate with the available soil water holding capacity.

1.2 Characteristics of an operationally viable soil survey

One possible solution to the problems associated with applying soil survey information for estimating forest productivity is to implement an abbreviated soil sampling protocol that could a) be feasibly implemented at a higher sampling intensity, b) be paired with remotely-sensed information, and c) provide estimates of soil water availability in the key upper rooting zones. Since the majority of field time and effort expended in soil survey is spent digging soil pits, describing the soil profile, and collecting samples for laboratory analysis, a method that focused on observing the textural class of only the surface soil horizons may be adequate for site-specific indices of AWHC and therefore could offer an operational tool that could feasibly become part of a timber cruise or stand exam protocol. For this approach to soil sampling to be useful, one key assumption would have to hold, that is, the surface soil texture and water holding capacity are correlated with these same characteristics in deeper soil horizons of the soil at that location.

1.3 Terrain analysis

Geostatistical interpolation methods such as kriging have been used to predict the spatial distribution of some soil attributes at large scales, but patterns of variation in soils are difficult to predict at small scales using these techniques (McKenzie and Ryan, 1999). To increase the predictive capability of soil samples from the field, environmental variables derived from digital terrain models can be used to stratify the landscape for optimized sampling and spatial coverage (McKenzie and Ryan, 1999). The use of terrain analysis in describing soil distribution across a landscape forms the basis for pedometrics, a branch of soil science that applies rigorous statistical methods to relate soils to topographic and climatic information (McBratney et al., 2000). This type of double sampling takes advantage of recent advances in remote sensing technology and computing power to blend high-resolution, remotely-sensed spatial datasets with precisely located field observations.

Light Detection and Ranging (LiDAR) is a remote sensing technique that can produce high-resolution (< 1 m) digital terrain models. Digital terrain models are built to model topographic features and can subsequently be used to calculate terrain indices to explain vegetation distribution and productivity in some areas (Iverson et al., 1997). Spatial distributions of soil moisture and soil series across a landscape have been described with respect to topography, hydrology, and soil samples using topographic analysis and geophysical remote sensing (Lin et al., 2006; Murphy et al., 2011; Ryan et al., 2000). In addition to LiDAR, techniques such as gamma radiometric remote sensing can be used to obtain information about soils (e.g., particle size, parent material) that may contribute to the spatial variability of soil properties (McKenzie and Ryan, 1999; Ryan et al., 2000). The pairing of remotely sensed data with field observations is made more powerful by the precise matching of spatial locations by global positioning systems (GPS).

1.4 Topographic controls on water availability

In Mediterranean climates, water availability during the growing season is a function winter precipitation and its magnitude relative to field capacity (as determined by soil texture, structure, and depth), and growing season inputs from precipitation and subsurface flow. As one of many soil-forming factors, topography has a profound influence on the first and last of these hydrological processes. Topography controls the vertical distribution of soil particles both within the soil profile, and across the vertical range of a hillslope. Additionally, it controls the spatial and temporal patterns of subsurface flow throughout the year.

Soil moisture availability during the growing season is the primary variable of interest for assessing the potential productivity of Douglas-fir. In a comparison of the productivity of Douglas-fir in western Oregon and New Zealand, Waring et al. (2008) demonstrated that productivity is much higher in New Zealand because there is more precipitation during the growing season than in western Oregon. If soil water stored during the winter is the predominant source for trees during the growing season, then sites with access to deep soil horizons, higher inherent AWHC, and inputs from horizontal subsurface flow should be the most productive. The use of terrain analysis in assessing the latter characteristic is promising since digital elevation models are relatively easy to obtain and analyze. Using DEM-derived terrain indices to fine-tune estimates of growing season water availability may help approximate the relative amount of inputs from subsurface flow. For example, Baggaley et al. (2009) showed that several topographic wetness indices were reasonably well-suited to predicting soil moisture levels at various times of the year when combined with information from a low-resolution soil survey.

1.5 Forest productivity

Site quality has historically been incorporated into predictions of forest productivity in North America through the use of site index, a bioassay of resource availability measured by height attained by dominant and co-dominant trees at some reference age. However, the effort to find correlations between site index and edaphic site factors have met with varying degrees of success (Carmean, 1975;

Monserud et al., 1990; Steinbrenner, 1979). Topography has long been known to influence site productivity; however, quantifying this influence has been challenging because topography represents a complex gradient of many environmental factors that include incident solar radiation, potential evapotranspiration, and associated influences on parent material weathering rates, soil texture, soil structure, and soil depth. The relationship between forest productivity and slope, aspect, and elevation can be modeled using trigonometric transformations of slope and aspect that were first proposed by Stage (1976) and later improved by Stage and Salas (2007); however, these interactions vary regionally and have yet to be documented in northwestern Oregon.

The use of site index in growth and yield models is very appealing because it is relatively easy to measure and distinguishes stands with rapid height growth rates from those with slower height growth rates, and similarly distinguishes stands with differences in volume yields that are attributable to differences in top height of the stands. However, site index as a bioassay may be influenced by silvicultural activities like thinning, fertilization, and genetic tree improvement, as well as fluctuations in climatic factors, so cannot be assumed to be fixed across successive growth periods or even successive rotations. The procedure for estimating site index also involves a degree of subjectivity in selecting ‘site trees’, and opportunities for error arise when measuring top heights of dominant trees in mature stands, particularly in mature stands, and when measuring their total or breast height age. In principle, site index provides an easily observed estimate of height growth response to factors that govern site fertility for net primary production.

Site index, however, provides limited insight into mechanisms by which various soil and climatic factors interact functionally to drive trends in productivity across the landscape. Perhaps of even greater concern, site index does not account for differences in site stockability, or basal area carrying capacity, a dimension that contributes to significant variability in volume production potential among stands with a common site index (Assmann, 1970; Curtis, 2006; Hamilton and Christie, 1971). Observed differences in basal area or volume carrying capacity for a given top height inspired Assmann (1970) to distinguish between “height quality classes” and “mai-quality classes”, and to base yield tables on “yield classes”. These yield classes captured the integrative influence of soil and climatic factors on both height and basal area growth potential. Yield differences for a given top height have been corroborated by many others and have brought life to the debate about the validity or performance of site index, and to Eichorn’s rule which states that a species’ volume yield for a given mean top height will be equal at maximum stand density regardless of site index (Skovsgaard, 2009; Skovsgaard and Vanclay, 2008).

1.6 Objectives

The overarching objective for this study was to explore alternative methods for operational estimation of soil characteristics without the laborious exercise of excavating soil pits. Two potentially useful relationships between deep soil profile characteristics and several more easily observed attributes were tested to answer these questions:

- Can a textural assessment of the top 10 cm of mineral soil provide an index for the full soil profile? Specifically, is there a correlation between surface soil textural components (i.e., sand, silt, clay, coarse fragment content) and AWHC for the entire soil profile?

- Can DEM-derived topographic indices help refine estimates of available water supply by accounting for the relative amount of inputs from subsurface flow during the growing season?

- Can a combination of surface soil samples and a spatially extensive assessment of the relative soil water supply as indicated by DEM-derived topographic indices be used to assess the productive potential of forest area in Oregon's Coast Ranges?

To address the first question (Chapter 2 of this thesis), we examined the correlation between textural components of the top 10 cm of the soil and the weighted average (by depth) for the top 100 cm using two independent datasets, one from a geographically extensive soil survey in southwestern Oregon, and one from a geographically concentrated soil survey in northwestern Oregon's Coast Range (Panther Creek Study Area). Additionally, we examined the capacity of surface soil texture for predicting relative soil moisture as water becomes limiting during the end of the growing season in western Oregon. To address the second question (Chapter 3 of this thesis), we analyzed a time series dataset of soil moisture observations at Panther Creek, employed terrain analysis methods to characterize the topography of the area, and used linear regression to assess the relationships between topography and patterns of growing season soil moisture dynamics. The results of the analyses described above provided a theoretical foundation for our assessment of local gradients in forest productivity and their response to corresponding gradients in soil properties and topographic conditions in the Panther Creek Watershed (Chapter 4 of this thesis).

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Chapter 2 Relationships between surface soil texture and deep-soil characteristics

Abstract

Water holding capacity of forest soils is a major determinant of Douglas-fir productivity in the Coast Ranges and Cascsade foothills of western Oregon. Existing soil maps appear too coarse for stand-level assessment of productivity, and conventional soil pits are too time consuming to use as an operational tool to accompany inventory measurements, stand exams, or timber cruises. Given a sufficiently high correlation between the textural class of surface layers of forest soils and either deeper layers or estimates of the total water holding capacity, quick assesments with a standard soil probe might enhance current information available from mapped soil units provided by the Natural Resources Concervation Service. The use of upper soil textural class to infer deeper-soil characteristics of forest soils was tested by analysis of 426 soil pits from two independent datasets in western Oregon. Results of linear regression analysis show that surface soil texture appears to provide a reasonable estimate of several deeper-soil characteristics, including percent clay, percent sand, and coarse fragment content.

2.1 Introduction

A substantial body of forest soils research has been devoted to explaining the relationships between soil attributes and forest productivity. These "soil-site studies" focus on observations of the apparent response by individual species to the range of soil conditions commonly found within a specified region. In the Douglas-fir region, the most widely referenced study which discusses the specific site and soil attributes that influence forest productivity is Steinbrenner's (1979) publication, *Forest soils productivity relationships of the Douglas-fir region.* Steinbrenner identified several key soil attributes that were correlated with site index: soil depth, depth of the "A" horizon, proportion of clay in the "B" horizon, and coarse fragment content. This work did not explore soil nutrient amount, concentration, or availability; rather, it focused on physical characteristics that related to soil water holding capacity and cation exchange capacity, and that did not require extensive laboratory analysis for estimation. Steinbrenner's (1979) work was focused predominantly on soil mapping, so did not address approaches to implementing operational soil assessments within stands or among groups of adjacent stands for the purpose of fine-tuning silvicultural regimes or for incorporating site-specific soil characteristics into forest growth and yield models.

Forest soils in topographically complex systems common in the Douglas-fir region tend to be highly spatially variable, and modern soil maps such as those available through the Natural Resources Conservation Service's Web Soil Survey are not intended to be interpreted for site-specific prescription at the scale of a forest stand. In order to get more accurate and spatially explicit maps of the soil characteristics that influence a stand's productivity and subsequent response to silvicultural treatments, more intensive soil sampling must be implemented. While relatively few soil parameters are probably necessary to significantly enhance the use of soil factors to understand patterns in forest productivity across the landscape, soil survey protocols traditionally entail digging deep soil pits so that the entire soil profile can be characterized. This procedure tends to be very labor-intensive and, especially in topographically heterogeneous regions such as western Oregon's Coast Ranges, subsequent efforts at mapping soil characteristics from widely dispersed soil pits do not yield a great deal of information that can be applied to understanding growing conditions within a forested stand (Moore et al., 1993).

One possible solution to the problems associated with applying soil survey information for estimating forest productivity is to implement an abbreviated soil sampling protocol that could a) be feasibly implemented at a higher sampling intensity, b) be paired with remotely-sensed information, and c) provide estimates of soil water availability in the key upper rooting zones. Since the majority of time and effort expended in soil survey is spent digging and analyzing the soil samples, a method that focuses on observing the surficial soil only would allow more samples to be taken within a stand. For such a sampling method to be useful, one key assumption would have to hold, that is, the surface soil texture and water holding capacity are correlated with these same characteristics in deeper soil horizons of the soil at that location.

The objective of this study was to assess the correlations between surface soil textural components (i.e. sand, clay, coarse content) and the factors that available water holding capacity (AWHC) for the entire soil profile. We recognize that there are many soil characteristics with complex vertical patterns within the soil profile (e.g. soil organic carbon, N, P); however our goal was to focus specifically on physical and structural characteristics that influence soil water availability and to assess the viability of using a surface soil sample to infer properties of the rooting zone. Without such a tool, the prospect for integrating soils information into growth models and designing site-specific silvicultural regimes is not encouraging, despite the extensive work that has been done on characterizing forest soils.

2.2 Methods

Data

The data used in this analysis were collected as part of two studies: the Panther Creek LiDAR Project sponsored by the USDI-Bureau of Land Management in Yamhill Co., Oregon, and the Southwest Oregon Growth and Yield Project implemented as part of the Fundamental Forestry Intensified Research (FIR) Program in southwestern Oregon. The soil pits within Panther Creek were excavated during a survey of 35 locations within the 3,200 ha study area. Laboratory analysis of the soil samples was performed by the Natural Resources Conservation Service in Salem, OR. During the soil survey operation, a network of 35 soil moisture monitoring stations were installed adjacent to each of the pits, with EC-5 soil moisture sensors set up for continuous monitoring on Decagon EM-50 analog data loggers.

The southwestern Oregon soil pit observations were collected at 391 locations across southwestern Oregon. Data were collected from these soil pits during the summers of 1981, 1982, and 1983.

In each soil pit from both studies, horizon depth, textural class, and coarse fragment content of each identifiable soil horizon was recorded. Particle size distributions (% sand/silt/clay) for each horizon were assigned based on the expected values for each textural class published by Rawls et al. (1998). A cursory estimate of AWHC was produced using a modified version of the pedotransfer functions in Rawls et al. (1982):

$$\begin{aligned} AWHC = \theta_{FC} - \theta_{WP} = (0.2576 - 0.0020 \times \%sand + 0.0036 \times \%clay) - \\ (0.026 + 0.005 \times \%clay) \end{aligned} \quad [2.1]$$

where θ_{FC} is the volumetric water content (cm^3/cm^3) at field capacity (-0.33 bar), and θ_{WP} is the volumetric water content at the plant wilting point (-15 bars). The original equations in Rawls et al. (1982) included the positive effect of soil organic matter on volumetric water content, but for this analysis we left that term out.

Analysis

Weighted averages for each of the textural components and AWHC were compiled for the entire profile down to the parent material and separately for each of the top 10 cm, top 25 cm, top 50 cm, and top 100 cm of the Panther Creek and southwestern Oregon soil pits. The values for the top 10 cm were based on the textural class of the first mineral soil horizon unless the first soil horizon was less than 10 cm deep, in which case a weighted average of the first two soil horizons to 10 cm was calculated. To assess the correlation between the texture of the surface soil and the weighted average textural component composition of the different subsets of the first meter of soil, simple linear regression models were fit to predict each deeper-soil textural component as a function of the surface value. All data manipulation and analyses were carried out using R Statistical Software (R Core Team, 2016).

2.3 Results

The results of the analysis of the relationship between percent sand and clay of the surface soil and that of the top 100 cm are depicted in graphically in Figure 2.1, and summarized in Tables 1-3.

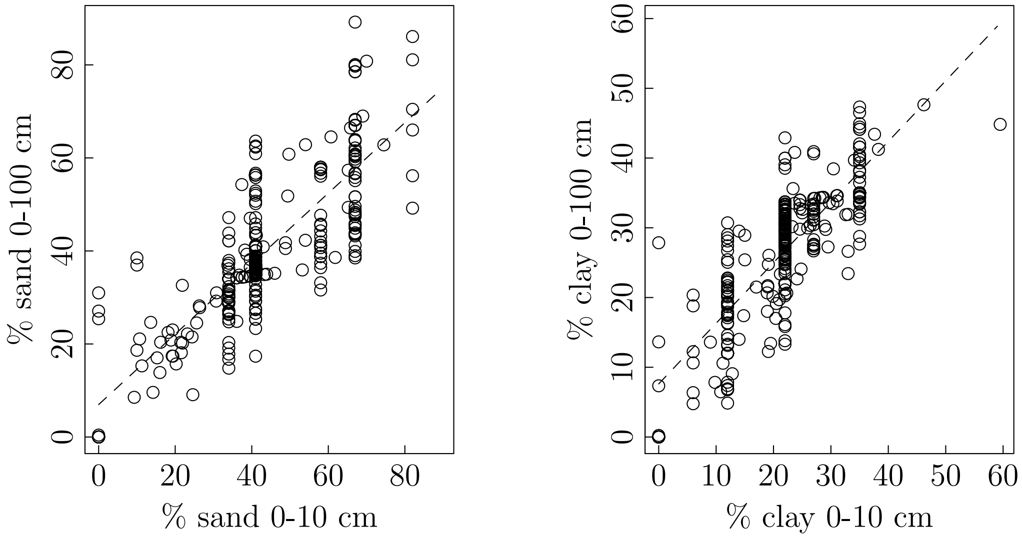

Figure 2.1: The relationships between soil particle % in the top 100 cm and in the top 10 cm in the 426 soil pits from Panther Creek and southwestern Oregon: a) % sand, and b) % clay. The dashed lines represent the predicted % sand/clay for a given surface condition from a simple linear regression of the respective textural attribute.

Sand

The following model was fit to predict average % sand of the top 100 cm of mineral soil (*sand*.100) as a function the % sand in only the top 10 cm (*sand*.10):

$$sand.100 = \beta_{10} + \beta_{11} sand.10 + \varepsilon_1 \qquad [2.2]$$

where β_{10} and β_{11} are parameters to be estimated from the data, ε_1 is the error term with $\varepsilon_1 \sim N(0, \sigma_1^2)$, and *sand*.100 and *sand*.10 are defined above.

Table 2.1: Simple linear regression parameter estimates and fit statistics for predicting % sand of top 100 cm from % sand of only the top 10 cm of the Panther Creek and southwestern Oregon soil pits.

Parameter	Estimate	Std. Error	P-value
β_{10}	6.9689	1.1585	< 0.0001
β_{11}	0.7577	0.0256	< 0.0001
$\sigma = 8.2$	$R^2 = 0.67$		df = 424

Clay

The following model was fit to predict average % clay in the top 100 cm of mineral soil ($clay.100$) as a function of the % clay in only the top 10 cm ($clay.10$) in the Panther Creek and southwestern Oregon soil pits:

$$clay.100 = \beta_{20} + \beta_{21} clay.10 + \varepsilon_2 \qquad [2.3]$$

where β_{20} and β_{21} are parameters to be estimated from the data, ε_2 is the error term with $\varepsilon_2 \sim N(0, \sigma_2^2)$, and $clay.100$ and $clay.10$ are defined above.

Table 2.2: Simple linear regression parameter estimates and fit statistics for predicting % clay of top 100 cm from % clay of only the top 10 cm of the Panther Creek and southwestern Oregon soil pits.

Parameter	Estimate	Std. Error	P-value
β_{20}	7.6148	0.7505	< 0.0001
β_{21}	0.8693	0.0312	< 0.0001
$\sigma = 5.5$	$R^2 = 0.65$		df = 424

Coarse fragment content

The following model was fit to predict average % coarse fragment content (by volume) in the top 100 cm of mineral soil ($coarse.100$) as a function of the % coarse content in only the top 10 cm ($coarse.10$) of the Panther Creek and southwestern Oregon soil pits:

$$coarse.100 = \beta_{30} + \beta_{31} coarse.10 + \varepsilon_3 \qquad [2.4]$$

where β_{30} and β_{31} are parameters to be estimated from the data, ε_3 is the error term with $\varepsilon_3 \sim N(0, \sigma_3^2)$, and $coarse.100$ and $coarse.10$ are defined above.

Table 2.3: Simple linear regression parameter estimates and fit statistics for predicting % coarse fragment content in the top 100 cm from % coarse fragment content of only the top 10 cm in the Panther Creek and southwestern Oregon soil pits.

Parameter	Estimate	Std. Error	P-value
β_{30}	5.02318	1.23049	< 0.0001
β_{31}	0.85713	0.03223	< 0.0001
$\sigma = 14.6$	$R^2 = 0.62$		df = 424

AWHC

The following model was fit to predict average AWHC (%) in the top 100 cm of mineral soil ($awhc.100$) as a function of the AWHC in only the top 10 cm ($awhc.10$) of the Panther Creek and southwestern Oregon soil pits:

$$awhc.100 = \beta_{40} + \beta_{41} awhc.10 + \varepsilon_4 \qquad [2.5]$$

where β_{40} and β_{41} are parameters to be estimated from the data, ε_4 is the error term with $\varepsilon_4 \sim N(0, \sigma_4^2)$, and $awhc.100$ and $awhc.10$ are defined above.

Table 2.4: Simple linear regression parameter estimates and fit statistics for predicting AWHC (%) of the mineral soil in the top 100 cm from AWHC (%) of only the top 10 cm in the Panther Creek and southwestern Oregon soil pits.

Parameter	Estimate	Std. Error	P-value
β_{40}	2.66886	0.25490	< 0.0001
β_{41}	0.76913	0.02148	< 0.0001
$\sigma = 1.3$	$R^2 = 0.75$		df = 424

2.4 Discussion

Based on the results of this analysis, there appears to be a strong relationship between the texture of the surface soil and texture of the entire soil profile, suggesting correlations between the corresponding AWHC of surface layers and the deeper soil profile. These results indicate that sampling the surface soil may in fact yield at the very least site-specific index of AWHC for the entire profile, allowing for sampling at a higher intensity without being limited by operational constraints. This number and spatial extent of these samples should subsequently yield spatially precise estimates of the gradients in soil water availability both within- and between stands. Many deep soil characteristics undoubtedly cannot be estimated using surface soil textural assessments, however the option to replace rigorous protocols for soil pit samples with spatially extensive samples of surface soil may provide practitioners with a chance to obtain more reliable indices of soil texture across their ownership than estimates currently available through existing soil survey databases. If the mechanisms that determine forest productivity can improve the accuracy of growth models by using site factors such as growing season water availability, surface soil observations could be used to achieve the goal of site-specific predictions of forest growth and yield, and enhanced reliability of predicted responses to silvicultural treatments.

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Chapter 3 Terrain analysis and potential influence of lateral flow on microsite water availability in a mountainous area in northwestern Oregon Coast Ranges

Abstract

Soil moisture availability limits Douglas-fir productivity throughout much of its range in the U.S. Pacific Northwest. During the growing season, water available for plant growth includes soil water at field capacity at the beginning of the growing season, recharge from growing season precipitation, and subsurface lateral flow in steep, complex terrain. GIS-based terrain analysis has facilitated the development of various estimates or indices of lateral flow into points on a landscape. This type of terrain analysis and surface soil observations were used to predict relative soil moisture availability based on continuous soil monitoring that included the summer drought period in a forested watershed in the Coast Ranges of northwestern Oregon. The soil moisture data were collected continuously at 84 locations within the Panther Creek watershed during 2012, 2013, 2014, and 2015. Topographic wetness index and slope were the best terrain indices for predicting soil moisture availability during July, and the proportion of sand and clay in the surface mineral soil horizon were effective in calibrating predictions of soil moisture availability at each of the monitoring locations.

3.1 Introduction

To increase the predictive capability of soil samples from the field, environmental variables derived from digital terrain models can be used to stratify the landscape for optimized sampling and spatial coverage (McKenzie and Ryan, 1999). The use of terrain analysis in describing soil distribution across a landscape forms the basis for pedometrics, a branch of soil science that applies rigorous statistical methods to relate soils to topographic/climatic information (McBratney et al., 2000). This type of double sampling takes advantage of recent advances in remote sensing technology and computing power to blend high-resolution, remotely-sensed spatial datasets with precisely located field observations. Combined with principles of hydropedology that describe the movement of surface water through the soil profile, terrain indices that describe drainage patterns across a landscape may be useful for predicting surface soil moisture conditions by accounting for sub-surface lateral flow of water.

Light Detection and Ranging (LiDAR) is a remote sensing technique that can produce high-resolution (< 1 m) digital elevation models. Digital elevation models (DEMs) are built to model topographic features and calculate terrain indices which have been shown useful for explaining vegetation distribution and productivity in some areas (Iverson et al., 1997). Other techniques such as gamma radiometric remote sensing can be used to obtain information about soils (e.g., particle size, parent material, moisture) that helps explain the spatial variability of soil properties (McKenzie and Ryan, 1999; Ryan et al., 2000), however these methods are not as widely used as LiDAR.

Spatial distribution of soil moisture and soil series across a landscape have been described with respect to topography, hydrology, and soil sampling strategies using topographic analysis and geophysical remote sensing (Lin et al., 2006; Murphy et al., 2011; Ryan et al., 2000). DEM-derived terrain indices can help approximate the relative amount of inputs from subsurface flow and fine-tune estimates of growing season water availability. For example, Baggaley et al. (2009) showed that several topographic wetness indices improved predictions of soil moisture levels at various times of the year when combined with information from a low-resolution soil survey.

Remote sensing-assisted estimates of relative soil moisture availability would be very useful in the Pacific Northwest region of the United States, where soil moisture availability during summer drought at the end of the growing season is thought to limit forest productivity. Soil moisture during the growing season is a function of the difference between inputs in the form of precipitation, groundwater, and subsurface flow, and outputs in the form of plant evapotranspiration, and soil surface evaporation. Terrain indices show promise for describing the potential inputs from subsurface flow, which could be an important factor in relative soil water availability in complex terrain, especially during summer drought when soil moisture reserves have been exhausted by evapotranspiration. If terrain indices can be used to help predict subsurface flow across complex topography, then predictions of soil water availability and the productive potential of areas like Oregon's Coast Ranges may be improved.

Our objective in this study was to test the efficacy of terrain indices for describing the distribution of relative soil moisture availability across a topographically complex landscape by accounting for potential inputs from subsurface flow during the dry season. The Panther Creek LiDAR Study Area is an ideal laboratory for assessing the influence of topography on soil moisture levels because it has full LiDAR coverage, a 1-m resolution DEM, and 34 permanent soil moisture monitoring stations each accompanied by a quantitative soil pit description and a detailed forest inventory.

3.2 Methods

3.2.1 Study area

The field data used in this analysis were collected during the summer of 2015 in five intensively-managed Douglas-fir stands within the Panther Creek Study Area in western Yamhill Co., OR. The study area, hereafter referred to as Panther Creek, is composed of 2,500 hectares of publicly- and industrially-managed forestland, with the primary landowners being the Bureau of Land Management (BLM), Weyerhaeuser Co., the Hancock Timber Resource Group, and the City of McMinnville. The study area was designed as a laboratory for experimentation with forest inventory techniques that utilize light detection and ranging (LiDAR) technology, but several complementary projects installed at Panther Creek make it a valuable resource for studying the effects of physical site characteristics on forest productivity. At 34 locations across the study area, a detailed soil pit was described and documented by the Natural Resource Conservation Service (NRCS) for use by a multi-disciplinary team researching various aspects of forest land management. At each of these 34 surveyed locations, a mini-meteorological station with soil moisture sensors was installed and continues to record air temperature and humidity at 0.5-hour intervals and soil temperature and moisture at 2-hr intervals. LiDAR flights have been conducted several times since 2009 and a 1-meter resolution digital elevation model (DEM) and an accompanying set of 1-meter resolution canopy surface models (2009, 2012, 2015) were available for mapping and terrain analysis purposes.

Panther Creek is situated on the east edge of the Oregon Coast Ranges (45.2962° N latitude, $-123.3507°$ W longitude). Forest cover is predominantly Douglas-fir (*Pseudotsuga menzesii*) plantations with mixtures of big leaf maple (*Acer macrophyllum*), vine maple (*Acer circinatum*), red alder (*Alnus rubra*), western hemlock (*Tsuga heterophylla*), and western redcedar (*Thuja plicata*). Stand ages range from 10 to 115 years old at breast height. The climate is characterized by mild, wet winters that are typically followed by hot, dry summers that culminate with drought conditions during July and August. The soils at Panther Creek are primarily derived from sedimentary parent material and are generally deep and fertile. The primary soil orders present are andisols, ultisols, inceptisols, and alfisols.

3.2.2 Data

The analysis was performed on the soil moisture time series dataset from Panther Creek (e.g. Fig. 3.1) and a LiDAR-derived DEM that covered the Panther Creek study area. All terrain analysis was performed using various packages within R Statistical Software v. 3.2.5 (R Core Team, 2016). Terrain indices were calculated using a $25m^2$ resolution DEM that was derived from the original $1m^2$ resolution, LiDAR-derived DEM. Calculations of slope and aspect were completed using algorithms within the 'raster' package in R (Hijmans, 2015). Topographic wetness index (TWI) and topographic position index (TPI) were calculated using algorithms from the System for Automated Geoscientific Analysis (SAGA) in R through the package RSAGA (Conrad et al., 2015; Brenning, 2008). Upon completion of the terrain analysis, plot-level means of each topographic variable were extracted based on each plot's surveyed location and these values were attached to the plot summary dataset for use in the modeling process.

3.2.3 Analysis

The response variable selected to index relative water availability at each of the Panther Creek sites was the mean relative volumetric water content at 50 cm during the month of July ($rvwc.50$). Relative volumetric water content was calculated by comparing the volumetric water content measurements to the apparent field capacity for the soil at each site (estimated from the set of lowest volumetric water content readings during the winter) and expressing the observed value relative to

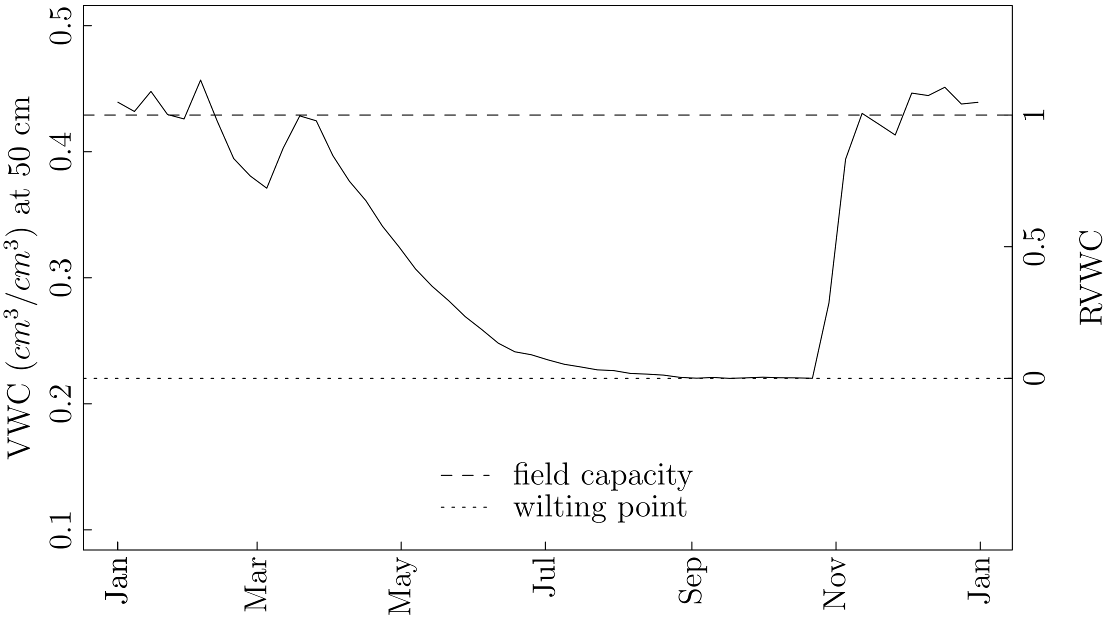

Figure 3.1: Example of soil moisture time series. 2015 weekly averages of volumetric water content at 50 cm for plot 200105 with empirical field capacity and wilting point.

this field capacity and the observed summertime minimum.

$$rvwc.50_{ty} = \frac{\theta_{ty} - \theta_{min_y}}{\theta_{FC_y} - \theta_{min_y}} \qquad [3.1]$$

where θ_{t_y} is the observed volumetric water content at time t in year y, θ_{min_y} is the summertime minimum VWC for year y, and θ_{FC_y} is the empirical field capacity for year y (Fig. 3.1).

This variable was selected because it provided an objective way to assess the amount of available water remaining in the soil at any given time. The mean relative volumetric water content during the month of July was chosen to represent the available soil water supply near the beginning of the summer drought period. We hypothesized that sites with greater available water holding capacities and greater inputs from subsurface flow should express higher levels of $rvwc.50$ in July than sites with lower available water holding capacities and lesser inputs from subsurface flow.

The influence of topography on water availability at the end of the growing season was assessed using linear regression models that predicted $rvwc.50$ as a function of several soil variables derived from the quantitative soil pit descriptions, vegetation density as indicated by stand density index in 2009 ($sdi.2009$), and one or more terrain indices.

3.2.4 Models

Linear regression models were fitted to the data to test the significance of and characterize the relationships between soil texture, topography, and relative soil moisture content at various times during the growing seasons of 2012, 2013, 2014, and 2015. To account for annual differences in precipitation, an indicator variable was included for each year, allowing each plot's relative volumetric water content to be analyzed separately for each year. To detect the influence of topographic wetness index and slope, the proportions of sand and clay in the surface soil were included as covariates in order to account for differences in soil properties among the plots. Precipitation was not included as a covariate because precipitation during the summer months is minimal, and the sensors at each soil monitoring station collected throughfall precipitation rather than total precipitation. Inputs via throughfall during the summer drought were unlikely to penetrate the surface organic horizon.

3.3 Results

The following linear regression models were fitted to assess expected drivers of mean relative volumetric content in July across the Panther Creek sample points. Model 3.2 predicts $rvwc.50$ as a function of topography and vegetation density, model 3.3 does the same but with surface soil textural characteristics added as covariates, and model 3.4 predicts $rvwc.50$ as a function of only surface soil texture and vegetation density.

$$\log(rvwc.50) = \beta_{10} + \beta_{11} slope + \beta_{12} twi + \beta_{13} sdi.2012 + \beta_{14-16} year_j + \varepsilon_1 \qquad [3.2]$$

$$\begin{aligned} \log(rvwc.50) = \beta_{20} + \beta_{21} sand.10 + \beta_{22} clay.10 + \beta_{23} slope + \\ \beta_{24} twi + \beta_{25} sdi.2012 + \beta_{26-28} year_j + \varepsilon_2 \end{aligned} \qquad [3.3]$$

$$\log(rvwc.50) = \beta_{30} + \beta_{31} sand.10 + \beta_{32} clay.10 + \beta_{33} sdi.2012 + \beta_{34-36} year_j + \varepsilon_3 \qquad [3.4]$$

where β_{i0} - β_{i8} were parameters to be estimated from the data, $year_j$ was the indicator variable for year$_j$ (j = 2013, 2014, and 2015), ε_k was the error term for model k with $\varepsilon_k \sim N(0, \sigma_k^2)$, and all other variables described above. The results of the regression analyses are displayed in Figure 3.2 and summarized in Tables 3.1, 3.2, and 3.3.

Table 3.1: Parameter estimates for model 3.2 predicting relative soil moisture availability as a function of topography and stand density.

Parameter	Estimate	Std. Error	p-value
β_{10}	-3.0134	0.4357	< 0.0001
β_{11}	0.0155	0.0037	0.0001
β_{12}	0.1793	0.0495	0.0004
β_{13}	0.0009	0.0002	< 0.0001
β_{14}	-0.4505	0.1215	0.0003
β_{15}	-0.8644	0.1225	< 0.0001
β_{16}	-1.3319	0.1237	< 0.0001
$\sigma = 0.478$		$R^2_{adj} = 0.56$	

Table 3.2: Parameter estimates for model 3.3 predicting relative soil moisture availability as a function of surficial texture, topography, and stand density.

Parameter	Estimate	Std. Error	p-value
β_{20}	-4.3126	0.4763	< 0.0001
β_{21}	0.0309	0.0062	< 0.0001
β_{22}	0.0162	0.0039	0.0001
β_{23}	0.0158	0.0038	0.0001
β_{24}	0.2015	0.0462	< 0.0001
β_{25}	0.0009	0.0002	< 0.0001
β_{26}	-0.4374	0.1105	0.0001
β_{27}	-0.8531	0.1114	< 0.0001
β_{28}	-1.3181	0.1125	< 0.0001
$\sigma = 0.435$		$R^2_{adj} = 0.64$	

Table 3.3: Parameter estimates for model 3.4 predicting relative soil moisture availability as a function of surficial soil texture and stand density.

	Estimate	Std. Error	p-value
β_{30}	-2.4938	0.3060	0.0000
β_{31}	0.0264	0.0067	0.0001
β_{32}	0.0191	0.0041	0.0000
β_{33}	0.0006	0.0001	0.0001
β_{34}	-0.4252	0.1201	0.0006
β_{35}	-0.8387	0.1211	0.0000
β_{36}	-1.2945	0.1222	0.0000
$\sigma = 0.473$		$R^2_{adj} = 0.57$	

3.4 Discussion

Linear regression analysis of mean relative volumetric water content in July across the monitoring sites at Panther Creek showed that in a given year, water avail-

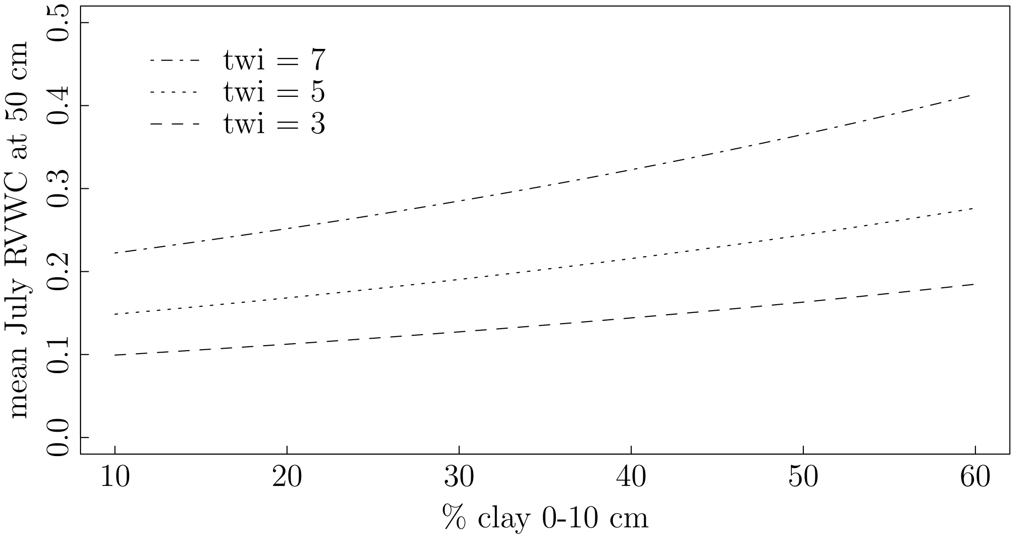

Figure 3.2: Predicted mean relative VWC at 50 cm during month of July across the range of surface soil clay content at the Panther Creek soil monitoring sites and at several levels of topographic wetness index.

ability is positively correlated with surface clay content and topographic wetness index. Surprisingly, available water supply was positively correlated with stand density index suggesting that greater vegetation density is not constraining the availability of water at the end of the growing season. We speculate that the positive relationship between soil moisture availability in July and vegetation density is a result of inputs via hydraulic redistribution within the soil profile by the mature trees, a phenomenon which has been documented in a moist Douglas-fir ecosystem by Brooks et al. (2002). Another surprising result was the positive relationship between $rvwc.50$ and slope; however, graphical analysis of the data showed that steep slopes occurred in both high and low topographic positions, so that steep incline may be on average more likely to lead to inflow of subsurface water as to excessively well-drained conditions.

The positive correlation with topographic wetness index and the added benefit of soil survey information is consistent with the findings of Baggaley et al. (2009) even though this study was conducted in a forested system with a very different climate. Adding the surface soil textural information improved predictive ability relative to the model with only topographic variables; however, the models with only soil attributes or terrain indices had roughly equivalent predictive ability.

The regression analysis from model 3.3 was also performed separately for each of the years 2012, 2013, 2014, and 2015. The results for 2012 and 2013 confirm a statistically significant positive relationship between twi and soil water availability in July, however the relationship is not significant at level $\alpha = 0.05$ for the years 2014 and 2015. This result suggests that the relationship between moisture availability and topographic position as indicated by twi depends upon the climate of a given year, and probably relates to the potential amount of excess water available for lateral flow, or to the magnitude of vapor pressure deficits and intensity of evapotranspiration for that year.

Overall, the best predictions of soil water availability were made using a combination of surface soil textural attributes and several terrain indices. The assessment of growing season water availability across a complex terrain such as Panther Creek shows that topographic wetness index and slope provide insight into the spatial patterns of summertime soil moisture availability and that predictions are improved by incorporating surface soil information. Because terrain analysis can be performed relatively cheaply across a large area of interest, applications which require estimates of relative soil moisture availability in topographically complex forested areas may be aided by the wall-to-wall coverage offered by topographic indices such as topographic wetness index. To further refine predictions of soil moisture conditions, surface soil sampling could be implemented during other forest inventory data collection efforts.

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Chapter 4 Using remotely-sensed topographic information and surface soil observations to quantify productive potential of forest areas in western Oregon

Abstract

Observations of basal area productivity and site index of Douglas-fir (*Pseudotsuga menzesii*) plantations in a 2,300-ha forested area in northwestern Oregon were related to topographic and surface soil characteristics to identify drivers of within- and between-stand gradients in forest productivity. Estimates of periodic basal area growth, height increment, and site index from LiDAR-derived canopy surface models were modeled as a function of initial stand conditions and various combinations of physical site factors. The most influential site factors included trigonometric transformations of aspect, slope, and topographic position. Productivity measured by basal area increment reached its maximum on sites that slope approximately to the south-southwest on the shoulder of ridges. In contrast, productivity measured by height increment and site index reached their maxima on sites that sloped approximately to the north. Surface soil textural attributes were not found to explain any variance in basal area productivity, however clay content was positively correlated with site index. The results of this exploration provided some insights into the environmental gradients that determine forest productivity

of Douglas-fir in this region.

4.1 Introduction

Knowledge of ecological processes and physical site factors that limit forest productivity provides an important perspective on classifying site quality (Carter and Klinka, 1990). Site characteristics such as soil properties and drainage partly determine plant species composition, but the physical site characteristics that influence forest productivity are complex and their functional mechanisms are seldom understood to a degree that warrants incorporation into criteria for management decisions. In addition to our incomplete understanding of mechanisms driving net primary production, part of the difficulty of incorporating topographic and soil attributes into forest growth and yield models and subsequent silvicultural decisions arises from the inherent spatial variability of these characteristics and the challenges this creates in developing useful stand-level predictors. While the magnitude of this effect may vary regionally, it has been demonstrated that there is substantial local (within-stand) variation in productivity both in height- and basal area growth potential (Skovsgaard, 2009). Since climate does not vary at such a local scale, within-stand variability in forest productivity is likely a product of local variability in topography and soils, so if there are direct mechanistic or indirect correlative relationships between topography and forest productivity, remote sensing and terrain analysis are very promising tools because they can remove some of the subjectivity introduced by ground-sampling local topography and automate the calculation of topographic indices pertaining to subsurface movement of water, soil particles and nutrients.

The objective of this study was to explore operational field methods for assessing soil water holding capacity and topographic characteristics that potentially influence sub-surface flow of soil water, with the ultimate goal of better representing biophysical indicators of forest productivity in forest growth and yield models. Likewise, recognition of local gradients in productivity would aid in fine tunning of silvicultural prescriptions. Detailed soil-site studies of small research areas require conventional soil pits that would be prohibitive in an operational setting (Miller et al., 2004). If soil information holds any promise for improving the practice of silviculture on an ownership level, relevant soil characteristics must be mapped and/or interpolated; or, a method for quick on-site soil assessments must be developed. The latter could only be regarded as an index or perhaps a variable correlated with the functional attributes of interest (e.g., plant available water holding capacity), but would obviate the need to dig a full soil pit if the information sacrificed does not overwhelm the more limited information that could be gained by quick site visits.

Site quality

Site quality has historically been incorporated into predictions of forest productivity in North America through the use of site index, a measure of the height attained by dominant and co-dominant trees at some reference age, but the effort to find correlations between site index and edaphic site factors has met varying degrees of success (Carmean, 1975; Monserud et al., 1990; Steinbrenner, 1979). Topography has long been known to influence site productivity; however, quantifying this influence has been challenging because topography represents a complex gradient of many environmental factors that include incident solar radiation, potential evapotranspiration, and associated influences on parent material weathering rates, soil texture, soil structure, and soil depth. The relationship between forest productivity and slope, aspect, and elevation can be modeled using trigonometric transformations of slope and aspect that were first proposed by Stage (1976) and later improved by Stage and Salas (2007); however, these interactions vary regionally and have yet to be documented in northwestern Oregon.

The use of site index in growth and yield models is very appealing because it distinguishes stands with rapid height growth rates from those with slower height growth rates, and similarly distinguishes stands with differences in volume yields that are attributable to differences in top height of the stands. However, site index is a bioassay that may be influenced by a stand's silvicultural regime, genetics, and relatively short-term fluctuations in climatic factors, so cannot be assumed to be fixed across successive growth periods or even successive rotations. The procedure for estimating site index also involves a degree of subjectivity in selecting 'site trees', and opportunities for error arise when measuring top heights of dominant trees, particularly in mature stands, and when measuring their total or breast height age. In principle, site index provides an easily observed estimate of height growth response to factors that govern site fertility. Site index, however, is limited by its inability to describe the mechanisms by which various soil and climatic factors drive trends in productivity across the landscape. Perhaps of even greater concern, site index does not account for differences in site stockability, or basal area carrying capacity, a dimension that contributes to significant variability in volume production potential among stands with a common site index (Assmann, 1970; Curtis, 2006; Hamilton and Christie, 1971). Observed differences in basal area or volume carrying capacity for a given top height inspired Assmann (1970) to distinguish between "height quality classes" and "mai-quality classes", and to base yield tables by "yield classes". These yield classes captured the integrative influence of soil and climatic factors on both height and basal area growth potential. Yield differences for a given top height have been corroborated by many others and have brought life to the debate about the validity or performance of site index, and to Eichorn's rule which states that the volume yield for a given mean top height will be equal regardless of site index (Skovsgaard, 2009; Skovsgaard and Vanclay, 2008).

Carrying capacity

Silvicultural research has revealed that forest stands have an inherent 'carrying capacity' for trees, first described as the 'maximum stand density index' by Reineke (1933). The maximum stand density index (SDI) corresponds to the maximum number of 10-inch DBH trees that can exist on a site. This limit contributes to the process of crown class differentiation and the onset of competition-induced mortality (self-thinning) well before the maximum size-density limit is reached. Maximum SDI is generally understood to correspond to the maximum amount of live, respiring biomass that can be supported by the resources on a site (e.g., water, nutrients, light). Although the actual live biomass is a fraction of total mass or volume, the quantity conventionally referred to as biomass is correlated with the mass of actual live, respiring cells for a given species. The existence of a size-density limit in forest systems is undisputed and foresters generally have a good understanding about the types of sites that can carry a higher density. The specific mechanisms that control the upper limit of stand density, however, have not yet been represented in a modeling framework, although many models allow the user to specify a site-specific maximum if the default value does not seem to pertain.

The prevalence of a maximum SDI is widely accepted for a given species in a given region, but differences in the carrying capacities within a species are not as widely recognized and apparently cannot be easily explained by any biotic characteristics (Hasenauer et al., 1994). Although there are generally accepted values for SDI_{max} in many tree species, self-thinning will begin at different levels of density depending on the quality of growing conditions at the site (Pretzsch, 2009). For example, DeBell et al. (1989) demonstrated drastically different maximum size-density limits for plantations of loblolly pine (*Pinus taeda*) in Hawaii and the southeastern US, likely as a result of more favorable growing conditions at the site of the Hawaiian installation.

The quality of forest growth conditions for a given site can be evaluated by identifying the set of resources which limit growth at various times of the year and characterizing the availability of those resources. However, levels of deficiency are poorly understood, even for the more common macronutrients like nitrogen, calcium, and potassium. In western Oregon, the climate is characterized by mild, wet winters and warm, dry summers and it follows that forest growth in this region is often limited by some combination of nutrient and soil water availability during the growing season (Brix, 1979). Water availability can vary greatly within a local area due to the combination of orographic precipitation effects and local variation in soil properties (Gessel et al., 1990). One soil characteristic that controls water availability to plants is available water holding capacity (AWHC). AWHC is approximately equivalent to the amount of water available to vegetation during the growing season in the absence of summertime precipitation. It has not yet been demonstrated that AWHC is correlated with a site's carrying capacity, but this is due in part to the difficulty of obtaining reliable stand-level estimates of soil characteristics that determine AWHC.

Application

Many factors have contributed to the difficulty of relating edaphic site factors to forest productivity, including the spatial variability of soil properties, cost and difficulty of observing soils, changing genetics and silvicultural practices, and a poor understanding of the mechanistic relationships between tree growth and soil characteristics, particularly in interaction with climatic variables. The last items on this list are particularly troubling, but there is a potential for biologically-informed observational studies to expose some of the mechanisms behind the influence of a site's topography and soil on forest productivity. One application where understanding the sources of local variation in site productivity will be essential is in the interpretation of silvicultural experiments. Skovsgaard (2009) demonstrated that the effect of thinning on volume yield in Sitka spruce stands in Denmark varied with several site characteristics including depth to water table and depth of sandy soil horizons within the soil profile, implying that results of the thinning experiment would have been misleading if the variability in site conditions observed between plots within each experimental block had not been accounted for in the analysis. Miller et al. (2004) similarly demonstrated the influence of soil attributes on evoking somewhat anomalous results in the original Wind River spacing trial, the oldest Douglas-fir spacing trial in the US Pacific Northwest (PNW).

4.2 Study area

The field data used in this analysis were collected during the summer of 2015 in five intensively-managed Douglas-fir stands within the Panther Creek Watershed in western Yamhill County, OR (45.2962° N latitude, $-123.3507°$ W longitude). The study area, hereafter referred to as Panther Creek, is composed of 2,500 hectares of publicly- and industrially-managed forestland, with the primary landowners being the Bureau of Land Management (BLM), Weyerhaeuser Co., the Hancock Timber Resource Group, and the City of McMinnville.

Panther Creek is situated on the east edge of the Oregon Coast Ranges. Forest cover is predominantly Douglas-fir (*Pseudotsuga menzesii*) plantations with mixtures of big leaf maple (*Acer macrophyllum*), vine maple (*Acer circinatum*), red alder (*Alnus rubra*), western hemlock (*Tsuga heterophylla*), and western redcedar (*Thuja plicata*). Stand ages range from 10 to 115 years old at breast height. The climate is characterized by mild, wet winters that are typically followed by hot, dry summers that culminate with drought conditions during July and August. The soils at Panther Creek are primarily derived from sedimentary parent material and are generally deep and fertile. The primary soil orders present are andisols, ultisols, inceptisols, and alfisols.

The study area was originally intended to serve as a laboratory for experimentation with forest inventory techniques that utilize light detection and ranging (LiDAR) technology, but there have been several additional projects installed at Panther Creek that make it a valuable resource for studying the effects of physical site characteristics on forest productivity. At 34 locations across the study area, a conventional soil profile analysis was implemented by the Natural Resource Conservation Service (NRCS) to complement a multi-disciplinary research project on forest inventory, soil carbon storage and dynamics, environmental controls on forest productivity, and numerous other topics. At each of the 34 soil pits, a weather station and soil moisture monitoring array was installed to collect air temperature and humidity data at 0.5-hour intervals and soil temperature and moisture data at 2-hr intervals. LiDAR flights have been conducted several times since 2009 and a 1-meter resolution digital elevation model (DEM) and an accompanying set of 1-meter resolution canopy surface models (2009, 2012, 2015) are available for mapping and terrain analysis purposes.

4.3 Methods

4.3.1 Stand selection

The five stands that were selected for sampling are fully-stocked Douglas-fir plantations between 25 and 40 years total age. Stands that fit this description are well-suited to the use of basal area growth as an indicator of productivity because they have reached a stage of stand development during which it can be reasonably assumed that the trees are fully utilizing a site's available resources and that stand density will not yet be severely affected by self-thinning suppression mortality. Because stand management histories were not readily available for some stands prior to the beginning of the field season, some stands were eliminated from the population due to recent thinning. Each of the stands aged between 30 and 40 years had been pre-commercially thinned many years before, but not recently enough to influence the 5-year (2009-2014) basal area increment.

4.3.2 Plot layout and placement

Stands were sampled by installing a series of circular, evenly-spaced, 0.02-ha (0.05 ac) fixed-radius (8 m) plots along several transects (Figure 4.2). Transects were designed to cross a range of drainage conditions while remaining in areas fully-

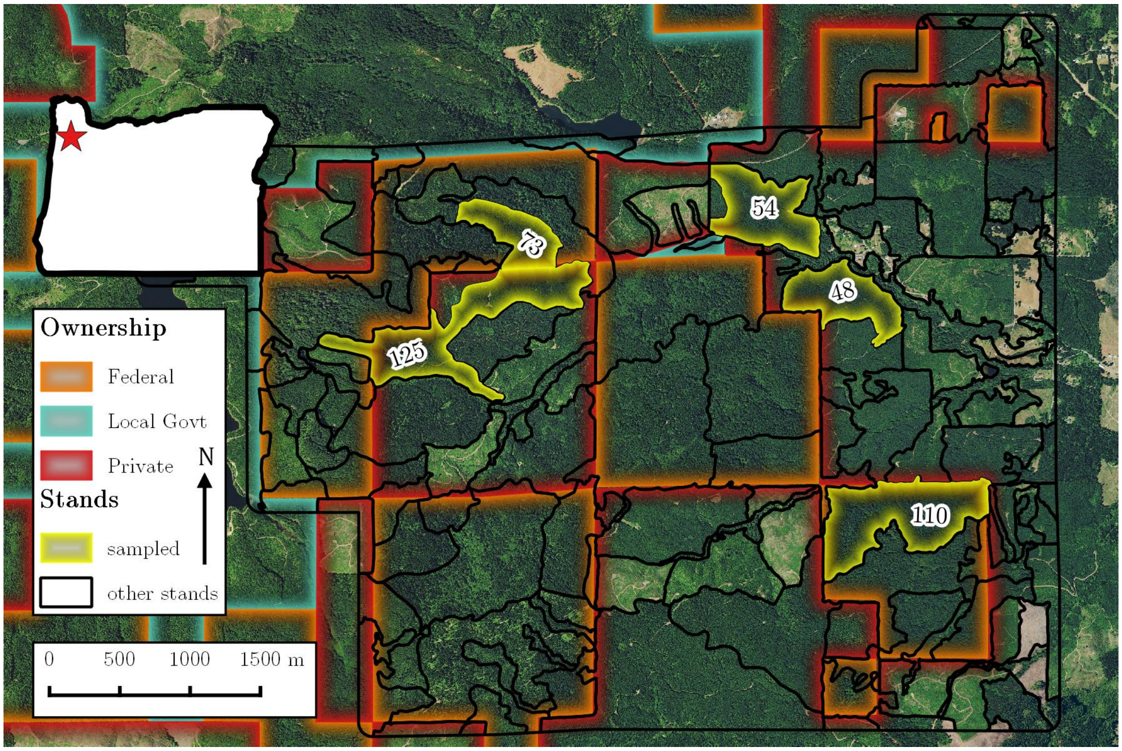

Figure 4.1: Map of Panther Creek Study Area, sampled stands are outlined in yellow.

stocked with Douglas-fir. This was accomplished by identifying areas with a) contiguous Douglas-fir cover on color infrared aerial imagery and b) a wide range in microtopographic drainage conditions (as indicated by maps of topographic wetness index, TWI). The targeted spacing between plots was 25 to 30 m depending on the slope of the terrain. Locations of plots that landed in areas with significant hardwood cover or canopy gaps were shifted to the nearest location where Douglas-fir cover was dominant.

In two stands (54 and 73), several parallel transects were installed to form

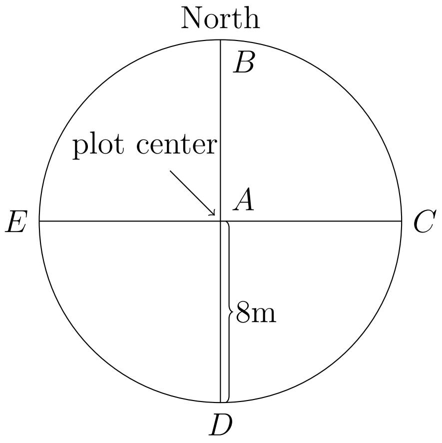

Figure 4.2: Schematic of plot layout. Soil samples were taken at points labeled A-E and pooled into a composite sample for each plot.

a grid of plots to be used in a geostatistical surface interpolation of potential forest productivity and corresponding soil attributes, with the latter providing an assessment of optimum sampling intensity for surface soil characteristics across a stand.

4.3.3 Tree measurements

All plot trees with DBH>10 cm were measured for DBH (nearest 0.1 cm) and 5-year radial increment at breast height (nearest mm). Breast height was marked on the uphill side of each tree and radial increment cores were collected on a randomly assigned side-slope side of each tree. In order to measure a full 5-year periodic increment, the current growing season's growth was ignored and growth rings for only the five prior growing seasons were measured. Each tree's current

DBH measurement included the partial growth from the 2015 growing season, but this growth contributed a negligible amount to the estimate of each plot's current basal area.

4.3.4 Basal area increment estimation

In order to calculate a plot-level basal area increment, it was first necessary to create a DBH record for each tree at the beginning of the growth period (2009). This was accomplished by subtracting 2x the 5-year radial increment from the current (2014) diameter. Plot-level basal area estimates were calculated for 2009 and 2014 by summing the basal areas of each tree both at the beginning and end of the growth period. Five-year basal area increment for each plot was reported as the difference between basal area in 2009 and 2014.

4.3.5 Site index and height increment estimation

Estimates of site index for each plot were based on the the 95th percentile of the canopy height values from the canopy surface model for 2012 and the stand's breast-height age for the same year. The canopy surface model was derived by calculating the difference between the elevations of the first (highest) return and the lowest (ground) return from the LiDAR flight, which is approximately equivalent to the height of the canopy surface at each 1 x 1 meter raster cell. The 95th percentile of the canopy height model was chosen to represent the average height of dominant-and co-dominant trees on the plot. The heights for each pixel within the 8-m radius circle surrounding each plot center were calculated by clipping the canopy height raster for each 0.02 hectare plot and extracting the 95th percentile value for the distribution of height values. Plot-level height increment was estimated by the difference between the 95th percentiles of the canopy height surfaces for 2012 and 2015.

4.3.6 Soil sampling

A composite soil sample of the top 10 cm of mineral soil was collected at each plot using a 33” AMS soil probe. Each composite sample consisted of one sample from plot center, and four samples at the plot’s perimeter (one in each cardinal direction). Samples were placed in labeled plastic bags and saved for textural assessment. Textural classes (e.g. sandy clay loam, silty clay, etc.) were assigned to each soil sample using a dichotomous key that considered ribboning and grittiness.

4.3.7 Terrain analysis

All terrain analysis was performed using various packages within R Statistical Software v. 3.2.5 (R Core Team, 2016). Terrain indices were calculated using a $25m^2$ resolution DEM that was constructed from the original $1m^2$ resolution, LiDAR-derived DEM. Calculations of slope and aspect were completed using algorithms within the ‘raster’ package in R (Hijmans, 2015). Topographic wetness index

(TWI) and topographic position index (TPI) were calculated using algorithms from the System for Automated Geoscientific Analysis (SAGA) in R through the package RSAGA (Conrad et al., 2015; Brenning, 2008). Upon completion of the terrain analysis, plot-level means of each topographic variable were extracted based on each plot's surveyed location and these values were attached to the plot summary dataset for use in the modeling process.

4.3.8 Analysis

All data preparation and multiple linear regressions were performed in R Statistical Software (R Core Team, 2016).

Response variables

Several different response variables were considered for representing productivity at the plot level, including basal area periodic annual increment ($ba.pai$, $m^2/ha/year$), basal area periodic relative annual increment ($ba.pri$, $\%/year$), percent departure from the expected basal area increment for a given initial density ($ba.detrend$, %), site index (si, expected height at age 50), and height increment of dominant- and co-dominant trees derived from successive LiDAR flights ($ht.inc$). We settled on using $ba.pai$ and $ht.inc$ as the best analogous pair of horizontal- and vertical measures of productivity because models to predict these variables could be most easily translated to existing growth and yield modeling frameworks.

For site productivity mapping, an ideal measure of productivity would be independent of current stand conditions. Several examples of growth indices that fit that description include *ba.pri* and *ba.detrend*. *ba.detrend* relativizes observations of basal area increment for basal area at the beginning of the growth period relative to the mean observation for a given initial density (*ba.*0), allowing comparison of growth rates among plots with different initial densities (Berrill and O'Hara, 2014). Relative growth rates, such as *ba.pri*, have commonly been applied in analyses of plant growth and can be interpreted as a type of growth efficiency for plot/tree attributes (Pommerening and Muszta, 2015, 2016).

Explanatory variables

Because this study was exploratory in nature, a wide variety of topographic and soil characteristics had to be tested for their influence on productivity. To achieve this objective, many combinations of explanatory variables had to be tested. Table 4.1 contains a list of the explanatory variables that were tested in the candidate models described below. Topographic position index describes the relative elevation of each cell compared to all cells in a circular neighborhood around it, and is computed on an arbitrary scale that ranges approximately from -3 for draws and +3 for ridgetops for this study area (Guisan et al., 1999).

Table 4.1: List of dependent and independent variables tested in models for describing various aspects of plot-level patterns in forest productivity in five stands at the Panther Creek Watershed in western Oregon.

Variable	**Label**	**Units**	**Mean**	**Range**
Basal area periodic annual increment	$ba.pai$	$m^2/ha/year$	1.1	0.6 : 2.2
3-year height increment	$ht.inc$	m	4.2	2.9 : 5.5
site index	si	expected height (m) at 50 years	39	26 : 48
Initial stand density index	$sdi.0$	# 25 cm trees/ha	788	403 : 1130
Stand breast height age	$bh.age$	years	35	25 : 37
Elevation	$elev$	meters	255	128:363
Slope	slope	%	37	4: 82
Aspect	aspect	radians	2.3	0.1 : 6.2
$\%slope \times cos(aspect)$	$slope.cos.aspect$	-	-	-
$\%slope \times sin(aspect)$	$slope.sin.aspect$	-	-	-
Potential incoming solar radiation	$solar$	kWh/m^2	1228	826 : 1467
Topographic position index	tpi	$-2 < tpi < 2$	0	-1.4 : 1.8
% clay content 0-10 cm mineral soil	$pct.clay$	%	40	10 : 58

4.3.9 Statistical modeling

Various linear and non-linear models were explored using a combination of data transformations, all-subsets regression, and modification of the models with the strongest predictive power to arrive at models that provided some biological insights into the relationship between different measures of productivity and the available environmental and stand structural variables.

4.4 Results

4.4.1 Final models

The final models for basal area periodic annual increment (*ba.pai*), top height increment (*ht.inc*), and site index (*si*) were as follows:

$$\begin{aligned} log(ba.pai) &= \beta_{10} + \beta_{11} log(sdi.0) + \beta_{12} bh.age + \beta_{13} slope + \beta_{14} tpi + \beta_{15} elev \\ &\quad + \beta_{16} slope \times cos(aspect) + \beta_{17} slope \times sin(aspect) + \varepsilon_1 \end{aligned} \qquad [4.1]$$

$$\begin{aligned} log(ht.inc) &= \beta_{20} + \beta_{21} log(ht.0) + \beta_{22} bh.age + \beta_{23} slope + \beta_{24} tpi + \beta_{25} elev \\ &\quad + \beta_{26} slope \times cos(aspect) + \beta_{27} slope \times sin(aspect) + \varepsilon_2 \end{aligned} \qquad [4.2]$$

$$si = \beta_{30} + \beta_{31} elev + \beta_{32} tpi + \beta_{33} solar + \beta_{34} pct.clay + \beta_{35} pct.clay^2 + \varepsilon_3 \qquad [4.3]$$

where $\beta_{i0} - \beta_{i9}$ are parameters to be estimated from the data, ε_i is the random error term with $\varepsilon_i \sim N(0, \sigma_i^2)$.

4.4.2 Basal area PAI

The model described by Equation [4.1] was the final product of an exploration of the physical site characteristics that influence basal area productivity in the study area ($R^2 = 0.52$). The model coefficients describe the relationships within this system and could serve as a guide for the collection of a more extensive modeling dataset (Table 4.2)

As expected, initial stand density variables account for the majority of the variance explained by the model, but the high-resolution topographic variables derived from the DEM appear to have some predictive power. Surface soil particle size percentages provided no additional predictive power as covariates for describing *ba.pai*. After testing for multicollinearity, it was found that the soil texture variables had no significant relationships to the covariates selected for the model, so they were not excluded from the model; therefore, it was concluded that the soil variables were not excluded from the model because their effects were already represented in the retained covariates. Rather, the surface soil variables were ap-

Table 4.2: Parameter estimates and fit statistics for Model [4.1] describing the response of the natural log of periodic annual basal area increment (*ba.pai*) to initial stand structure and environmental attributes

Parameter	**Estimate**	**Std. Error**	**p-value**	**Rel. Importance (%)**
β_{10}	-1.9963	0.8806	0.0256	-
β_{11}	0.6449	0.0929	0.0000	26.4
β_{12}	-0.6536	0.2134	0.0028	5.7
β_{13}	-0.0006	0.0015	0.6965	1.0
β_{14}	0.0504	0.0242	0.0401	4.7
β_{15}	0.0007	0.0004	0.0780	7.5
β_{16}	-0.0013	0.0009	0.1579	4.0
β_{17}	0.0018	0.0007	0.0125	3.0
$\sigma = 0.1613$		$R^2 = 0.52$		df = 99

parently insufficient to depict the influence of soil on basal area productivity, soil conditions in general did not influence basal area productivity on these sites, or soil texture and associated AWHC of deeper soil layers were more important (and their effect may or may not have been at least partly accounted by retained covariates). Basal area increment peaked on south-southwest facing aspects at high topographic positions and predictions increased with slope and elevation.

4.4.3 Height increment

The height increment model had the weakest predictive power and did not yield great insight into the site factors that drive height growth at the plot level (Equation [4.2] and Table 4.3). Height increment peaked on southeast facing aspects, responded positively to increasing topographic position and slope, and decreased

Table 4.3: Parameter estimates and fit statistics for Equation [4.2] describing the response of the natural log of periodic annual top height increment (*ht.inc*) to initial stand structure and environmental attributes.

Parameter	**Estimate**	**Std. Error**	**p-value**	**Rel. Importance (%)**
β_{20}	1.6832	0.4642	0.0005	-
β_{21}	0.4870	0.1288	0.0003	7.6
β_{22}	-0.5332	0.1718	0.0025	5.3
β_{23}	0.0021	0.0010	0.0277	9.0
β_{24}	0.0114	0.0169	0.5034	0.4
β_{25}	-0.0003	0.0002	0.2293	3.5
β_{26}	-0.0018	0.0006	0.0028	3.5
β_{27}	0.0012	0.0004	0.0076	9.3
$\sigma = 0.0996$		$R^2 = 0.39$		df = 99

with increasing elevation.

4.4.4 Site index

The variable that stands out as significant to determining site index is potential incoming solar radiation (*solar*), while topographic position and elevation are also considerably influential (Table 4.4). Given the relatively low elevations of these sites on the Willamette Valley fringe, it was not too surprising that site index increased with elevation due to the higher precipitation and lower potential evapotranspiration expected as sites rise above the valley floor. The percent clay in the upper soil did have significant predictive power for this response variable, in contrast to basal area increment and top height increment (Equation [4.3] and Table 4.4).

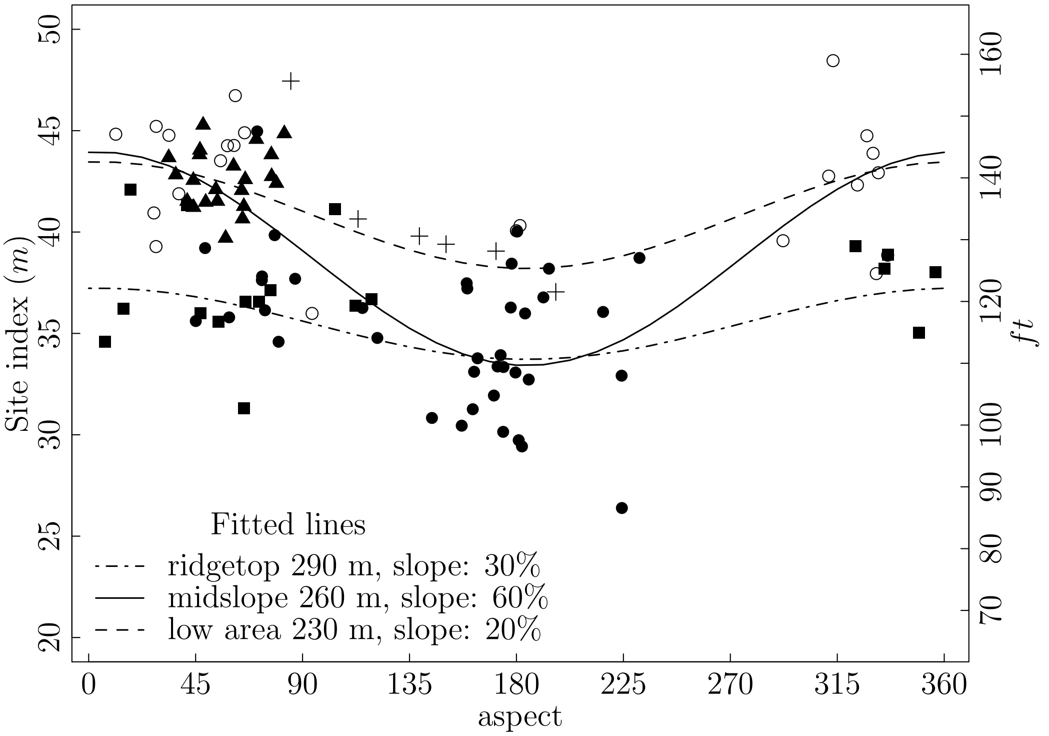

Figure 4.3: Observed and predicted site index (equation [4.3]) for a plot with a canopy height corresponding to the sample median ($ht.0 = 25$ m) at three different topographic positions: $tpi = -1.5$ (draw), 0 (midslope), 2.0 (ridgetop).

4.5 Discussion

Examination of the regression parameters allows us to quantitatively assess the influence of physical site characteristics on productivity after accounting for differences in initial stand conditions. The relationships implied by these results are specific to Panther Creek, however they provide insight into the sources of local variation in productivity which, in concert with larger-scale gradients in climate

Table 4.4: Parameter estimates and fit statistics for Model [4.3] describing the response of site index (si) to initial stand structure and environmental attributes.

Parameter	**Estimate**	**Std. Error**	**p-value**	**Rel. Importance (%)**
β_{30}	43.2988	3.98186	0.0000	-
β_{31}	0.0344	0.0049	0.0000	19.7
β_{32}	-2.5615	0.4061	0.0000	18.5
β_{33}	-0.0150	0.0016	0.0000	35.8
β_{34}	0.3485	0.1728	0.0464	1.2
β_{35}	-0.0051	0.0023	0.0282	1.3
$\sigma = 8.7$		$R^2 = 0.66$		df = 101

(e.g. precipitation, growing degree days, etc.), determine productivity across the landscape. Comparison of results for the three measures of productivity provide a potentially insightful perspective on the allocation of resources to horizontal and vertical growth in response to physical site characteristics that determine limitations of available water and solar radiation.

4.5.1 Initial stand conditions

Plot-level growth is highly dependent upon the stand conditions at the beginning of the growth period. For basal area growth the expected increment was positively correlated with initial stand density index ($sdi.0$), and similarly expected height increment increased with higher initial height ($ht.0$). Stand age ($bh.age$) was negatively correlated with both basal area- and height increment. These results are consistent with the biological expectation for growth rates of stands within the age range of the sample (25 to 37 years breast-height age). Douglas-fir is known for

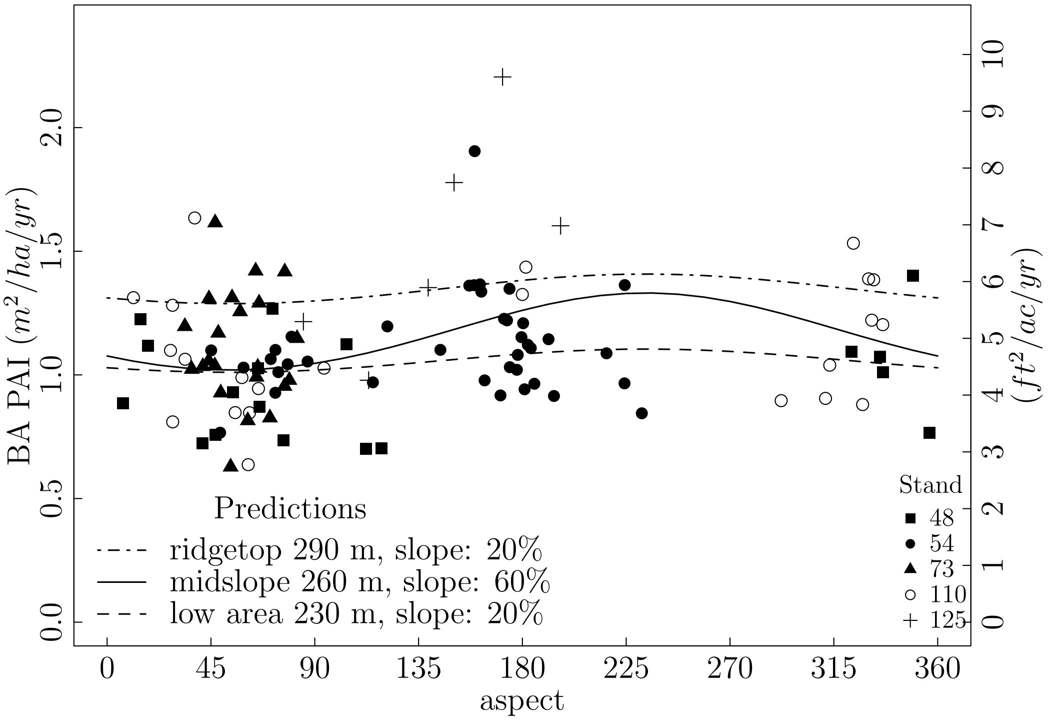

Figure 4.4: Observed and predicted basal area periodic annual increment *ba.pai* predicted from equation [4.1] for three topographic positions: $tpi = -1.5$ (draw), 0 (midslope), 2.0 (ridgetop). Initial density was set to the sample mean ($sdi.0 = 800$).

a prolonged period of rapid height growth, and the sampled stands had not yet reached the top height at which height growth rates start to decline. Similarly, net basal area growth of the sampled stands had not yet begun to decline as a result of self-thinning mortality so the positive correlation between stand density and basal area periodic annual increment was not surprising.

4.5.2 Elevation

Elevation is a complex environmental gradient – in mountainous areas such as Panther Creek, ridgetops will experience greater precipitation, lower temperatures, have lower potential evapotranspiration, and lower probability of water-stressed conditions for plants. Elevation does not explain much variance in basal area or height growth, however, elevation is highly correlated with topographic position index (tpi) when viewed at the hillslope scale and over the limited geographic scope of the Panther Creek Watershed, so some of the influence of elevation is going to be accounted for by the inclusion of tpi as a covariate.

4.5.3 Aspect

Inclusion of cosine- and sine-transformed aspect, and their interaction with slope, allows an optimal (and least optimal) aspect for productivity to be estimated from the data while considering the fact that aspect should have minimal influence in flat areas, i.e., where slope = 0 and maximal influence in areas with steep slopes (Stage, 1976). The trigonometric transformations allow aspect to be represented as a continuous variable in regression where the value for 360° is the same as the value for 0°. According to these data, the optimal aspect for basal area productivity is approximately 225° (southwest) while minimal growth is observed at 45° (northeast). This result is consistent with similar analyses of basal area growth of several conifer species in the Intermountain West (Stage, 1976). Optimal aspect shifts for height increment to 150° (south-southeast) and minimal growth is observed at 330° (north-northwest). In contrast, the optimal aspect for site index is approximately 45° (northeast). It is important to note that site index for stands of this breast height age (25-37 yrs) are forecasts of the expected top height in another 13-25 years, based on cumulative growth performance over the last 25-37 years.

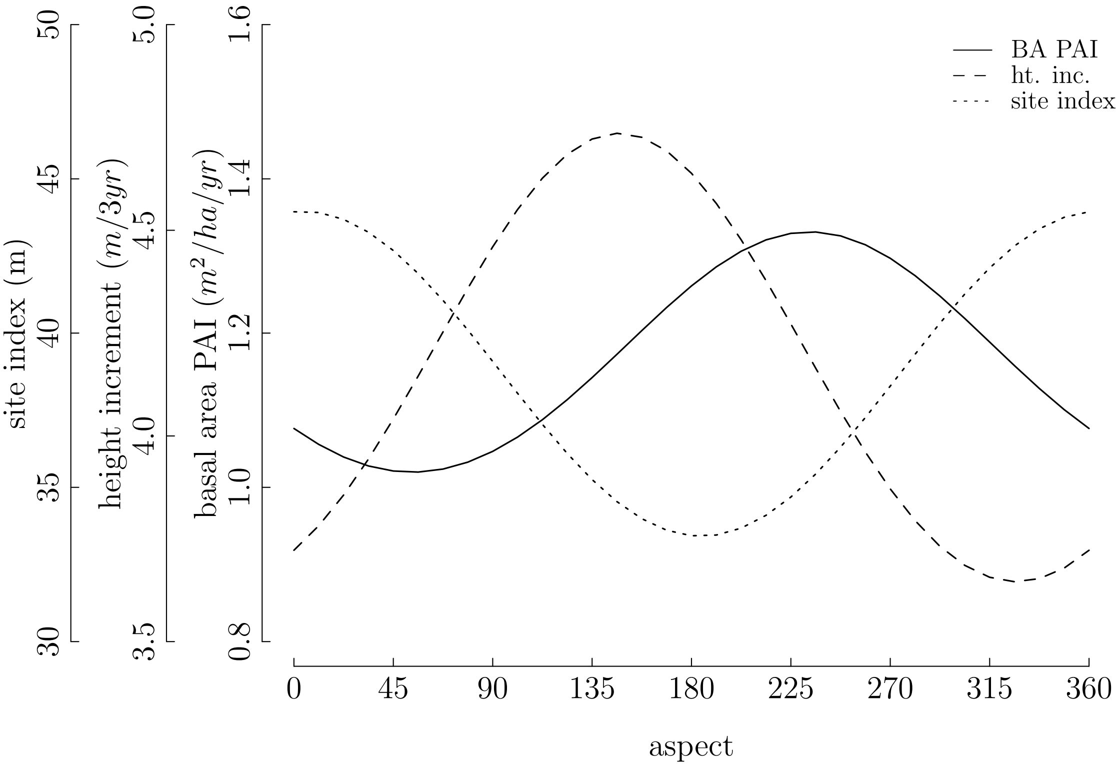

Figure 4.5: Predicted *ba.pai*, *ht.inc*, and *si* for plots in a midslope position ($tpi = 0$, $slope = 60\%$), with stand conditions corresponding to the sample medians ($ht.0 = 25$ m, $sdi.0 = 800$)

4.5.4 Topographic position

Site index and basal area PAI are oppositely correlated with topographic position (*tpi*). Topographic position index is basically an expression of relative slope position, with negative values indicating low-lying conditions and high values indicating ridgetops. The theory that late summer water availability would be higher in low-lying areas and that such conditions would increase productivity formed the basis for our decision to orient transects along topographic gradients. However, the results of this analysis suggest that the hypothesis that productivity increases in lower topographic positions with high potential evapotranspiration, large amounts of soil moisture inputs from subsurface flow, and a minimal growing season water deficit is overly simplistic. The horizontal- and vertical components of productivity appear to respond differentially to the environmental gradients imposed by the range of topographic position. These results reaffirm the work of Carmean (1954) and Steinbrenner (1979) who found that site index was positively correlated with the depth of the soil profile. Analysis of the soil pit data from the network of quantitative soil pits at Panther Creek shows that soils tend to be shallower at high topographic positions than in lower areas near the bottom of draws.

The observation that high topographic positions are optimal for basal area growth at this stage of stand development while sites in low topographic positions tend to have higher site index values suggests that (in addition to topographic controls on soil depth) the constraints imposed on potential incoming solar radiation by topography may be influential in determining the optimal allocation of resources to horizontal and vertical growth. This result appears to be consistent with findings in mature coastal redwood in California, as reported by Berrill and O'Hara (2016). One possible explanation is that trees in low-lying areas are at a disadvantage to surrounding trees with respect to light competition, which might provide an incentive for rapid height growth.

4.5.5 Interaction between slope and aspect

The interaction between the Stage (1976) transformations of slope and aspect describe how the amplitude of the response to aspect diminishes with decreasing slopes. This effect is built into equations [4.1] and [4.2] as the interaction between slope and both the cosine of aspect and the sine of aspect; as slope approaches zero, the terms representing aspect in the models also drop to zero (regardless of aspect). This interaction is implicitly built into equation [4.3] in the variable $solar$, which represents an estimate of potential incoming solar radiation and therefore also accounts for slope, aspect, and elevation.

4.5.6 Limitations

The reliability of height increment estimates, however, may be limited by the plot-level height increment estimation method. We cannot be sure that the instruments and sensors used to collect the LiDAR data were consistent across the successive flights (2009, 2012, 2015), so it is possible that the 95th percentile of the canopy

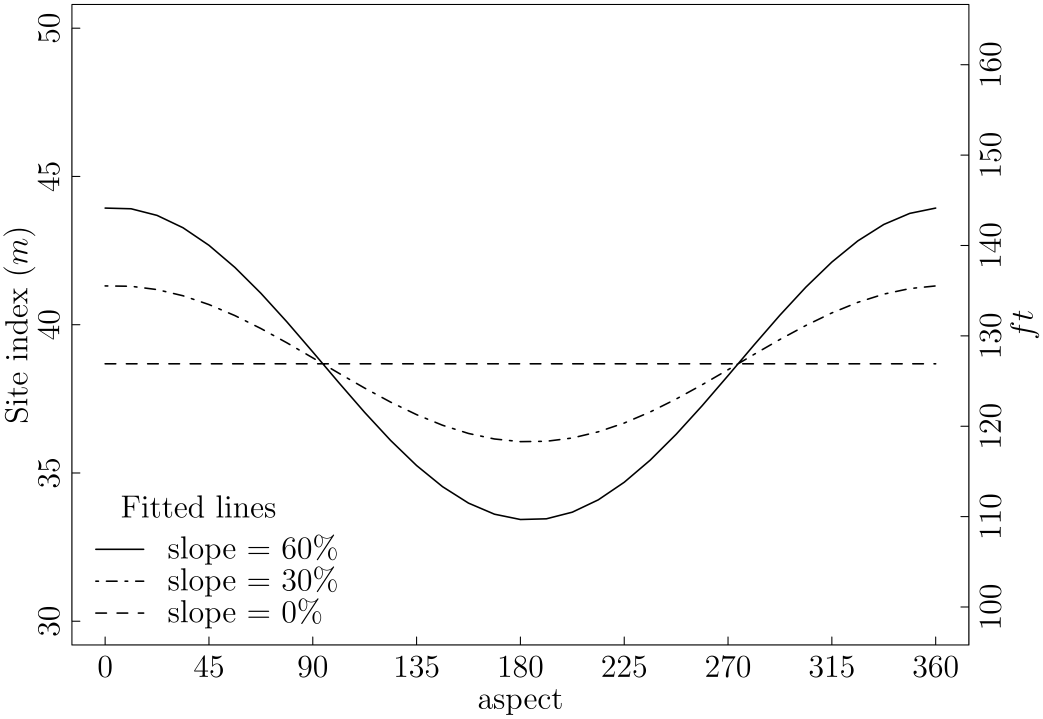

Figure 4.6: Predicted site index (equation [4.3]) for a plot with a canopy height corresponding to the sample median ($ht.0 = 25$ m) at three different slopes: 60%, 30%, and 0%.

height model could be representing something different in each year. Site index estimates were based on the estimated plot-level height in 2012. We are most confident in the 2012 canopy height model because the sensor used during that year was reported to have the highest proportion of canopy surface returns.

Since our intent was to identify the physical factors that contribute to the variability of site productivity within a small area, the stand to which each plot belonged was not included as an explanatory variable in the final models. A mixed-effects model may have accounted for some additional variability in productivity across these data by differentiating stands that exhibit a higher or lower productivity response to soil and topographic characteristics from those that do not; however, a stand-level random effect would not lend any insight to the question of mechanistic drivers of site productivity, unless they could suggest some stand-level covariates that account for at least part of a stand-scale environment effect. Any stand-scale effects would be difficult to bring into the model, however, because only five stands were sampled.

4.6 Conclusion

The shift in aspect at which the various productivity measures peak is a potentially significant discovery from a silvicultural perspective (Fig. 4.5), bringing into focus several possible explanations for local differences in site productivity.

To follow up on this work, a similar study with tree-level volume increment estimates could be used to assess the influence of topography and soils on volume productivity and explore the possibility of topographic controls on allometric relationships in Douglas-fir.

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Chapter 5 General Conclusion

We have explored the utility of several methods for describing the soils and topography of a forested areas, and demonstrated their suitability for applications in forest growth and yield modeling. Integration of the results from each chapter reveals a fresh perspective on the assessment of productive potential of forested areas in northwestern Oregon using a combination of surface soil observations and DEM-derived terrain indices to characterize the quality of growing conditions as determined by water availability and potential incoming solar radiation.

The primary objective of the first chapter of this thesis was to address a common issue that arises when attempting to incorporate soils information into growth models: traditional soil survey methods provide very detailed information at a limited number of points that may describe several common soil series in an area, but do not provide an estimate or description that can be associated with an entire stand with any reliability. Our results show that there are strong correlations between surface soil characteristics and the average value for the top 100 cm of mineral soil, which suggests that even a crude estimate of the surface soil texture may serve as an index for some properties of the top 100 cm. Even if these correlations are weak, incorporation of a surface soil sample into existing forest inventory protocols could facilitate more reliable indices of soil texture across forested areas than estimates currently available through existing soil survey databases. We anticipate a critical review of this assessment from the forest soils community, but thus far, soil maps derived from widely-dispersed soil profile descriptions have proven inadequate for use in forest growth predictions, forcing us to seek alternative sampling strategies.

Soil moisture availability during summer drought is a function of soil properties and topography. The results reported in Chapter 3 show that DEM-derived terrain indices such as topographic wetness index and slope can be used to estimate soil moisture conditions towards the end of the annual drought of northwestern Oregon's Coast Range. Presumably, topographic wetness index accounts for inputs from subsurface flow which supplement the amount of available water determined by soil texture and structure.

We based our approach to modeling productivity across Panther Creek (Chapter 4) on the findings of the preceding chapters. While the results of the productivity analysis from the fourth chapter are specific to the Panther Creek Watershed, it appears that gradients in topography and, to a lesser degree, soil properties are driving local variability in productivity as measured by basal area increment and site index. Aspect, slope, and topographic position were the strongest predictors for all measures of productivity, but the aspect and topographic position at which productivity was maximized varied among basal area periodic annual increment, height increment, and site index. This finding raises several questions pertaining to the dependence of both allometric relationships and the allocation of resources to vertical- and horizontal growth on gradients in moisture availability and incoming solar radiation.

Since the sample acquired for the productivity analysis did not include any estimates of periodic mortality, we could not directly address the question of environmental factors that determine stockability or carrying capacity. However, it is possible that a stand's trajectory across the size-density surface could be indicative of carrying capacity before maximum stand density is reached. A follow-up study that includes a multiple re-measurements of plots placed across the gradients of topographic position and aspect could finally allow us to explain specific environmental factors that determine carrying capacity.

The correlations between forest productivity and the environmental gradients represented by soils and topography that we documented in this thesis show promise for refining predictions of Douglas-fir growth by including site-specific physical characteristics as covariates in growth models. While the surface soil sample did not yield a great deal of insight into gradients in productivity, the observation that surface soil texture can serve as an index for textural components for the top 100 cm may provide a theoretical framework for supplementing existing soil maps with a relatively inexpensive soil sampling protocol.

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