Defining and Estimating Forest Productivity Using Multi-Point Measures and a Nonparametric Approach

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Major in Natural Resources
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by
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Authorization to Submit Thesis

This thesis of Halli J. Hemingway, submitted for the degree of Master of Science with a Major in Natural Resources and titled "Defining and Estimating Forest Productivity Using Multi-Point Measures and a Nonparametric Approach," has been reviewed in final form. Permission, as indicated by the signatures and dates below, is now granted to submit final copies to the College of Graduate Studies for approval.

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Abstract

Accurate measures of forest site productivity are essential for forest management planning. The most common measure of site productivity is breast height age site index (BHASI) – the expected height at a reference age. Error from including early growth in productivity estimates, and limited applicability of any one BHASI model warrant development of alternative methods. Exploring alternatives may only be necessary if regional BHASI models are not accurately predicting growth rates.

We compared modeled height growth rates for Rocky Mountain Douglas-fir (Pseudotsuga menziesii var. glauca) to felled-tree measurements to evaluate relative performance of a regional BHASI model. An orthogonal sampling design ensured samples were collected across a range of site factors known to influence Douglas-fir growth rates. Growth rates for each 10 m section were calculated and compared to BHASI modeled growth rates. The regional BHASI model under-predicted growth rates from breast height to 30 m. Observed growth rates from 10 to 30 m accounted for the majority of under-prediction relative to BHASI modeled growth rates. An alternative multi-point method of defining site productivity (10-meter site index) is described.

We explored the accuracy of productivity predictions using 10-meter site index and a nonparametric approach. Using climate, soil, and topographic data along with felled tree measurements, we compared five possible models to estimate forest productivity. Model parameters, performance, and predictions were compared. Twelve validation sites were used to test accuracy of model predictions. Model performance was significantly improved when smoothing span values were optimized and elevation was added as a predictor. A four-predictor nonparametric model with a bias-corrected Akaike information criterion optimized smoothing span value produced the most accurate results and was used to produce forest productivity maps for the study area. The large resolution of currently available climatic data and the complex nature of the study area landscape necessitate a topographic variable for accurate productivity predictions. Defining productivity using 10-meter site index and estimating landscape scale productivity using an optimized nonparametric approach produced the most accurate forest productivity estimates.

Acknowledgements

I would like to thank my major professor Dr. Mark Kimsey for his encouragement and guidance throughout this project. I also thank Jim Arney for his time, expertise, patience, and inspiration to pursue this project to completion. I also thank Ann Abbott for her gentle encouragement and statistical expertise. I thank Andrew Nelson for his contributions to increasing my forestry knowledge and expertise. The final product was greatly improved as a result of their participation. I would also like to thank the faculty and staff of the Department of Forest, Fire, and Rangeland Sciences at the University of Idaho for a fulfilling, supportive graduate experience.

This study was supported by funds from the Forest Biometrics Research Institute and Bennett Lumber Products, Inc. Lastly, I would like to thank my employer, Bennett Lumber Products, Inc. for allowing me to pursue this graduate degree and further my forestry education. This would not have been possible without your tremendous support and encouragement.

Dedication

This thesis is dedicated to RJ. Your love, patience, and encouragement have made this possible. Lord knows the country that we've seen.

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Statement of Contribution

I declare that the research presented in this Thesis represents original work that I carried out during my studies at the University of Idaho. The two multi-authored papers that are included here include Mark Kimsey. Mark helped with project planning and design and reviewed manuscripts before submission. I completed all data gathering and field work, data analysis, and writing of manuscripts.

Chapter 1: Introduction

Accurate and reliable measures of tree growth rates and overall site productivity are essential for growth and yield estimation of forested landscapes and general forest resource management (Kayahara et al., 1998; McKenney and Pedlar, 2003; Skovsgaard and Vanclay, 2013; Spurr and Barnes, 1980). Understanding productivity of forestland is essential in sustainable management and preservation of forest ecosystems (Skovsgaard and Vanclay, 2013; Weiskittel et al., 2011). Knowledge of productivity is especially important for land managers whose primary goal is producing wood fiber for harvest (Mola-Yudego, 2011; Rossi et al., 2009; Weiskittel et al., 2011). Making sound decisions about harvest, restoration, fuels treatment, and sustainability requires an understanding of growth dynamics in relation to different forest site conditions (Grier et al., 1989).

The most common measure of forest site productivity is breast height age site index (BHASI) – the expected height at a reference breast height (1.4 m) age. BHASI has been used for over a century to quantify forest productivity (Batho and Garcia, 2006). Because site productivity is closely related to the height of dominant trees on a given site (Spurr and Barnes, 1980), and BHASI is easily measured in the field, this method has been the most widely used measure of site productivity to date (Kimsey et al., 2008; Monserud et al., 2006; Parresol et al., 2017; Seynave et al., 2005).

When using BHASI, tree age at breast height (BH) and total height are commonly used in a regional site index equation to estimate site index. These site index curves and equations were developed to describe height growth and age for a range of site conditions within a region. Because forest growth rates are not universal, many site index equations and curves have been developed to describe growth for the diversity of tree species, locations, and conditions that occur around the world (Auchmoody and Rexrode, 1984; Cochran, 1979; Monserud, 1984; Rayner, 1991; Zlatanov et al., 2012). Site index equations and curves have been developed for managed and unmanaged forests, distinct forest locations, and afforested farmland (Barrett,1978; Dolph, 1987; Johansson, 2011).

The first stem-analysis based site index equations and growth curves for Rocky Mountain Douglas-fir (Pseudotsuga menziesii var. glauca) in the Inland Northwest, USA were developed by Monserud (1984). Prior to 1984, most inland northwest land managers used site index curves developed for coastal or east-side Cascade range Douglas-fir (Cochran, 1979; King, 1966). The availability of site index curves based on stem-analysis data from northern Idaho and western Montana was a marked improvement. Monserud's (1984) objective was to develop height-age curves that would be applicable for Douglas-fir occurring in even-aged, uneven-aged, and mix-species stands. At the time, geospatial technology to properly stratify the landscape for productivity sampling was not available. Instead, Monserud (1984) assigned a habitat type to each sampled location and tried to sample equally in each of 5 habitat types. To date, no other height-age growth curves have been developed for Rocky Mountain Douglas-fir.

Early users of BHASI recognized its shortcomings and expected that it may be abandoned for a more accurate method (Frothingham, 1918). BHASI assumes that one point of height/age measurement is sufficient to describe the entire range of tree growth (Zeide, 1978). Disturbance, the presence of uneven-aged stands, afforestation of previously cleared land, and stands that are converted to different species all produce barriers to measurement of BHASI (McKenney and Pedlar, 2003). In addition, a high level of measurement error is associated with BH age increment cores (Clark and Hallgren, 2004). Error is also introduced when a specific site index equation is applied to a forest with different conditions and growth rates than those used to build the site index equations. Additional error from early life history growth responses may be introduced by using BHASI to define forest productivity (Arney et al., 2009; Day et al., 1960; Frothingham, 1918; Wakeicy and Marrero, 1958).

The absence of systematic sample site stratification based on site conditions known to effect productivity adds error to specific BHASI estimates. Combinations of climatic, topographic, and edaphic factors have shown potential for describing variability in tree growth rates (Bontemps and Bouriaud, 2014). The majority of these predictive studies included measures of precipitation, temperature, soil, and topography, (McKenney and Pedlar, 2003; Sabatia and Burkhart, 2014; Seynave et al., 2005; Watt et al., 2015). Many of the currently used BHASI curves were developed before technology to perform an accurate landscape scale stratification was readily available (Cochran, 1979; King, 1966; Monserud, 1984).

The large quantity of formulas to describe the same height-age relationship suggests they are of limited value (Zeide, 1978). Because of error due to early tree growth, measurement error, lack of sample stratification, and limited applicability of any one BHASI model, a new approach to define productivity of forestland is needed. However, an alternative approach may only be necessary if regional BHASI models are not accurately predicting site height growth potential.

Examining the potential causes of the sigmoidal height growth pattern of individual trees provides understanding useful to selection of an alternative measure of productivity. Dominant and codominant trees typically display a period of slow, but increasing growth as they become established (phase 1), followed by a period of maximum growth rates (phase 2), followed by a period of decreasing growth (phase 3) (Bond et al., 2007; Marmoller, 1947; Mcardle et al., 1949; Zedaker et al., 1987). Phase 1 growth rates are more influenced by management action or inaction than inherent site productivity (Harrington and Schoenholtz, 2010; Miller et al., 1993; Newton and Hanson, 1998). As trees become established, phase 2 growth is directly influenced by site productivity (Nishizono et al., 2008; Spurr and Barnes, 1980). Tree size and site limiting factors cause tree growth to level-off and decline in phase 3 (Weiner and Thomas, 2001). This understanding suggests that any direct productivity measure should include phase 2 growth and should avoid phase 1 and 3 growth. The "two-point" principle provides a method to characterize tree growth and site productivity without the need for site index equations (Zeide, 1978). Measuring more than one height-age pair for a given tree may provide a better estimate of site productivity, particularly if the two points are located along the bole less influenced by early stand development (Zeide, 1978).

A relatively new approach involving felled-tree measured height-growth rates from 10 to 20 m may provide a more robust method to define site productivity by eliminating phase 1 and 3 error (Arney, 2017; Hemingway and Kimsey, 2020). The 10-meter Site Index Method (10MSI) uses a measured tree growth rate (meters/decade) from 10 to 20 m heights to define site productivity (Arney, 2017). Because this period of growth coincides with phase 2, it may be a more reliable measure of productivity.

Due to time, financial, and forest composition constraints, it is not possible to directly measure forest productivity across large landscapes at fine scales. In the last several decades, numerous efforts have been made to estimate forest productivity indirectly from environmental variables (Bontemps and Bouriaud, 2014; Coops et al., 2011; Kimsey et al., 2008; McKenney and Pedlar, 2003; Parresol et al., 2017; Watt et al., 2010). Most of these attempts have used BHASI to define productivity and relate to site variables. Many recent investigations with small geographic ranges show a fair to high goodness of fit, while predictive models for larger geographic extents tend to show reduced performance (Bontemps and Bouriaud, 2014).

A recent synthesis of productivity predictive approaches (Bontemps and Bouriaud, 2014) suggested that the weaknesses of BHASI warranted alternative, direct productivity measurements to relate to environmental factors for predictive models. Bontemps and Bouriaud (2014) recommended a geocentric approach where biophysical factors are directly correlated to site productivity measures rather than the hybrid geocentric-phytocentric approach that results from using BHASI (Bontemps and Bouriaud, 2014). Balanced sampling across the different factors influencing tree growth and careful attention to the problem of intrinsic correlations of predictors were also identified as key elements of predictive models (Bontemps and Bouriaud, 2014).

The problems in applying linear models to species responses with multiple interacting predictors have been clearly stated in other ecological disciplines (Cade and Noon, 2003; Huston, 2002), but have not been broadly addressed in forestry. The particular benefits of using non-parametric multiplicative regression (NPMR) for representing species responses to multiple predictors has been shown in ecological research (McCune, 2006), but has not been widely applied in site-growth studies. Combining a well-balanced 10MSI sampling design with a non-parametric statistical technique to account for collinearity of predictors should provide the improvements recommended by Bontemps and Bouriaud (2014) and should result in accurate productivity estimations.

Chapter 2: A Multi-Point Felled Tree Validation of Height-Age Modeled Growth Rates

Forthcoming in *Forest Science*

Abstract

Accurate measures of forest site productivity are essential for forest management planning. The most common measure of site productivity is breast height age site index (BHASI) – the expected height at a reference age. Error from including early growth in productivity estimates, and limited applicability of any one BHASI model warrant development of alternative methods. Exploring alternatives may only be necessary if regional BHASI models are not accurately predicting growth rates. We compared modeled height growth rates for Rocky Mountain Douglas-fir (Pseudotsuga menziesii var. glauca) to felled-tree measurements to evaluate relative performance of a regional BHASI model. An orthogonal sampling design ensured samples were collected across a range of site factors known to influence Douglas-fir growth rates. Growth rates for each 10 m section were calculated and compared to BHASI modeled growth rates. The regional BHASI model under-predicted growth rates from breast height to 30 m. Observed growth rates from 10 to 30 m accounted for the majority of under-prediction relative to BHASI modeled growth rates. An alternative multi-point method of defining site productivity is described. More research comparing BHASI and alternative methods is needed given the growth rate error associated with one-point site productivity assessment.

Introduction

Accurate and reliable measures of tree growth rates and overall site productivity are essential for growth and yield estimation of forested landscapes and general forest resource management (Kayahara et al., 1998; McKenney and Pedlar, 2003; Skovsgaard and Vanclay, 2013; Spurr and Barnes, 1980). Understanding the productivity of forestland is especially important for land managers whose primary goal is producing wood fiber for harvest (Mola-Yudego, 2011; Rossi et al., 2009; Weiskittel et al., 2011).

The most common measure of forest site productivity is breast height age site index (BHASI) – the expected height at a reference breast height (1.4 m) age. BHASI has been used for over a century to quantify forest productivity (Batho and Garcia, 2006). Because site productivity is closely related to the height of dominant trees on a given site (Spurr and Barnes, 1980), and BHASI is easily measured in the field, this method has been the most widely used measure of site productivity to date (Kimsey et al., 2008; Monserud et al., 2006; Parresol et al., 2017; Seynave et al., 2005).

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The absence of systematic sample site stratification based on site conditions known to effect productivity adds error to specific BHASI estimates. Combinations of climatic, topographic, and edaphic factors have shown potential for describing variability in tree growth rates (Bontemps and Bouriaud, 2014). The majority of these predictive studies included measures of precipitation, temperature, soil, and topography, (McKenney and Pedlar, 2003; Sabatia and Burkhart, 2014; Seynave et al., 2005; Watt et al., 2015). Many of the currently used BHASI curves were developed before technology to perform an accurate landscape scale stratification was readily available (Cochran, 1979; King, 1966; Monserud, 1984).

The large quantity of formulas to describe the same height-age relationship suggests they are of limited value (Zeide, 1978). Because of error due to early tree growth, measurement error, lack of sample stratification, and limited applicability of any one BHASI model, a new approach to define productivity of forestland is needed.

The "two-point" principle provides a method to characterize tree growth and site productivity without the need for site index equations (Zeide, 1978). Measuring more than one height-age pair for a given tree may provide a better estimate of site productivity, particularly if the two points are located along the bole less influenced by early stand development (Zeide, 1978). Measured tree growth rates between 10 and 20 m (10MSI) may be a more robust way to define site productivity and eliminate early stand development bias (Arney et al., 2009).

A 10MSI approach would alleviate reliance on BHASI models developed to capture local or regional site effects. However, this alternative approach may only be necessary if regional BHASI models are not accurately predicting site height growth potential.

Therefore, the objective of the current study was to determine if a regional BHASI model is accurately predicting tree height growth rates across a range of site conditions. To approach this objective, we investigated the research question: do Monserud (1985) growth curves accurately describe total, early, mid, and late life tree height growth rates for a range of site conditions in our study area?

Methods and Materials

Study area

The study area covers an area of over 560,000 ha of forestland in north central Idaho, USA (Figure 2.1). This study area includes diverse moisture regimes, terrain attributes, and habitat types. Elevation ranges from 294 m in the southeast to 1938 m in the northeast. Mean annual precipitation (MAP) ranges from 50 to 160 cm. A diversity of soil conditions exists with soil depths to restrictive layers ranging from 33 to >200 centimeters. Volcanic ash from the eruption of Mount Mazama and loess deposits from the Columbia Basin are common surface mantles in the study area. While this area supports a diversity of tree species, Douglas-fir has a wide ecological amplitude across the study area and is therefore well suited as a test species.

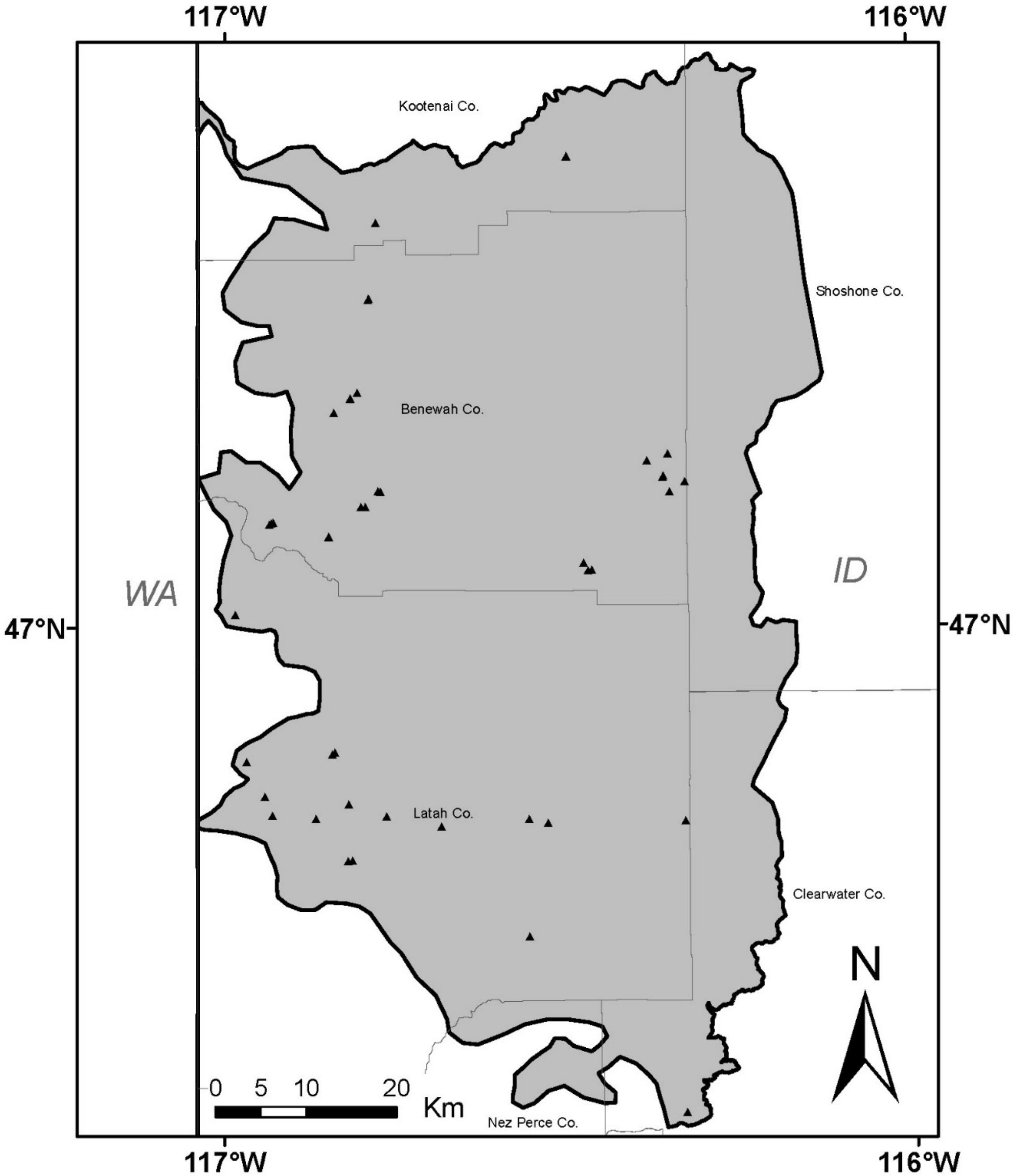

Figure 2.1. Study location.

Study area stratification and selection of sample locations

We stratified the study area into 27 strata using MAP, growing season days greater than 10° C (GDAY), and soil depth to restrictive layer. This ensured sampling covered the range of site conditions known to impact Douglas-fir height growth (Brown and Loewenstein, 1978; Curt et al., 2001; Green et al., 1989).

We applied a one-acre point grid to the entire study area, and populated each grid point with elevation, MAP, GDAY, and soil depth to restrictive layer. Elevation data was obtained from a 30m United States Geological Survey (USGS) digital elevation model (DEM). Secondary topographic derivatives (slope and aspect) were created using the Surface geoprocessing tool in the ArcGIS 10.6 Spatial Analyst toolbox. MAP data was extracted from Oregon State University's PRISM (Parameter-elevation Regressions on Independent Slopes Model) 1981-2010 normals climate layers (Oregon State University, 2012). Soil depth to restrictive layer data was obtained from Soil Survey Geographic data (SSURGO) (Natural Resources Conservation Service, 2018). Elevation, MAP, and soil depth maps were overlaid on the one-acre point grid, and all data associated with each point grid location was extracted using GIS data extraction techniques. All data was manipulated using ArcGIS 10.6.

We calculated growing season days greater than 10° C at the hillslope level using elevation, aspect, slope, distance to nearest limiting horizon, and degrees latitude north. This localization was conducted to ensure we accounted for frost pockets commonly found in the dendritic landscapes of the region. This analysis was performed using the Forest Projection and Planning Software (FPS) (Forest Biometrics Research Institute, 2018) and these values were assigned to each grid point. Although growing season days greater than 5° C is more widely used in agriculture (Taylor, 1967), we used a 10° C threshold because it has been identified as a more appropriate baseline temperature for Douglas-fir (Brix, 1967; Helms, 1965).

Three levels of MAP, three levels of GDAY, and three levels of soil depth were used to stratify the study area for selection of suitable sample locations. For each stratum, a location less than 960 m in elevation and a location greater than 960 m in elevation were chosen to provide double samples if possible. This provided a balanced, orthogonal sample design across all macro-site conditions (Figure 2.2).

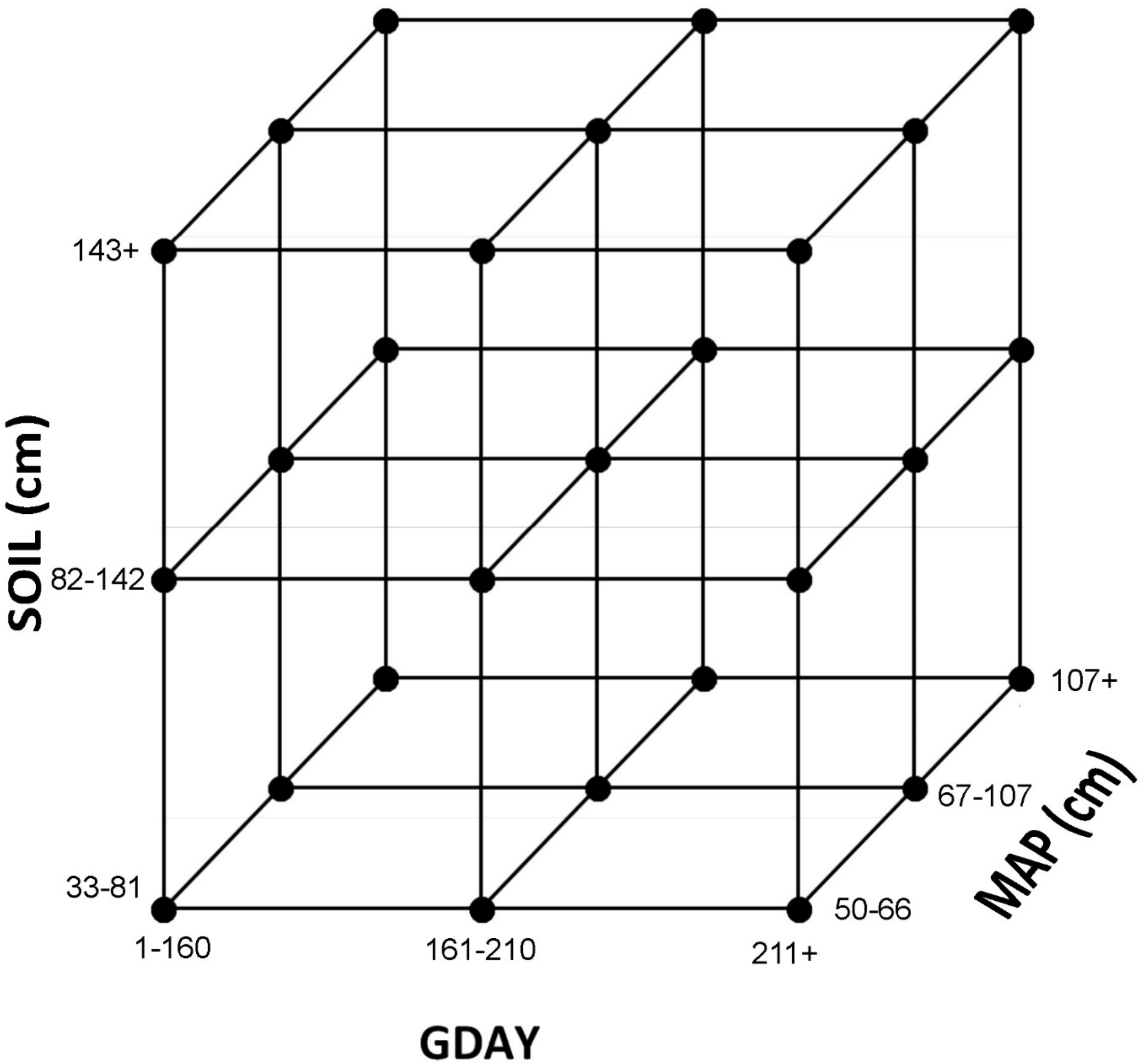

Figure 2.2. Balanced orthogonal sampling matrix.

Sample locations were randomly selected from each of the 27 strata. These locations were then evaluated for presence of Douglas-fir and accessibility. If the selected site was not suitable for sampling, another site was randomly selected and evaluated. This iterative process resulted in 44 sample sites across the 27 strata. The diversity of soil, topographic, and climatic conditions for sample locations is shown in Table 2.1. The diversity of stand conditions for sample locations is shown in Table 2.2.

Table 2.1. The range of orthogonally sampled site conditions for sampled locations.

Sample Site Conditions	**Range**
Elevation (m)	595 - 1356
Growing Season Days (>10° C) (days)	88 - 230
Soil depth to restrictive layer (cm)	43 - 200
Annual precipitation (cm)	56 - 135

Table 2.2. The range of stand characteristics for the sampled locations.

Sample Site Stand Characteristics	**Range**	**Mean**	**Standard Deviation**
Basal Area (m2/ha)	7.5 - 51.0	31.3	12.1
Relative Stand Density	9 - 76	42	16
Crown Competition Factor	43 - 277	175	65
Quadratic Mean Diameter (cm)	10.4 – 53.4	29.0	10.8

Sampling

Samples were collected in May and June of 2018. At each sample location, we identified 2-5 dominant or codominant Douglas-fir measurement trees by visual inspection. To be selected, a tree had to appear healthy and free of defect and damage, represent a dominant or co-dominant crown position, contain a crown ratio of at least 40%, and be at least 20 m and preferably 30 m in total height. These trees were cored at BH to ensure no presence of stem decay or past suppression. Trees were cut and sectioned at the stump (0.3 m), BH (1.4 m), 10 m, 20 m, and 30 m. We obtained ocular ring counts at each section. A summary of the ring counts is shown in Table 2.3. Total tree height was also measured.

Table 2.3. Sample tree ring count summary.

	Ring Count Summary		
Sample Tree Height	**Range**	**Mean**	**Standard Deviation**
Stump (0.3m)	38 – 162	89	24
Breast Height (1.4 m)	33 – 157	84	24
10 m	18 – 122	61	21
20 m	2 – 85	36	19
30 m	3 – 57	24	13

A total of 99 naturally regenerated trees across 44 suitable sample sites were cut down and measured. Two or three sample trees were felled per site. Total heights ranged from 21.2 to 39.0 m with a mean of 29.4 m and a standard deviation of 4.2 m. Age at stump height (0.3 m) ranged from 38 to 162 years with a mean of 89 years and a standard deviation of 24 years. We used all sampled trees for growth calculations if they included the segments being evaluated. Some of the sample trees (n=13) were not yet 30 m tall, so they were not included in the BH to 30 m and 20 to 30 m growth rate calculations and comparisons.

Observed 30 m and 10 m segment growth rates of sample trees

Tree segment growth rates were calculated for all sample trees using the ring counts obtained at BH, 10, 20, and 30 m heights.

BH to 30 m growth rates were calculated for all trees using

$$m/d = \frac{286}{RC_{BH} - RC_{30}} \tag{1}$$

where m/d is the observed growth rate in meters per decade, 286 is the number of meters over which we calculated the growth rate (28.6 m) multiplied by 10 to convert to m per decade, RC_{BH}= ring count at BH and RC_{30}= ring count at 30 m height.

BH to 10 m growth rates were calculated for all trees using

$$m/d = \frac{86}{RC_{BH} - RC_{10}} \tag{2}$$

where m/d is the observed growth rate in meters per decade, 86 is the number of meters over which we calculated the growth rate (8.6 m) multiplied by 10 to convert to m per decade, RC_{BH}= ring count at BH and RC_{10}= ring count at 10 m height.

We calculated 10 to 20 and 20 to 30 m growth rates for all trees using

$$m/d = \frac{100}{RC_j - RC_{j+10}} \tag{3}$$

where m/d is the observed growth rate in meters per decade, 100 is the number of meters over which we calculated the growth rate (10 m) multiplied by 10 to convert to m per decade, j = 10 or 20 m, RC_j= ring count at j height, and RC_{j+10}= ring count at j+10 height.

BHASI for sampled trees

Monserud (1985) provides differing site index and height growth equations based on habitat type. We did not include habitat type in this study. Because of this, the site index equation and height growth equations we used reflect the option for no habitat type information. BHASI was calculated for all sampled trees using

$$\hat{S} = 11.822 - 0.855(lnA)^2 + 0.0066 * A * lnA + 0.4305 * H + 28.415 * H/A \tag{4}$$

where $\hat{S}$ is BHASI, A=BH age, and H= total height – 1.37 m (Monserud, 1985).

Regional BHASI model predicted total heights and BH ages

In order to compare the sample tree measured growth rates to the predicted BHASI model (Monserud, 1985) growth rates, we calculated predicted total height by year of BH age for each sample tree. We calculated a predicted total height for each year from 1 to the year when predicted growth reached 30 m. This series of predicted total heights for each sample tree was calculated by adding 1.37 m to the most widely used Douglas-fir height growth BHASI equation for the study area (Monserud, 1985). The resulting formula was

$$\widehat{TH} = 1.37 + \frac{12.923 * (3.2808 * (S - 1.37))^{0.3488}}{1 + e^{9.7278 - 1.2934 * lnA_n - 0.9779 * ln(3.2808 * (S - 1.37))}} \tag{5}$$

where $\widehat{TH}$ was the predicted total height, S was the calculated Monserud (1985) site index for each sample tree, and A_n was the BH age from 1 to the year when predicted growth reached 30 m.

Using the Monserud (1985) predicted total heights by year of BH age, we recorded the predicted BH age when the predicted height was equal to 10, 20 and 30 meters for each sample tree.

These predicted BH ages were used to calculate predicted growth rates for each sample tree. A summary of these predicted BH ages is provided in Table 2.4.

Table 2.4. Summary of predicted breast height ages.

	Predicted Breast Height Age Summary		
Predicted Height	Range	Mean	Standard Deviation
10 m	15 – 36	23	5
20 m	32 – 85	52	12
30 m	57 – 167	94	26

Regional BHASI model predicted 30 m and 10 m segment growth rates

We used the predicted BH ages at 10, 20, and 30 meter heights from section 2.6 to calculate predicted growth rates for all sampled trees. Predicted BH to 30 m height growth rates were calculated using

$$m/d = \frac{286}{BHA_{30}} \tag{6}$$

where m/d is the predicted growth rate in meters per decade, 286 is the meters over which we calculated the growth rate (28.6 m) multiplied by 10 to convert to m per decade, and BHA_{30}= predicted BH age when the tree is 30 m tall.

Predicted BH to 10 m growth rates were calculated for all sample trees using

$$m/d = \frac{86}{BHA_{10}} \tag{7}$$

where m/d is the predicted growth rate in meters per decade, 86 is the number of meters over which we calculated the growth rate (8.6 m) multiplied by 10 to convert to m per decade, and BHA_{10}= predicted BH age when the tree is 10 m tall.

We calculated predicted 10 to 20 and 20 to 30 m growth rates for all sample trees using

$$m/d = \frac{100}{BHA_j - BHA_{j+10}} \tag{8}$$

where m/d is the predicted growth rate in meters per decade, 100 is the number of meters over which we calculated the growth rate (10 m) multiplied by 10 to convert to m per decade, j=10 or 20 m, BHA_j= predicted BH age at j, and BHA_{j+10}= predicted BH age at j+10.

Comparing observed and predicted growth rates

All predicted and observed growth rates were compared using analysis of covariance and Tukey HSD techniques in R with a 95% confidence level (R Core, 2018). We used the aov() function to fit a relationship between growth rates and Monserud (1985) site index with a covariate indicating if the growth rate was observed or predicted. The p-value of the covariate was compared to alpha=0.05 to determine significant difference between observed and predicted growth rates. If the difference was significant, we used the TukeyHSD() function to determine the magnitude of the difference.

We also used linear regression to compare the relationship between observed and predicted growth rates to a 1:1 relationship. This provided additional information about the type and direction of growth rate differences.

Results

Sample tree BH to 30 m growth rates (n=86) ranged from 1.8 to 5.6 m per decade with a mean of 3.6 ± 0.9 (mean ± standard deviation) m per decade. Similarly, Monserud estimated BH to 30 m growth rates ranged from 1.7 to 5.0 m per decade with a mean of 3.3 ± 0.8 m per decade. The mean difference between observed and predicted BH to 30 m growth rates was 0.32 ± 0.03 m per decade ($p<0.001$) (Figure 2.3).

BH to 10 m growth rates of sampled trees (n=99) ranged from 1.6 to 7.9 m per decade with a mean of 4.3 ± 1.3 m per decade. Monserud estimated BH to 10 m growth rates ranged from 2.4 to 5.7 m per decade with a mean of 3.9 ± 0.8 m per decade. On average, observed BH to 10 m growth rates were 0.37 ± 0.17 m per decade higher than predicted BH to 10 m growth rates ($p<0.001$) (Figure 2.3).

Sample tree 10 to 20 m growth rates (n=99) ranged from 2.0 to 6.3 m per decade with a mean of 4.3 ± 1.1 m per decade. Monserud estimated 10 to 20 m growth rates ranged from 2.0 to 5.9 m per decade with a mean of 3.7 ± 0.9 m per decade. The mean difference between observed and predicted 10 to 20 m growth rates was 0.64 ± 0.10 m per decade ($p<0.001$) (Figure 2.3).

Observed 20 to 30 m growth rates of sample trees (n=86) ranged from 1.3 to 5.6 m per decade with a mean of 2.9 ± 0.9 m per decade. Monserud estimated 20 to 30 m growth rates ranged from 1.2 to 4.2 m per decade with a mean of 2.6 ± 0.8 m per decade. On average, observed 20 to 30 m growth rates were 0.44 ± 0.10 m per decade higher than predicted 20 to 30 m growth rates ($p<0.001$) (Figure 2.3).

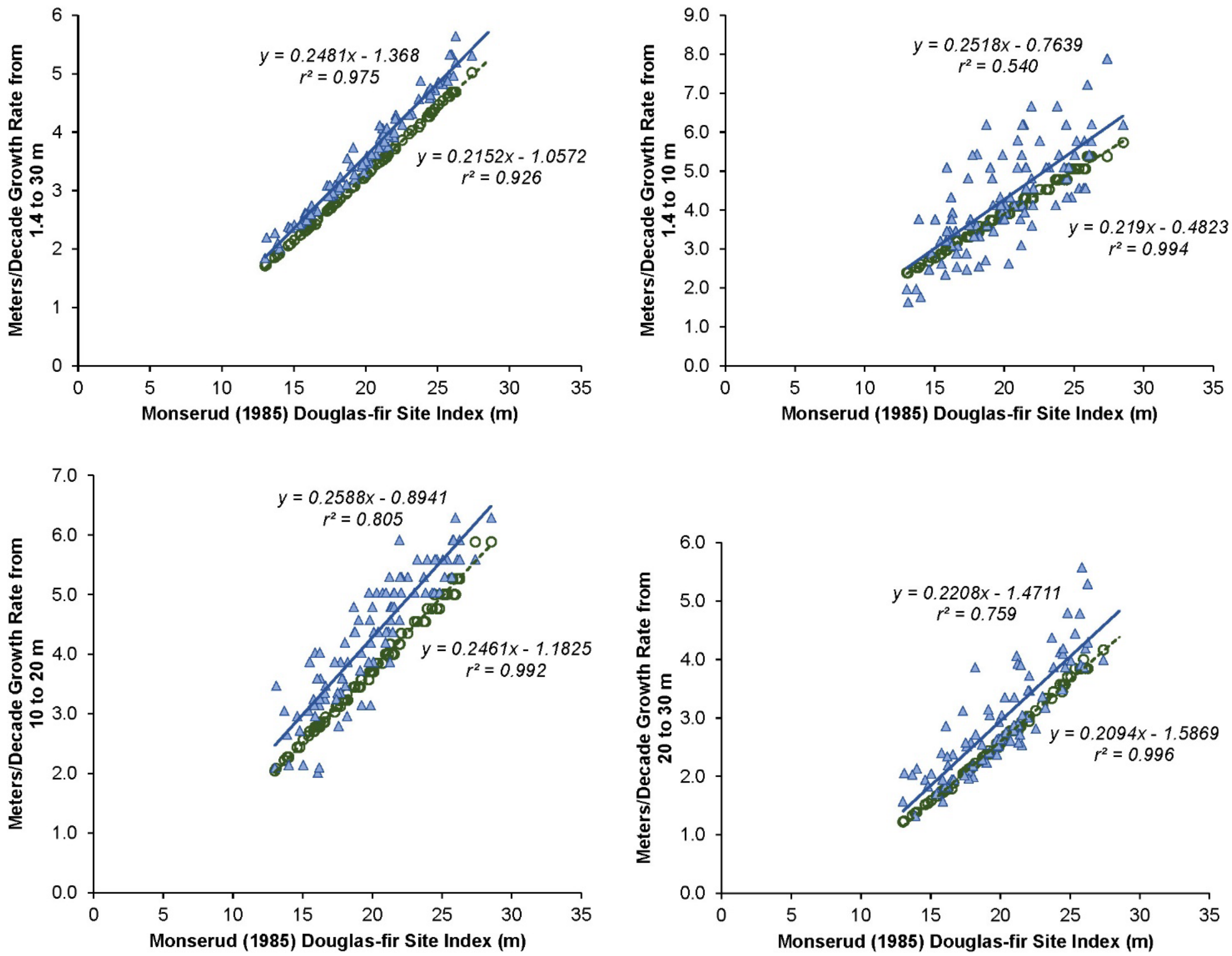

Figure 2.3. Monserud estimated and observed growth rates across the range of observed site index values.

The relationship between observed and predicted growth rates of trees compared to a 1:1 relationship showed consistent underprediction of BH to 30 m growth rates. However, for the BH to 10 m segment of slower growing trees, and in a few cases for the 10 to 20 m and 20 to 30 m segments of select trees, Monserud (1985) overpredicted growth rates (Figure 2.4).

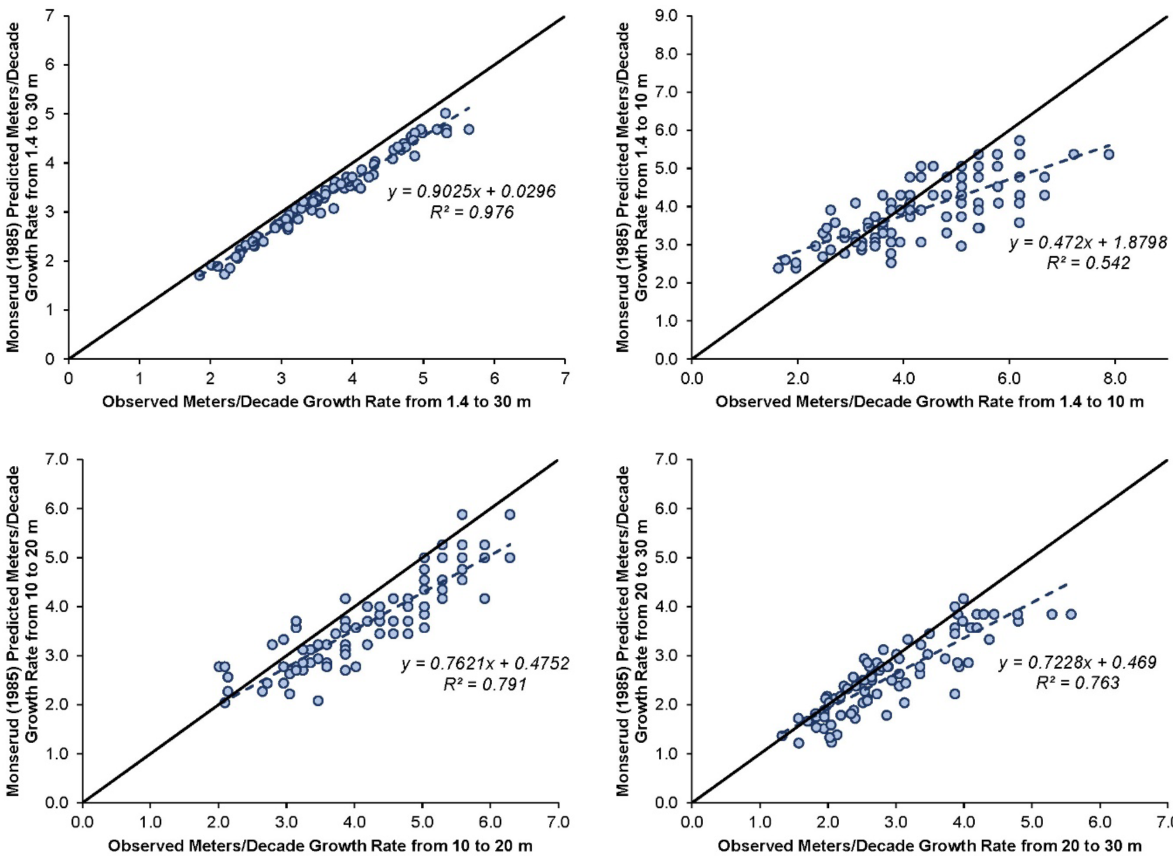

Figure 2.4. Relationship between Monserud estimated and felled tree two-point growth rates.

Discussion

While Monserud (1985) provides the only Douglas-fir site index curves for our region, these curves did not accurately estimate growth rates for our study area. Monserud (1985) under-predicted tree height growth rates from BH to 30m. Because we do not have access to the original data used to build the BHASI model, and there are no associated confidence intervals provided with the BHASI equations, we must assume there is a significant difference.

All sample trees were naturally regenerated and occurred in stands with low-intensity management. It is reasonable to assume that growth rate differences would be more pronounced for intensively managed, and/or planted stands (Bennett et al., 2003; Davis et al., 2009; Stage, 1958; Stage et al., 1988).

Using a fixed height-age curve that was fit through lower stem growth most likely causes under-prediction of total tree growth rates. The resulting height difference, on average, is 1.5 m for a

50 BH age tree in our study. When these differences are compounded across an entire forest inventory, the underestimation of height and associated volume is problematic.

Stand characteristics such as density, relative spacing, and composition can significantly impact height growth (Chase et al., 2016; Saud et al., 2016; Vickers et al., 2014; Yih and Douglas, 2011). Significant variation in height growth for a single species plantation at different sites within the same geographical range has been shown to affect the accuracy of site productivity prediction (Lynch et al., 2016). We ensured that the orthogonal sampling design covered the range of climatic, topographic, and edaphic conditions in the study area. This method of sampling also ensured the stand conditions in these sample sites covered wide ranges of stand density, relative spacing, and composition. Although the stand conditions at the sample sites varied greatly, the predicted height growth rates were consistently low. The consistent underprediction of growth rates by this regional BHASI model across a wide range of site and stand conditions gives further credibility to developing alternative methods to define productivity.

Measurement and early growth errors in BHASI productivity measurements compound when models are created to estimate forest productivity for unsampled locations using site conditions as predictors. Minimizing error in sample location measurements by using 10MSI will most likely reduce error in a final predictive model. Future research comparing model performance of BHASI and 10MSI productivity prediction models is needed.

Forest managers could use 10MSI and relative early and late life growth rate estimates to localize growth rate projections to their particular location and specific set of site conditions. Error from using a site index equation that was developed using different forest conditions than the target forest would be eliminated.

The 10MSI site productivity estimation method may provide a more universal approach that could be applied across a wider range of forests and forest conditions, however research comparing BHASI growth rate estimates to felled tree measurements in other regions is advised.

Chapter 3: Estimating Forest Productivity Using Site Characteristics, Multi-Point Measures, and a Nonparametric Approach

Submitted to *Forest Science*

Abstract

Understanding productivity of forestland is essential in sustainable management of forest ecosystems. The most common measure of site productivity is breast height age site index (BHASI). Despite wide acceptance, BHASI has limitations as a productivity measure and can compound error in predictive models. We explored the accuracy of productivity predictions using an alternative productivity measure (10-meter site index) and a nonparametric approach. An orthogonal sampling design ensured samples were collected across the range of conditions known to influence tree growth rates. Using climate, soil, and topographic data along with 10-meter site index measurements, we compared five possible models to estimate forest productivity. Model parameters, performance, and predictions were compared. Twelve validation sites were used to test accuracy of model predictions. Model performance was significantly improved when smoothing span values were optimized and elevation was added as a predictor. A four-predictor nonparametric model with a bias-corrected Akaike information criterion optimized smoothing span value produced the most accurate results and was used to produce forest productivity maps for the study area. The large resolution of currently available climatic data and the complex nature of the study area landscape necessitate a topographic variable for accurate productivity predictions.

Introduction

Understanding productivity of forestland is essential in sustainable management and preservation of forest ecosystems (Skovsgaard and Vanclay, 2013; Weiskittel et al., 2011). Making sound decisions about harvest, restoration, fuels treatment, and sustainability requires an understanding of growth dynamics in relation to different forest site conditions (Grier et al., 1989).

The most common measure of forest productivity is breast height age site index (BHASI) – the expected height at a reference breast height (1.37 m) age. In the past, forest managers have used this method along with regional site index curves or equations to define site productivity. Despite wide acceptance, BHASI has limitations as a productivity measure. Barriers to measurement for some forest conditions (McKenney and Pedlar, 2003), a high level of measurement error (Clark and Hallgren, 2004), and error from including early life growth of trees in the estimates (Arney, 2017;

Wakeicy and Marrero, 1958) restrict the utility of BHASI. Field estimation of BHASI is sometimes impossible due to inadequate stand health or composition (Kayahara et al., 1998).

In the last several decades, numerous efforts have been made to estimate forest productivity indirectly from environmental variables (Bontemps and Bouriaud, 2014; Coops et al., 2011; Kimsey et al., 2008; McKenney and Pedlar, 2003; Parresol et al., 2017; Watt et al., 2010). Most of these attempts have used BHASI to define productivity and relate to site variables. Many recent investigations with small geographic ranges show a fair to high goodness of fit, while predictive models for larger geographic extents tend to show reduced performance (Bontemps and Bouriaud, 2014).

A recent synthesis of productivity predictive approaches (Bontemps and Bouriaud, 2014) suggested that the weaknesses of BHASI warranted alternative, direct productivity measurements to relate to environmental factors for predictive models. Bontemps and Bouriaud (2014) recommended a geocentric approach where biophysical factors are directly correlated to site productivity measures rather than the hybrid geocentric-phytocentric approach that results from using BHASI (Bontemps and Bouriaud, 2014). Balanced sampling across the different factors influencing tree growth and careful attention to the problem of intrinsic correlations of predictors were also identified as key elements of predictive models (Bontemps and Bouriaud, 2014).

The problems in applying linear models to species responses with multiple interacting predictors have been clearly stated in other ecological disciplines (Cade and Noon, 2003; Huston, 2002) , but have not been broadly addressed in forestry. The particular benefits of using non-parametric multiplicative regression (NPMR) for representing species responses to multiple predictors has been shown in ecological research (McCune, 2006), but has not been widely applied in site-growth studies.

Examining the potential causes of the sigmoidal height growth pattern of individual trees provides understanding useful to selection of an alternative direct measure of productivity. Dominant and codominant trees typically display a period of slow, but increasing growth as they become established (phase 1), followed by a period of maximum growth rates (phase 2), followed by a period of decreasing growth (phase 3) (Bond et al., 2007; Marmoller, 1947; Mcardle et al., 1949; Zedaker et al., 1987). Phase 1 growth rates are more influenced by management action or inaction than inherent site productivity (Harrington and Schoenholtz, 2010; Miller et al., 1993; Newton and Hanson, 1998). As trees become established, phase 2 growth is directly influenced by site productivity (Nishizono et al., 2008; Spurr and Barnes, 1980). Tree size and site limiting factors cause tree growth to level-off and decline in phase 3 (Weiner and Thomas, 2001). This understanding suggests that any direct productivity measure should include phase 2 growth and should avoid phase 1 and 3 growth.

A relatively new approach involving felled-tree measured height-growth rates from 10 to 20 m may provide a more robust method to define site productivity by eliminating phase 1 and 3 error (Arney, 2017; Hemingway and Kimsey, 2020). The 10-meter Site Index Method (10MSI) uses a measured tree growth rate (meters/decade) from 10 to 20 m heights to define site productivity (Arney, 2017). Because this period of growth coincides with phase 2, it may be a more reliable measure of productivity. Combining a well-balanced 10MSI sampling design with a non-parametric statistical technique to account for collinearity of predictors should provide the improvements recommended by Bontemps and Bouriaud (2014) and should result in accurate productivity estimations.

The Forest Projection and Planning Software (FPS) (Forest Biometrics Research Institute, 2018) provides tools to develop 10MSI predictive models using a non-parametric regression technique. This software was developed by the Forest Biometrics Research Institute and is currently being used by 82 forestry organizations managing over 4.8 million hectares (Forest Biometrics Research Institute, 2019). Despite increasing interest and use of these techniques, there has been no research to date regarding the accuracy or performance of 10MSI as a measure of productivity in a site index prediction model. Likewise, no research examining FPS modeling strategies and parameters has been done.

Because 10MSI is a direct site productivity measure and may reduce error in predictive models, we wanted to further investigate its use in a geocentric site index prediction model. We also wanted to evaluate the relative accuracy of FPS generated predictions. Therefore, the objectives of the current study were to (1) determine relative accuracy of FPS predicted 10MSI in our study area, (2) explore alternative, non-parametric modeling parameters and approaches to generate 10MSI predictions, and (3) produce and evaluate GIS maps of 10MSI for the study area.

To approach these objectives, we asked the following questions: (1) what is the relative accuracy of FPS predicted 10MSI in our study area, (2) are there alternative model parameters that improve model performance, and (3) what does the 10MSI pattern in the study area tell us about regional productivity?

Methods and Materials

Study area

The study area includes an area of approximately 560,000 ha of forestland in north central Idaho, USA (Figure 3.1). This area includes varied precipitation regimes, topographic attributes, and forest communities. Elevation ranges from 1938 m to 294 m from northeast to southeast. Mean annual precipitation (MAP) ranges from 50 to 160 cm. Soil depths to restrictive layers range from 33 to >200 cm. Common surface soil mantles include volcanic ash from the eruption of Mount Mazama and loess deposits from the Columbia Basin. This area supports a diversity of tree species. Douglas-fir has a wide ecological amplitude across the area and is therefore well suited as a test species.

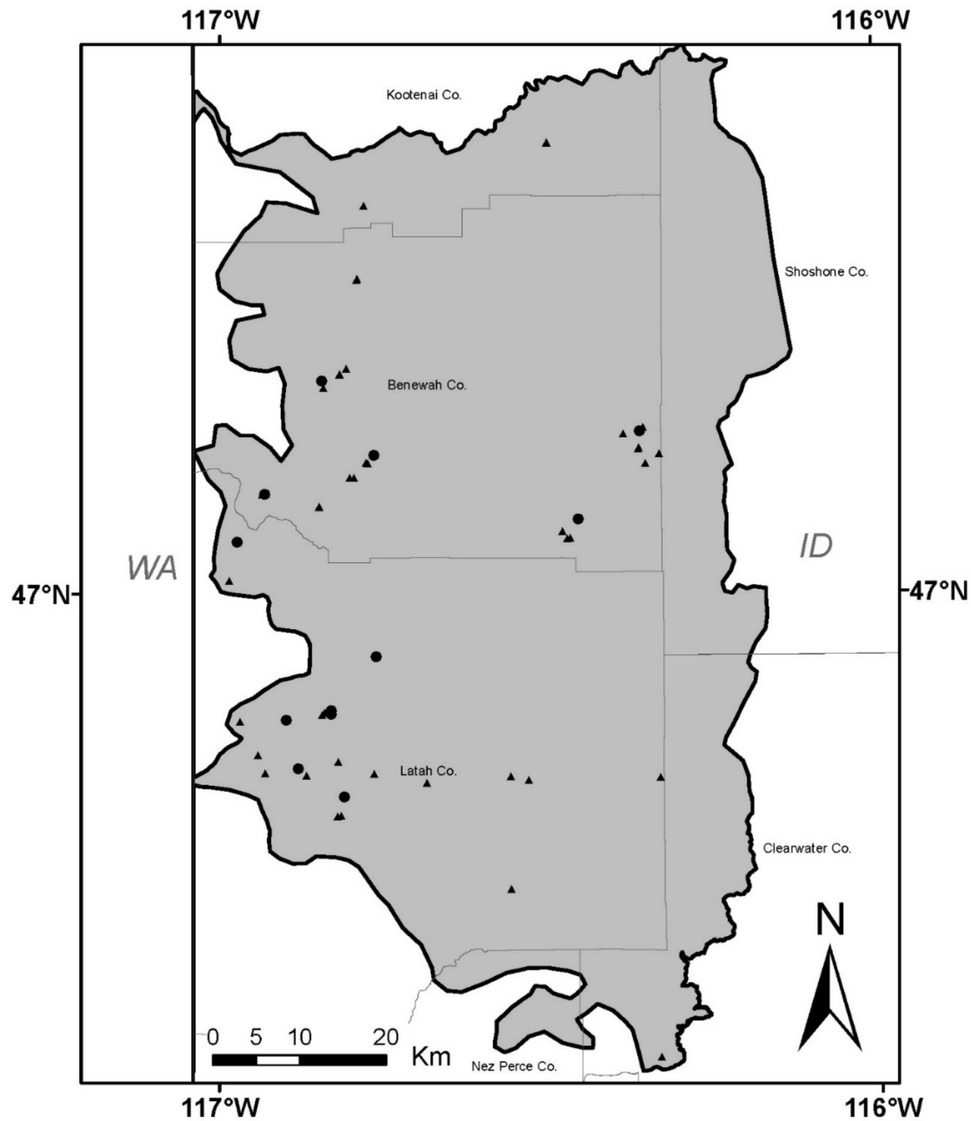

Figure 3.1. Study location.

Study area stratification and selection of sample locations

In order to ensure sampling covered the range of site conditions known to impact Douglas-fir height growth (Brown and Loewenstein, 1978; Curt et al., 2001; Green et al., 1989), the study area was stratified using MAP, growing season days greater than 10° C (GDAY), and soil depth to restrictive layer (SOIL).

We populated a study area wide 0.4-hectare point grid with elevation, MAP, GDAY, and SOIL. Elevation data was obtained from a 30m United States Geological Survey (USGS) digital elevation model (DEM). Slope and aspect layers were created using the Surface geoprocessing tool in the ArcGIS 10.6 Spatial Analyst toolbox. MAP data was extracted from Oregon State University's PRISM (Parameter-elevation Regressions on Independent Slopes Model) 1981-2010 normals climate layers (Oregon State University, 2012). SOIL was obtained from Soil Survey Geographic data (SSURGO) (Natural Resources Conservation Service, 2018). All data was manipulated using ArcGIS 10.6.

We calculated growing season days greater than 10° C at the hillslope level using elevation, aspect, slope, distance to nearest limiting horizon, and degrees latitude north. This localization was necessary to account for frost pockets commonly found in the dendritic landscapes of the region. This analysis was performed using FPS (Forest Biometrics Research Institute, 2018) and these values were assigned to each grid point. Although growing season days greater than 5° C is a more common agricultural measure (Taylor, 1967), we used a 10° C threshold because it has been identified as a more appropriate baseline temperature for Douglas-fir (Brix, 1967; Helms, 1965).

Three levels of MAP, three levels of GDAY, and three levels of SOIL were used to stratify the study area for selection of suitable sample locations. This resulted in 27 distinct strata. For each stratum, a location greater than and less than 960 m in elevation were chosen to provide double samples if possible. This provided a balanced, orthogonal sample design across all macro-site conditions (Figure 3.2).

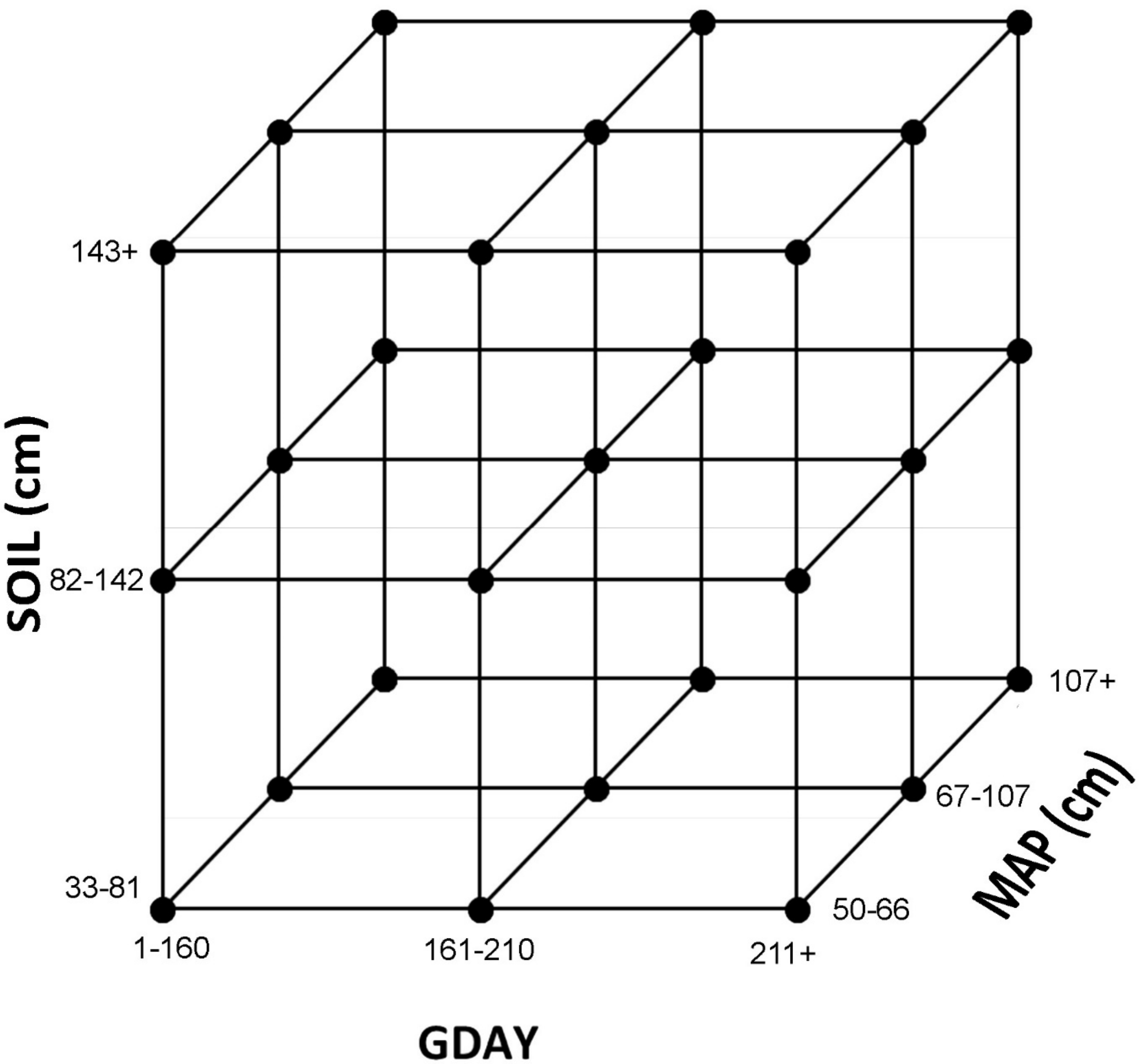

Figure 3.2. Balanced orthogonal sampling matrix.

Sample locations were randomly selected from the group of 0.4-hectare point grid locations in each of the 27 strata. These locations were then evaluated for presence of Douglas-fir and general accessibility. If the selected site was not suitable for sampling, another site was randomly selected and evaluated. This iterative process resulted in 44 sample sites across the 27 strata. The diversity of soil, topographic, and climatic conditions for sample locations is shown in Table 3.1. The diversity of stand conditions for sample locations is shown in Table 3.2.

Table 3.1. The range of orthogonally sampled site conditions for sampled locations.

Sample Site Conditions	Range
Elevation (m)	595 - 1356
Growing Season Days (>10° C) (days)	88 - 230
Soil depth to restrictive layer (cm)	43 - 200
Annual precipitation (cm)	56 - 135

Table 3.2. The range of stand characteristics for the sampled locations.

Sample Site Stand Characteristics	Range	Mean	Standard Deviation
Basal Area (m^2/ha)	7.5 - 51.0	31.3	12.1
Relative Stand Density	9 - 76	42	16
Crown Competition Factor	43 - 277	175	65
Quadratic Mean Diameter (cm)	10.4 – 53.4	29.0	10.8

We used the orthogonal sampling matrix to select 12 additional sampling locations for validation purposes. These sites were selected to cover the range of soil depths, annual precipitation, and growing season days that exist in the study area. The data from these sites was not included in model development, but was used post-model development to test accuracy of predictions. Sampling procedures were similar for both model-development and validation sample sites.

Sampling

Samples were collected in May and June of 2018. At each sample location, we identified 2-5 dominant or codominant Douglas-fir measurement trees by visual inspection. To be selected, a tree had to appear healthy and free of defect and damage, represent a dominant or co-dominant crown position, contain a crown ratio of at least 40%, and be at least 20 m in total height. These trees were cored at BH to ensure no presence of stem decay or past suppression. Trees were cut and sectioned at the stump (0.3 m), 10 m, and 20 m. We obtained ocular ring counts at each section. A summary of the ring counts is shown in Table 3.3.

Table 3.3. Sample tree ring county summary.

	Ring Count Summary		
Sample Tree Height	**Range**	**Mean**	**Standard Deviation**
Stump (0.3m)	38 – 162	89	24
10 m	18 – 122	61	21
20 m	2 – 85	36	19

A total of 123 naturally regenerated trees across 44 suitable sample sites and 12 validation sites were cut down and measured. Two or three sample trees were felled per site.

We calculated 10MSI for all trees using

$$10MSI = \frac{10_m * 10_{yrs}}{RC_{10} - RC_{20}} \qquad (1)$$

where 10MSI is the observed 10 to 20 m growth rate in meters per decade, 10_m is the number of meters over which we calculated the growth rate, 10_{yrs} is the years in a decade, RC_{10}= ring count at 10 meters, and RC_{20}= ring count at 20 meters. After two trees were cut down and measured, we compared the tree's respective 10MSI. If one tree showed a difference greater than 0.9 m per decade from the previous tree, we selected and sampled another tree to validate the productivity measure for that site. Mean 10MSI was calculated for each of the 44 sample sites and the 12 validation sites from individual tree 10MSI values.

Generating an FPS 10MSI model

We used FPS (Forest Biometrics Research Institute, 2018) and the process outlined in Arney (2017) to generate 10MSI predictions across our study area. In brief, we input the 44 sample location 10MSI measurements, and sample site MAP, SOIL, and GDAY. We also supplied FPS with the 0.4-hectare grid populated with MAP, SOIL, and GDAY. FPS uses a non-parametric regression technique with a locally weighted smoothing parameter. The local polynomial is fitted using weighted least squares, giving more weight to points similar to the point whose response is being estimated in the range of the data set. Points that are less similar to the predicted point are given less weight. FPS includes all observation points whether similar or dissimilar in each prediction (SPAN=1).

Evaluating optimum smoothing span

In order to evaluate if the NPMR smoothing span used by FPS is over smoothing the data, we used R (R Core, 2018) to generate a locally estimated scatterplot smoothing (LOESS) model using the same predictor variables used by FPS. We then used the LOESS.AS function to generate an optimum smoothing span value for this model using bias-corrected Akaike information criterion (AICC) and generalized cross validation (GCV) methods(Golub et al., 1979; Hurvich et al., 1998). We compared the Pearson correlation coefficients of the FPS three-predictor (FPS3) model, the three-predictor AICC optimum span (3OS1) model, and the three-predictor GCV optimum span (3OS2) model to assess relative model performance.

Creating an alternative 10MSI model

We explored the effect of adding elevation as a predictor in a non-parametric model with an optimized smoothing span value. The MAP data we used had a 800-m resolution, so adding a higher resolution topographic variable should improve model performance (Bontemps and Bouriaud, 2014).

Using a nonparametric LOESS function in R (R Core, 2018), we created a 10MSI predictive model using elevation, GDAY, MAP, and SOIL as predictors. We used the LOESS.AS function to generate an optimum smoothing span value for this four-predictor model using AICC and GCV.

We compared Pearson correlation coefficients between the FPS3, 3OS1, 3OS2, four-predictor AICC optimum span (4OS1), and four-predictor GCV optimum span (4OS2) models to assess relative model performance.

Validating FPS and Alternative Model Predictions

We compared FPS3, 3OS1, 3OS2, 4OS1 and 4OS2 model predicted 10MSI to observed 10MSI at each of the 12 validation sites. We calculated an 80% confidence interval for each model predicted 10MSI and determined if the observed 10MSI was within that confidence interval.

Raster map production

Using the best performing model, we generated raster maps of 10MSI for our study area. We applied the nonparametric 10MSI model to the 0.4-hectare point grid of unsampled locations using the predict() function in R. The model was applied to each of the grid points and associated predictor attributes to produce 10MSI predictions and model standard error values for the entire study area. Grid points with predictions outside the range of sampled 10MSI values were removed from the final predictive datasets. The 0.4-hectare predicted 10MSI point grid and standard error point grid were converted to raster datasets with a 0.4-hectare grid size for visualization purposes.

Results

Observed 10MSI (n=44) for sample sites ranged from 2.1 to 6.1 m per decade with a mean of 4.3 ± 1.0 (mean ± standard deviation) m per decade. Observed 10MSI (n=12) for validation sites ranged from 3.7 to 6.1 m per decade with a mean of 4.7 ± 0.7 m per decade.

The FPS3 model with FPS default span value (1.0) had a Pearson correlation coefficient between observed and predicted 10MSI at sample locations of $r = 0.60$. The LOESS.AS optimized span value for a 3-predictor model using AICC was equal to 0.73. The 3OS1 model had an $r = 0.79$. The LOESS.AS optimized span value using GCV was equal to 0.60. The 3OS2 model had an $r = 0.89$. The AICC optimized span value for the 4OS1 model was equal to 0.93. The 4OS1 model had an $r = 0.85$. The GCV optimized span value for the 4OS2 model was equal to 0.74. The 4OS2 model had an $r = 0.94$ (Table 3.4).

Table 3.4. Model parameters and fit comparisons.

Model	SPAN	Predictors	Sample Sites r	Sample Sites p	Validation Sites % within 80% CI
FPS 3-Predictor Model (FPS3)	1	MAP GDAY SOIL	0.60	<0.001	58%
3-Predictor AICC Optimum Span (3OS1)	0.73	MAP GDAY SOIL	0.79	<0.001	83%
3-Predictor GCV Optimum Span (3OS2)	0.60	MAP GDAY SOIL	0.89	<0.001	75%
4-Predictor AICC Optimum Span (4OS1)	0.93	MAP GDAY SOIL ELEV	0.85	<0.001	100%
4-Predictor GCV Optimum Span (4OS2)	0.74	MAP GDAY SOIL ELEV	0.94	<0.001	92%

Seven of the twelve validation site observed 10MSI were within the 80% confidence interval of the FPS3 model predictions. Observed 10MSI was within the 80% confidence interval of the 3OS1 model predicted 10MSI for 10 of the 12 sites. Similarly, 9 of the 12 sites observed 10MSI was within an 80% confidence interval of the 3OS2 model predictions. Observed 10MSI was within an 80% confidence interval of the 4OS1 model predicted 10MSI for all 12 of the validation sites. Eleven of the twelve validation site observed 10MSI were within the 80% confidence interval of the 4OS2 model predicted 10MSI (Figure 3.3).

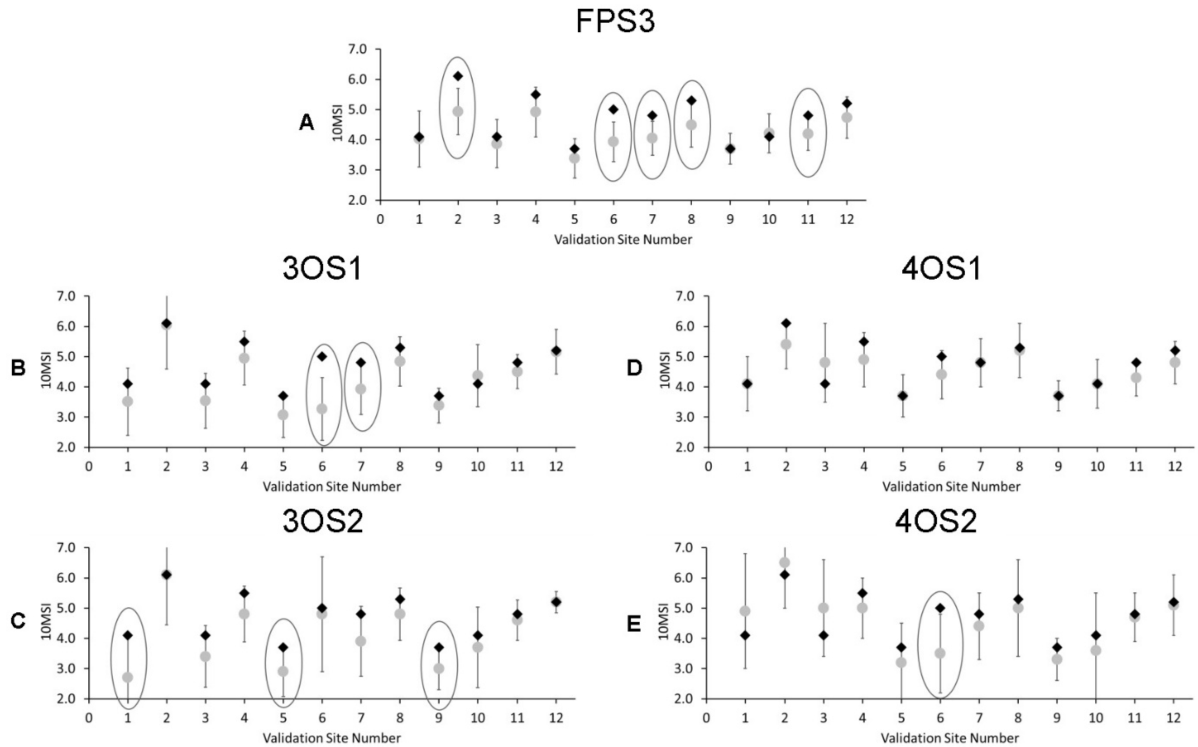

Figure 3.3. Observed (black diamond) and predicted (gray circle) 10-meter site index (10MSI) for 12 validation sites.

While the 4OS1 model had a slightly lower Pearson correlation coefficient than the 3OS2 and 4OS2 models, it more accurately predicted 10MSI for the validation sites. The 4OS1 model was chosen to produce productivity and standard error maps of the study area (Figures 3.4 & 3.5).

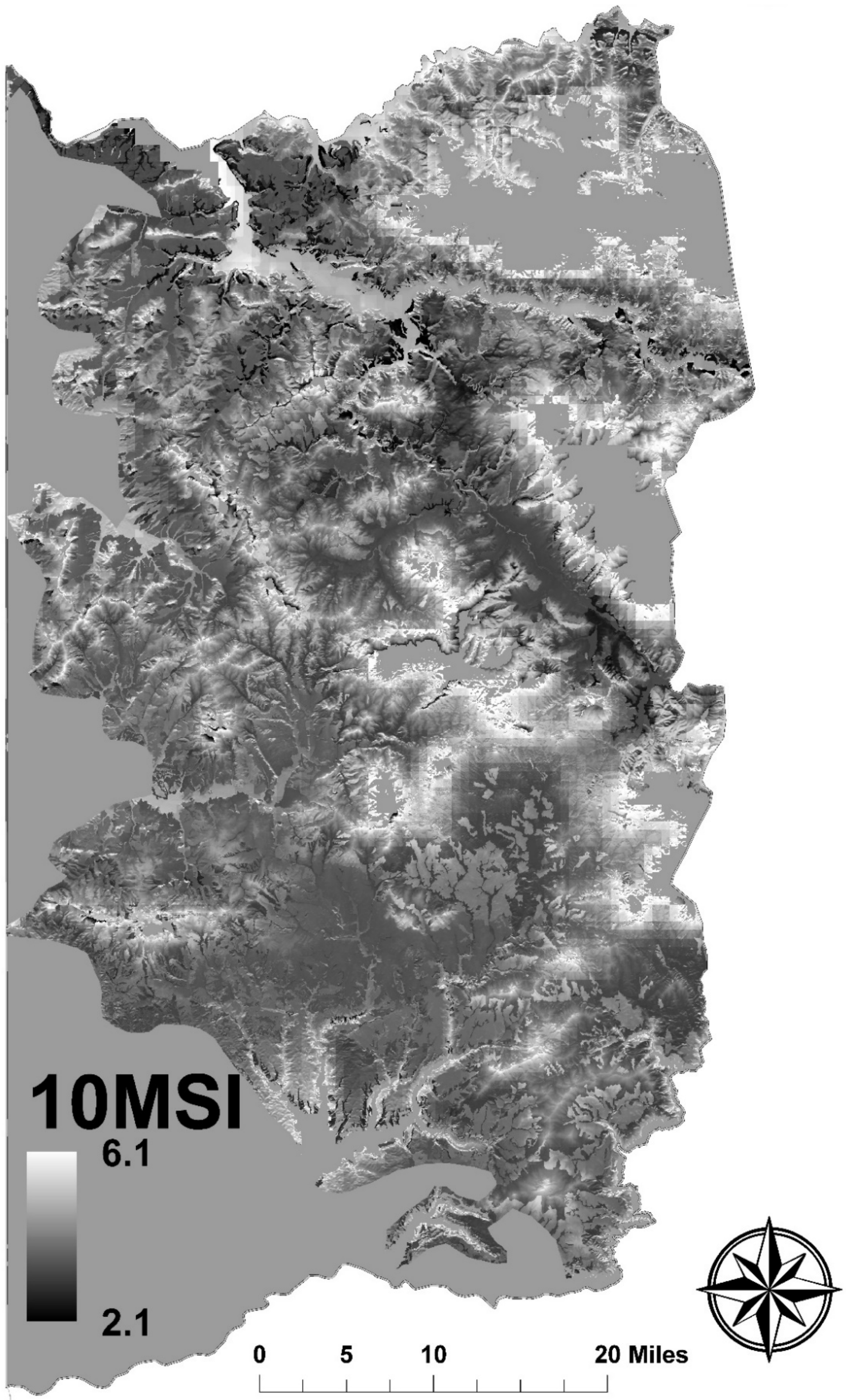

Figure 3.4. 10MSI predictions.

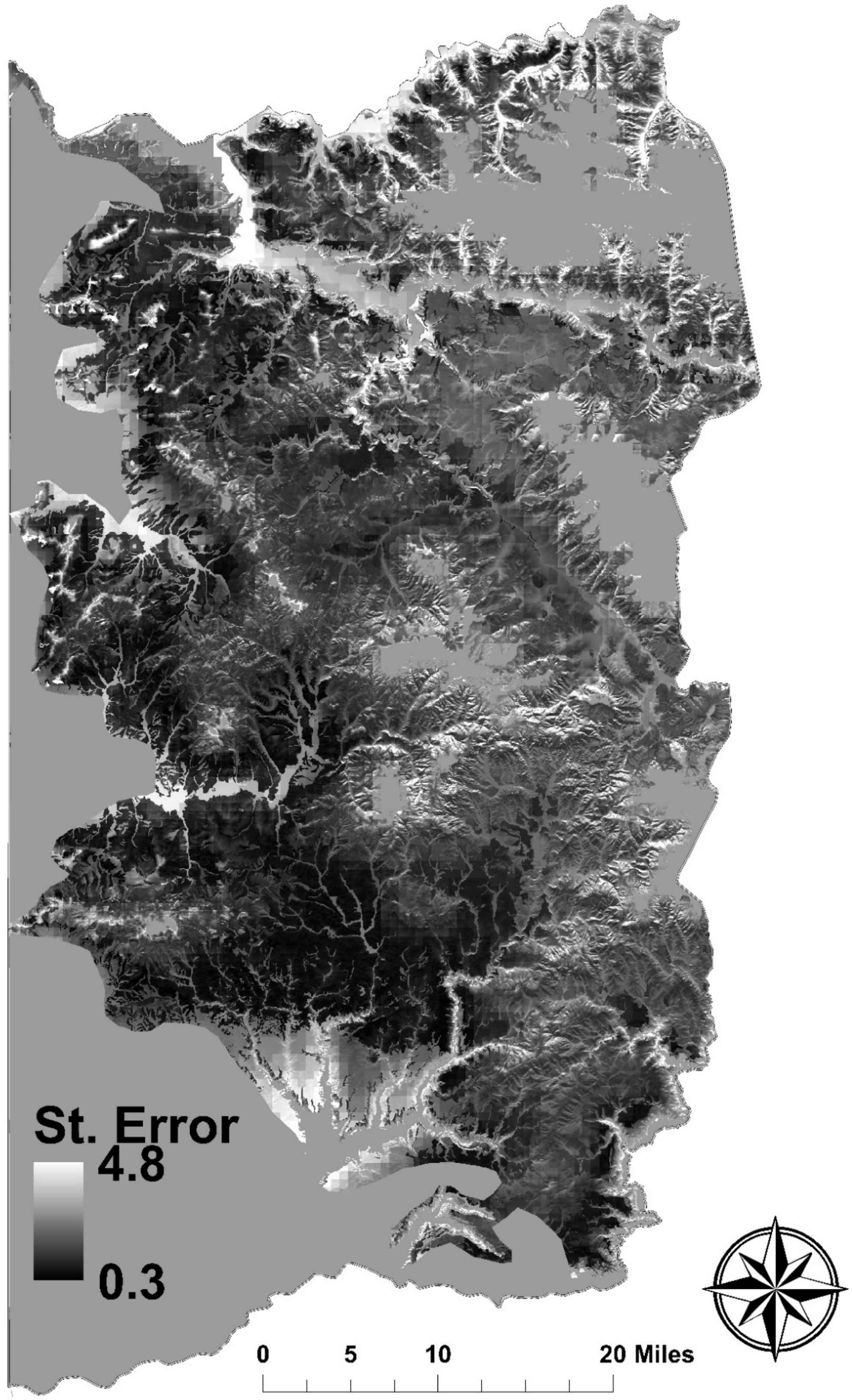

Figure 3.5. Standard error of 10MSI predictions.

Discussion

The weaknesses that BHASI introduces into productivity prediction models warrant the use of a direct productivity measure to relate to site factors for modeling. 10MSI is a direct productivity measure that can be related to environmental factors in a predictive model. When combined with a well-designed orthogonal sample and a non-parametric approach, a 10MSI predictive model should provide accurate estimates of productivity.

However, FPS generated 10MSI predictions were only moderately accurate across the range of conditions in our study area. FPS tended to underpredict 10MSI for our 12 validation sites. This less than desirable accuracy is most likely caused by the tendency of the FPS model to over-smooth the data, and the large resolution of the climatic data used in this study (800 m).

Model fit and accuracy was improved when the smoothing span value was optimized. However, predictions for some validation sites were not accurate. This suggests that a 3-predictor model with MAP, SOIL, and GDAY may not be fully capturing the variability in productivity across the landscape.

Model fit and accuracy was further improved when elevation was added as a fourth predictor. The 4-predictor model with an AICC optimized span value predicted all 12 validations sites accurately. The combination of adding elevation as a predictor and optimizing the smoothing span value using the AICC approach produced the most accurate predictions of the five models we evaluated. Similar to the findings of Hurvich et al. (1998), we found that AICC tends to undersmooth less than GCV.

The Forest Biometrics Research Institute may be able to improve FPS 10MSI predictions by allowing users to adjust smoothing span values. Including elevation as a predictor will improve predictions, particularly within the Inland Northwest region of the United States.

Our results indicated that forest productivity in this area follows an elevation gradient with many of the higher productivity areas at higher elevations. Lower elevation areas that have relatively low growing season days (frost pockets) have lower productivity. Soil depth has a positive influence on productivity when combined with adequate precipitation and higher numbers of growing season days.

Chapter 4: Conclusion

While Monserud (1985) provides the only Douglas-fir site index curves for our region, these curves did not accurately estimate growth rates for our study area. Monserud (1985) under-predicted tree height growth rates from BH to 30m. Because we do not have access to the original data used to build this BHASI model, and there are no associated confidence intervals provided with the BHASI equations, we must assume there is a significant difference.

All sample trees were naturally regenerated and occurred in stands with low-intensity management. It is reasonable to assume that growth rate differences would be more pronounced for intensively managed, and/or planted stands (Bennett et al., 2003; Davis et al., 2009; Stage, 1958; Stage et al., 1988).

Using a fixed height-age curve that was fit through lower stem growth most likely causes under-prediction of total tree growth rates. The resulting height difference, on average, is 1.5 m for a 50 BH age tree in our study. When these differences are compounded across an entire forest inventory, the underestimation of height and associated volume is problematic.

Stand characteristics such as density, relative spacing, and composition can significantly impact height growth (Chase et al., 2016; Saud et al., 2016; Vickers et al., 2014; Yih and Douglas, 2011). Significant variation in height growth for a single species plantation at different sites within the same geographical range has been shown to affect the accuracy of site productivity prediction (Lynch et al., 2016). We ensured that the orthogonal sampling design covered the range of climatic, topographic, and edaphic conditions in the study area. This method of sampling also ensured the stand conditions in these sample sites covered wide ranges of stand density, relative spacing, and composition. Although the stand conditions at the sample sites varied greatly, the BHASI predicted height growth rates were consistently low. The consistent underprediction of growth rates by this regional BHASI model across a wide range of site and stand conditions gives further credibility to developing alternative methods to define productivity.

10MSI is a direct productivity measure that can be related to environmental factors in a predictive model. When combined with a well-designed orthogonal sample and a non-parametric approach, a 10MSI predictive model provided accurate estimates of productivity. Specifically, a 4-predictor model with an AICC optimized span value predicted all 12 of our validation sites accurately. The combination of adding elevation as a predictor and optimizing the smoothing span value using the AICC approach produced the most accurate predictions of the five models we evaluated. Similar to the findings of Hurvich et al. (1998), we found that AICC tends to undersmooth less than GCV.

FPS generated 10MSI predictions were only moderately accurate across the range of conditions in our study area. FPS tended to underpredict 10MSI for our 12 validation sites. This less than desirable accuracy is most likely caused by the tendency of the FPS model to over-smooth the data, and the large resolution of the climatic data used in this study (800 m). The Forest Biometrics Research Institute may be able to improve FPS 10MSI predictions by allowing users to adjust smoothing span values. Including elevation as a predictor will improve predictions, particularly within the Inland Northwest region of the United States.

Our results indicated that forest productivity in this area follows an elevation gradient with many of the higher productivity areas at higher elevations. Lower elevation areas that have relatively low growing season days (frost pockets) have lower productivity. Soil depth has a positive influence on productivity when combined with adequate precipitation and higher numbers of growing season days.

Defining forest productivity using 10-meter site index is a fundamental change in the way forest managers and researchers have defined forest productivity to date, but this method is more accurate and broadly applicable. Productivity predictive models using 10-meter site index and a non-parametric approach will improve our understanding of landscape scale productivity.

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