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Estimating forest site productivity using airborne laser scanning data and Landsat time series

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Abstract

Site productivity, an important measure of the capacity of land to produce wood biomass, is traditionally estimated by applying species-specific, locally designed models that describe the relation between stand age and dominant height. In this paper we present an approach to derive chronosequences of stand age and height estimates from remotely sensed data to develop site productivity estimates. We first utilised an annual Landsat time series to identify areas of stand replacing disturbances and to estimate the time-since-disturbance, a proxy for stand age. Airborne Laser Scanning data were used to provide estimates of dominant height for these stands. Non-linear regression was used to fit a site productivity guide curve for stands aged 7 to 32 years. Existing and developed productivity models, together with remote sensing and inventory data as inputs, were used to validate the site productivity model in three different comparisons. Site productivity was overestimated by 0.70 m (RMSE = 5.55 m) relative to existing forest inventory estimates; further, 89% of remote sensing estimates were within ±1 derived site class of the forest inventory estimates. We conclude that the presented approach is suitable for estimating site productivity for young stands in areas that lack wall-to-wall forest inventory data.

Introduction

Sustainable forest management requires accurate information on a range of forest stand attributes. This information, collected during forest inventories, is crucial for evaluating current and projected conditions of a forest, as well as being critical for assessing the consequences of management decisions. Among all possible forest attributes, the potential of a site to produce biomass remains one the most important as this information is fundamental for decisions

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regarding optimal species composition, rotation age, allowable cut and most importantly, to forecast future timber yield (Bontemps and Bouriaud, 2014). However, in countries such as Canada, which practice extensive forestry and which have vast tracts of unmanaged forests (i.e., areas are not managed and not protected from natural disturbance such as wildfire) (Stinson et al., 2011), wall-to-wall forest inventories do not exist for all forested areas (Wulder et al., 2004). Knowledge of site productivity in these areas is important for projecting biomass accumulation over time, estimating recovery post-disturbance, understanding the impacts of climate change, and for spatially explicit carbon budget modelling.

The most common approach for measuring forest site productivity is site index (SI), which describes a forest stand as a relation between tree age and height (Skovsgaard and Vanclay, 2008). Site index or height age curves have conventionally been constructed by modelling the height growth of a subset of the largest trees at a given location and for a given species, according to the concept that stand dominant height is correlated with stand volume (Green et al., 1989; West, 2004). The projected height of the stand at 50 years is then used as an index of potential site productivity allowing estimates to be compared across sites and across stands of different ages. Traditionally, site index curves have been developed for major commercial tree species in managed forests (e.g. Mitchell and Polsson, 1988), on a regional basis (i.e., coastal versus interior), with different approaches for estimating site index often used for different stages of stand development (British Columbia Ministry of Forests, 1999). As the data required to support conventional estimates of site productivity typically do not exist in unmanaged forest areas, alternative data sources and measures of productivity are needed to support the aforementioned information needs.

Remotely sensed data can be used to estimate both stand age and dominant height, the two attributes most commonly used to characterize site productivity. The available archive of Landsat data represents more than 40 years of observations, and since 1984, has been acquired at 30 m spatial resolution with consistent spectral resolutions across multiple sensors (White and Wulder, 2014) all systematically calibrated to promote interoperability (Chander et al., 2009). Time series analyses of annual Landsat imagery enables detection and mapping of stand replacing disturbances and their attributes such as spatial location, extent, and date (Schroeder et al., 2011), which is often based on analyzing the spectral trajectories (Hermosilla et al., 2015; Huang et al., 2010; Kennedy et al., 2010). Time since disturbance can then be used as a proxy for estimating stand age (Lefsky et al., 2005; Pan et al., 2010).

Three-dimensional point clouds acquired with Airborne Laser Scanning (ALS) have become a common tool used in forest inventories (Wulder et al., 2013), by providing the capability to generate accurate estimates of stand height, volume and basal area (Evans et al., 2006; Popescu et al., 2004; Reutebuch et al., 2005). Most of the methods that allow for the estimation of stand biomass or volume are based on the distribution of point height values, described by descriptive statistics such as maximum, mean, standard deviation, percentiles, or proportions (Gobakken and Næsset, 2005; Hollaus et al., 2007; Magnussen and Boudewyn, 1998). The ability of the laser beam to pass through small openings in the forest canopy allows for a three-dimensional assessment of forest structure (Coops et al., 2007; Falkowski et al., 2009), including height measurements (Andersen et al., 2006; Hollaus et al., 2006; Næsset and Økland, 2002) which allow for the accurate estimation of the dominant tree height (Næsset, 1997; Wulder et al., 2010).

This potential of remote sensing data to produce both wall-to-wall estimates of forest stand age and dominant height provides the opportunity to examine how these two data types can be used

together to map forest site productivity. Such an approach would have considerable applicability to unmanaged forests where forest inventories are not regularly conducted (i.e., in northern Canada) (Falkowski et al., 2009; Wulder et al., 2007).

The objective of this paper is to demonstrate how ALS point clouds and an annual time series of Landsat imagery can be combined to provide an indicator of potential site productivity. To do so we develop a forest site productivity chronosequence using a series of stands in an area of coastal temperate rainforest in British Columbia, Canada. Landsat time series data are used to detect landscape disturbances, delineate stand boundaries, and infer stand age (at 30 m resolution), whilst ALS data are used derive a canopy height model (CHM) which is used to estimate dominant tree heights within these stands. We estimate potential site productivity using the height-age sequences as the input growth reference data and apply the resulting model to estimate potential site productivity within the study area. We validate the model in managed forest areas, using site index values available from forest inventory data. We conclude by discussing the strengths and weaknesses of the presented methodology, and discuss the applicability of this method for estimating site productivity in young stands.

Methods

Study area

The study area is located on northern Vancouver Island, British Columbia, Canada (Figure 1), within the Coastal Western Hemlock biogeoclimatic zone (CWH) (Meidinger and Pojar, 1991). The climate in this region can be characterized by high annual precipitation ($\mu = 2228$ mm), mild winters, and cool summers. Highly productive, temperate rainforests in this area are dominated by

western hemlock (*Tsuga heterophylla*). According to the forest inventory data, the average age of stands was 144 years (σ = 127 years). The average rotation age in the study area is 80 years.

Forest inventory data

Forest inventory data were used to provide reference information for forest stand age, dominant height, and site productivity (site index). This data was compiled according to standard provincial forest inventory procedures in Canada (Gillis and Leckie, 1993), using a two-phase approach whereby in the first phase, forest stands are delineated using aerial photography and then stand attributes such as age, height, and species composition are interpreted from the air photos (Ministry of Forest Lands and Natural Resource Operations, 2014). In the second phase, ground plot measurements are used to model and validate attributes such as diameter at breast height, volume, species, age, and site index. Depending on stand age, site index was derived using one of the three methods officially used in British Columbia (Mah and Nigh, 2003; Watts and Tolland, 2005). Height-age models or site index curves were used to estimate site index for stands that have 30 to 140 years of growth above breast height. For stands outside this age range, growth intercept models or SIBEC (Site Index – Biogeoclimatic Ecosystem Classification) method were used (British Columbia Ministry of Forests, 1999). These models, developed from field samples of a limited number of sample trees, require species, age, and dominant height as input information.

Landsat time series

We compiled a times series (1984–2011) of satellite images acquired by both Landsat TM and ETM+ sensors over the study area (WRS Path 51, Row 25). For each year, a single image was selected based on its acquisition date (i.e., between June and September) and amount of cloud cover (i.e., as minimal as possible). In total, 28 images were downloaded from the United States

Geological Survey (USGS) Landsat archive (Table 1) in standard terrain corrected (Level 1T) format. Surface reflectance was generated using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS, Masek et al., 2006).

ALS point clouds

ALS point clouds were acquired in 2012 using Optech ALTM3100EA scanning system (Table 2). The average first return point density was 11.6 points/m^2. The "ground" class was derived with the standard processing routines (Axelsson, 2000) and was used to normalize the point elevations to height above ground level. A Canopy Height Model (CHM) was then generated, representing maximum height above ground for each 5 x 5 m pixel. The data were processed using a combination of tools available in FUSION (McGaughey, 2014) and LAStools (Isenburg, 2014) software packages.

Detecting disturbances using Landsat time series

An approach based on the Vegetation Change Tracker (VCT) algorithm (Huang et al., 2010) was used to detect stand-replacing disturbance events and attribute these events to the correct disturbance year. The approach is based on spectral trend analysis of annual Landsat time series and involves two major steps. First a forest training mask is created annually from each Landsat scene by visually inspecting dense vegetation cover during the year 2000 from the version 5 MODIS vegetation continuous field (VCF) product collected in 2000 (Dimiceli et al., 2011), the Landsat normalized differenced vegetation index (NDVI), and a true colour composite (used instead of dark image substraction). The NDVI and VCF values for dense forest identified in the year 2000 images were then used to define thresholds for creating the forest mask for each image in the time series. The year 2000 was chosen as it was closest to the median year in the time series for the VCF. In the second step, disturbances are mapped from a time series analysis of the

disturbance index (DI; Healey et al., 2005, used instead of the integreated forest z-score) using trend rules and logic. The DI is a linear combination of the brightness, wetness, and greenness components of the tasseled cap transformation (Crist, 1985; Healey et al., 2005). Pixels with DI values that exceed an upper and lower threshold for three consecutive years are classified as disturbed. The upper and lower thresholds of the DI used for mapping stand-replacing disturbance were 600 and -200, respectively based on Pickell et al., (2014).

The algorithm produces polygons that represent stand-replacing disturbance events (disturbance map, Figure 2A). These outputs typically require some post-processing to remove single-pixel polygons and create homogenous objects, considered analogous to forest stands (Wulder et al., 2008). The outputs for our study area were first generalized by removing patches less than 5 pixels in size (0.45 ha) (Figure 2B). Then, each polygon was refined using the ALS-derived CHM layer (Figure 2C). The finer spatial resolution of the CHM layer (5 x 5 m) allowed for the creation of homogenous stands, by grouping pixels into objects with standard deviation of canopy heights limited to less than 5 m. A 1 ha (100 x 100 m) grid was then imposed over the study area, representing the sampling frame. Sample units found completely within disturbed areas were then selected and subsequently used to develop the age-height site productivity model (Figure 2D). From the disturbance date, we calculated the time since disturbance (TSD) and used this as a proxy for stand age (Pan et al., 2010). To improve the disturbance mapping accuracy, 3 consecutive years were required to establish a trend and detect a disturbance, therefore the maximum year of detected disturbance was 2009 and the TSD values ranged from 3 to 28 years.

Adjusting stand age

The Landsat time series enables an estimate of TSD, but does not account for the time it takes for new trees to be established at the site. From a silvicultural perspective, regeneration delay is the

period of time between harvesting and stand establishment. The regeneration delay in our study area is typically two years for planted stands and four years for naturally regenerated stands (Pedersen, 1996). Since we did not have any information concerning the method of stand establishment from the data available, we were conservative and used the maximum average regeneration delay for this area (4 years). Therefore, our estimate of stand ages was TSD plus four years, with this adjusted stand age used for subsequent model development. The stands we analyzed had an adjusted stand age range of 7 to 32 years.

Estimating stand dominant height using ALS data

Dominant height was estimated for each sample unit following the method proposed by Næsset (1997) and modified by (Wulder et al., 2010). With this method, a stand or sample unit is divided into 10 x 10 m cells and maximum height is computed for each of the cells using the raw point cloud. The final dominant height estimate is calculated as the weighted mean of all the maximum heights, with the number of non-ground returns within each cell used as the weight. This method is similar to the official definition of dominant height used in British Columbia (Watts and Tolland, 2005); however, given the nature of LiDAR measurements, the largest trees are selected based on height, rather than diameter at breast height. As demonstrated by Gatziolis (2007), there is no significant difference in plot site index values when estimated using site trees selected by DBH versus height.

Chronosequence analysis and curve fitting

The 1 ha sample units had a TSD value from the disturbance map, corrected for the regeneration lag, and a value for dominant height from the ALS data. We used this information to develop a chronosequence of height estimates. To develop the potential site productivity model we applied the guide curve method, following the methodology presented by Mathiasen et al. (2006) and

Edminster et al. (1991). In this approach, a curve is first fit to the height-age measurements and confidence intervals are calculated. The site productivity model is derived by calculating the proportional distance between the given height and age values and the modelled guide curve.

A Chapman-Richards model was used based on Fekedulegn et al. (1999), which has the following form:

$$h = \beta_1 * \left(1 - e^{\beta_2 * age}\right)^{\beta_3} + \varepsilon \qquad (1)$$

where *h* is dominant height [m], *age* is an estimated age of a sample unit [years] and βs are regression model parameters. The model was fit to height-age measurements using the Levenberg-Marquart nonlinear least squares algorithm (Elzhov et al., 2013) in two stages. After the initial fit, variance was calculated for each year and its reciprocal values used as weights during the second model fit. This additional step produces a lower residual standard error by decreasing the impact of years containing many highly variable samples versus years that have fewer, but less variable observations. The 95% confidence intervals of the individual predictions were calculated and a separate curve was fit into lower confidence interval values for each year.

To derive the final model curves for given height and age values, we again followed the method presented by Mathiasen et al. (2006). The distance proportion (*p*) for given age was calculated as the difference between the guide curve height value and given height value, divided by the difference between the guide curve and modelled lower 95% confidence interval:

$$p = \frac{h_G - h_T}{h_G - h_L} \qquad (2)$$

where p is the distance proportion, h_G is the height value derived from the guide curve for given age [m], h_L is the height value derived from the modelled lower 95% confidence interval for given age [m] and h_T is the height of a sample tree [m].

The reference age was set to the maximum year in the chronosequence (i.e. 32 years). The site productivity equation was then constructed in the following form:

$$SP = h_{G\_ref} - (h_{G\_ref} - h_{L\_ref}) * p \tag{3}$$

where SP is the estimated site productivity [m], h_{G_ref} is the value of the guide curve at the reference age [m] and h_{L_ref} is the value of the modelled lower 95% confidence interval for the reference age [m].

Site productivity classes and model validation

To validate our site productivity model, we first derived site productivity classes from the inventory site index values using standard conversion tables developed by the Province of British Columbia (British Columbia Ministry of Forests, 1981; 1994). The productivity classes were derived by dividing the difference between the upper and lower confidence intervals at reference age into 4 equal parts (i.e., good, medium, poor, and low). These productivity classes were then used as strata, from which we randomly selected 30 validation plots (10 x 10 m in size) from each stratum, for a total of 120 validation plots. For each plot, we extracted the reference age, dominant height, and site index value from the forest inventory data, and dominant height and age as estimated from the ALS and Landsat disturbance map, respectively. We then compared the reference and predicted values by calculating the bias (absolute and relative), RMSE (absolute and relative), and correlation coefficient. A Wilcoxon signed rank test was used to test

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the null hypothesis that the median difference between the compared values was zero. Bias and

RMSE were calculated as follows:

$$bias = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i) \tag{4}$$

$$bias\% = \frac{bias}{\bar{y}} * 100 \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{6}$$

$$RMSE\% = \frac{RMSE}{\bar{y}} * 100 \tag{7}$$

where: n is the number of validation plots, y_i is the reference value for plot i, $\hat{y}_i$ is the predicted

value for plot i, and $\bar{y}$ is the mean of the reference variable.

We initially compared age and dominant height estimates from the forest inventory and the

remotely sensed chronosequence for the 120 validation plots. We then compared productivity

estimates generated from the remotely sensed chronosequence data to estimates derived from the

forest inventory data (British Columbia Ministry of Forests and Range, 2004), using the latter as

the reference. In order to understand and differentiate between errors resulting from the use of

different models and errors resulting from different input data, we performed three different

comparisons. The first two comparisons evaluated the use of different input data for the same

model, whereas the third compared different models and different input data. First, utilizing the

site index models used in British Columbia (Mitchell and Polsson, 1988), we calculated site

index for each of the 120 validation plots using forest inventory (SI_{INV}) and remotely sensed

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chronosequence (SI_{CS}) data as inputs. Second, we used the site productivity model we developed in this study, and calculated site productivity for the validation plots using forest inventory (SP_{INV}) and remotely sensed chronosequence (SP_{CS}, Figure 5, Table 3) input data. Our third and final analysis compared productivity estimates from the site index and our own developed productivity model (SP_{CS}), using forest inventory data and remotely sensed chronosequence data, respectively. It should be noted that for this final comparison, site index values were calculated for a base age of 32 years (SI_{INV32}) to enable comparison with our model outcomes (which are also calculated for the base age of 32 years). Recall that site index is typically calculated using base 50 years. The three aforementioned comparisons enabled robust validation of model outcomes and provided insights into potential sources of errors in our approach.

Apart from direct comparison of the site productivity estimates, for the third comparison we also compared site productivity classes. These classes were first derived for the inventory site index, again for the same base age used in the modelling (i.e. 32 years). The range of site productivity estimates (dominant heights) at the reference age was divided into 4 equal classes: low, poor, medium and good, which follows methods used in British Columbia (British Columbia Ministry of Forests, 1981; 1994) and other regions (Huang et al., 1994). We then applied the derived break values to the site productivity estimates for the validation plots and compared them by calculating the number of times the class differences were less than or equal to one.

Results

Detecting disturbances using Landsat time series

The disturbance mapping algorithm detected 3133 stand-replacing disturbances within our study area, dating from 1984 to 2009 and representing a total area of 15,787 ha (or approximately 13% of the total study area). The average area of the disturbed stands, after refinement, was 5.03 ha. A

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total of 2006 one ha sample units were used to build a chronosequence (Figure 3). On average, each disturbed stand contained 3.6 sample units. The distribution of TSD values for the sample units was not uniform across the chronosequence, with the maximum number of samples associated with TSD = 10, and several years having less than 10 sample units. Only one year (TSD = 25), had no samples in the chronosequence. The minimum and maximum dominant height values for the sample units were 2.18 m and 21.52 m respectively, with an average dominant height of 6.87 m and standard deviation of 3.38 m (Figure 4).

Chronosequence analysis and curve fitting

Our site productivity model, with the Chapman-Richard curve fitted to the height-age estimates, had a residual standard error of 2.76 m. We checked for homoscedasticity by plotting the model residuals against age and observed homogeneity of variance. The distribution of the residuals was accepted as normal, with mean value of -0.03 and standard deviation of 2.02 m. The regression coefficients for both the final guide curve model and the lower 95% confidence interval model are presented in Table 3.

At the base age of 32 years the value of the guide curve was 11.53 m, whereas the value of the lower 95% confidence interval was 4.73 m. Using these values and the distance proportion formula (p) we constructed the final form of the site productivity equation as follows (Figure 5):

$$SP = 11.53 - 6.81 * \frac{h_G - h_T}{h_G - h_L} \tag{8}$$

$$h_G = 109.06 * (1 - e^{-0.0041*age})^{1.0705} \tag{9}$$

$$h_L = 44.72 * (1 - e^{-0.0041*age})^{1.0705} \tag{10}$$

Site productivity classes

The difference, in metres, between the upper and lower confidence intervals (18.34 and 4.73 m at reference age, respectively) was divided into four equal site productivity classes (i.e., good, medium, poor, and low), with each class having a width of 3.40 m at reference age (Figure 6). We applied our productivity model to all disturbed stands detected with Landsat time series and assigned the stand to the appropriate productivity class, as described above (Figure 7). The input values for the site productivity model—dominant height and stand age—were estimated using the same methods as for the sample units, although entire disturbed stands rather than sample units were used. The "Good" site class was most prevalent, representing 39.4% of the disturbed area.

Model validation

We compared our model outcomes to reference values obtained from forest inventory data using 120 validation plots (10 x 10 m). We compared age and dominant height estimates, as well as productivity estimates for three scenarios: site index model used in British Columbia (Mitchell and Polsson, 1988) using inputs from forest inventory and remotely sensed data; our model developed using Chapman-Richards curve-fitting with inputs from forest inventory and remotely sensed data (Table 3, Figure 5); and lastly, the two different models with the different input data. Comparison of dominant height estimates indicated that bias was on average 1.13 m (27.0%), with an RMSE of 4.32 m (62.9%). A comparison of plot age estimates indicated that Landsat disturbance map had a bias of 2.2 years (10.5%) and an RMSE of 3.8 years (18.6%). For both dominant height and age comparisons, p-values from the Wilcoxon test indicated that there is significant difference between the medians of the compared variables.

Generally, comparisons between model and reference estimates of productivity yielded similar results (Table 4, Figure 8). For all comparisons, estimates of site index or site productivity generated from the remotely sensed chronosequence data were greater than the reference values generated from the forest inventory data. For comparison 1, which evaluated different data inputs to the official site index model for western hemlock, use of the remotely sensed chronosequence data as input resulted in an average overestimation of dominant height by 0.79 m or 6.54%. Likewise for comparison 2, which evaluated different data inputs into the productivity model developed in this study, use of the remotely sensed chronosequence data as input resulted in an overestimation of 1.15 m or 16.47%, which was the greatest difference with the reference data amongst all comparisons. The third comparison, which compared estimates generated from the two different models (each with different input data), indicated that when the remotely sensed chronosequence data was used, an overestimate of 0.70 m or 10.1% resulted. For all comparisons, the results of the Wilcoxon test indicated that for all 3 comparisons the remote sensing-based estimates of site productivity were significantly different than those derived with the forest inventory reference data. The difference in site productivity class (Figure 9) generated from the values in the third comparison, showed that 47.0% of samples were labeled as the same class while 88.9% were within ±1 class value of the reference data.

Discussion

In this research, we demonstrated a method of using a chronosequence of height and age estimates to develop an indicator of forest site productivity exclusively from remotely sensed data sources. The method utilizes Landsat imagery to detect areas of forest disturbance and estimate time since disturbance as a proxy for age, as well as ALS point clouds to estimate stand dominant height. By integrating information extracted from these two sources of spatial data we

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established a chronosequence of sample units from which we obtained a good approximation of stand growth. We used the chronosequence to develop a model of site productivity, demonstrating that remotely sensed data sources have potential to provide such information in areas that may be lacking detailed forest inventory information. The accuracy of age and dominant height estimates is crucial for the proper development of forest productivity models such as site productivity curves (Ni and Nigh, 2011). Conventionally, site productivity curves are derived via field measures and destructive sampling, enabling very accurate estimates of both tree age (via core samples), and tree height (via direct measurement). Stand dominant height, or top height, is commonly estimated in the field as the average height of the largest 100 trees (by diameter) per ha (Hägglund, 1981) or by an analogous definition of the largest diameter site tree (tree selected for the dominant height measurement) in a 0.01 ha plot (Forest Productivity Council of British Columbia, 1998). This method for estimating dominant height has been shown to produce less biased estimates than approaches that merely average the heights of a random sample of co-dominant and dominant trees in the stand (Mailly et al., 2004). Our process for estimating dominant height from the ALS data seeks to emulate this approach, and has been shown to produce heights that more closely correspond to field measurements (Næsset, 1997) and operational definitions of top height (Wulder et al., 2010). There should be no doubt that the conventional approach for generating estimates of site index from field measurements will have a greater level of absolute accuracy for any given site; however, because this approach is time consuming, labour intensive, and expensive, sample sizes used to estimate site index curves are typically very small, particularly given the broad geographic conditions over which these curves are often applied (e.g. Mitchell and Polsson, 1988). Using the chronosequence approach presented herein, enabled by ALS and Landsat data, it is possible to derive a much larger sample

of stands across a broader range of stand conditions. These factors, combined with the very accurate estimates of height provided by the ALS data, provide a robust approach for estimating potential site productivity that is in keeping with methods used in a conventional approach. Moreover, the fact that it is possible to measure the dominant stand height for any location covered during ALS data acquisition, is critical for creating a model that covers a range of site productivity over large areas. ALS point cloud-based height estimates are accurate at the single tree-, plot- and stand-level in mature (Andersen et al., 2006; Brandtberg et al., 2003; Means et al., 2000; Næsset and Økland, 2002; Persson et al., 2002) as well as in young stands (Næsset and Bjerknes, 2001).

The presented approach is useful for assessing forest site productivity in any location with available ALS point clouds and a record of Landsat images. The developed model is based on a large number of sample units that cover a broad range of site productivity, which is the main advantage of the approach presented, particularly when compared to conventional methods, whereby models are often developed from a limited number of samples and, more importantly, are often not suitable for use in young stands (hence separate site index models for young stands in British Columbia, e.g. Nigh, 1999). As an example, the site productivity model for western hemlock, the most common species in the study area, is dated (Wiley, 1978) and was developed on 90 plots with heights ranging from 18 to 40 m and ages ranging from 60 to 130 years (breast height age). Growth intercept models designed specifically for stands below the age of 30 are problematic to apply for species such as western hemlock, which lack distinct branch whorls (Nigh, 1996).

In general, the validation of the developed model with existing site productivity estimates from forest inventory data showed relatively good agreement with low bias. Performing the three

comparisons allowed us to assess how differences in the input data influence model output, and gain a greater understanding of the potential sources of error. The initial comparison of the age and dominant height estimates indicated that both these variables were overestimated by the RS data relative to the inventory estimates. Consistent with these findings, our modelled site productivity (using RS data only) was also overestimated relative to the inventory data. Similar values for bias, RMSE, and correlation coefficients for all three comparisons we conducted, indicate general agreement between the input data and, what is of greater importance, between the two compared site productivity models. All comparisons demonstrate that the estimates are in most cases (88.9% of validation plots) within ± 1 productivity class of the reference (inventory) data, and the mean difference between the two is not exceeding typical differences between existing site productivity models for different species or regions (e.g., Mitchell and Polsson, 1988). These findings are in keeping with those of previous research in similar forest environments, which also indicated an underestimation of SI derived from forest inventory data (Tompalski et al., 2015; Wulder et al., 2010).

Wulder et al. (2010) demonstrated the capacity of ALS data to augment existing estimates of site productivity. In that study, 42% of stands analyzed had an ALS-derived site class that was greater than the inventory site class, whilst 77% of stands were within ± 1 site class of their inventory SI class. In recent work by Tompalski et al. (2015), stand dominant height was consistently underestimated in the inventory by an average of 3.68 m (compared to ALS-derived estimates), whilst 73.1% of stands had an ALS-derived site class that was within ± 1 site class of their original SI class.

Véga and St-Onge (2009) presented an approach to map forest site productivity using chronosequences derived from remotely sensed data. Height-age sequences were derived for jack

pine (*Pinus banksiana* Lamb.) dominated forest stands in Quebec, Canada, using a time series of

canopy height models derived from scanned historical aerial photographs and an ALS-derived

terrain model. In this study, the authors applied an existing height-age model to estimate site

index, with the remotely sensed data providing alternate inputs to forest inventory data. The

authors obtained an average bias of 0.76 m, very similar to the 0.79 m bias reported here for

comparison 1 (Table 4). However, the authors also report an RMSE of 2.41 m, which is about

one-third of our RMSE for comparison 1 (7.92 m). The larger RMSE in our case may result from

our estimate of stand age. A time series of historical aerial photography (with repeated measures

for the same stands over time) can provide a precise estimate of stand age and height, albeit over

a much smaller area. Véga and St-Onge (2009) identify the importance of multiple repeat

measures to improve the reliability of age and SI estimates. Other studies have likewise

substituted remotely sensed measures of height in existing height-age models to derived

estimates of site productivity (Holopainen et al., 2010; Wulder et al., 2010). Holopainen et al.

(2010) estimated forest site types (5 classes) with ALS-based dominant height estimates in Scots

pine (*Pinus sylvestris* L.) and Norway spruce (*Picea abies* L. *Karst.*) dominated stands. The

authors report an overall classification accuracy of 70.9%, with overestimation observed for the

lower productivity classes.

Unique to our study is not just the application, but the actual development of a height-age model

based solely on remotely sensed data sources. As height-age models are often regionally

developed, their portability across a range of environmental conditions cannot be assumed (Chen

et al., 1998). There are however certain limitations associated with the approach presented

herein. For example, an adjustment must be made to the time since disturbance estimates

provided by the Landsat time series to account for regeneration delay and the temporal difference

between disturbance date and stand age (Bradford et al., 2008). In our study area, information on the typical length of this regeneration delay was available to us and could be used to adjust our estimates of stand age. In unmanaged forest area, heuristics based on environmental conditions and natural regeneration rates can similarly be used to enable this type of adjustment. We also assumed that any treatment related to forest management did not significantly influence the site productivity reflected by the relation of dominant height and age. This assumption may not hold in areas where stands are actively managed.

Although the detected disturbances provide a reliable source of information about the time when a disturbance occurred (Pickell et al., 2014), these estimates are still prone to errors, resulting from cloud cover, terrain shadowing, or haze (Thomas et al., 2011). Moreover, applying a constant adjustment to TSD for all stands in order to more accurately represent stand age (i.e., the actual time of stand establishment post-harvest) undoubtedly lead to either overestimates or underestimates of true stand age, because in reality, regeneration delay is highly variable. As new stands are rarely established in the same year as harvesting occurs, it is necessary to somehow account for discrepancies between TSD and stand age. It is also worth noting that conventional sources of stand age information (e.g., forest inventories) can have errors (Bradford et al., 2008), and that the impact of the error on derived height-age models is somewhat variable (Ni and Nigh, 2011). Furthermore, a chronosequence built on stand-replacing disturbances detected with Landsat TM and ETM+ sensors will be limited to 1984. In our study, we were not able to model stand growth after the age of 32 years. As Landsat data acquisition continues into the future, it will become possible to extend the chronosequence, however, at present, the approach demonstrated herein will be applicable only in younger stands.

Our model includes no information on tree species. It is widely accepted that different tree species have different growth patterns and species-specific models are constructed to increase the accuracy of site productivity estimates (Bontemps and Bouriaud, 2014; Skovsgaard and Vanclay, 2008). There have been a proliferation of species-specific models in the literature, sometimes providing conflicting results, and there have been efforts in the forest management community to reduce the number of models and move toward more species-independent approaches (Nigh, 2001). In locations dominated by single tree species or species with similar growth patterns, species-independent approaches based on age and dominant height are plausible and may provide an estimate of site productivity that is suited to the information need.

Conclusions

In this study, we integrated a time series of Landsat imagery and ALS point clouds to provide an indicator of forest site productivity. The disturbance detection algorithm was used to map forest disturbances and estimate time-since-disturbance, and ALS point clouds were used thereafter to estimate dominant height on 1 ha sample units. A chronosequence of height estimates was developed from these data and was used to develop a site productivity model. We validated the model by comparing the productivity estimates with estimates from forest inventory data on 120 independent validation plots, which resulted in a bias of 0.70 m and an RMSE of 5.55 m (comparison 3). The results of our research suggests there is utility in combining Landsat time series and ALS data to develop indicators of productivity in areas that lack forest inventory information. Such information is required in these areas to support a range of information needs, such as increasing our understanding of climate change impacts, aiding in the estimation of post-disturbance recovery, and enabling spatially explicit carbon budget models.

Acknowledgements

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Tables

Table 1. List of Landsat scenes used in the study.

Scene id	Acquisition date	Cloud cover [%]
LT50510251984172PAC00	20/06/1984	1
LT50510251985222PAC00	10/08/1985	9
LT50510251986273PAC00	30/09/1986	20
LT50510251987180PAC00	29/06/1987	4
LT50510251988199PAC00	17/07/1988	0
LT50510251989249PAC00	06/09/1989	28
LT50510251990268PAC00	25/09/1990	16
LT50510251991271PAC00	28/09/1991	28
LT50510251992258PAC00	14/09/1992	13
LT50510251993260PAC00	17/09/1993	34
LT50510251994263PAC00	20/09/1994	12
LT50510251995266XXX04	23/09/1995	10
LT50510251996253PAC00	09/09/1996	10
LT50510251997223PAC00	11/08/1997	30
LT50510251998162PAC00	11/06/1998	14
LE70510251999253PAC00	10/09/1999	5
LE70510252000240EDC00	27/08/2000	6
LT50510252001250LGS01	07/09/2001	0
LT50510252002157LGS01	06/06/2002	10
LT50510252003224PAC02	12/08/2003	22
LT50510252004195EDC00	13/07/2004	50
LT50510252005245PAC02	02/09/2005	37
LT50510252006248PAC02	05/09/2006	3
LT50510252007251PAC02	08/09/2007	3
LT50510252008206PAC04	24/07/2008	0
LT50510252009208PAC01	27/07/2009	3
LT50510252010227GLC02	15/08/2010	0
LT50510252011230PAC00	18/08/2011	29

Table 2 ALS data characteristics

Sensor	ALTM3100EA
Aircraft Speed	240 km/h
Data Acquisition Height	700 m AGL
Swath width	323 m
Scan angle	±12.5°
Beam divergence	0.3 mrad
Wavelength	1064 nm
Overlap	75%
Pulse Repetition Rate	70 KHz
Scan Frequency	65 Hz
Number of Returns Per Pulse	4
Point Density	11.6 pt./m^2

Table 3. Result of the model parameter estimates.

parameter	Estimate
guide curve	
$\beta 1$	109.07
$\beta 2$	-0.0041
$\beta 3$	1.0705
lower 95% confidence interval	
$\beta 1$	44.721
$\beta 2$	-0.0041
$\beta 3$	1.0705

Table 4. The results of the comparisons of site productivity estimates. In all sets n=120. SI – site index calculated with equations used in British Columbia and input data from forest inventory (SI_{INV}) or from chronosequence of dominant height values (SI_{CS}); SP – site productivity calculated with the developed model and input data from forest inventory (SP_{INV}) or from chronosequence of dominant height values (SP_{CS}); SI_{INV32} – site index calculated with inventory data for the reduced based age (32 years). In all sets n=120.

Validation set	Bias [m]	Bias [%]	RMSE [m]	RMSE [%]	R	p-value (Wilcoxon test)
Comparison 1 (SI_{CS} - SI_{INV})	0.79	6.54	7.92	46.86	0.66	0.54
Comparison 2 (SP_{CS} - SP_{INV})	1.15	16.47	5.72	58.28	0.61	0.13
Comparison 3 (SP_{CS} - SI_{INV32})	0.70	10.07	5.55	53.02	0.63	0.52

Figures
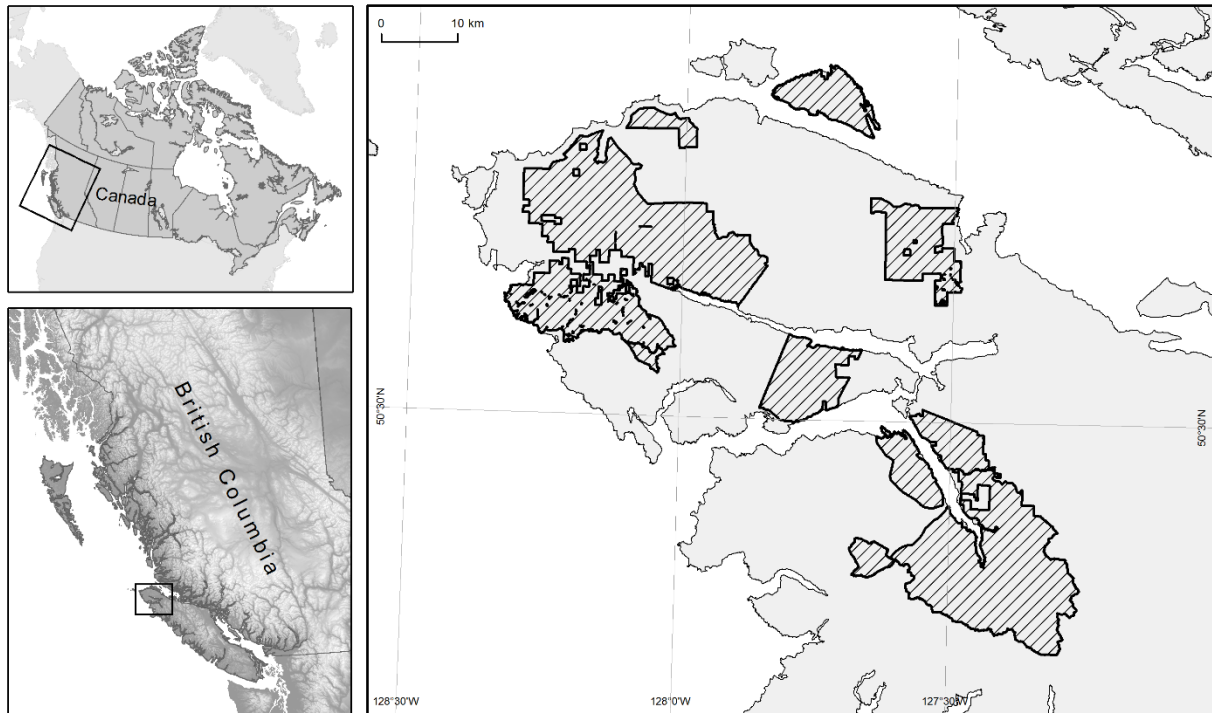
Figure 1. Study area location. The hatched areas indicate where ALS was acquired in 2012.
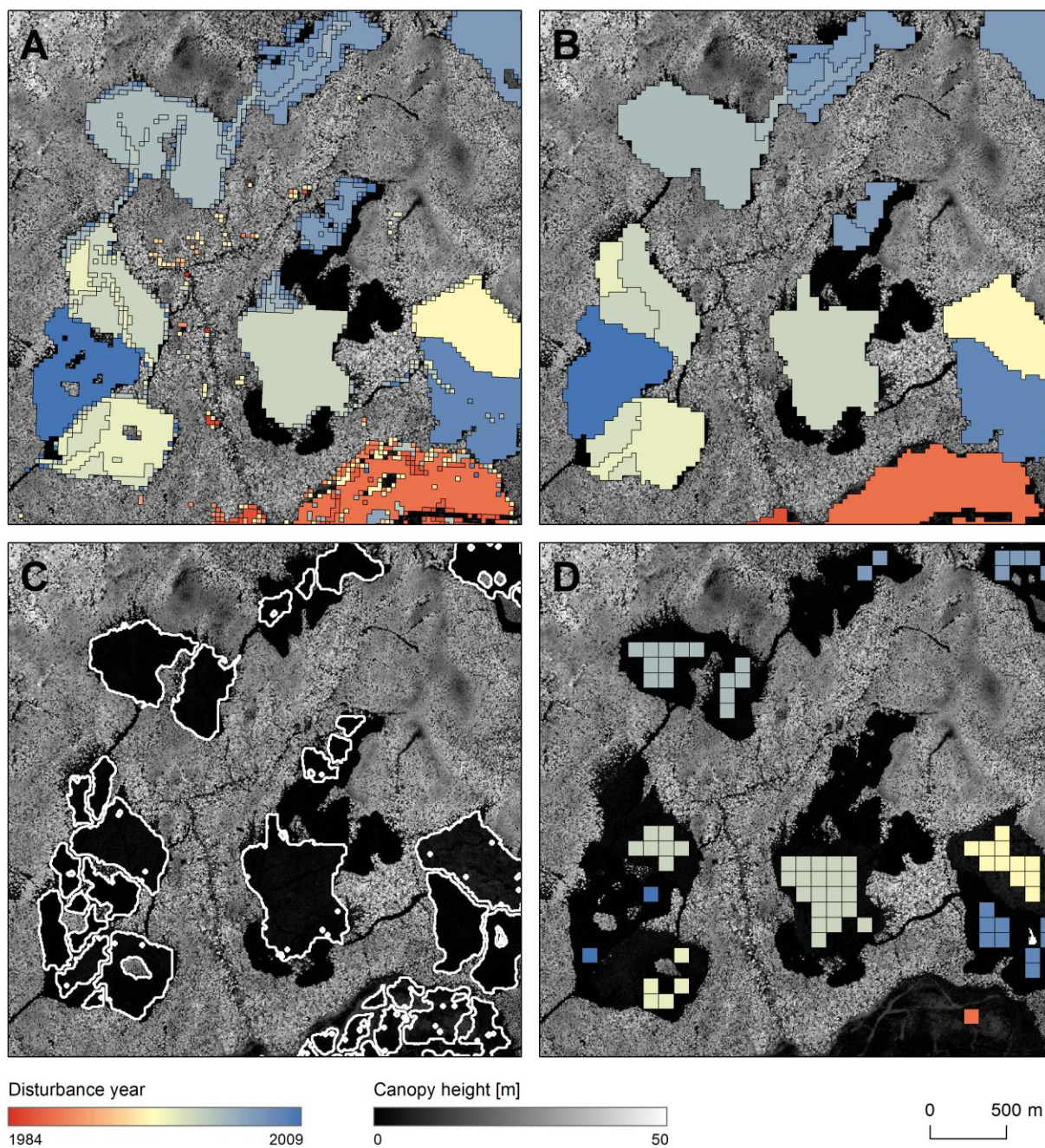
Figure 2. A representative subset of the study areas on which a method of finding sample units (100 x 100 m) in the detected stand-replacing disturbances is demonstrated. A – Disturbance areas (stands) detected with Landsat time series; B – stands are generalized; C – The borders of the stands are refined using CHM; D – 100 x 100 m sample units are placed inside the stands.
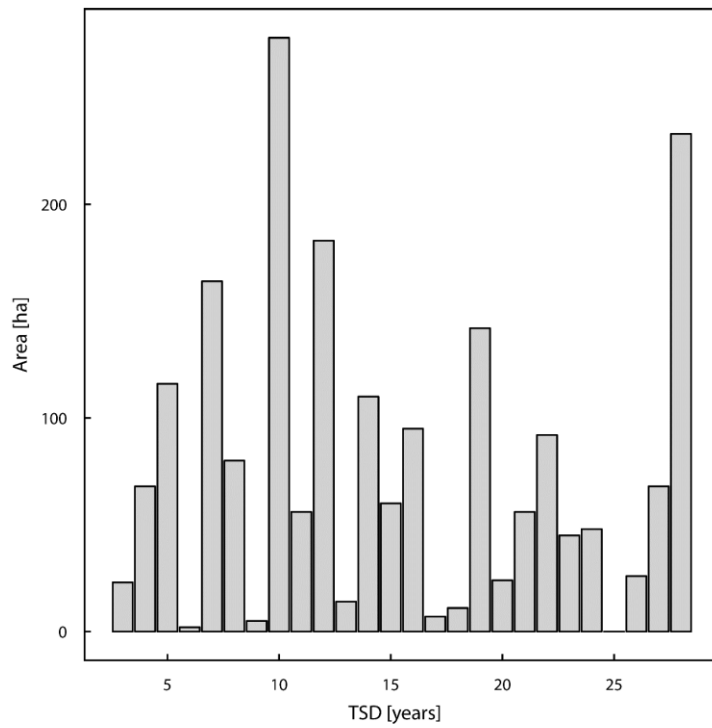
Figure 3. Distribution of time since disturbance (TSD) by area, for the sample units (n = 2006).
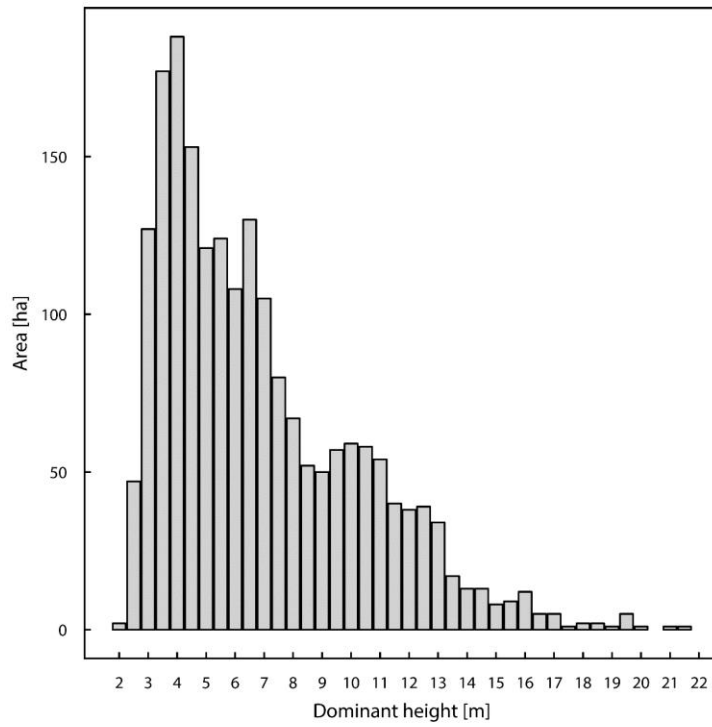
Figure 4. Histogram of dominant height calculated for the sample units (n = 2006).
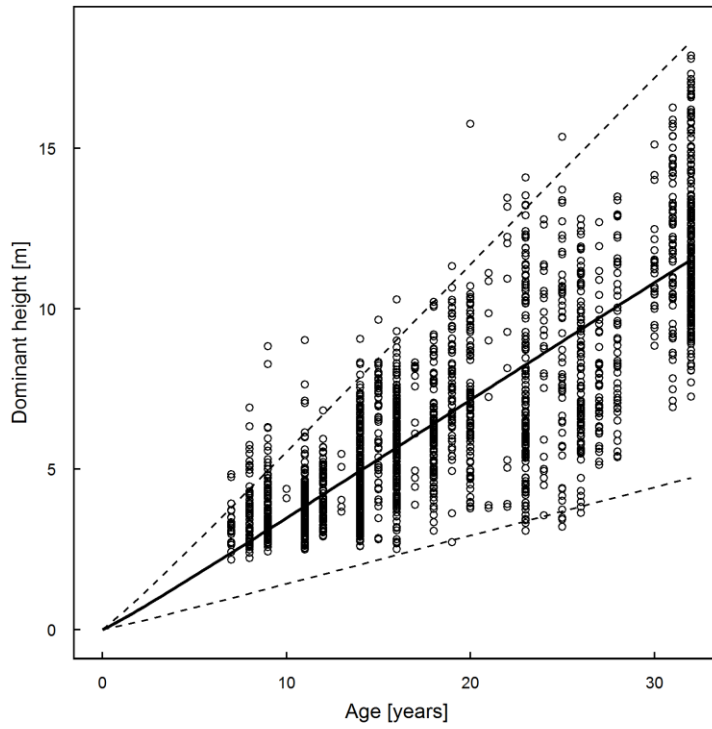
Figure 5. Guide curve fitted in the height-age measurements. 95% confidence intervals presented as dashed lines.
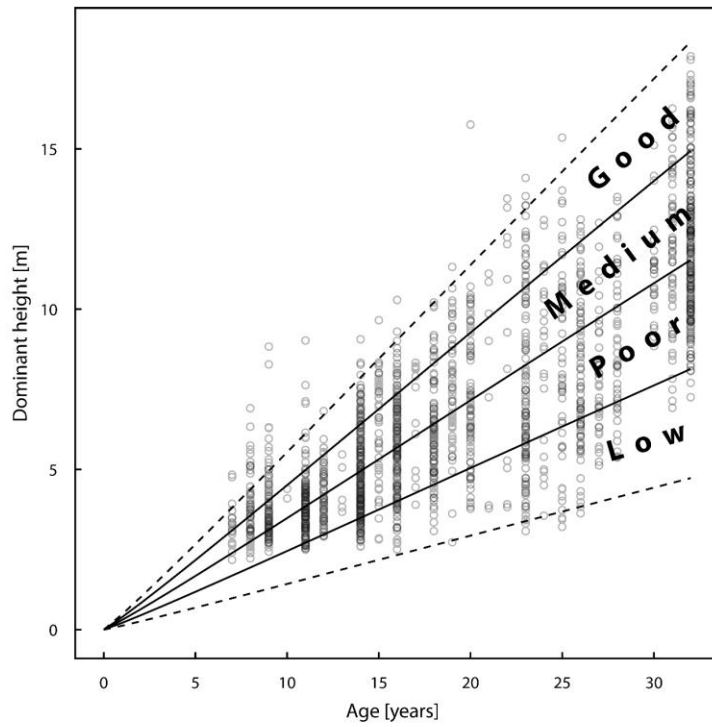
Figure 6. Derived site productivity classes plotted together with the height-age data used to construct them. Dashed lines indicate 95% confidence intervals.
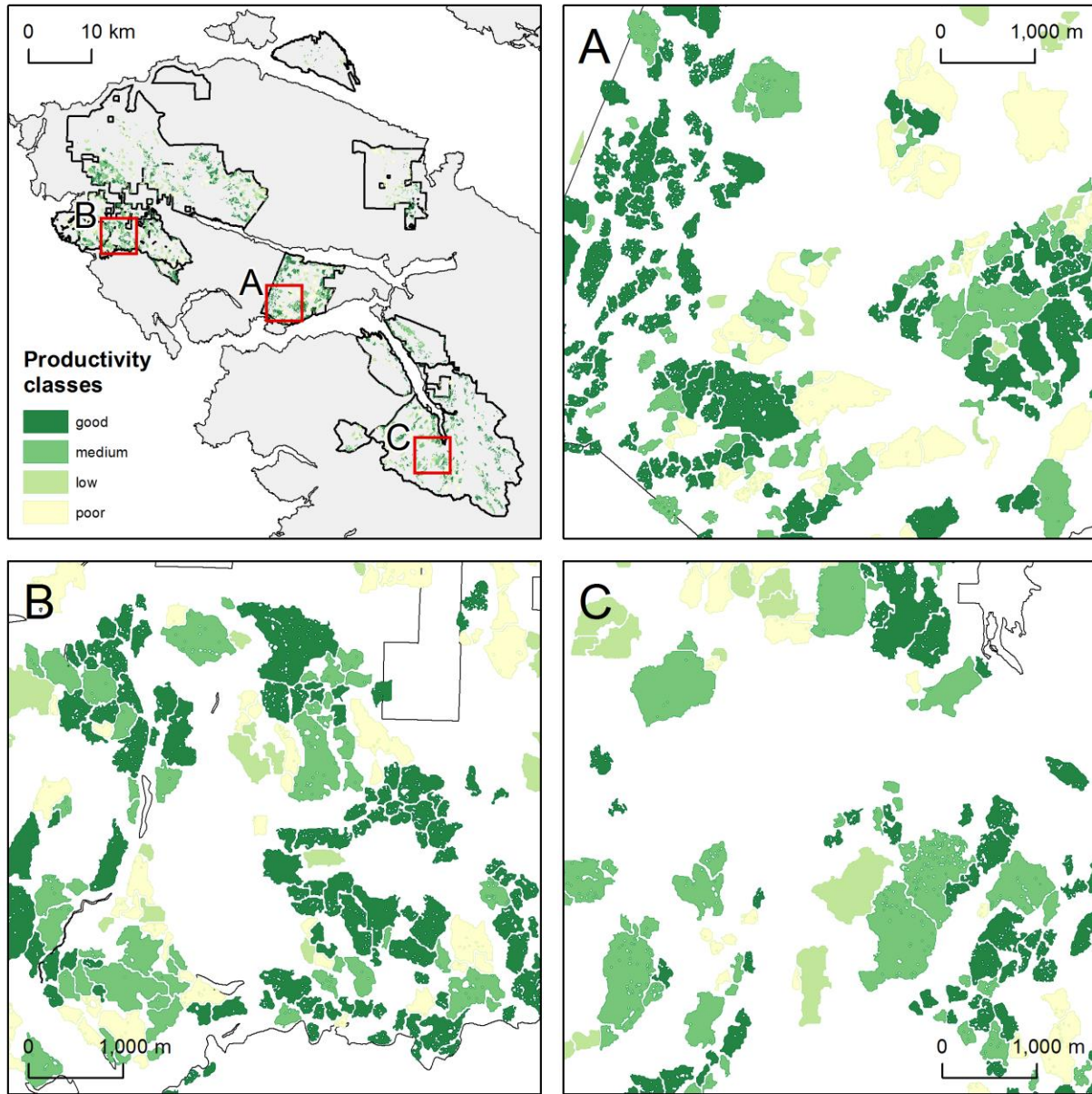
Figure 7. Site productivity map derived with the developed model. Three example areas (A, B and C) shown in larger scale to demonstrate the spatial variability of the site productivity classes.
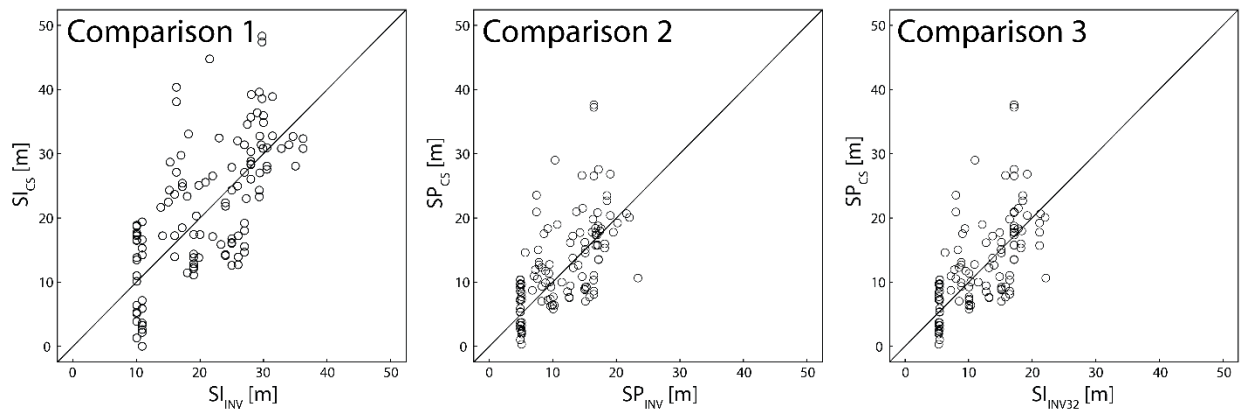
Figure 8. Scatterplots presenting the comparison of the productivity estimates in three sets. SI – site index calculated with equations used in British Columbia and input data from forest inventory (SI_{INV}) or from chronosequence of dominant height values (SI_{CS}); SP – site productivity calculated with the developed model and input data from forest inventory (SP_{INV}) or from chronosequence of dominant height values (SP_{CS}); SI_{INV32} – site index calculated with inventory data for the reduced based age (32 years). In all sets n=120.
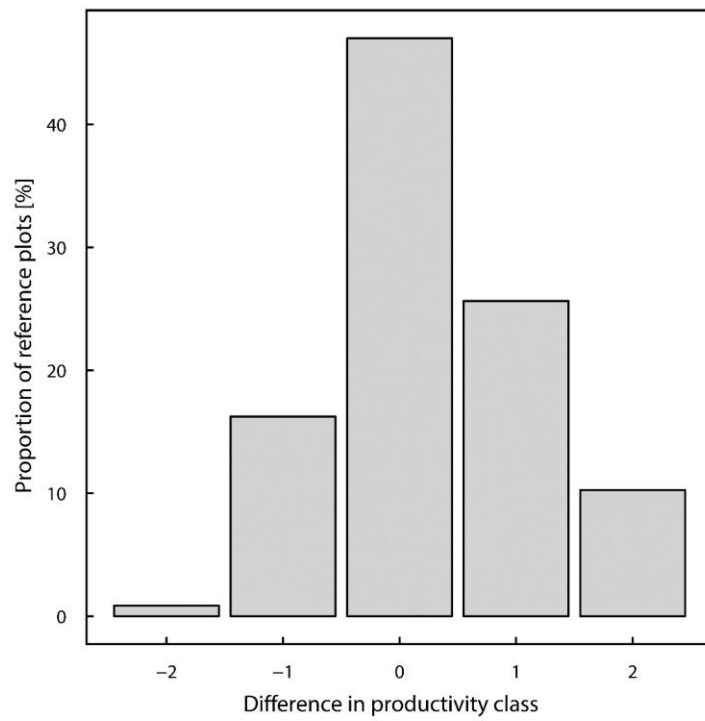
Figure 9. Distribution of the productivity class difference values (model-derived class – reference site class).