**Dissertationes Forestales 268**

# Improving local forest growth prediction by terrain-derived attributes, airborne $\gamma$-ray, and leaf area index

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Academic dissertation

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## ABSTRACT

Forest growth information is important in forest management and planning, and it is an issue of concern for various stakeholders. Therefore, accurate information about potential growth in forested landscape is needed. Forest growth has been traditionally assessed by way of modeling, however models fitted for a larger area tend to be biased when applied to local settings, and there is thus a crucial need for localization or other ways to improve the growth prediction of such models. There are various ways to achieve this improvement, one of which is by introducing new data elements. Consequently, this presented research used the known effect of topography on soil moisture content to achieve growth prediction improvements for local forest growth. A total of 9987 tally trees and 1118 sample trees distributed in 197 plots were used to examine the suitability of using terrain attributes derived from digital terrain model (DTM), airborne γ-ray and leaf area index (LAI) data, in improving pre-existing diameter at breast height (dbh) model for a five-year period (id5) in southeastern Finland. Statistical examinations of the mixed effect modeling (linear and non-linear) and multilayer perceptron modeling were used in the analysis. The results varied between sample trees and species. The best root mean square error (RMSE) improvements of the national model were obtained for broadleaved trees, followed by pine and spruce. All of the γ-ray (γk, γu, and γth) windows were shown to be significant in eliminating the local bias. The effect of the DTM source showed that a higher resolution with a lower focal neighborhood is the best combination for quantifying terrain attributes, notably the Topographic Wetness Index (TWI). The growth prediction improvement tended to be more accurate in less fertile site types of *Vaccinum* site type and *Calluna* site type. LAI demonstrated improvement when combined with terrain attributes, especially intensity-based LAI. The presented study concludes that the newly introduced elements are suitable for improving local forest growth prediction and reduced the RMSE of pre-existing model for dbh increment. However, further research is needed to confirm these findings, e.g. using larger geographical extents and attribute variations.

**Keywords**: airborne gamma-ray, diameter increment, forest, LiDAR, terrain attributes, topographic wetness index, tree growth

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## LIST OF ORIGINAL ARTICLES

This dissertation is based on the following articles, which are referred to by the Roman numerals I–III in the text. Articles I and II are reprinted with the kind permission of the publisher. The body of the dissertation summarizes the overall objectives, methodology, and findings, therefore, this dissertation is meant to be read alongside the included articles. Article III is the author version of the submitted manuscript.

**I**. Mohamedou, C., Tokola, T., & Eerikäinen, K. (2014). Applying airborne gamma-ray and DEM-derived attributes to the local improvement of the existing individual-tree growth model for diameter increment. *Remote Sensing of Environment*, 155, 248–256. http://doi.org/10.1016/j.rse.2014.08.033

**II**. Mohamedou, C., Tokola, T., & Eerikäinen, K. (2017). LiDAR-based TWI and terrain attributes in improving parametric predictor for tree growth in southeast Finland. *International Journal of Applied Earth Observation and Geoinformation*, 62, 183–191. http://doi.org/10.1016/j.jag.2017.06.004

**III**. Mohamedou, C., Korhonen L. Eerikäinen, K. & Tokola, T. (2018), Using LiDAR-based modified topographic wetness index, terrain attributes with leaf area index in improving a single-tree growth model in southeastern Finland.
Submitted Manuscript.

Cheikh Mohamedou was the first and corresponding author, responsible for the data analyses and writing of the papers –he also acted as corresponding author for the overall dissertation. Professor Timo Tokola incepted the research ideas, as well as supervising and co-authoring the papers. Dr. Kalle Eerikäinen contributed to various stages of the analyses and writing, by co-authoring and improving the quality of the final articles and through continuous discussion of the technical details involved. Dr. Lauri Korhonen provided his expertise through co-authoring and providing theoretical and practical guidelines in formulating Article III.

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# GLOSSARY OF ABBREVIATIONS

| | |
|---|---|
| ACI | All echo type index |
| AIC | Akaike information criterion |
| CI | Canopy Cover Index |
| CT | *Calluna* site type, site type according to Cajander (1926) |
| dbh | Diameter at breast height |
| DEM | Digital Elevation Model |
| DTM | Digital Terrain Model |
| FCI | First Cover Echo Index |
| GTK | Geological Survey of Finland |
| ICI | Intensity-based Cover Index |
| id5 | future dbh, in centimeter increments for a 5-year period |
| LAI | Leaf Area Index |
| LBias | Local bias |
| LiDAR | Light Detection and Ranging |
| LMA | Ratio between leaf mass and leaf area |
| LME | Linear mixed-effects model |
| MLP | Multilayer perceptron (MLP) |
| MT | *Myrtillus* site type, according to Cajander (1926) |
| NLME | Non-linear mixed effect modeling |
| NModel | National model, referred to by Pukkala et al. (2013) |
| OMT | *Oxalis-Myrtillus* site type, according to Cajander (1926) |
| REML | Restricted maximum likelihood |
| RMSE | Root mean square error |
| SD | Standard deviation |
| TWI | Topographic Wetness Index |
| VT | *Vaccinum* site type, according to Cajander (1926) |
| γ-ray | Airborne gamma-ray |
| γk | Potassium window of airborne gamma-ray |
| γth | Thorium window of airborne gamma-ray |
| γu | Uranium window of airborne gamma-ray |
| $R^2$ | coefficient of determination |

# 1 INTRODUCTION

## 1.1 Background

The volume of growing stock in the forested landscape is one of the most important parameters in forest management and planning. Specific information about trees and stand potential growth are invaluable tools for various stakeholders, and not specifically for forest managers or planners (Vanclay 1994; Soares et al. 1995; Ledermann & Sterba 2006; Räty & Kangas 2007; Sironen 2009). Particularly, this information is at the core of forest simulation systems, scenario modeling and systems that contribute to the future development of forest stands (Kellomäki et al. 1992; Siitonen et al. 1996; Hynynen et al. 2005; Tokola et al. 2006; Rasinmäki et al. 2009). Since growth information is important and crucial in dealing with the forested landscape, accurate information is needed. (Bugmann 2001; Burkhart & Tomé 2012). Forest growth has been traditionally assessed by modeling, which is an established and effective way to overcome the difficulties associated with the direct measurement of trees, which include issues such as unmeasured parameters, the costs associated with conducting the measurements, and the slowness of the process itself (Burkhart and Tomé 2012; Temesgen et al. 2005).

In most cases, models fitted for larger areas tend to be locally or even regionally biased, and there is always a need for localization (Räty & Kangas 2007; Räty & Kangas 2010; Sironen 2009; Fortin et al. 2016). The uncertainty arising from applying growth models at a national level can reach up to 60% (Fortin et al. 2016). Thus, it is generally challenging to explain the whole range of variations in a sample-based national model fitted for a large area, even for a species-specific measure, and as a result, there is a genuine need for localization (Sterba et al. 2002; Burkhart & Tomé 2012).

Localization or the improved local prediction in the presented research is a process in which the local bias is removed or significantly diminished (Sterba et al. 2002; Räty & Kangas 2007; Räty & Kangas 2010). It is different from the localization that is reported in the literature (see Hall & Bailey 2001). There are several ways to achieve localization in models fitted for a larger area, inter alia, fitting the national model in each region, removing non-significant variables from the original lists of the models, or even creating new models for different regions and fitting the data each time. Alternatively, it is possible to apply spatial indices to create homogenous areas where the values are clustered. If the national model is seen to have non-homogenous residuals, then a process of localization is worthwhile (Räty & Kangas 2007). Another alternative is to introduce local elements or new variables, and this latter approach is used in the presented research by means of the ground remote sensing data of soil moisture content. It has been observed that a possible way to improve local forest growth predictions is by using the proxy of soil moisture as a tool to enhance growth estimations, therefore, the local elements that are introduced in the presented research aiming to improve growth prediction are Digital Terrain Model (DTM) - derived attributes, airborne gamma-ray data, and the vegetation effect expressed as leaf area index (LAI) (Chen & Black 1992).

## 1.2 Forest growth and terrain attributes

The growth of forested trees is controlled by many factors (Oberhuber & Kofler 2000). Soil moisture is a critical element in various hydrological properties within the ecosystem (Wilson et al. 2005). Especially, the spatial distribution of a forest ecosystem and the forest productivity are seen to be more influenced by water supply than any other single factor (Kramer & Boyer 1995). However, there are many factors affecting soil moisture content, and prominent among these is the topography (Wang & Klinka 1996). The effect of topography on forest growth is well established, as topography affects moisture content and other soil attributes (Fritts 1974; Villalba et al. 1994; Oberhuber et al. 1998; Anning et al. 2013; Byun et al. 2013; Galiano et al. 2013; Adams et al. 2014). Moore et al. (1993) found a significant correlation between soil attributes such as phosphorus content, pH, organic matter, A-horizon thickness, and the quantified terrain attributes based on topography and attributes derived from DTM data.

Terrain topography can be expressed digitally in the form of a DTM which is one of the most widely used spatial data models, and used for various purposes including quantifying terrain attributes that indicate soil moisture. Such data is also important in creating the canopy height models which are used in forest inventories (Sterenczak et al. 2013), therefore, the first element to be introduced when seeking to improve local predictions of growth is the DTM, which is by definition an ordered array digital representation of the earth surface elevation, and can be represented in various formats such as Triangulated Irregular Networks (TINS), grids, or contour based models (Moore et al. 1991; Tokola et al. 2000). DTM-derived attributes can be divided into two main groups: the primary attributes such as slope, aspect, hillshade, plan and profile curvature, catchment area, and compound attributes which are obtained through the primary attributes such as wetness indices like the Topographic Wetness Index (TWI) (Beven & Kirkby 1979; Sørensen et al. 2006). Notably, TWI presents one of the more widely used topography-based indices of soil moisture content (Moore et al. 1993; Mummery 1999; Gessler et al. 2000; Kokkila 2002; Bou Kheir et al. 2009), and two of the best known topographic wetness indices are the steady topographic wetness index (i.e. TWI) and the dynamic wetness index (Beven & Kirkby, 1979; Moore et al. 1993; Barling et al. 1994; Sørensen and Seibert 2007).

In the presented research, special focus will be given to the most widely used steady TWI. TWI has been used directly or indirectly to assess specific phenomena within the ecosystem; for instance, to predict the hydrological characteristics of wetland areas (Grabs et al. 2009), for the assessment of drainage patterns, vegetation type and soil type (Murphy et al. 2011), to estimate soil organic matter content (Schwanghart & Jarmer 2011), for the assessment of plant richness and distribution (Luoto et al. 2002; Zinko et al. 2005; Wang et al. 2014), and also for tracking tree species-specific ecological behavior (Petroselli et al. 2013). In direct line with presented research, many studies have used TWI to inspect tree growth (Piovesan et al. 2008; Byun et al. 2010; Seo & Park 2010; Byun et al. 2013; Galiano et al. 2013; Adams et al. 2014). The importance of TWI correlates with other terrain attributes, notably the terrain convexity, solar radiation, slope and aspect. The convexity (Iwahashi and Pike, 2007) has been used in a similar manner to TWI, for instance, in the estimation of large-diameter tree distribution and biomass (Xu et al. 2015), forest site index estimation (Wang et al. 2007), tree species distribution (Lin et al. 2013; Wang et al. 2014), and above-ground biomass storage (Shen et al. 2016). Solar radiation derived from topography (as discussed by Gates 1980; Nikolov & Fox 1994; Rich et al. 1995; Fu & Rich 2002) is fundamental to many biophysical processes due its role in regulating and maintaining water balance (Fu & Rich 2002), and has proven useful in explaining patterns and trends in forest growth (Dong et al, 2012). However, a fuller discussion of the focused applications of this parameter is beyond the scope of the presented study. Nevertheless, terrain attributes derive their importance in principle from topography, and it can therefore be seen as an instrumental tool in many forestry-related studies (Fritts 1974; Oberhuber et al. 1998; Anning et al. 2013; Byun et al. 2013; Galiano et al. 2013; Adams et al. 2014).

## 1.3 Airborne gamma-ray

The second sources of remote sensing data in the presented research is the airborne gamma-ray (γ-ray). Representing the naturally emitted radiation from the earth's crust, the data measures the abundance of Potassium, Thorium, and Uranium. The relation between the influx of γ-ray radiation decline with an increasing soil moisture content can be seen (Grasty 1997; Minty 1997)**,** and assuming the site quality is well linked to moisture content (which directly or indirectly affects the tree growth), then relationships between γ-ray and moisture content and ultimately forest tree growth can be established.

The applications of airborne γ-ray include but are not limited to soil texture and mapping, snow and peat research, and mineral exploration. For instance, γ –ray data has been used in forestry applications such as pine suitability mapping (Hyvönen et al. 2003) and forest site index estimation (Wang et al. 2007). However, its application in improving local growth predictions in boreal forest conditions has yet to be explored.

## 1.4 Vegetation effect

The effect of vegetation was added as a third element and extra component in the presented research. Related to its application, it was hypothesized that vegetation cover and density have an influence on soil moisture (Ladson & Moore 1992; Western et al. 2002). The vegetation effect in presented research is expressed as the leaf area index (LAI: Chen & Black 1992). LAI is an increasingly used measure of vegetation density, and is linked to the most vital processes which are closely associated with plant growth such as evapotranspiration, carbon dioxide flow, and light interception (Cattanio 2017). Additionally, it is also seen as a possible predictor of tree growth in boreal forest conditions (Härkönen et al. 2013).

In spite of the fact that the concept of using DTM derived attributes (either primary or secondary), airborne γ-ray and LAI in forested landscape studies is not a new approach per se, the exploration of the suitability of such data as a proxy of soil moisture in improving the local forest growth predictions offers a gap in the research literature that the presented dissertation looks to fill, particularly in relation to local south boreal forest conditions.

## 1.5 Dissertation objectives

The main objectives of the presented research was to test the suitability of terrain-derived attributes (particularly TWI, airborne γ-ray and LAI) in improving the pre-existing single tree growth model for future diameter at breast height (dbh) for a 5 year period (id5) developed by Pukkala et al. (2013) (hereafter, termed as the national model: NModel). The objectives were extended to demonstrate the effect of DTM sources and characteristics (filling, cell size, and focal neighborhood statistics) and the effect of the calculation source on compound terrain attributes. The second main aim was to compare statistical modeling (i.e. Mixed effect modeling (see Pinheiro & Bates 2002), multilayer perceptron (see Bishop 1995; Haykin 2009) and a possible combination of information (e.g. species-specific, site type, and soil type) on improvements of the prediction of future dbh radial increments for a period of 5 years.

# 2 MATERIALS AND METHODS

## 2.1 Overview of datasets

The dissertation consists of three sub-studies in which different approaches and data sources were analyzed. The studies were carried out in Finland at two sub-study areas within the same forest zone (i.e. the south boreal forest zone). Data consisted of two main groups, namely field data and remote sensing data (DTM, Airborne gamma-ray and LAI). In Sub-Study I, the source of DTM was photogrammetry based DTM. In Sub-Study II and Sub-Study III, the source of DTM was LiDAR data. The field data used during studies I–III was the same. The following sections of this chapter describe the filed data and the remote sensing data sources, the methods followed in this dissertation, and finally the evaluation criteria used in various stages of the dissertation.

## 2.2 Field data

The study area was located in southeastern Finland (**Figure 1**), and lies in a south boreal forest zone. The study area consisted of two sub-areas, namely Kiihtelysvaara (ca. 62°31′ N; 30°10′ E) and Matalansalo (ca. 62°.30′N; 28°.47′ E). Field data consisted of 1118 sample trees which were distributed in 197 sample plots. The total number of tally trees was 9987. Forest stands were randomly selected from the forest data to represent all of the development stages of the forest (e.g. young stands, maturing stands, and mature stands). However, the sample plots were placed subjectively to reflect their stand structure and compositions, and avoiding edge overlap (i.e. the sample plot is completely within the particular forest stand). Three rectangular sample plot sizes were used (20 m × 20 m, 25 m × 25 m, and 30 m × 30 m), and a fixed radius of 9 m was used for circular sample plots. The plots represent four forest types (Cajander 1926) which are *Oxallis Myrtillus* type (OMT), *Myrtillus* type (MT), *Vaccinum* type (VT) and *Calluna* type (CT). The majority of site types fell within the OMT and MT classifications. The proportion of tree species were as follows: Scots pine (*Pinus sylvestris* L.) 67%, Norway spruce (*Picea abies* L.) 13%, and broadleaved trees 19% (mainly Silver birch (*Betula pendula* Roth), downy birch (*Betula pubescens* Ehrh.) and aspen (*Populus tremula* L.)). The soil types reflected mainly mineral soil with an occurrence of peat soil throughout the study area. The majority of sample plots were drawn from the Kiihtelysvaara sub-area study site due to issues related to data availability at the time of conducting the presented research. The forest growth concerning the dbh increments for a period of five years was measured in the laboratory as the increment borer (by measurements of the annual rings). These growth readings were available only for the sample trees.

## 2.3 Remote sensing data

The study data has various sources, and composed of three main categories. Dependent on the stage of the research, the data source was updated accordingly. It is noteworthy that the DEM in Sub-Study I refers to the DTM term used in the subsequent Sub-Studies (II & III). The two terms were used interchangeably, but the term DTM was reverted to as it is a more accurate way to describe the dataset available.

*2.3.1 Digital terrain model (DTM) and processing*

In Sub-Study I, a DTM of 25 m resolution was used. It was obtained from the National Land Survey of Finland and was mainly based on photogrammetry. In Sub-Studies II and III, a LiDAR-based DTM was used. The LiDAR data were collected separately at the two sub-areas. At Kiihtelysvaara, pulses were collected with an ALTM Gemini laser scanning system operated at an altitude of 600–700 above ground level, using an angle of view of 26° and a side overlap of 55%. This resulted in a swath width of 320 m. At Matalansalo, the altitude was 1500 m above sea level with an angle view of 15°, which resulted in a swath width of 800 m. The system of laser scanning was an Optech ALTM 2033 LiDAR system. A nominal density of 0.7 pulses/m$^2$ and 11.9 pulses/m$^2$ were used for Matalansalo and Kiihtelysvaara, respectively. The point cloud was classified and interpolated according to the process described by Axelsson (2000), resulting in a DTM of 1 m resolution. DTM (Sub-Study I) and LiDAR-based DTM (Studies II and III) were the basis for the extraction of various terrain attributes and indices. In Sub-Study I, attributes were derived from the DTM with the original cell size. However, in the subsequent analyses of Studies II and III, three characteristics were examined to see their effect.

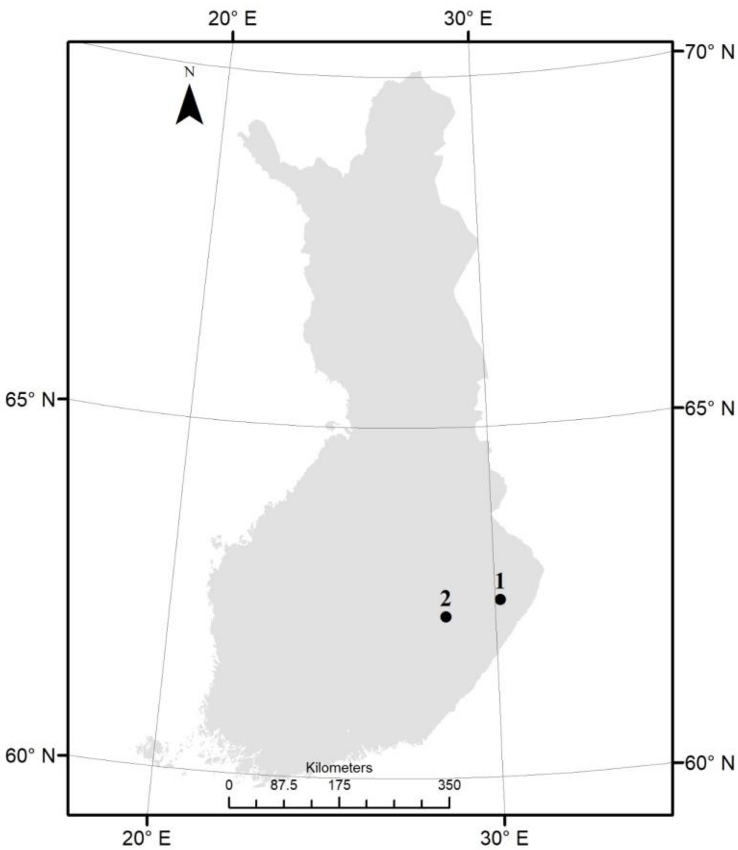


**Figure 1.** The study area location: 1 denotes the Kiihtelysvaara sub-study area, 2 denotes the Matalansalo sub-study area.

These characteristics were the filling process of the DTM (Tarboton et al. 1991), cells size changes, and the focal statistics of neighborhood cells. Different resolutions were created by resampling the created DTM resolution of 1 m (nearest neighborhood) into 5 m, 10 m, 15 m, 20 m, 25 m and 30 m sizes. From each resolution (cell size), the mean focal neighborhood cells at different circular radii (2 m, 3m, 4 m, 5 m, 6 m, 7 m, 8 m, 9 m and 10 m) were applied to each cell. In total, 140 DTM rasters were created (Sub-Study II). All rasters were projected to meet the uniform Finnish coordinated system (ETRS-TM35FIN). A plot size of 30 m was set as the basis from which to extract the mean values of the derived terrain attributes.

In actuality, many attributes were extracted from the DTM data. However, only those which were shown to be significant are presented here. Namely, *solar energy (*wh/m$^2$) was defined as the amount of solar radiation within the growing season, and was calculated according to the process described by Fu & Rich (2002). *Terrain slope* was set as the rate of change in elevation, where each cell has a value representing the maximum change in elevation in relation to its neighborhood cells (Burrough & McDonnell 1998). *Terrain curvature* is the standard curvature of the planner and profile on a cell-by-cell basis (Moore et al. 1991). Terrain convexity was defined within a specific search radius, and as the ratio of cells which have a positive curvature to all valid cells (Iwahashi & Pike 2007). *Elevation* (m) represents the elevation of cells above sea level. *Terrain aspect* was defined as the orientations of slope, where each cell has a value that represents the direction from 0° - 360°, and where cells with zero slope were assigned values of -1 (flat areas).

*TWI* (Beven & Kirkby 1979) as represented by compound terrain attributes was calculated as follows (**Eq. 1**)

$$TWI = \ln (As/\tan \beta), \quad \textbf{(1)}$$

Where *As* denotes the specific catchment area and $\beta$ is the slope of the terrain surface (Jenson & Domingue 1988; Tarboton et al. 1991).

The TWI and modified TWIs were used alongside each other in Sub-Study III. There were several modified TWIs. In $TWI_h$ (according to the index proposed by Hjerdt et al. (2004), the local slope (β) **(Eq. 1)** was substituted with a downslope distance gradient. $TWI_t$ was obtained according to the process described by Temimi et al. (2010) (see **Eq. 2).** The modified TWI incorporating LAI values was obtained by weighting the specific catchment area in **Eq. 1** with the corresponding LAI, based on the cover index type obtained through LiDAR. Cover index type were obtained by equations (see **Eq. 3, 5, 6**)

$$TWI_t = \ln(A) - \ln(A \times \tan(\alpha)) \times \mathrm{e}^{-\mu \times LAI}\ , \quad (\mathbf{2})$$

where A denotes the contributing area and α is the local slope of terrain surface.

*2.3.2 Airborne gamma-ray data (γ-ray data)*

The airborne gamma-ray data was obtained from the Geological Survey of Finland (GTK). It composed of three windows representing the concentration of Potassium, Thorium, and Uranium. These are therefore referred to as the *Potassium* (*γK) window,* the *Thorium (γTh) window,* and the *Uranium window (γU).* Uranium and Thorium are detected through their product-decay series, while Potassium is detected directly (Grasty 1997; Zhang et al. 1998; Wilford 2002; Hyvönen et al. 2005). The measurement unit of the radiometric survey was in count per seconds (cps). The corrected airborne measurements were converted to a ground equivalent (K indicated in percentage, while Thorium and Uranium indicated in ppm). The interpolation of airborne gamma-ray data used a cell size of 50 m. The mounted aircraft spectrometry was conducted at an altitude of about 30–40 m, and the flight line interval was 200 m. In the presented research, the ratios between windows were calculated as they are less affected by the possible attenuation within the γ-ray windows.

*2.3.3 Leaf area index*

The LiDAR data was used as the basis to obtain the LAI values, depending on the echo types returned. Three different canopy cover indices were calculated using LAI theories (Morsdorf et al. 2006; Solberg et al. 2009). *First cover echo index* (FCI) is represented in **Eq. 3**. *All echo types index* (ACI) is represented in **Eq. 5 (**Morsdorf et al. 2006; Richardson et al. 2009), and the *intensity-based cover index* (ICI) is represented in **Eq. 6 (**Hopkinson & Chasmer 2009**)**

$$FCI = \frac{\sum \mathrm{Single}_{\mathrm{canopy}} + \sum \mathrm{First}_{\mathrm{canopy}}}{\sum \mathrm{Single}_{\mathrm{All}} + \sum \mathrm{First}_{\mathrm{All}}}, \qquad \mathbf{(3)}$$

All echos (LiDAR pulses) has to be classified as first, first of many, intermediate, and last. Moreover, echos above 2 m were classified as canopy hits, and the remainder as ground hits. The estimation of near vertical canopy gap fraction (obtained as 1 – cover index) can be converted to represent an effective LAI (Miller 1967) as shown in **Eq. 4**.

$$LAI_e = -\beta \ln(1\text{-}\mathrm{CI}), \qquad \mathbf{(4)}$$

Where $LAI_e$ is the effective leaf area index, and *CI* denotes the canopy cover index extracted from LiDAR. The values of $\beta$ reported in the literature were used since no local values were available (Korhonen & Morsdorf 2014). Values of 1.6, 2.6 were used for FCI and ACI types (assuming that the foliage angle distribution is random), however, the value of 2 was used for the ICI type.

The effective LAI will have an unknown amount of error as the true value of LAI is not known, even though in practice the cover indices are unbiased. In general, such a coarse estimation has shown usefulness in growth model prediction (Härkönen et al. 2013). The LAI obtained by different cover indices are hereafter referred to as LAIfci, LAIaci, and LAIici. The LAI type used to create the $TWI_t$ (**Eq. 2**) was obtained using the LAIfci cover type.

$$ACI = \frac{\sum \mathrm{Single}_{\mathrm{canopy}} + \mathrm{First}_{\mathrm{canopy}} + \mathrm{Intermediate}_{\mathrm{canopy}} + \mathrm{Last}_{\mathrm{canopy}}}{\sum \mathrm{All}}, \qquad (\mathbf{5})$$

$$ICI = \frac{\left(\frac{\sum I_{\text{ground single}}}{\sum I_{\text{total}}}\right) + \left(\sqrt{\frac{\sum I_{\text{ground last}}}{\sum I_{\text{total}}}}\right)}{\left(\frac{\sum I_{\text{first}} + \sum I_{\text{single}}}{\sum I_{\text{total}}}\right) + \left(\frac{\sum I_{\text{intermediate}} + \sum I_{\text{last}}}{\sum I_{\text{total}}}\right)}, \tag{6}$$

where *I* denotes the LiDAR pulse, *First, Intermediate, Last* denote the LiDAR pulse number, *Single* denotes the number of pulses, and *canopy, ground* denote the pulse classification.

## 2.4 Descriptive statistics

The *id5* was larger in mineral soil compared to peat soil, with a mean of 1.19 cm and 0.71 cm for mineral and peat soils respectively. However, the mean of the study area as a whole was 1.13 cm for the sample trees. In the Matalansalo sub-area, the id5 ranged from 0.18-4.37 cm with a standard deviation (SD) of 0.78 and a mean of 1.71 cm. In the Kiihtelysvaara sub-area, the *id5* ranged from 0.07 cm to 3.26 cm with a mean of 0.99 cm and an SD of 0.58. The descriptive statistics details are presented in **Table 1 and Table 2**.

**Table 1.** Descriptive statistics of the modeling data. $dbh_{jk0}$ denotes the *dbh* of the sample trees at the beginning of the growing period in centimeters, and $dbh_{jk5}$ denotes the *dbh* at the end of the growing period of five years in centimeters. *TWI, Convexity, Aspect* and *Elevation, Solar, γk, γTh, γU* are independent variables. LBias denotes the independent variable. **Table 1.a**, represents the data used in Sub-Study Ⅱ & Sub-Study Ⅲ**. Table 1.b** represents the data used in Sub-Study I.

| **Table 1.a** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Sample trees, Matalansalo, n = 223 | | | | | Sample trees, Kiihtelysvaara, n = | | | |
| Variable | Min | Max | Mean | SD | Min | Max | Mean | SD |
| *id5, cm* | 0.18 | 4.37 | 1.71 | 0.78 | 0.07 | 3.26 | 0.99 | 0.58 |
| $dbh_{jk0,\ cm}$ | 4.12 | 42.15 | 17.09 | 6.87 | 1.44 | 45.20 | 15.74 | 7.00 |
| $dbh_{jk5,\ cm}$ | 5.50 | 43.50 | 18.79 | 6.71 | 1.90 | 47.35 | 16.73 | 7.20 |
| *LBias* | -1.27 | 3.15 | 0.28 | 0.76 | -1.50 | 2.80 | -0.06 | 0.54 |
| *TWI** | 3.58 | 5.37 | 4.45 | 0.34 | 5.20 | 11.98 | 8.72 | 1.57 |
| *CONVEXITY* | 29.00 | 57.85 | 45.36 | 4.87 | 0.20 | 59.85 | 46.31 | 9.60 |
| *ASPECT* | 50.92 | 278.01 | 168.01 | 44.94 | -1.0 | 301.35 | 166.08 | 60.13 |
| *ELEVATION* | 87.21 | 132.13 | 108.69 | 10.72 | 133.0 | 148.35 | 138.99 | 3.86 |
| **Table 1.b** | | | | | | | | |
| Sample trees, n= 1118 | | | | | | | | |
| $dbh0_{jk}$, cm | 1.44 | 45.20 | 16.00 | 6.99 | | | | |
| $dbh5_{jk}$, cm | 1.90 | 47.35 | 17.14 | 7.15 | | | | |
| $id5_{jk}$, cm | 0.07 | 4.37 | 1.13 | 0.69 | | | | |
| *LBias* | -1.50 | 3.15 | 0.01 | 0.60 | | | | |
| *γk* | 0.00 | 2.56 | 1.19 | 0.40 | | | | |
| *γth* | 0.82 | 8.32 | 4.43 | 1.33 | | | | |
| *γu* | 0.00 | 2.49 | 1.14 | 0.51 | | | | |
| *TWI* | 5.21 | 15.46 | 8.53 | 1.87 | | | | |
| *Solar(x1000)* | 472.66 | 661.42 | 520.84 | 49.96 | | | | |

*TWI* here refers to the (Beven & Kirkby,1979)*

**Table 2.** The descriptive statistics of the modeling data (most dominant site type according to Cajander (1926) $dbh_{jk0,}$ cm denotes the dbh at the beginning of the growing period in centimeters, and $dbh_{jk5,}$ cm denotes the dbh at the end of the growing period of five years in centimeters. SD denotes the Standard Deviation of the sample trees (Sub-Study III). Independent variables are the modified *TWIs* and *LAI* determined by different cover types.

| | *LAIfci* | *LAIlci* | *LAIaci* | $TWI_o$ | $TWI_h$ | $TWI_t$ | $TWI_{LAIfci}$ | $TWI_{LAIlci}$ | $TWI_{LAIaci}$ | $dbh_{jk0}$ | $dbh_{jk5}$ | *id5* | *LBias* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **MT site type, *n* = 462** | | | | | | | | | | | | | |
| Min | 1.07 | 0.28 | 1.32 | 3.58 | 4.16 | 1.77 | 3.27 | 1.89 | 3.20 | 3.11 | 3.90 | 0.07 | -1.27 |
| Max | 5.51 | 4.39 | 6.49 | 11.98 | 7.55 | 3.80 | 7.15 | 5.64 | 6.88 | 43.99 | 45.05 | 4.33 | 2.80 |
| Mean | 2.71 | 1.25 | 2.68 | 6.83 | 5.22 | 2.32 | 4.76 | 3.83 | 4.74 | 16.07 | 17.37 | 1.30 | 0.16 |
| SD | 0.88 | 0.85 | 0.99 | 2.19 | 0.85 | 0.43 | 0.83 | 0.81 | 0.80 | 6.69 | 6.81 | 0.74 | 0.64 |
| **VT site type, *n* = 460** | | | | | | | | | | | | | |
| Min | 1.06 | 0.26 | 1.17 | 3.67 | 4.15 | 1.70 | 3.41 | 2.70 | 3.51 | 1.44 | 1.90 | 0.07 | -1.50 |
| Max | 4.41 | 5.74 | 9.23 | 11.86 | 7.75 | 4.01 | 11.27 | 10.21 | 11.37 | 38.58 | 39.00 | 3.21 | 2.10 |
| Mean | 1.99 | 0.58 | 1.90 | 8.85 | 4.57 | 2.23 | 5.24 | 3.89 | 5.19 | 16.08 | 16.99 | 0.91 | -0.22 |
| SD | 0.59 | 0.53 | 0.74 | 1.89 | 0.62 | 0.44 | 1.20 | 1.22 | 1.21 | 6.82 | 6.95 | 0.52 | 0.46 |

## 2.5 Generalization of sample tree information

The id5 information was available only for the sample trees. In order to obtain the information for the tally trees (e.g. $dbh_{jk0}$, at the beginning of the growing period), the characteristics of the sample trees needed to be generalized to cover the tally trees. For this purpose, separate models were constructed for each of the sub-areas using non-linear mixed effect modeling (NLME: see Pinheiro & Bates 2002). The random-effect components of the models were specified for random stand effects only in the Matalansalo sub-study area, but random plot effects were accounted for in both sub-areas using the restricted maximum likelihood (REML).The general formula used was in the following form (**Eq. 7**)

$$id5_{ijk} = exp\left(\left(\beta 1 + u_{si} + u_{pij}\right) + \beta 2 * ln\left(dbh0_{ijk}\right) + \beta 3 * {dbh0_{ijk}}^2 + \beta 4 * Zns_{ij} + \beta 5 * Zb_{ij} + e_{ijk}\right), \qquad \textbf{(7)}$$

where $id5_{ijk}$ is the future dbh increment for a period of five years of tree $k$ (cm) in a stand location $i$ within plot $j$, $dbh0_{ijk}$ is the dbh at the beginning of the growing period. $\beta 1$, $\beta 2$,…., $\beta n$ are the parameters for fixed effect of the REML modeling, $e_{ijk}$ is the random error term of the model, $u_{pij}$ is the parameter for random plot effects, and $u_{si}$ is a parameter for random stand effects. $Z_{bij}$ is a dummy variable indicating the existence of a broadleaved tree, while $Z_{nsij}$ is a dummy variable indicating the existence of Norway spruce. A correction factor was applied as half of the residual of the model to compensate for the bias induced by the back transformation (see Duan 1983).

The transformation of *dbh* at the beginning of the growing period proved to be both influential and highly significant. The existence of birch and spruce had an obvious effect in Matalansalo sub-area, however, little effect was seen in Kiihtelysvaara for broadleaved existences, and only for the existence of spruce. In general, the models of generalization expressed good model fits, and it was seen as beneficial to construct separate models. The $dbh0_{ijk}$ of the tally trees was then obtained by subtracting the predicted dbh increment (obtained from Eq. 7) from the $dbh5_{ijk}$ of each tally tree. In this process, we used the predictors of the random effects as provided by the fit of the model. In order words, we took advantage of the sample tree, for which we observed dbh0, whenever they were available to predict the random effects. The predictor of the random effects were then reinserted in the model in order to obtain more accurate predictions before estimating the dbh0 of the tally trees.

The use of tally trees was restricted only in constructing the local variables necessary to obtain the input for the national model. In the subsequent and further analysis, only the sample trees were used and not the tally trees.

## 2.6 Estimating local bias (LBias)

The national model (NModel: hereafter referred to as Pukkala et al. 2013) was set as the reference for forest growth improvement for single tree growth model. The model was selected due to its simplicity and practicality, and offers a species-specific non-linear prediction model for the dbh increment for a five-year period. Moreover, it is a natural exponential function form for the dbh increment. The intercept term includes the site effect, expressed in relation to the forest site types described by Cajander (1926), and the temperature sum (as the summation of the daily temperature of those days when the temperature exceeds the threshold of 5°). The concept of competition was expressed in the national model by noting a basal area larger than the subject tree (Vanclay 1994) and the skewness of the *dbh* distribution, as well as the species-specific value of the basal area in large trees.

In subsequent analyses, the dependent variable was set as local bias (LBias), which is illustrated in **Eq. 8.**

$$LBias_{jk} = y_{jk} - \hat{y}_{jk}, \qquad (8)$$

where $y_{jk}$ is the measured $id5_{jk}$ (cm), $\hat{y}_{jk}$ is the predicted $id5_{jk}$ (cm) obtained using the NModel.

The analysis of id5 improvement occurred exclusively within the sample trees as the records of growth measurements of id5 were only available for the sample trees, and not the tally trees. The improved prediction of id5, is therefore:

$$id5_{jk}[NModel] + LBias_{jk}. \qquad (9)$$

In addition to the mixed effect modeling, the *LBias* was further estimated using the Multilayer Perceptron (MLP), which is an alternative modeling to the traditional regression modeling as it is less susceptible to the noise and outlier problem within the data (see Bishop 1995; Haykin 2009). It also has been used in forestry applications to estimate various forest and stands parameters, from human-induce forest wildfire, site index, trees' height and dimeter, and volume (Vega-Garcia et al. 1996; Aertsen et al. 2010; Soares et al. 2011; Diamantopoulou & Özçelik 2012). The settings of three layers (i.e. input, hidden, and output) was adopted. The MLP was initially run to reduce the number of variables and for selecting those which were seen as most important. The testing data was set to 30%, and the training data was set to 70%. The training proceeded until an acceptable convergence was reached.

Various methodological options were tested in the course of the dissertation. The effects on id5 were examined in: 1) soil types with and without the inclusion of the peat effect; 2) only mineral soil; and 3) examining both mineral and peat soil by taking into account the DTM-derived attributes and airborne γ-ray data (Sub-Study I), and focusing on the effect of DTM characteristics on TWI as important and widely used terrain attributes (Sub-Study II). In the latter study, the effect of DTM cell size, focal neighborhood cell, and DTM filling were analyzed in detail, in addition to the effect of the calculation source. In Sub-Study III, the analysis further examined the effect of vegetation in combination with terrain attributes on the improvement of id5. As a final consideration, the site types were also examined to see their possible effect in all three studies included in this dissertation.

## 2.7 Evaluation criteria

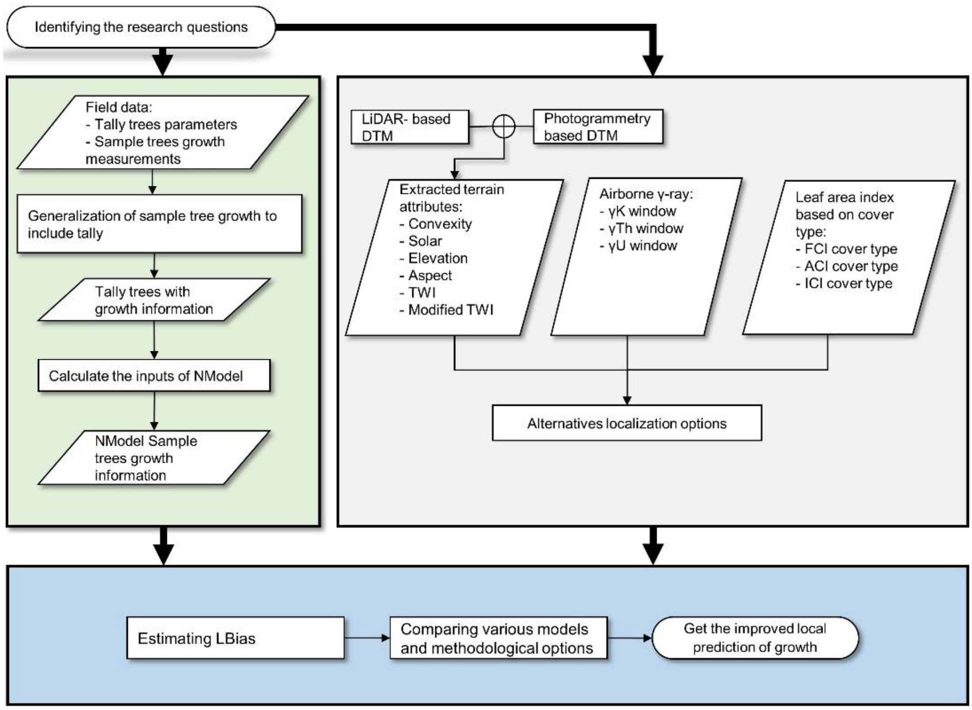


**Figure 2.** Data sources and workflow components followed in the dissertation.

The performance of different constructed models was evaluated by the root mean square error (RMSE), BIAS in addition to the relative percentage of BIAS (BIAS %), and the relative percentage of RMSE (RMSE %).
The relative RMSE and BIAS were obtained by dividing the absolute RMSE and BIAS by the means of respective values of the observation, and multiplying the quotient by 100. **Eq. 10**, **Eq. 11** illustrate the RMSE and BIAS.

$$RMSE = \sqrt{\sum_{s=1}^{n} \frac{(y_s - \hat{y}_s)^2}{n}}, \qquad (10)$$

$$BIAS = \sum_{s=1}^{n} \frac{(y_s - \hat{y}_s)}{n} \qquad (11)$$

where $y_s$ is the observed value and $\hat{y}_s$ predicted value and $n$ is the number of observations.

Other criteria were the Akaike information criterion (AIC), Weighted AIC (**Eq. 12**), and The $\Delta_i$ (calculated as the difference between a specific model and the minimum AIC within a set of models).

$$WeightedAIC = \frac{exp\left(\frac{-\Delta_i}{2}\right)}{\sum_{r=1}^{R} exp\left(\frac{-\Delta_r}{2}\right)}, \qquad (12)$$

The weighted AIC (**Eq. 12**) was obtained as the ratio of the $\Delta i$ of the candidate model to the R candidates set of models. The strength of evidence in comparison was based on the criteria of $\Delta_{aic}$, where $\Delta i$ levels $\leq 4$ have substantial support, $\Delta i \leq 9$ have considerably less support, and models having an $\Delta i > 10$ have essentially no support (see Burnham & Anderson 2002). In regard to the $R^2$ marginal and $R^2$ conditional measures (the coefficient of determination), the R marginal was used to indicate the fixed part in mixed effect modeling, while the R conditional was used to indicate the combined effect (see Nakagawa & Schielzeth 2013; Johnson 2014). The statistical level of significance was set at p-value = < 0.05. The significance of the RMSE changes was conducted by means of an f-test. **Figure 2** offers a summary of the methodological steps followed in this dissertation.

# 3 RESULTS

## 3.1 Airborne gamma-ray and terrain attributes (Sub-Study I)

### *3.1.1 Generalization of sample tree information*

The generalization process described in Sub-Study I resulted in two good findings; first that the application of separate models based on location is beneficial, and second that the non-linear approach was quite a good fit for the specific task outlined, which was to generalize the information from sample trees to also include tally trees. The intercept term in the constructed models was negative in both sub-areas. The standard error of the parameters went from 0.0002 to 0.3884 in Matalansalo, while in Kiihtelysvaara the Standard error went from 0.0527 to 0.1991. The estimated variance for random stand effects was 0.1284 in the Matalansalo area, and the plot random effect was 0.0231 in Matalansalo and 0.1338 in Kiihtelysvaara.

### *3.1.2 Soil type effect*

When examining the effect of soil type on the improvement of id5 prediction, LBias was used as the dependent variable in the analysis. The testing of peat soil effect (per se excluding the terrain attributes and γ-ray effect) resulted in weak results which were not good enough to support proceeding (e.g. the intercept term was highly insignificant). Likewise, the species-specific application did not result in better outcomes.

When exploring trees on mineral soil, all of the variables were significant, although the terrain attributes and γ-ray were not significant aside from their interaction form. The expected effect of solar energy was assumed to be positive on the LBias estimation, and therefore on the improvement of id5 predictions. Modeling LBias on mineral soil produced relatively good results. When examining all soil types, the improvement and general trend was fairly similar to that seen with mineral soil, and only minor differences related to the interaction of γk and broadleaved trees seen as increasing the magnitude in cases of all soil types.

### *3.1.3 Application of the id5 prediction improvements in all soil types*

In light of the examined options, all soil types were adopted and included peat effect as a variable of the improved NModel. Taken together, the results suggested that applying the improvement to all soil types, with variables (terrain attributes and γ-ray), including peat effect, and using the output of the fixed part of the NModel would be advantageous as confirmed by the AI criteria. Drawing snap results from the variables used in the analysis and modeling LBias, the TWI and γth are outlined as prominent variables, both showing a goodness of fit. γth generally showed better results for pine and broadleaved species, however, a high concentration of γth shows little growth prediction improvement, and this was especially noted for pine.

TWI has the ability to express moisture and therefore the potential to affect growth as per the hypothesis of the presented research. The results showed clear evidence of its usefulness through examining the TWI wetness classes. TWI yielded increasingly good results for spruce, especially in wet areas (with a high TWI value). This is an important finding because spruce is one of the species with no evidence of tangible improvement of the id5 prediction featured in Sub-Study I. The expected effect of variables' parameters related to expressing moisture (e.g. γth and TWI) was negative, however, the solar energy model parameter offered positive signs.

The effect of site type was also examined (Sub-Study I), and as expected, the site type had a noticeable effect on the values of RMSE improvement. Examining OMT and MT site types, the RMSE improvement change for the sample trees was about 5 %. Likewise, in the less fertile soil of VT and CT, the RMSE improvement was about 9%.

The bias was also clearly changed. For instance, if the same procedure was applied in more fertile site types, the bias decreased from 0.1675 to 0.0482, and in less fertile site type from 0.2063 to 0.0699 for the NModel and Improved model, respectively. The effects of site types were further analyzed in Sub-Study II, in which the source DTM was updated with LiDAR data. Again, it showed clear evidence to support the hypothesis that within less fertile site types, a change in RMSE is tangible and the procedure of local growth prediction is more accurate.

### 3.2 DTM source characteristics effect on TWI calculation (Sub-Study II)

Within Sub-Study I, the results for spruce were the less clear in terms of RMSE improvements. However, the spruce RMSE was relatively better in some areas with higher wetness indices. However, these results encouraged a closer focus on terrain attributes that was conducted in Sub-Study II, based on different DTM sources.

The characteristics of filling process, cell size, and the focal statistics of neighborhood cells were studied. The criteria of comparing TWI calculated by different algorithms and based on LiDAR data was also examined. The filling process showed no clear trending differences from 140 DTM raster when looking at the value of AIC as a main criterion. Likewise, increasing the cell size towards lower resolution did not improve the estimations of LBias by TWI and other terrain attributes, however, it could be seen that as the cell size increases from 1 m to 30 m there were two downward peaks (lower AIC) pointing at cell sizes of 1 m and 15 m (this taking into account the focal statistics of neighborhood cells). By examining the resolution of 1 m (hypothesized as optimal size) and its different focal neighborhood statistics, in addition to other resolutions (5 m through 30 m), there was no evidence that more accurate results would be obtained by utilizing a larger cell size. Overall, no specific effects were seen from increasing cell size, focal neighborhood statistics, or filling, and this was further confirmed by application of the $R^2$ marginal and $R^2$ conditional.

In light of these findings, it has been determined that a cell size of 1 m with focal statistics of neighborhood cells of 2, and based on unfilled DTM is the best alternative when looking to extract TWI and other terrain variables (namely: convexity, aspect and elevation). However, the TWI was calculated based on different algorithms that were available (i.e. $TWI_a$, $TWI_b$, and $TWI_c$), depending on the way the specific catchment area had been calculated. Based on all of the sources of calculation and by modeling the LBias using each TWI type in addition to terrain attributes, the RMSEs were lowered significantly when compared to the NModel. $TWI_a$ and $TWI_b$ were quite similar in bias elimination and RMSE reduction, and this is perhaps due to the fact that they represent the same feature but have a different calculation source.

The examination of the variation partitions revealed that TWI itself represents 10 % of the total variations, and 20 % when viewed together with other terrain attributes. These variations were derived from the fixed part of the mixed model. The scattered data (predictions improvement vs observed) showed that sample trees are the least scattered, followed by spruce and broadleaved species. Due to their dominance, pine showed a similar pattern to the sample trees. However, the improved model showed clear trends compared to the NModel, so it can be concluded that an improvement in the model was evident. As a final observation, it was seen that in Sub-Study II, the VT site type offers significant RMSE improvement for all tree species, while the MT site type offered better improvements for spruce.

### 3.3 Modified TWI and LAI (Sub-Study III)

The effects of the modified TWI and LAI on id5 prediction improvement were explored in Sub-Study III. In the results, the most prominent variables (i.e. variables with a potential of offering significant results) were plotted against id5 as a box plot. The variability of id5 reflected various effects, e.g. $TWI_h$ has a clear effect on id5, while its values increase. The use of a downslope gradient area instead of the traditional slope (Burrough & McDonnell 1998) has a reverse effect on id5 when compared with $TWI_o$. Furthermore, the variability of $TWI_o$ was seen to be greater in dry locations, while the variability of Id5 in $TWI_h$ was seen to be greater in relatively wet locations. In the case of LAIfci, the variability of id5 was fairly similar (1.18 cm to 0.92 cm) except in wet locations where it was 0.49 cm to 0.81 cm. Convexity has a fairly constant variability, and terrain with a higher convexity demonstrated less id5 variability. These results suggested that there is evidence of the sensitivity of the id5 towards terrain attributes (e.g. TWI) and TWI modified by LAI.

Different models were constructed to estimate the LBias in several groups. AIC, $\Delta_{aic}$ and weighted AIC formed the basis for ranking the model. A total of 7 models groups were used, with a last specific group with only TWI and terrain attributes (see Sub-Study III for further details). In most cases, the LAIici improved the ability to estimate the LBias, however, there was no tangible difference between LAIaci and LAIici (based on the evaluation criteria) as $\Delta_{aic}$ offered *considerably less support* (when comparing the two LAIs based on cover type). However, the LAIfci was seen to offer "*essentially no support*".

In addition to TWIh, the original TWI expressed a goodness of fit for estimating the LBias. All of the constructed models showed a reduction of the RMSE of different magnitudes, although similar patterns were seen to those observed in Sub-Study II. The statistical modeling (LME and MLP) yielded different results. MLP did not add value to improving the id5 prediction, especially for broadleaved species.

As in Sub-Study I and Sub-Study II, in Sub-Study III the LME was also seen as influential, and the RMSE of the improved model in the case of sample trees with the inclusion of LAI (TWI, LAI and terrain attributes) was 0.4041. However, with inclusion of TWI in modified form and terrain attributes, the improvement was not ideal (RMSE improvement of 0.4362 cm in sample trees).

The terrain elevation was a significant factor when seen in conjunction with LAI. The variables which were seen as significant in MLP were partially seen to overlap, as did variables from the LME results. As expected, the variable effect (model parameters) on growth estimation was positive in the case of LAI. Surprisingly, the TWI was also positive but this was probably due to the effect of the inclusion of LAI as a TWI component.

# 4 DISCUSSION

Taken together, the overall results suggest that terrain attributes (especially TWI, γ-ray, and LAI) are suitable and instructive in reducing the RMSE of the national model, and offer better predictions of the id5. The species-wise results were varied, with best improvements being seen within broadleaved sample trees, and with moderate improvements being seen in pine.

## 4.1 Extending sample trees information

The generalization process was a necessary and crucial step that many of the subsequent analyses depended on. Therefore, special caution was exercised when dealing with the constructions of the models for the generalization of the sample trees, so as to include the tally trees as well.

Generally, large-scale forest inventories are likely to be characterized by a low number of sample trees (Eerikäinen 2009). However, measuring growth directly is an appropriate means of obtaining more accurate outcomes (Mehtätalo 2004a). In light of the above, the presented research expected a minor error from the tally trees, as the information derived from them was used only to construct necessary parameters to calculate the input of the national model. Modeling to estimate local bias, and subsequently, the analyses to improve id5 prediction was undertaken exclusively within the sample trees, where the growth measurements were available. The results are persuasive enough to determine that the generalization was sufficient to meet the aims of the particular tasks conducted within the presented research.

However, there are limitations of this approach as in practice, the basal area of plot five year ago might be bigger than what was predicted by taking into account the possible mortality. However, theses discrepancies are minor as the development of stands in general within south boreal forest is slow in nature besides there was no noticeable harvesting or dead trees within the particular selected managed stands. There were also statistical challenges associated with use of the presented approach of generalization as the variable treated as the dependent variable (i.e. id5) is different from the variable of interest (e.g. $dbh0_{ijk}$) necessary for calculation of input of national model. An alternative approach could be the use of Bayes' theorem (Casella & Berger 2002). Although we do not expect major differences between the predictions from the nonlinear mixed model and those obtained through the use of Bayes theorem, the latter would certainly be more rigorous and robust. This remains to be developed.

## 4.2 Trees species response

The tree species response to the local prediction improvements were varied, and this may be explained to some degree by the fact that average diameter increment patterns differ by forest tree species (see Fortin et al. 2008). The results have shown that models in mineral soil have an advantage in reducing the RMSE, and constructing separate models has been seen as a useful approach by which to address different soil types (see Hynynen et al. 2002). However, the lack of an adequate number of observations in peat soil hinders this possibility. It is noted that the national model was in fact applied to both soil types.

Spruce demonstrated only a slight improvement in RMSE regardless of the many options that were tested (Sub-Study I). This might be due to several factors, inter alia, the relatively low numbers of the spruce dataset within the sample trees (n=145), and the nature of the growth patterns of the species itself, which as shade tolerant, could regenerate and survive in the understory for a long period (Mehtätalo 2004a). The slow growth of spruce as shade-tolerant compared to pine may also be influential, as the latter species is light-demanding and can respond immediately to changes in local conditions (Miina 1994). Another explanation could be that spruce species are less affected by changes in soil moisture content which result from changes in topography or changes in altitude (see Magnuszewski et al. 2015), and the national model had been fitted with pine as the main species. However, these assumptions could have been valid in cases of the source DTM being of higher cell size (as seen in Sub-Study I). A further explanation that can be seen as important was the source of the DTM. This was seen in Sub-Study II, where the DTM source was LiDAR-based, and here the RMSE changed from 0.6159 to 0.4098 (sample trees) in the improved model and spruce finally showed good results especially in MT soil types. However, it is still noteworthy that in the VT site type, spruce again showed significant changes in RMSE. But, bearing in mind that spruce trees are unlike other species, this cannot be seen as a decisive observation in terms of site type effect.

The presented dissertation found that broadleaved species experienced the best improvements in RMSE, and there are many factors that may explain this observation. Although the national model applied in the presented dissertation gave a better general prediction for broadleaved species compared with the model presented by Hynynen et al. (2002), there was still significant regional bias seen in the national model, as a result, it could be that the large regional bias explains the good improvements that were seen in RMSE. It is also possible that the anomalies seen with broadleaved trees increased as the broadleaved species were aggregated and treated as birch. The low number of other broadleaved species (e.g. aspen) rendered it impractical to construct a growth model for each species at the time, however, it is important to observe that birch accounted for the majority of broadleaved trees (62%). Birch trees are also known for their sensitivity to stand age (e.g. Zasada et al. 2014), therefore these findings must be taken with some caution because there are other potentially influential factors such as the tree maturity stage (see Binkley et al. 2002; Mehtätalo, 2004a; Zasada et al. 2014).

The forest site type has been in use for several decades, and it is quite usual to take this information into consideration in relation to growth. In the presented research, more fertile soil types (OMT & MT) (Sub-Study I, II) offered more accurate results when applied to broadleaved species and spruce, but this is mostly due to the lower number of spruce trees that occur on less fertile site types. Pine, on the other hand, expressed good RMSE improvements in less fertile site types (VT), albeit that the change was moderate because the proportion of pine only slightly raised in less fertile site types. It is noteworthy, that within the VT site type, basically all of the species-wise results demonstrated a significant RMSE change when comparing the national model with the improved model (Sub-Study II).

The intercept in local bias modeling was included in the model and not omitted. However, this might to a certain extent lead to overoptimistic bias correction. However, removing statistically significant intercept was not beneficial in the presented research, particularly when the introduced elements used for improving the local dbh predictions are important. Besides, the inclusion or removal of intercept in the modeling still debatable and some usual statistics measures become incomparable in case of intercept and no intercept model situations (see Hahn 1977; Casella 1983). It is on the other hand noteworthy to explore the effect of intercept and no intercept models but this was beyond the scope of presented research.

The use of RMSE was deemed to be an appropriate, however, there is a concern over using it (see Willmott & Matsuura 2006; Willmott & Matsuura 2005), and in the mixed effect modeling if there is limited number of sample plots. This due to the sensitivity of RMSE to the hierarchal structure of the data, where a possible inducing of bias from the sampling error and not only from the unknown true error of the national model. However, sample plots number was adequate and presenting the variations within study area. Besides, RMSE is widely used in environmental studies (Willmott & Matsuura 2006; Willmott & Matsuura 2005), easy to interpret and understood by many researchers, yet robust statistical measure. Nevertheless, any statistical measure is likely to capture one aspect of error characteristics (Chai & Draxler 2014). RMSE was kept as evaluation criteria to maintain the aspect of simplicity and comparability between different models but obviously it has limitations likewise any other statistical measures (Chai & Draxler 2014; Willmott & Matsuura 2005).

## 4.3 Airborne gamma-ray effect

The application of γ-ray yielded relatively good results, and despite the coarse resolution, the three windows (γK, γTh, γU) showed significant contributions to the improvement when seen in interaction form. γK was not abundant in the study area. On the other hand, pine showed moderate improvement in relation to γK, which correlated with an expectation that this would render moderate results for pine, as similar studies of site suitability of pine had shown that γK was an efficient predictor (Hyvönen et al. 2003). Pine trees were almost equally distributed between the forest site types (VT+CT, 54%; OMT, MT, 44%), and accurate results were also achieved in less fertile soil types. Empirically, the proportion of soil clay content correlates with a relatively high concentration of γTh and a low concentration of γK, and is also an indication of other resistance minerals (Wilford 1992). The clay content of soil has an importance in tree growth as it has the ability to retain moisture and nutrients (Wilford 1992; Bierwirth et al. 1996). The γTh in presented study held equal significance with solar energy in mineral soils, with results slightly in favor of solar energy. In general, the radiometric distribution patterns and their effects always present a complex picture that is not simple to interpret, and as such they require more caution (Bierwirth et al. 1996).

## 4.4 Terrain attributes and wetness index

Terrain attributes were instrumental in improving the national model throughout the study, however, not all of the tested attributes were influential. In the three sub-studies, TWI was one of the most widely used compound terrain attributes. The results have demonstrated how TWI may be used as a tool in improving growth prediction, and also demonstrate how earth geodiversity information can be utilized. TWI proved to be significant in all studies, either in its original or modified form. The effect of DTM source characteristics on TWI results revealed no clear evidence on the accuracy of the model when increasing the cell size of the source DTM. It is acknowledged that information loss might occur, and in the early results (Sub-Study I), the RMSE improvement was less, perhaps due to the relatively coarse resolution of DTM. Similar results have also been obtained in other studies (e.g. Band et al. 1995; Bruneau 1995; Aryal et al. 2008).

The results of Sub-Study I encouraged further examinations that tested higher resolutions. The suitability of smaller DTM cell size in the presented research was expected to a certain extent, however, TWI computation is dependent on the landscape pattern and the phenomena being examined, (see Sørensen & Seibert 2007). Therefore, the exploration of this option (cell size) was worthwhile. It is important to realize that in general, the scale and extent of the data (i.e. the source DTM) have an effect on outcome accuracy (e.g. Luoto & Hjort 2006), and as a result, an increase in the use of the high-resolution DTM in environmental management can be expected (Seibert et al. 2007). On the other hand, the filling effect of the DTM did not have any particular effect, aside from increasing the focal statistics of neighborhood cells. However, the effect of cell size was not ruled out, and it can be assumed that the scope of the study (e.g. its focus on id5 prediction improvement) and its geographical extent could have masked such effects. Pointing towards this, in another related study, it was found that the focal statistics of neighborhood cells were found to have some sound effects on soil mapping (see Smith et al. 2006).

The computation method of TWI (Sub-Study II) showed no evidence of RMSE changes, however, it is worth noticing that the $TWI_a$ and $TWI_b$ results were the same despite having different computation sources, while the $TWI_c$ was different from the others by way of the calculation itself. The argument here was to compare three of the most common computation sources in terms of id5 prediction improvement. The fact that the D8 algorithm used in ESRI ArcView (Jenson & Domingue 1988) is the most widely used algorithm in GIS packages (Schmidt & Persson 2003) was convincing enough to adopt the $TWI_a$ in improving the id5 prediction, besides implementing a lower cell size and focal statistics of neighborhood cells. TWI contributed substantially to the total variations explained (10%) when modeling local bias. The other terrain attributes tested in the presented dissertation contributed well to the total variations, and these results are in line with similar findings for estimating other forest parameters such as large trees biomass distributions (Xu et al. 2015). Again, TWI has been seen to be a robust approach that can be used for a wide range of applications, and even in the health sector, TWI has been found to be significant in modeling the malaria habitat (McCann et al. 2014).

The usefulness of modified TWI has been well recognized in many studies, and can be applied for various purposes (Barling et al. 1994; Borga et al. 2002; Hjerdt et al. 2004; Qiu 2009; Temimi et al. 2010; Lei et al. 2016). However, in the presented research (Sub-Study III) it did not prove useful when testing to exclude the effect of LAI, or including LAI in conjunction with terrain attributes. It is rather difficult to explain this outcome, at least in regard to using LAI as a modified element in the TWI. One possible reason for this could be that capturing the LAI once during the growing season and ignoring the temporal resolutions of LAI. While preliminary, these results could suggest that a spatially weighted regression could offer an alternative approach, as featured in the study by Zhao et al. (2010) that used LAI for plant distribution estimates.

Terrain elevation was seen as a significant factor in estimating local bias (Sub-Study II, III). Even though the elevation was not specifically targeted, it was tested as altitude has a known effect on tree growth (Coomes & Allen 2007). However, the results of the presented research matched those reported in earlier studies (Monserud & Sterba 1996; Adams et al. 2014; Magnuszewski et al. 2015). In addition, the same effect has been reported by different studies in different climate zones, e.g. temperate zones (in the presented dissertation), and semi-arid zones (Adams et al. 2014), and this lends support to the findings. The effect of altitude was also proven to be significant and small differences in altitudes have been seen to affect some forest trees species (Magnuszewski et al. 2015). For the sake of discussion, one could argue that the effects of the elevation may reflect the vertical distance to the groundwater, and not to allude to any low variations of elevation within the study area, therefore this particular observation must be interpreted with caution.

*Solar energy* was expected to be influential as light is a crucial element in many biochemical processes for plant growth, and especially in the process of photosynthesis which directly affects growth (Bartelink 1998; Dong et al. 2012). This variable was seen to be efficient in estimating the local bias in mineral only soil and in situation of both soil type (i.e., mineral and peat soil). These findings are in alignment with other similar studies, for instance those estimating the forest site index (Wang et al. 2007).

Aspect as a terrain attribute was neither influential nor significant in Sub-Study I and Sub-Study III, but significant in Sub-Study II (i.e. where the source of the DTM had been updated). It has been seen that most of the forest species react to changing aspects (Monserud & Sterba 1996), and the effect was included due to its potential as an indirect indicator of solar energy in the local microsite. These results seemed to be consistent with the findings in Sub-Study I, where the possible effect of aspect was clear because of a possible masking of the solar energy variable. In the results, both variables were seen to express a similar effect.

Terrain convexity was shown to have great significance when it was introduced (Sub-Study II). As anticipated, the results revealed that convexity has a positive effect on modeling the local bias, and therefore has an impact on id5 prediction, and ultimately on RMSE improvement. The positive effects were somewhat unexpected as negative effects were anticipated with regard to the other variables which express moisture (e.g. the TWI and peat presence). These results may be explained by considering how terrain convexity may have influenced air humidity in the local microsite, rather than reflecting the soil moisture itself (Lin et al. 2103). Convexity demonstrated little effect when used with LAI and modified TWI (Sub-Study III) in both LME modeling and MLP modeling. However, in MLP modeling where variable curvature is seen as significant, these discrepancies are negligible, as the convexity represented cells with a positive curvature.

## 4.5 Vegetation effect

With regards to LAI, the presented research attempted to examine the possible effect of LAI on local growth prediction improvement. The findings revealed that in the three LAIs based on cover type (i.e. LAIfci, LAIici and LAIaci), their accuracy in improving Id5 prediction was varied. The intensity based LAI (LAIici) mostly had a lower AIC in estimating the local bias. However the intensity itself comes with some difficulties associated with its application, inter alia, the need for range calibration, problems of variable sensor design, and the normalization of automatic gain (see Korhonen & Morsdorf 2014). Therefore, the use of LAIfci is more reliable if no field data is available, as it is based on the FCI cover index type. However, the LAIfci did not yield better accuracies when compared with LAIici and LAIaci. It was found that LAIaci offered the second best alternative to improve id5 prediction, following LAIici (observing the $\Delta_{aic}$ ), no significance found between LAIici and LAIaci. As a result, it is possible to say here that the application of LAIaci for growth prediction improvement is more suitable than using LAIici. The results improved slightly with the inclusion of LAI and modified TWI along with other terrain attributes (Sub-Study III), and the application of both LAI and terrain attributes are comparable in terms of the improved changes in RMSE (0.4041 cm with LAI + terrain attributes + TWI; 0.4362 cm with TWI + terrain attributes). The high LAI tended to coincide with a high TWI (Griebel et al. 2016), therefore, even though the application of LAI was not ideal, both terrain attributes and LAI can be used to improve the id5 prediction. Furthermore, other similar index of the ratio between leaf mass and leaf area (LMA) could be have also good alternatives to be used in the presented research, it is a good indicator of the most difficult to measure such as the physiological properties of plants directly related to growth (Temesgen & Weiskittel 2006). The LMA shares these similarities with LAI, however, the available such data (e.g., LMA) was a limiting factor.

### 4.6 MLP modeling

MLP modeling was tested in Sub-Study III. Contrary to expectations, it yielded rather poor results in terms of accuracy, as reflected in RMSE improvement. In general, only poor species-specific results were revealed, and in case of broadleaved species, there was no RMSE improvement. Although MLP does not require any prior knowledge about the relevancy of variables, prior knowledge was used in this research to include the most relevant variables. However, the poor results were still unexpected. These findings highlight some of the difficulties associated with the application of MLP in this particular context, unlike physical systems where MLP is seen to perform better (Wastney et al. 1999). Nevertheless, MLP is characterized with the same robustness as LME, as long as the convergence is followed (Gaudart et al. 2004).

## 5 CONCLUSIONS

The presented dissertation has generally demonstrated the suitability and usefulness of the introduced elements of terrain attributes, TWI, γ-ray, LAI to improve the predictions of an existing single-tree growth model for dbh increment for a five-year period. The presented research provides further evidence of the hypothesis that topography affects soil moisture, and in turn forest growth. The presented results are significant in extending our knowledge in a number of areas. Specifically, it was seen that γ-ray windows are suitable for the particular task in the presented research and improve the id5 prediction and result in good RMSE changes. However, the species responses were not the same, and the most prominent results occurred within broadleaved tree species. In general, the accuracy of id5 predictions was higher on less fertile site types compared to more fertile soil types. TWI in its original form with a higher resolution, lower focal statistics of neighborhood cells, and an unfilled DTM source provided a good basis from which to compute TWI, in addition to the use of D8 as a source algorithm. LAI suitability for improving the id5 prediction was comparable with the use of terrain attributes and TWI. Although, LAIici is empirically shown in the presented research to be the best cover type, LAIaci is perhaps more suitable due to difficulties associated with the use of LAIici. The statistical modeling of LME seems to be appropriate when modeling the local bias and improved the id5 prediction. However, in any other studies, limitations of the presented study are acknowledged, namely, that the geographical extent of the study may be seen to hinder the generalizability of several of the tested options.

Particularly, the relatively low number within some species (e.g., spruce) and low variations among the independent variables render some of the findings to be only indicative. However, the research has introduced and tested some promising methodological alternatives, and the results have raised new possibilities and perspectives for the local improvement of tree growth prediction. Further research with a wider geographical scope is needed to confirm these findings, and testing the segmentation approach (Räty & Kangas 2010) over a larger geographical extent and with increased attribute variations with a combination of terrain attributes, γ-ray, and LAI could be an appealing direction for future research.

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