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Effects of ground vegetation on terrestrial laser scanning-derived digital terrain models in boreal forests

Noora Tienaho[a], Tuomas Yrttimaa[a,b], Matti Vaaja[c], Ninni Saarinen[a] and Mikko Vastaranta[a]

[a]School of Forest Sciences, University of Eastern Finland, Joensuu, 80101, Finland; [b]Department of Forest Sciences, University of Helsinki, Helsinki, 00790, Finland; [c]Department of Built Environment, Aalto University, Aalto, 00076, Finland

ABSTRACT
Digital terrain models (DTMs) represent bare ground topography and are essential for studying forest characteristics. Terrestrial laser scanning (TLS) is widely used for forest characterization and DTM derivation, but ground vegetation affects the reliability of DTM. This study quantified vertical errors in TLS-derived DTMs caused by ground vegetation in boreal Scots pine (*Pinus sylvestris*) forests and assessed their impact on diameter at breast height (DBH), stem volume, and stand volume. Bitemporal TLS campaigns were conducted at four one-hectare test sites in Finland, where controlled burnings removed ground vegetation between the measurements. This created 12,452 burned cells (1 × 1 m), while 7619 intact cells served as controls. Comparing pre- and post-fire DTMs revealed that post-fire DTMs were, on average, 8–13 cm lower. Burned cells exhibited greater absolute change (|ΔDTM|) and related root mean square difference (RMSD). Taller vegetation led to higher ΔDTM values. A 10 cm DTM overestimation caused systematic errors in tree and forest attributes: DBH was underestimated by 1.3 mm (0.6%), stem volume by 4.8 dm^3 (3.1%), and total stem volume by ~3 m^3/ha (1.3%). This study quantifies ground elevation overestimation and tree attribute underestimation when DTMs include ground vegetation in boreal forests.

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DEM; DTM; controlled burning; lidar; surface differencing; terrestrial laser scanning

Introduction

A digital elevation model (DEM) is a critical tool for representing topography and analysing geographical data across multiple disciplines. DEMs are commonly applied in orthophoto production, urban planning, and hydrological modelling (Dávila-Hernández et al. 2022; Saati et al. 2008; Wani and Nagai 2021). From DEMs, numerous topographic variables can be derived, including slope, aspect, and wetness indices. Three-dimensional geospatial data, such as point clouds obtained through laser scanning or digital photogrammetry, are commonly used to determine object positions in XYZ coordinates, where the Z-coordinate represents elevation relative to a known geoid. However, vegetation analysis requires information on height above the ground, rather than height above sea level. For mapping and monitoring vegetation structure, DEMs are used to subtract ground elevation from above-sea-level heights.

In short, a DEM is a numerical representation of elevations on a topographic surface, quantifying vertical distances between surface points and a reference datum, such as mean sea level. DEMs can be generated using triangulated irregular networks (TINs), which create a mesh of triangles connecting points across the surface. Typically, TINs are interpolated into regular 2D grids, with each grid square containing data on coordinates and elevation (Guth et al. 2021; Hirt 2014; Oksanen 2006). DEM is a broad term often including both digital terrain models (DTM) and digital surface models (DSM). DTM specifically represents the bare ground of the topographic surface, while DSM depicts the uppermost layer, encompassing elements such as vegetation and buildings (Guth et al. 2021; Hirt 2014; Oksanen 2006). In forest applications, the subtraction of DSM and DTM is considered as a canopy height model (CHM) commonly used in forest structural assessment. This study focuses on the elevation of the bare ground, and therefore the term DTM is used.

The observations required for generating DTMs can be obtained using various technologies, such as photogrammetry, radar, and lidar, and platforms including satellites, aircraft, and ground-based sensors. The choice of data source depends on the desired spatial scale and the

CONTACT Noora Tienaho noora.tienaho@uef.fi School of Forest Sciences, University of Eastern Finland, P.O. Box 111, Joensuu, 80101, Finland

surface of interest. For example, in dense forests, aerial imagery may only capture the upper canopy layers (Guth et al. 2021; Hirt 2014), whereas technologies capable of penetrating vegetation enable the determination of both DSM and DTM. Airborne laser scanning (ALS) and terrestrial laser scanning (TLS) are routinely employed for characterizing the ground surface (e.g. Baltensweiler et al. 2017; Montealegre et al. 2015). ALS is preferred for large-scale mapping tasks like national elevation models due to its efficiency and broad coverage. TLS, on the other hand, provides detailed elevation models for smaller, localized areas, making it valuable for small-scale mapping and monitoring applications, such as field surveys supporting forest research or forestry. While ALS may encounter limitations in canopy penetration due to its large footprint and sparser point density (Guarnieri et al. 2009), TLS excels in providing a more detailed representation of the ground with hundreds of ground points per square meter (Muir et al. 2017). However, the oblique view of TLS may result in a longer optical path through vegetation than a nadir view of ALS, potentially occluding the ground surface (Coveney and Fotheringham 2011). If forest measurements are conducted using TLS, it is reasonable to derive a local DTM from the same dataset to avoid errors caused by combining different data sources.

It has been observed that DTMs tend to be overestimated with both ALS and TLS (Baltensweiler et al. 2017; Fan et al. 2014; Guarnieri et al. 2009; Hodgson and Bresnahan 2004; Hopkinson et al. 2005; Jurjević et al. 2021). However, the error sources are not well understood or thoroughly quantified. In general, when TLS is used to measure topography and derive a DTM, errors arise due to various factors, including errors in displacements, scan co-registration, point cloud georeferencing, and interpolation (Coveney and Fotheringham 2011; Fan and Atkinson 2015; Su and Bork 2006). Topographic characteristics, such as steep slopes or complex terrain, can also affect the accuracy of a DTM. However, a major source of error is likely attributable to vegetation cover (Coveney and Fotheringham 2011). Dense vegetation causes occlusion, impeding laser penetration to the ground (Baltensweiler et al. 2017; Fan et al. 2014). Even in flat, open terrains, ground vegetation has been found to impact ground representation accuracy (Coveney and Fotheringham 2011). Nevertheless, the influence of different vegetation types on DTM accuracy remains poorly understood, and obtaining comprehensive data on this topic remains challenging.

When evaluating the DTM accuracy, datasets are typically compared against a higher accuracy validation dataset, such as points collected with a total station or a differential global positioning system (DGPS) (Fan and Atkinson 2015; Guarnieri et al. 2009; Muir et al. 2017). However, with these evaluation methods, the number of measurement points is limited. Another challenge is integrating entirely different, point-based measurement data with raster-based DTMs in a way that ensures the impact of vegetation is not obscured by the difficulties of combining the datasets. To evaluate how ground vegetation affects the accuracy of DTMs derived from TLS measurements, the most direct approach would be to conduct bitemporal TLS measurements with vegetation removal conducted between these two measurements (Fan et al. 2014). Removing ground vegetation is impractical for extensive areas, but controlled burning provides an opportunity for this. Controlled or prescribed burnings serve various purposes, from reducing fuels to ecosystem restoration. They are often low-intensity fires that specifically target vegetation and fuels on the forest floor (Warner et al. 2020). Typically, the vegetation on the forest floor is not entirely consumed by the fire, resulting in a mosaic of burned and unburned areas (Tienaho et al. 2024). However, with TLS measurements, these areas can be distinguished, facilitating the comparison of DTMs exclusively in the areas where the ground vegetation has burned.

To better understand how ground vegetation affects TLS-derived DTMs, this study aims to assess the characteristics of DTMs with and without ground vegetation. Specifically, the study addresses the following questions: (1) to what extent are elevation values higher when ground vegetation is included in the dataset used to generate the DTMs, (2) how does the height of ground vegetation (i.e. vegetation classes) affect these differences, and (3) how do DTM inaccuracies (i.e. ground height overestimation) propagate to tree and forest attributes such as DBH, stem volume, and total stand volume. Altogether, this work demonstrates the magnitude of uncertainty potentially associated with TLS-based approaches to forest characterization, with a focus on how DTM estimation accuracy influences subsequent analyses of forest structural characteristics.

To achieve this, forested areas were characterized using TLS point clouds captured before and after controlled burnings carried out in Finnish boreal forests. The DTMs and surface models were generated to characterize topography and ground vegetation height before and after the fire. The surface models were then utilized to identify areas exposed to the fire – considered as burned areas where vegetation was removed – and control areas where vegetation remained unchanged.

Experiments were conducted to assess whether the pre-fire DTM (i.e. the DTM with ground vegetation) demonstrated higher elevations compared to the post-

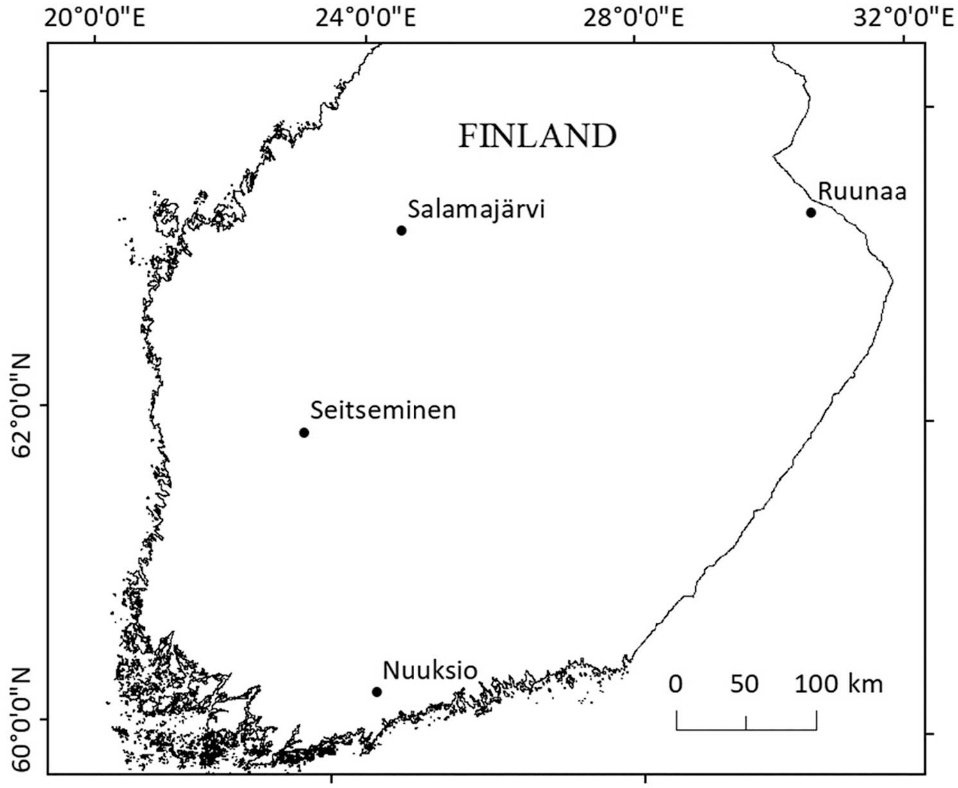

Figure. 1. Four controlled burning sites in southern Finland. Seitseminen and Nuuksio were burned in 2021 and Ruunaa and Salamajärvi in 2022.

fire DTM (i.e. the DTM without ground vegetation), which are expected to more accurately represent ground elevation due to the removal of occluding vegetation. To ensure that any observed deviation between the DTMs resulted from the changes in vegetation covering the ground rather than geolocation errors between the datasets, the change between pre- and post-fire DTMs (ΔDTM) and related root mean square difference (RMSD) were analysed in both burned and control areas. It was assumed that burned areas would exhibit higher absolute ΔDTM and RMSD values compared to unburned control areas.

Material and methods

Experimental setup

The study was carried out at four test sites in Finland (Figure 1), where controlled burnings were conducted by Metsähallitus, a state-owned enterprise, during the summers of 2021 and 2022, as part of ecological restoration efforts. The test sites are located in the central or southern boreal zone and are predominantly covered by Scots pine (*Pinus sylvestris*). The forest types include dry and sub-xeric heath, classified as *Calluna* and *Vaccinium* types according to Cajander's (1926) forest site type system, which is based on indicator species in ground vegetation. At each site, a sample plot of approximately one hectare was established, where TLS was employed to characterize both the topography and forest structure before and after the controlled burnings. The time interval between the measurements varied from 3 to 11 weeks (Table 1). Figure 2 provides visual illustrations of one of the controlled burning sites before and after the fire.

Data acquisition and processing

TLS measurements were conducted using a Riegl VZ-400i time-of-flight laser scanner (RIEGL Laser Measurement Systems, Horn, Austria), operating at a wavelength of 1550 nm. This scanner captures multiple returns from each emitted laser pulse and provides a 100° vertical field of view and a 360° horizontal field of view. The scanner functioned with a pulse repetition rate of 600 kHz, recording up to eight returns per each emitted laser pulse. The scanner had a beam divergence of 0.35 mrad at $1/e^2$. Using the "Panorama 40" scan pattern, it achieved an angular resolution of 0.04° and a point spacing of 3.5 mm at a distance of 10 meters.

To ensure comprehensive point cloud coverage and minimize occlusion caused by vegetative structures,

Table 1. Geographical coordinates of the centre of each test site and dates of controlled burnings and pre- and post-fire terrestrial laser scanning (TLS) measurements.

Site	Coordinates (N, E)	Pre-fire TLS	Burning	Post-fire TLS
Nuuksio	60°19.484′, 24°32.349′	6 June 2021	7 June 2021	30 June 2021
Seitseminen	61°58.080′, 23°24.735′	20 June 2021	1 July 2021	6 September 2021
Ruunaa	63°22.814′, 30°30.132′	9 June 2022	30 June 2022	3 July 2022
Salamajärvi	63°17.267′, 24°37.976′	13 July 2022	16 August 2022	13 September 2022

the sample plots were scanned from multiple locations. The scanning distance has been observed to affect elevation estimation accuracy, with the most significant increase in overestimation occurring for distances greater than 15 m (Baltensweiler et al. 2017; Puttonen et al. 2015). The scan setup consisted of a regular 10 × 10 m grid for the scanner locations while avoiding scanning right next to trees. This approach resulted in an average of 120 scans per test site. Each scan required approximately 2 min, corresponding to the scanner's full rotation time, resulting in a data acquisition time of one to two days per test site.

For each test site, the individual scans were co-registered into a merged point cloud, and points with extreme reflectance values (< −25 dB and >5 dB) were filtered out. This standard procedure was conducted using the RiSCAN PRO software (version 2.14.1) provided by the scanner manufacturer. The scanner, which includes built-in orientation and positioning sensors such as an inertial measurement unit (IMU) and a global navigation satellite system (GNSS) receiver, enabled the collection and alignment of multi-scan point clouds without requiring external reference targets. The coordinates of the test site corners were determined using the Trimble Geo 7X (Trimble Inc., Westminster, USA), which is equipped with real-time extended (RTX) GNSS positioning technology. The merged point clouds were then clipped using polygons derived from these corner coordinates.

The pre- and post-fire TLS point clouds were independently processed using LAStools software (version 211218) (Isenburg 2021). Variations in the GNSS positioning accuracy between pre- and post-fire TLS measurements led to minor misalignments in the acquired point clouds. To ensure precise positioning for detecting changes from bitemporal point clouds, a rigid 3D transformation was applied to align the pre- and post-fire point clouds accurately. This involved manually identifying tie points (16 per site) common to both pre- and post-fire measurements, such as branch origins that had remained intact, and extracting the respective XYZ-coordinate pairs pre- and post-fire. The coordinates of these extracted tie points were then utilized to calculate XYZ-translation and XY-rotation along the Z-axis required to align the pre-fire point clouds with the post-fire ones. The alignments were reviewed visually and adjusted as needed to achieve the closest possible alignment. Accuracy assessment showed a mean difference of 1.5 cm in the XY-plane and 1.2 cm in the Z-direction, with corresponding RMSEs of 7.5 and 3.2 cm, respectively.

The point cloud coordinates were rounded to the nearest millimetre. To eliminate noisy points, the lasnoise tool in the LAStools software was utilized to remove such points with < 6 neighbouring points within a 2 cm radius. After denoising, the point clouds were downsampled and voxelized into a 5 mm 3D grid, ensuring uniform point density and removing excessive data records while still maintaining essential structural details. The classification of points into ground and non-ground points was performed using the lasground_new tool, following the approach detailed in Ritter et al. (2017). Pre- and post-fire DTMs were subsequently generated using the las2dem tool, which temporarily triangulates points into a TIN before rasterizing it into a DTM via linear interpolation. The last or only return laser pulse was utilized in this process to facilitate capturing the actual ground surface, minimizing the effect of the presence of ground vegetation in this respect. The DTMs were produced at a 1 m resolution, a commonly employed standard in forest applications.

Defining burned and control areas

Since the controlled burnings affected only the ground vegetation, points located more than 2 m above the ground surface were excluded from further analysis. To estimate the ground vegetation height, both pre- and post-fire point clouds were first normalized using post-fire DTMs, assuming it better describes the ground height due to the ground surface being more exposed after the fire. Vegetation surface models were then generated on a 2D grid at a 0.1 m resolution with each cell representing vegetation height, derived as the 99th height percentile of respective points. For cells lacking point returns, linear interpolation was performed using the mean values of the adjacent 9 × 9 cells to complete the surface models. The changes in ground vegetation height were estimated by subtracting the pre-fire

Figure 2. The test site Ruunaa three weeks before (left) and a few days after (right) the controlled burning, illustrating the process of ground vegetation removal. The ground vegetation is characterized by mosses and lichens with a mild coverage of lingonberry (*Vaccinium vitis-idaea*) and common heather (*Calluna vulgaris*).

surface models from the post-fire surface models. Negative values indicated a decrease in ground vegetation height caused by fire consumption, while positive values indicated an increase due to vegetation growth.

The changes in the ground vegetation height were then scaled to a 1 m resolution to identify surface areas exposed to fire and areas where the vegetation remained unchanged. A 1×1 m cell was classified as "burned" if $\geq 80\%$ of the respective 0.1×0.1 m cells showed a height decrease of > 5 cm, and as "control" if $\geq 50\%$ of the respective 0.1×0.1 m cells remained relatively unchanged, with an absolute height change of ≤ 5 cm. The 5-cm height threshold was chosen based on evaluation of pre- and post-fire point cloud alignment, to exceed the realized 3.2-cm RMSE recorded for the Z-coordinate accuracy. Cells where the ground vegetation changes did not meet these thresholds were excluded from further analysis. Based on this classification, the burned areas covered 3%–60% and control areas 10%–25% of the total area of the test sites (Table 2). The total burned area across all the test sites was 1.2 ha, while the control areas covered 0.8 ha. Figure 3 illustrates the point clouds depicting burned and control cells.

Table 2. Area of the test sites; number, percentage, and area of the 1×1 m burned cells and control cells.

		Burned cells			Control cells		
Site	Area (ha)	n	%	Area (ha)	n	%	Area (ha)
Nuuksio	1.1	3264	30	0.3	2495	23	0.2
Seitseminen	1.0	6125	60	0.6	999	10	0.1
Ruunaa	0.9	2788	32	0.3	1727	20	0.2
Salamajärvi	1.0	275	3	0.0	2398	25	0.2
Total	4.0	12,452	31	1.2	7619	19	0.8

Comparing pre- and post-fire DTMs to analyse the effect of ground vegetation

To evaluate the effect of ground vegetation on TLS-derived DTMs, ΔDTM was separately analysed within burned cells and control cells. The burned cells and control cells were compared to verify that any observed deviation between pre- and post-fire DTMs stemmed from the presence of vegetation in pre-fire point clouds and its absence in post-fire point clouds, rather than systematic elevation differences resulting from errors in measurements or co-registration. This comparison relied on ΔDTMs and RMSDs between the pre- and post-fire DTMs. The ΔDTMs were calculated by subtracting the pre-fire DTMs from the post-fire DTMs, and the mean ΔDTMs of burned and control areas were compared using Welch's two-sample t-test. Prior to the analysis, the datasets were verified to be normally distributed. The null hypothesis, assuming no differences between the means, was rejected if the p-value was ≤ 0.05. RMSD is calculated similarly to RMSE, but instead of assessing the difference between actual and predicted values, it seeks to determine the difference between two distinct sets of actual data. The equation for RMSD is as follows:

$$\mathrm{RMSD} = \sqrt{\frac{\sum_{i=1}^{n} (\mathrm{preDTM}_i - \mathrm{postDTM}_i)^2}{n}} \tag{1}$$

where RMSD = root mean square difference, *pre*DTM =

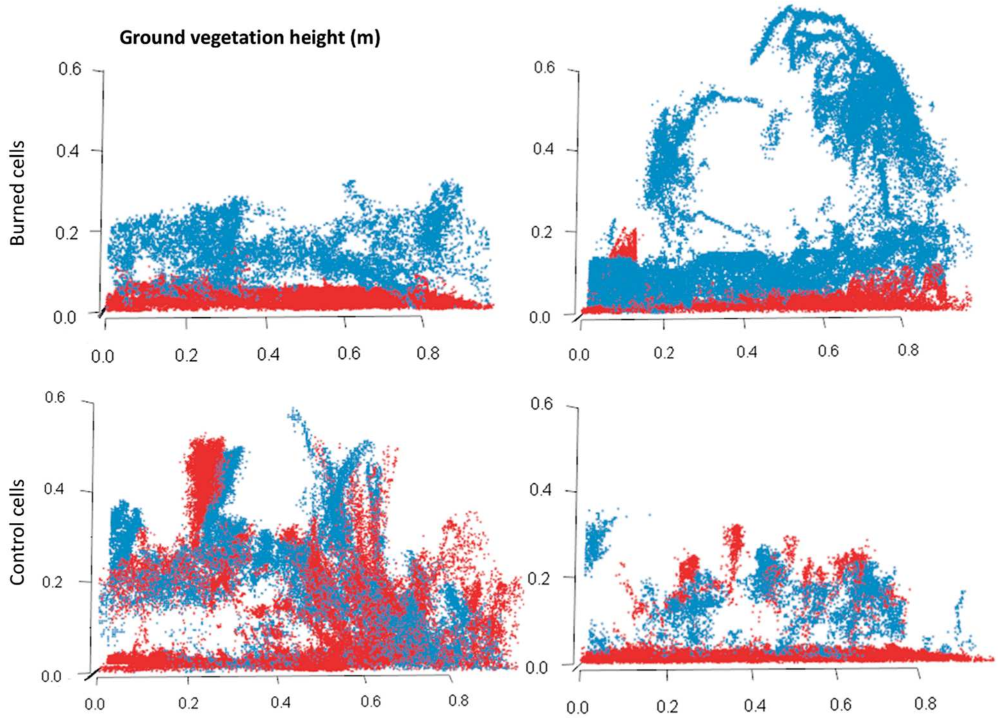

Figure 3. Side-view illustrations of 1 × 1 m point clouds from the Nuuksio test site showing pre-fire terrestrial laser scanning (TLS) measurements in blue and post-fire measurements in red, with two burned cells in the top row and two control cells in the bottom row.

pre-fire DTM, *post*DTM = post-fire DTM, and *n* = the number of observations. The statistical analyses were performed using the R software (version 2022.12.0).

To examine the effect of vegetation height on the DTM accuracy, the burned 1 × 1 m cells were divided into three classes based on their mean vegetation height before the fire: ≤ 15 cm, 15–30 cm, and >30 cm. The number of cells in each class was 1105, 6393, and 4951, respectively. ΔDTM was calculated for each class. The first class intends to represent ground vegetation mainly consisting of mosses and lichens. In the second class, the ground vegetation is more abundantly characterized by common heather (*Calluna vulgaris*) and lingonberry (*Vaccinium vitis-idaea*) twigs, increasing the vegetation height. The third class represents more fertile sites, characterized by, for example, bilberry (*Vaccinium myrtillus*) twigs and various grass species, where the vegetation height increases even further.

Table 3. Stand density (trees per hectare) and total stem volume (m^3 per hectare) at the test sites.

Site	Stand density (n/ha)	Stem volume (m^3/ha)
Nuuksio	369	205
Seitseminen	687	260
Ruunaa	948	274
Salamajärvi	919	272

To evaluate DTM estimation accuracy in the context of forest characterization, it was demonstrated how a possible DTM inaccuracy (i.e. ground height overestimation) affects the reliability of DBH and stem volume measurements of individual trees and, consequently, stand-level forest attributes such as total stem volume. To accomplish this, first all the trees within the study sites were detected from the post-fire TLS point clouds and their stem taper curves were measured based on respective point cloud reconstructions using automatic point cloud processing tools developed in Yrttimaa et al. (2019, 2020). The DBH was defined from the stem taper curves at the height of 1.3 m. The stem was considered as a sequence of vertical cylinders with dimensions corresponding to the stem taper curve estimates at 1-cm height intervals. The volume of each 1-cm stem section was computed using the formula for cylinder volume, and volumes of the cylinders were summed up for obtaining the total stem volume. The sampled trees represented an average DBH of 23.6 cm, ranging from 4.9 cm to 69.3 cm with a standard deviation of 8.3 cm. The stem volume averaged 222.7 dm^3 and ranged from 8.9 dm^3 to 1701.0 dm^3 with a standard deviation of 166.5 dm^3. Stand density and total stem volume per hectare were derived by counting the total number of trees detected from the post-fire

TLS point clouds and summarizing their volumes within each study site. These figures are presented in Table 3.

Second, a total of 100 trees were randomly sampled from each study site ($n = 400$ trees altogether) to conduct an experiment where the DBH was first measured for each tree assuming a height offset of 0–30 cm to the actual measurement height of 1.3 m. In other words, the stem diameter was obtained from the post-fire taper curves at 1-cm intervals from 1.30 m to 1.60 m, with the 1.30-m measurement height representing the correct measurement height at an offset of 0 cm and the 1.60-m measurement height representing the most extreme scenario where the ground level would be overestimated by 30 cm, leading to a respective 30 cm height offset for the DBH measurement (i.e. the diameter being measured at a height that is 30 cm higher on the stem, likely to underestimate the diameter due to stem tapering). For each height offset, a medium as well as a 99% confidence interval of the magnitude of diameter deviation from its actual value were computed based on observations among the studied trees.

Third, to assess the influence of possible DTM inaccuracy on stem volume estimation, the lowest part of the stem was concentrated on, as it is likely to be omitted if DTM is overestimated due to the presence of ground vegetation. Using the taper curve, the stem volume was calculated from the cylinders with the same height offset of 0–30 cm. In other words, the volume was first calculated including the cylinders from the height of 0 cm to the top of the tree (i.e. the actual stem volume), and then the stem volume was calculated between 1, 2, 3, … 30 cm and the top of the tree, moving one cm upwards at a time. This approach allowed for the assessment of the effects of ground vegetation on stem volume. Based on the observations throughout the studied trees, both a medium and a 99% confidence interval were computed for each height offset, characterizing the volumes of stem sections omitted due to possible DTM inaccuracy.

Table 4. Mean change in DTM (ΔDTM; pre-fire DTMs subtracted from post-fire DTMs) and root mean square difference (RMSD) between pre- and post-fire DTMs in burned and control areas.

	ΔDTM (cm)		RMSD (cm)	
Site	Burned	Control	Burned	Control
Nuuksio	−9 ± 11	2 ± 4	15	4
Seitseminen	−11 ± 7	−3 ± 5	13	6
Ruunaa	−8 ± 5	−5 ± 3	9	5
Salamajärvi	−13 ± 8	−2 ± 5	15	5
Average	−10 ± 8	−1 ± 5	13	5

To demonstrate how the uncertainty in DTM estimation-induced inaccuracies in individual tree-level characterization translated to stand-level forest characterization, it was computed how the realized height offset in stem volume estimation affected total stem volume estimation. This was accomplished by summarizing the volumes of the potentially omitted stem sections of the sampled trees within each study site (i.e. volume per 100 sample trees) and scaling their total volume with respect to the known stand density (number of trees per hectare) to obtain an estimate for the omitted volume per hectare due to DTM inaccuracy.

Results

With the removal of ground vegetation in the burned cells, pre-fire DTMs indicated ground surface levels that were, on average, 8–13 cm higher than the corresponding post-fire DTMs, depending on the test site (Table 4). These mean differences were statistically significant ($p < 0.001$) in all test sites. The mean ΔDTM across all sites was −10 cm in burned areas, while in control areas, it was notably lower at −1 cm. RMSD between the pre- and post-fire DTMs was approximately 13 cm in burned areas and 5 cm in control areas (Table 4), suggesting that the observed differences between the pre- and post-fire DTMs originated from changes in ground vegetation coverage rather than geolocation errors between the two datasets. The difference between pre- and post-fire DTMs varied considerably within the test sites, due to variations in vegetation height, as illustrated by the Nuuksio test site in Figure 4.

Analyses of ΔDTM within the three vegetation height classes showed that the abundance of ground vegetation affected the magnitude of DTM overestimation. The lowest vegetation class featured an average ΔDTM of −6 cm (standard deviation ±4 cm), the second class an average ΔDTM of −8 cm (±6 cm), and the third class, representing the highest mean vegetation within the 1 × 1 m grid cells, an average ΔDTM of −12 cm (±11 cm) (Figure 5). Statistical tests showed ΔDTM being significantly different ($p < 0.05$) for all vegetation classes.

In the context of forest characterization, the observed overestimation in DTM is likely to result in an underestimation of tree height and inaccurate stem diameter measurements due to an offset in the measurement heights. This, in turn, may lead to an underestimation of stem volume. The average ΔDTM of −10 cm resulted in DBH being measured with a respective offset at the height of 1.4 m instead of the actual 1.3 m measurement height. According to the experiments, this offset

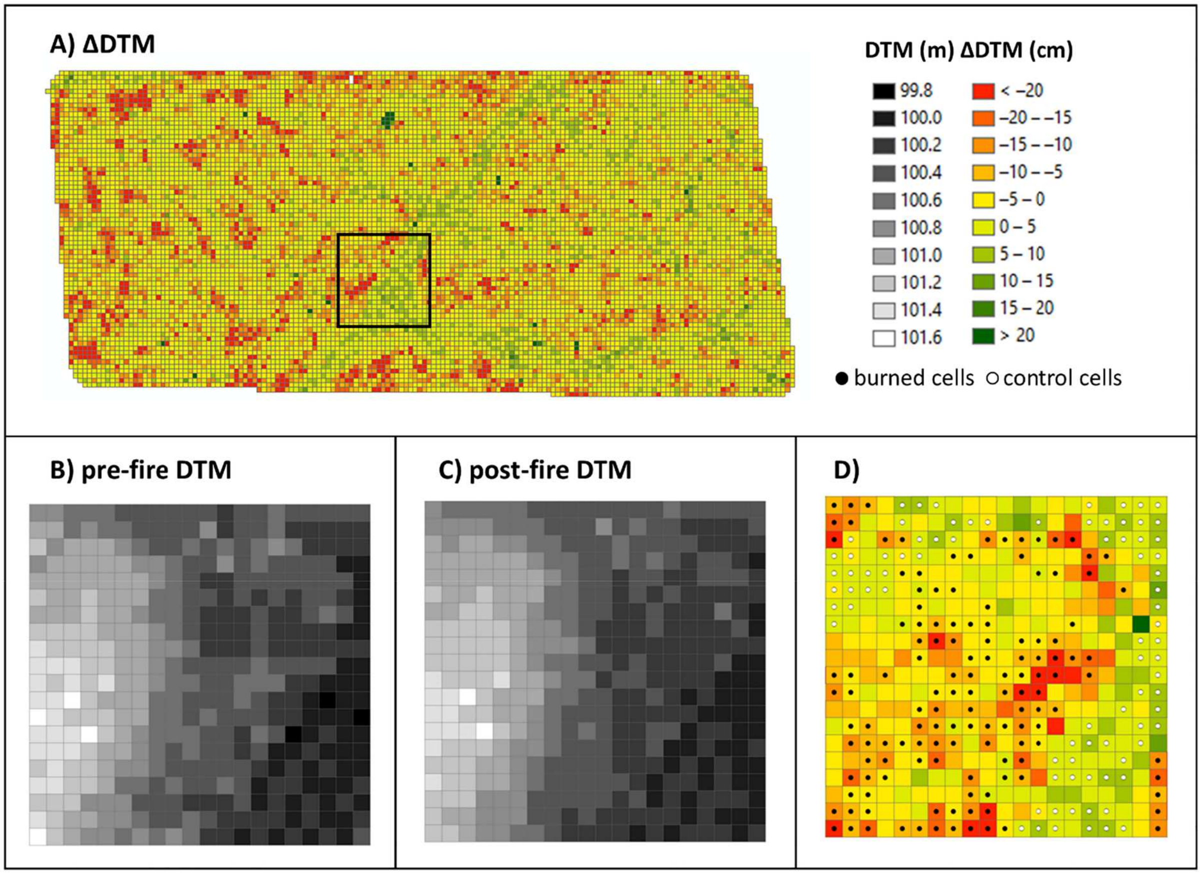

Figure 4. (A) Changes in the digital elevation models (ΔDTM; pre-fire DTMs subtracted from post-fire DTMs) of the test site Nuuksio (upper row). (B) A 20 × 20 m section of pre-fire DTM, (C) post-fire DTM, and (D) ΔDTM with points marking burned cells (black) and control cells (white) (bottom row).

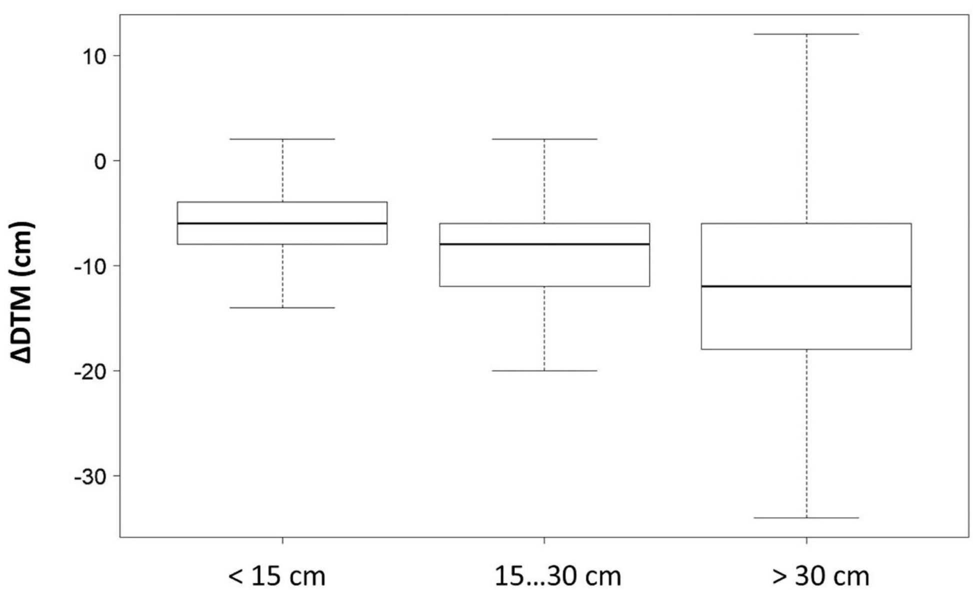

Figure 5. Changes in digital elevation models (ΔDTM; pre-fire DTMs subtracted from post-fire DTMs) within three classes representing different ground vegetation types based on their mean height above the ground within the investigated 1 m × 1 m cells. Negative values indicate overestimation of ground height due to vegetation (i.e. pre-fire DTM appearing higher than post-fire DTM). Bold lines represent the medians, boxes show the interquartile range (IQR), and whiskers extend to 1.5 × IQR, covering the range within a 99.3% confidence interval for normally distributed data. Outliers beyond this range are omitted for clarity.

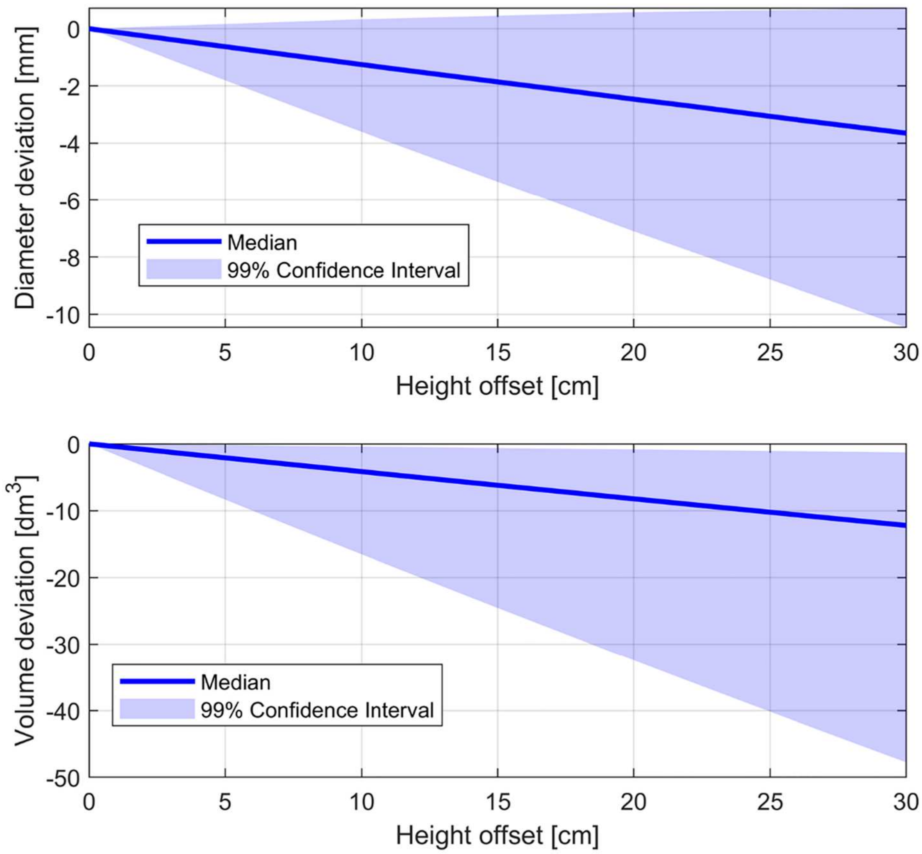

Figure 6. Illustration of the magnitude of stem diameter deviation (top) and volume (bottom) from their actual measured values when the measurement height offsets by 0–30 cm higher on the stem due to ground height overestimated because of the presence of ground vegetation. The bold line shows the median deviation, and the shading shows its 99% confidence interval among 400 randomly selected trees (100 trees across each of four test sites).

translated into a 1.3 mm (0.6%) mean underestimation of DBH, with the 99% confidence interval ranging from 0.1 mm overestimation to 3.7 mm underestimation (Figure 6). For the highest vegetation class, the observed statistical range in ΔDTM extended to approximately −30 cm (Figure 5), representing the most extreme DTM overestimation. This height offset meant a 3.6 mm (1.5%) mean underestimation in DBH with a 99% confidence interval ranging from 0.4 mm overestimation to 10.3 mm underestimation.

Besides DBH measurement, inaccurate DTM estimation also affects stem volume calculations. The realized −10 cm average ΔDTM meant that a corresponding stem section (i.e. the lowest 10 cm of it) was omitted when estimating total stem volume using pre-fire point clouds. Based on the analysis carried out with the studied trees ($n = 400$), the stem volume was underestimated by an average of 4.8 dm^3 (standard deviation ±3.6 dm^3), accounting for 3.1% of stem volume. With the most extreme case, the 30 cm height offset, the stem volume was underestimated by an average of 13.7 dm^3 (±10.3 dm^3), accounting for 8.8% of stem volume. At the stand level, overestimating the DTM by an average of 10 cm resulted in the total stem volume being also underestimated with magnitudes ranging from 2.7 m^3/ha (1.3%) in the test site Nuuksio to 3.6 m^3/ha (1.3%) in the test site Ruunaa.

Discussion

This study aimed to investigate the effects of ground vegetation on DTM estimation and demonstrate the findings in the context of point cloud-based forest characterization. The research involved removing ground vegetation through controlled burnings conducted at four boreal forest test sites, and characterizing topography and ground vegetation height before and after the burnings using TLS. It was assumed that post-fire DTMs would better capture ground surface, characterizing ground elevation at a lower level than corresponding pre-fire DTMs due to the absence of occluding vegetation. The findings of the study confirmed this, showing that ground elevation was characterized approximately 10 cm lower after vegetation removal, with the abundance of occluding vegetation – in terms of its height – increasing the observed height offset.

Analysis of ΔDTM values between burned and control cells confirmed that the observations were due to vegetation removal and not because of geolocation errors between the datasets, as the burned areas featured an average of 9 cm larger |ΔDTM| and 8 cm larger RMSD in the DTM values compared to the control areas. The observed inaccuracy in DTM estimation was shown to influence further structural analysis of individual trees. With ground elevation overestimated by an average of 10 cm, the corresponding offset in the DBH measurement height led to DBH being underestimated by a few millimetres. A more pronounced error was recorded from stem volume estimation, as the first 10 cm of the stem stumps were completely omitted in the analysis, resulting in the stem volume being underestimated by 4.8 dm^3 (3.1%) on average and its stand-level estimate by approximately 3 m^3/ha (1.3%).

Previous studies have consistently shown that TLS tends to overestimate DTMs by a few centimetres, up to approximately ten centimetres when compared to values derived from total station or DGPS points at a resolution of 0.3–1.2 m (Baltensweiler et al. 2017; Guarnieri et al. 2009; Jurjević et al. 2021). These findings align with the observations of this study, which showed that the presence of ground vegetation led to an 8–13 cm increase in observed elevation values. However, it is important to note that this study did not validate TLS-derived DTMs against independent observations of the true level of ground elevation. Instead, the focus was on evaluating the influence of ground vegetation on DTM estimation. Therefore, it was considered intuitive to examine differences between DTMs derived from independent TLS campaigns conducted before and after the removal of ground-occluding vegetation. Controlled burnings were employed as a means of vegetation removal, effectively exposing the ground surface. This experimental design enabled a direct assessment of the vegetation's impact on DTM estimation, aligning with the objectives of the study.

The analysis of ground vegetation effects on DTM estimation was conducted in burned cells, identified as areas where more than 80% of the corresponding 0.1×0.1 m cells exhibited a decrease in ground vegetation height exceeding 5 cm. This threshold was chosen to ensure that the detected changes in vegetation height were significant enough, especially given the alignment accuracy of 3.2 cm in the Z-direction for the pre- and post-fire point clouds. However, if a larger reduction in height had been used to define burned cells, the observed differences between the pre- and post-fire DTMs might have been even more pronounced. Similarly, for identifying control cells, a small change in vegetation height was permitted, which likely resulted in a mean RMSD of 5 cm between the pre- and post-fire DTMs in control cells. In the control cells as well, the post-fire DTM was generally lower than the pre-fire DTM, possibly because the control cells were defined such that only half of the area was to remain unchanged. However, at the Nuuksio test site, the mean ΔDTM in control cells was positive, indicating that the post-fire DTM was higher than the pre-fire DTM. This anomaly could be attributed to ground vegetation growth in the control cells between TLS measurements. This, however, does not affect the results of the study as the analyses focused on the burned cells, and this anomaly was found in control cells.

The magnitude of the observed differences between the pre- and post-fire DTMs – which were rather small eventually – is explained by the ground vegetation characteristics of the study sites. Approximately 60% of the investigated 1 m × 1 m grid cells featured a mean vegetation height < 30 cm, with the ground-occluding vegetation mainly consisting of feather mosses (*Pleurozium schreberi*, *Hylocomium splendens*) and dwarf shrubs (*Vaccinium myrtillus*, *Vaccinium vitis-idaea*) (Palviainen et al. 2005). The magnitude of DTM overestimation depends on forest and vegetation type. In dry and sub-xeric Scots pine stands, relatively low ground-layer vegetation was already found to cause an average bias of 8–13 cm. In denser forests with taller ground vegetation the effect can be expected to be stronger, whereas in sparser forests it may be smaller. The results can therefore be considered a conservative estimate of vegetation effects on TLS-derived DTMs, highlighting the need for further research across diverse forest ecosystems. To facilitate ground characterization for the conducted experiments, the data was acquired with a scanner capable of recording multiple returns per each emitted laser pulse by analysing the returning waveform signal, as suggested by Fan et al. (2014). Utilizing the last or only returns for DTM generation was also adopted to ensure that the ground surface was captured as accurately as possible through the occluding vegetation.

However, the observed systematic overestimation in ground elevation may also be influenced by the TLS measurement geometry. The scanner, mounted on a tripod approximately 1.7 m above the ground, transmits and receives signals at a low oblique angle to characterize the ground. This positioning can result in a longer optical path through vegetation compared to the nadir perspective of airborne sensors such as ALS (Coveney and Fotheringham 2011; Fan et al. 2014). As the distance from the TLS scanner increases, it becomes more likely that the laser returns assumed to represent the ground surface actually originate from ground vegetation. The applied scan setup with a 10×10 m regular grid of individual scans resulted in a theoretical maximum horizontal distance of approximately 7.1 m for ground surface observations and an off-nadir angle of 76.5° from the scanner. A denser grid (e.g. 5×5 m) would reduce the obliquity (resulting in a 3.5 m horizontal distance and a 64.3° off-nadir angle), but this would significantly extend the time required for completing the measurements. Alternatively, ALS's vertical measurement geometry could offer a more accurate ground surface characterization, albeit at the expense of resolution. Future research could involve comparing DTMs obtained through various remote sensing techniques. For example, handheld scanners and drone-based laser scanning offer promising alternatives that could potentially improve DTM estimation accuracy.

Although TLS provides millimetre-level accuracy in reconstructing forest structures, such as individual trees, the observed 10 cm uncertainty in ground elevation can introduce errors in structural analyses often requiring the removal of topography from the point clouds to extract specific height measurements for observations. As demonstrated in this study, estimates of tree stem diameters become underestimated if the measurement height is mistakenly defined higher than its actual position. The experiments showed that, in the most extreme case, the DTM can be overestimated by 30 cm which could result in up to a 10 mm underestimation in the DBH measurement. It should be noted that the tapering of the stems strongly affects the magnitude by which the diameter deviates from its actual value at a given height offset. Similarly, this uncertainty can lead to underestimations of tree height, stem volume, and associated woody biomass, all considered as critical metrics in forest inventories. Even minor DBH errors resulting from DTM offset due to vegetation may propagate into automated DBH estimation algorithms and increase discrepancies relative to field-measured reference data.

The potential errors in stem volume are more pronounced than those in diameter as the omitted stem sections are the thickest ones near the ground level. Even with the observed 10 cm height offset due to DTM inaccuracy, there was a notable underestimation of approximately 3 m^3/ha recorded in the stand-level estimate for total stem volume, stemming alone from the offset in the measurement height. It should be noted that the magnitude of stand-level underestimation depends on tree size distribution and stand density (i.e. trees per hectare). Accuracy of the point cloud-based estimates for forest inventory attributes are likely to be affected by other sources of uncertainties as well, one of which is the occlusion of trees – even partly or completely – that would result in inaccurate tree measurements or non-detection of all the relevant structures that would result in biased stand-level estimates. While the discrepancies originating from inaccurate DTM estimation may appear minor when observed at a single time point, they are likely to become even more significant when analysing subtle structural changes over time. However, if follow-up measurements are conducted at the same seasonal period, with relatively stable ground vegetation conditions, the impact of DTM-induced uncertainty on tree measurements can be considered rather minimal.

In addition, the relatively long interval between TLS measurements (3–11 weeks) may have affected the results due to vegetation regrowth. Conducting TLS campaigns closer to the burning dates or using more agile scanning technologies could improve accuracy, although practical constraints, such as weather conditions and reliance on externally conducted burnings, make precise timing challenging.

Conclusion

This study examined the effects of ground vegetation on TLS-derived DTMs in boreal Scots pine-dominated forests. Bitemporal TLS campaigns were conducted at four one-hectare test sites in Finland, with controlled burnings used to remove ground vegetation between measurements. This unique approach provided a precise and targeted analysis of the effects of vegetation. The main finding of the study was that, following the removal of ground vegetation, the DTMs showed an average height decrease of 10 cm. By comparing burned cells to unburned control cells, it was possible to confirm that the observed changes between pre- and post-fire DTMs were attributable to the presence of vegetation during pre-fire DTM generation and its absence during post-fire DTM generation. Additionally, taller ground vegetation resulted in greater uncertainty in DTM. Inaccurate DTMs can distort key forest attributes, and this study demonstrated that stem volume of individual tree was in fact underestimated by 3.1% and stand-level stem volume was underestimated by 1.3%. This experiment offered valuable insights for quantifying the uncertainties in DTM caused by ground vegetation improving

TLS applications in densely vegetated forested areas, highlighting the importance of addressing vegetation-induced uncertainty in topographic characterization.

Author contributions

N. T.: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Validation, Writing – original draft, Writing – review and editing. T. Y.: Conceptualization, Formal analysis, Methodology, Software, Supervision, Validation, Writing – review and editing. M. V.: Conceptualization, Methodology, Writing – review and editing. N. S.: Conceptualization, Methodology, Supervision, Writing – review and editing. M. V.: Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review and editing, Project administration, Resources.

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