Monitoring of Tree Fall Incidents using airborne LiDAR, Stereo Imagery, and Sentinel-2 Data

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Abstract

This study focuses on evaluating the capability of optical satellite data in monitoring trees with the potential to cause damage. The study focuses on the application of very high-resolution optical satellite data, specifically Pléiades and SkySat imagery, as a viable alternative to airborne LiDAR for monitoring tree fall risks. The comparative analysis of height estimations from optical satellite data against airborne LiDAR data unveils valuable information on adopting efficient strategies for managing vegetation risks, particularly those impacting power transmission systems. The outcomes of our research contribute substantially to ongoing initiatives aimed at developing vegetation management strategies along powerlines, offering valuable information for decision-makers involved in assessing and mitigating risks associated with tree falls.
Monitoring of Tree Fall Incidents using airborne LiDAR, Stereo Imagery, and Sentinel-2 Data

Sara Alibakhshi, Ruben Valbuena, Daniel Heinlein, Lauri Häme, Petri Pellikka

Abstract—Effective monitoring of trees and their associated risks such as tree fall hazards are essential for managing forest ecosystems and ensuring public safety. Using airborne Light Detection and Ranging (LiDAR) is a reliable alternative, but it faces challenges in terms of timely monitoring. In this study, we explore the use of very high-resolution optical satellite data (Pléiades and SkySat) as an alternative to airborne LiDAR for monitoring tree fall risks to enhance the cost-efficiency and accuracy of monitoring tree fall risks. We examined four distinct study areas located in Finland and Switzerland. The comparison of height estimations from optical satellite data against airborne LiDAR data revealed varying coefficient of determination (R2) values, ranging from 0.30m to 0.64m across the study sites. To discern the underlying factors driving this variation, we analyze land cover patterns, vegetation cover, and canopy surface roughness quantified by the Rumple Index, using airborne LiDAR, Sentinel-2, and a land cover dataset. Our results show the higher the canopy surface roughness, measured by the Rumple Index, the lower is the accuracy of stereo-based height measurements. In addition, stereo-based height measurements performed weakly, especially for trees less than four meter. While we acknowledge the uncertainties and limitations inherent in optical satellite data, it is noteworthy that stereo-based measurements can overall provide acceptable accuracy (ca. 96.57%) in detecting risky trees compared with LiDAR data. This study lays the groundwork for future studies to further investigate and refine stereo-based techniques, ultimately advancing the field’s capabilities in monitoring forests.

Index Terms—vegetation management and monitoring, tree height estimation, power transmission systems, Pléiades, SkySat, airborne LiDAR, Sentinel-2, Rumple Index.

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1. INTRODUCTION

Forests are essential for regulating the climate, enhancement of air quality, and the preservation of biodiversity [1-3]. Although forests provide numerous ecosystem services [4, 5], tree fall can pose risks to various types of infrastructure such as powerlines [6, 7]. The encroachment of vegetation on powerlines presents a significant and hazardous risk to power transmission systems, leading to widespread blackouts that affect millions of people and cause substantial damage [8, 9]. To address this issue, the development of efficient methods for monitoring and managing forest is crucial [10-12].

Traditional methods of monitoring tree characteristics through field surveys to remove dangerous trees are a common strategy for reducing the risk of tree falling risks [8]. However, this approach has proven to be expensive, time-consuming, and often lacks timely detection capabilities on a large scale [13]. Airborne laser scanning based on Light Detection and Ranging (LiDAR) sensors offers promising avenues for assessing the risk of tree-related damage more efficiently compared with traditional methods [7, 14-16]. However, the use of airborne LiDAR still faces several challenges when it comes to monitoring dangerous trees. Firstly, airborne LiDAR data acquisition is typically an infrequent undertaking, which poses limitations in terms of timely monitoring, as real-time information is crucial to effective tree hazard management [17]. Secondly, airborne LiDAR data acquisition tends to be expensive compared to satellite, needing specialized equipment and personnel involved in large-scale monitoring projects.

To address these challenges, the utilization of radar data or optical satellites with spatial resolutions in the sub-meter range data, which enables the application of stereo imagery techniques, presents a promising approach [18-22]. Using optical satellites requires acquiring two or more overlapping images from slightly different perspectives to extract three-dimensional information about tree height [23, 24]. Numerous studies have demonstrated the feasibility of using very high-resolution optical satellite data for canopy height estimation [25]. Compared with radar
or LiDAR data, optical satellite data can provide broader information of forests, such as information about tree health and species type, which make optical satellite data ideal to monitor ecosystems.

Although stereo images offer the advantage of high frequency and wider coverage data for monitoring trees and forest management practices (e.g., logging, thinning) compared with airborne LiDAR, their applicability for precise height measurements and the evaluation of tree fall damage risks must be carefully evaluated. Based on our thorough analysis of the available research, it has been observed that the accuracy of tree height estimation, which is essential for monitoring the risk of tree fall down, using stereo images exhibits a wide range of values, varying from relatively weak [26-29] to remarkably strong performance reported [18, 30, 31]. However, when it comes to monitoring the potential risks posed by individual trees, high precision, and accuracy are needed. This raises a crucial question: (1) can very high-resolution optical satellite data effectively replace airborne LiDAR as a reliable alternative for accurately monitoring tree fall risks? and (2) in which situation optical satellite data can be used to assess tree fall risks?

To address these research gaps, the present study aims to evaluate the capabilities of very high-resolution Pléiades and SkySat optical satellite images in measuring tree height and theoretically evaluating the risk of tree falls damage to powerlines and compare them with those of airborne LiDAR. In other word, this study aims to develop an algorithm to detect if a tree drop occurrence for any reason from snow damage to beetle attack, will cause the powerline damage or not. We mainly focus on monitoring tree-related powerline damage risk by estimating key parameters such as tree height, tree cover, and tree-to-powerline distance, and provide the comparison between the results of very high-resolution optical data and airborne LiDAR. Four sites in Finland and Switzerland were selected for detailed analysis. This study contributes to the ongoing efforts in developing an understanding of vegetation management along powerlines, to inform decision-makers in their endeavors to identify and mitigate risks associated with tree falls.

2. MATERIAL AND METHOD

2.1. Overview

The flow diagram in Fig. 1 depicts the key procedural steps employed in this study. We first obtained and preprocessed Pléiades and SkySat stereo images (Section 2.3.1) and employed the Satellite Stereo Pipeline (S2P) method to calculate tree height using optical data (Section 2.4.1). Additionally, we obtained airborne LiDAR data (Section 2.3.2) to estimate tree height and tree crown characteristics (Fig. 1, Section 2.4.2). We obtained ancillary data (Section 2.3.3) by calculating land cover map using European Space Agency (ESA) land cover map, Normalized Difference Vegetation Index (NDVI) maps using the Sentinel-2 data and the and the Rumple Index maps using airborne LiDAR data (Section 2.4.3). By integrating the layers and methods, we were able to gain valuable information about the land cover, vegetation cover, tree height, tree crown characteristics, and canopy surface roughness of the canopy within the study sites which were used to calculate the risks of tree falls (Section 2.4.4). Statistical analysis has been performed to compare the results of different study sites in Section 2.4.5.
2.2. Study sites

This project was funded by European Space Agency and aimed to explore the potential of stereo data in monitoring tree fall risks. Due to data availability, we have selected two study sites in Finland that we call Site 1 and Site 2 and two study sites in Switzerland that we call Site 3 and Site 4 (Fig. 1A and 2A in Supplementary material). Tab. 1 shows the areas, extents, and mean slopes, based on GMTED2010 Global Multi-resolution Terrain Elevation Data 2010 [32], of the four study sites. According to the Copernicus Global Land Cover Layers: CGLS-LC100 Collection 3 map, provided for the period 2015–2019 at 100-m spatial resolution [33], the majority of forests in Site 1 and 2 are evergreen needle-leaf forests, whereas the majority of forests in Site 3 and 4 are deciduous broad leaf and mixed forests. A more comprehensive analysis of land cover, NDVI, and topographic characteristics across these distinct study sites is provided in Section 3.
2.3. Material

2.3.1. Pléiades stereo images

The Pléiades satellite constellation, comprising two identical satellites (Pléiades 1A and Pléiades 1B), offers very high-resolution optical images with a revisit interval of 24 hours. Pléiades capture panchromatic images with a 70 cm nadir resolution and deliver them at a nominal resolution of 50 cm, covering a 20 km swath footprint. All Pléiades images in this study have been taken at the acquisition Mode PX. More information has been provided in Tab. 2.

Table 1. Details about the study sites.

<table>
<thead>
<tr>
<th>Site</th>
<th>Area (hectares)</th>
<th>Longitude (degree)</th>
<th>Latitude (degree)</th>
<th>Mean slope (degree)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site 1</td>
<td>5.97</td>
<td>27.42 to 27.43</td>
<td>61.42 to 61.43</td>
<td>1.01</td>
</tr>
<tr>
<td>Site 2</td>
<td>6.66</td>
<td>27.37 to 27.37</td>
<td>61.45 to 61.45</td>
<td>2.38</td>
</tr>
<tr>
<td>Site 3</td>
<td>18.96</td>
<td>8.88 to 8.89</td>
<td>47.26 to 47.27</td>
<td>13.47</td>
</tr>
<tr>
<td>Site 4</td>
<td>20.87</td>
<td>8.97 to 8.98</td>
<td>47.26 to 47.27</td>
<td>7.20</td>
</tr>
</tbody>
</table>

Table 2. Stereo image acquisition details for Pléiades satellites in different study sites in Finland and Switzerland.

<table>
<thead>
<tr>
<th>Site 1 and 2 (Pléiades 1A)</th>
<th>Acquisition date</th>
<th>Solar irradiance (watt/m²/micron)</th>
<th>Solar azimuth (degree)</th>
<th>Solar elevation (degree)</th>
<th>Along the track incidence (degree)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site 1 and 2 (Pléiades 1B)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Site 3 and 4 (Pléiades 1A)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Site 3 and 4 (Pléiades 1B)</td>
<td></td>
<td></td>
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</tbody>
</table>

2.3.2. Airborne LiDAR data

Airborne LiDAR data provides highly detailed information about the three-dimensional structure of landscapes [34, 35]. The airborne LiDAR data of all four sites (LAS format, version 1.4) were processed with the software las2las (version 201003) [36] and the R package lidR (version 4.0.3) [37]. The airborne LiDAR dataset used in this study was obtained from associated Head power companies in Finland and Switzerland and encompasses a point density of 105.76 pulses/m². The positional accuracy of the data is sub-meter with a scale factor of 0.01 applied to the X, Y, and Z coordinates. In the airborne LiDAR data of Sites 1 and 2, the coordinate reference system employed was ETRS89 / EUREF_FIN_TM35FIN. The points are categorized into 15 return categories, with the largest proportion falling under the first return category (6,334,428 points). In the airborne LiDAR data of Sites 3 and 4, the coordinate reference system employed in the data was CH1903+ / LV95. The point data was categorized into 15 return categories, with the largest proportion falling under the first return category (728,830 points).

2.3.3. Sentinel-2 and land cover data

We used ‘Copernicus Sentinel data [2023]’ to assess vegetation cover in our study sites. Sentinel-2 provides high-resolution, multi-spectral imaging data with a wide swath coverage, which provides data with...
a frequency of 5 days. Sentinel-2 Level-2A is atmospherically corrected using the Sen2Cor processor (version 2.5.5), by applying numerous atmospheric models, and measuring aerosol, and cloud masks.

We also utilized the ESA WorldCover 2021 product, which offers a high-resolution land cover map at a spatial resolution of 10 meters on a global scale. ESA land cover data is calculated by the intergeneration of Sentinel-1 and Sentinel-2 datasets and includes 11 distinct land cover categories [38]. The overall accuracy of the dataset is 76.7% by producing the dynamic yearly Copernicus Global Land Service Land Cover (CGLS-LC) [33].

2.4. Method

2.4.1. Tree height and tree crown estimation using airborne LiDAR

The acquisition and preprocessing of airborne LiDAR data were carried out in the lidR in R [37]. A crucial step in the preprocessing pipeline involved the generation of a Digital Terrain Model (DTM) through the application of a spatial interpolation technique on the visible ground points extracted from each study site [37]. Furthermore, we performed the classification of the 3D point cloud data into the ground and non-ground points using the progressive morphological filter [39].

We calculated the Digital Surface Model (DSM), which represents the height of a surface by selecting the highest point within the DTM map [40, 41]. Point-to-raster algorithms were employed, involving the establishment of a grid with a one-meter resolution to detect the highest point within each grid cell and assign it to the corresponding pixel. We then calculated the height map by calculating the difference between DTM and DSM. To enhance the quality and completeness of the height map, we adopted a technique that involved replacing each point with a small circle of known diameter to simulate the footprint of laser beams. This approach increased the point cloud density and facilitated the smoothing of the height map, effectively capturing the physical characteristics of the laser beams [37, 42].

As this study focuses on the risk of trees for powerlines, we segmented individual trees to create a mask of tree no tree. For doing that, we employed a watershed algorithm that involves treetops detection by utilizing a local maximum function in a variable window filter. This involved assigning the tag of a treetop to the highest cell within a circular window, where the size was dynamically adjusted based on the height observations of the cell at its center to segment individual trees [43, 44]. By progressively incorporating neighboring pixels surrounding each treetop into the corresponding tree object, we successfully terminated the segmentation process when another tree or the background region was encountered.

2.4.2. Tree height estimation using optical data

We employed S2P to calculate tree heights in each study site using Pléiades images [45]. The S2P provides a robust result in comparison with other methods for generating 3D elevation models from high-resolution stereo images obtained from Earth observation satellites [46, 47]. To accomplish tree height estimation from the optical data, we initiated the process by partitioning the input images into smaller tiles. This division allowed us to process the images at a local host computer and approximate the push broom camera using an affine camera model. By doing so, we could simplify the search for corresponding points between each stereo image pair. Next, we refined the calibration data for each tile. This step involved correcting any biases present in the Rational Polynomial Coefficients (RPC) functions, which are used to model the cameras, as explained in Pléiades Imagery User Guide. Pléiades stereo images are equipped with a pair of RPC functions that facilitate the conversion between image coordinates and geographic coordinates on the globe and allow for the mapping of three-dimensional points in object space to the image plane. In this projection, the 3D points are represented by their spheroidal coordinates in the World Geodetic System (WGS 84). By refining the calibration data, we ensured that the epipolar constraints derived from the camera parameters were as precise as possible. After calibrating the data, we performed stereo image rectification. This process involved adjusting the images to align the corresponding epipolar lines, which simplified the matching of points between stereo pairs. This step significantly improved the accuracy of the subsequent matching and reconstruction processes. For stereo matching, we used a standard algorithm to find correspondences between the rectified tile pairs. The algorithm determined the disparity between the images, which represents the difference in pixel coordinates of corresponding points. Finally, we combined the local refinements from all the processed tiles to compute a global correction of the calibration to ensure that there was the best possible continuity between the 3D points computed from different tiles to calculate DSM. As optical satellite data penetrate forests and directly be used for DTM, stereo image-
based approaches are typically required to obtain a DTM from different sources such as Shuttle Radar Topography Mission (SRTM) [48]. Although such datasets are widely and freely available, they have been subjected to limitations in accuracy and resolution. Hence, to ensure a fair assessment of differences in tree height estimation between airborne LiDAR and stereo methods [49], we utilized an accurate DTM obtained from airborne LiDAR data as a consistent baseline to calculate height maps. The DTM represents the terrain elevation, excluding above-ground features such as vegetation and buildings, and remains relatively stable through time.

2.4.3. NDVI, land cover map, and Rumple Index

To ensure the quality of Sentinel-2 data, we applied mask pixels classified as cloud shadow, cloud, and thin cirrus with a threshold of 20 percent. Next, we used Sentinel-2 data red band (Red) and the near-infrared band (NIR) at a 10-meter spatial resolution between 2019-01-01 and 2022-01-01 for calculating NDVI (Eq. 1). The NDVI represents vegetation cover, ranging from -1 to 1, where a value of -1 indicates bare land while a value of 1 indicates dense vegetation cover.

\[
\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \quad \text{(Eq. 1)}
\]

We utilized the Rumple Index which evaluates information measuring the horizontal and vertical variation of canopy structure [50, 51]. The Rumple Index (m²/m²) is calculated by dividing the total surface area of the canopy (including any gaps present on the surface) by the ground surface area. In order to compute this index, we used airborne LiDAR data (Section 2.3.1) and employed a method outlined by Parker et al. (2004), which involved creating a three-dimensional triangular irregular network using the grid points of the canopy surface. The Rumple Index is then calculated by summing the areas of all the triangles formed with this approach and dividing it by the ground surface area as shown in Equation (2):

\[
\text{Rumple Index} = \frac{3D \text{ canopy surface model area}}{\text{ground area}} \quad \text{(Eq. 2)}
\]

2.4.4. Identifying trees posing a potential danger

We developed a simple approach to identify trees posing potential danger in the vicinity of powerlines (Fig. 2). To this end, we assume the following abstractions: The surrounding terrain of the powerlines are of constant height, which we without loss of generality choose to be 0. A tree is equivalent to a tuple \((x,T)\), the tree top position is denoted as \(x \in \mathbb{R}^3\) and the highest point of the tree is exactly \(T \geq 0\) above it, i.e., its coordinates are \((x_1,x_2,T)\). A powerline is equivalent to a tuple \((a,b)\), with \(a \in \mathbb{R}^3\) and \(b \in \mathbb{R}^3\) so that the powerline is the line segment parallel to the ground from \(a\) to \(b\), and its height is denoted as \(H = a_3 = b_3\). If the line segment from \(a\) to \(b\) intersects the closed sphere with radius \(T\) and center \(x\), we call \((x,T)\) and \((a,b)\) in dangerous configuration. Assuming that the line segment from \(a\) to \(b\) extends infinitely, \((x,T)\) and \((a,b)\) are in a dangerous configuration if and only if the closest point \(p = (p_1,p_2,H) \in \mathbb{R}^3\) on the line through \(a\) and \(b\) is an element of the closed sphere with radius \(T\) and center \(x\). Let \(y = (p_1,p_2,0)\) and \(d\) the distance between \(x\) and \(y\). We consider the affine 2-dimensional space \(S\) spanned by the affine basis \(x, p\), and \((0,0,1)\). Then, \((x,T)\) and \((a,b)\) are in dangerous configuration if and only if \(p\) is an element of the closed circle of radius \(T\) with center \(x\) in \(S\). Equivalently, \(\sqrt{d^2 + H^2} \leq T\), which in turn is equivalent to \(H \leq \sqrt{T^2 - d^2}\).

We calculate raster layers for tree height \((T)\) and shortest distance to a powerline \((d)\) and use them to compute \(F = \sqrt{T^2 - d^2}\). As the height of the powerline is known to be at least \(H'\), we consider all pixels with \(F < H'\) as not dangerous. The remaining pixels are colored according to \(M\) meter bands, i.e., \(H' + Mi \leq F < H' + M(i + 1)\) for \(i \in \{0,1,\ldots\}\), representing increasing levels of risk.

We computed the Overall Accuracy (OA) as an evaluation metric for assessing the performance of stereo images in detecting dangerous trees. To evaluate the performance of the stereo images in detecting dangerous trees, we first constructed a contingency table \((CT)\) by comparing the data obtained from the stereo image analysis with the airborne LiDAR data [52]. Next, we calculated the OA as the ratio of the sum of correctly classified samples (SoCC) to the total number of samples (TNS) in the dataset multiplied by 100, according to the formula:

\[
\text{QA} = \frac{\sum \text{SoCC}}{\sum \text{TNS}} \times 100 \quad \text{(Eq. 3)}
\]
2.4.5. Statistical metrics

We computed the mean (µ) as a central measure of the data distribution. The mean is calculated as the sum of all data points divided by the total number of observations as shown in Equation (4):

\[
\mu = \frac{1}{n} \sum_{i=1}^{n} x_i
\]  

(Eq. 4)

We measured standard deviation (SD) measures the degree of variability or distribution for a set of data relative to the mean of the same data. SD is obtained from the variance as shown in Equation (5):

\[
SD = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \mu)^2}
\]  

(Eq. 5)

Skewness (SK) provides insights into the asymmetry of the distribution. It is calculated in Equation (6):

\[
SK = \frac{1}{\sqrt{n}} \frac{\sum_{i=1}^{n} (x_i - \mu)^3}{\sum_{i=1}^{n} (x_i - \mu)^2}
\]  

(Eq. 6)

The skewness value indicates the extent and direction of deviation from a symmetric distribution. A positive skewness indicates a longer tail on the right side of the distribution, while a negative skewness indicates a longer tail on the left side.

Kurtosis (K) similarly measures the shape of the distribution by assessing the presence of outliers or extreme values [53, 54]. It is calculated in Equation (7):

\[
K = \frac{1}{n \sqrt{\sum_{i=1}^{n} (x_i - \mu)^2}} \left(\frac{\sum_{i=1}^{n} (x_i - \mu)^4}{\left(\sum_{i=1}^{n} (x_i - \mu)^2\right)^2}\right)^{\frac{3}{2}}
\]  

(Eq. 7)

A positive kurtosis indicates a relatively peaked distribution, with more values concentrated around the mean and heavier tails compared to a normal distribution. Conversely, a negative kurtosis suggests a flatter distribution, with fewer values concentrated around the mean and lighter tails compared to a normal distribution.

Moreover, we computed the coefficient of variation (CV) as an additional measure of data variability. It provides a relative measure of variation independent of the scale of the data, so that larger values indicate greater variability, and allows for comparison and interpretation of variability across different datasets. It was calculated using Equation (8):

\[
CV = \frac{100 \cdot SD}{\mu}
\]  

(Eq. 8)

We used Cross-tabulation analysis, a statistical method to examine the relationship between two categorical variables, for comparing the risk of tree fall for powerlines measurements by airborne Lidar and stereo [55].

3. Results

3.1. Forest structure characteristics

The analysis of tree height measurements using airborne LiDAR data and stereo images and the
statistical analysis, including mean, maximum, minimum, median, standard deviation, $CV$, kurtosis, and skewness, have been performed to explore the key characteristics of the height characteristics in each study site (Tab. 3, Tab. 4, Fig. 4 and Fig. 4).

The forest height measurements obtained via airborne LiDAR data analysis in Table 3 shows the mean heights of the trees range from 7.71 meters (Site 1) to 12.58 meters (Site 3), implying substantial vertical variations across the sites. Site 3 exhibited the highest mean height of 12.58 meters, indicating the presence of relatively taller vegetation or structures within this area. However, Site 4 displayed the lowest mean tree height of 8.42 meters. Site 1 and 2 followed with a mean height of 7.71 meters and 9.74 meters, respectively. The maximum tree height records around 32 meters and the minimum height measures around zero (Tab. 4). The median height values span from 0.27 meters to 12.05 meters, which represent the varying central tendency of the height distributions within each site. Standard deviations range from 7.69 meters at Site 1 to 10.83 meters at Site 3, revealing the extent of height variability within the forest stands. Site 3 demonstrated the highest standard deviation of 10.83 meters, which indicates a greater diversity in height values. Site 2 and Site 4 also displayed relatively higher standard deviation values of 9.13 meters and 8.37 meters, respectively. In contrast, Site 1 exhibited the lowest standard deviation value of 7.69 meters, suggesting a more homogeneous distribution of heights. The coefficient of variation ranges from 86.12% to 131.26%, indicating relative variability in the height measurements across the sites. Site 1 and Site 2 also displayed notable variations with $CV$ values of 99.84% and 93.82%, respectively. Site 3 demonstrated a relatively lower $CV$ value of 86.12%.

Site 4 exhibited the lowest kurtosis value of -1.50, suggesting a relatively flat distribution of height measurements. Site 3 displayed a kurtosis value of -1.34. Site 2 and Site 1 exhibited kurtosis values of -1.23 and -0.79, respectively, reflecting slightly peaked distributions. On the other hand, Site 3 displayed the lowest skewness value of -0.10, indicating a relatively symmetrical distribution. Site 1 and Site 4 exhibited similar skewness values of -0.07, while Site 2 showed a slightly lower skewness of -0.05, suggesting slightly asymmetric distributions.

### Table 3. Forest height measurements using airborne LiDAR data for each site in meter units. The SD refers to standard division and the $CV$ refers to the coefficient of variation of height measurements.

<table>
<thead>
<tr>
<th>Site</th>
<th>Mean (m)</th>
<th>Max (m)</th>
<th>Min (m)</th>
<th>Median (m)</th>
<th>SD</th>
<th>$CV$ (%)</th>
<th>Kurtosis</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site 1</td>
<td>7.71</td>
<td>31.88</td>
<td>0</td>
<td>5.3</td>
<td>7.69</td>
<td>99.84</td>
<td>-0.79</td>
<td>-0.07</td>
</tr>
<tr>
<td>Site 2</td>
<td>9.74</td>
<td>32.00</td>
<td>0</td>
<td>6.15</td>
<td>9.13</td>
<td>93.82</td>
<td>-1.23</td>
<td>-0.05</td>
</tr>
<tr>
<td>Site 3</td>
<td>12.58</td>
<td>32.00</td>
<td>0</td>
<td>12.05</td>
<td>10.83</td>
<td>86.12</td>
<td>-1.34</td>
<td>-0.10</td>
</tr>
<tr>
<td>Site 4</td>
<td>8.42</td>
<td>32.00</td>
<td>0</td>
<td>0.27</td>
<td>8.37</td>
<td>131.26</td>
<td>-1.50</td>
<td>-0.07</td>
</tr>
</tbody>
</table>

The forest height measurements in Table 4 shows the mean heights obtained from stereo images vary across the study sites, ranging from 4.66 meters (Site 1) to 10.23 meters (Site 3). Site 2 exhibits the highest mean height of 10.14 meters and Site 4 displays the mean height of 5.36 meters. The maximum height measurements obtained from stereo images align closely with the airborne LiDAR data, reaching around 32 meters in all study sites. Similarly, the minimum height measurements from stereo images (Tab. 4) and airborne LiDAR (Tab. 3) both record values around zero. The median height values obtained from stereo images range from 1.25 meters to 12.66 meters, indicating varying central tendencies of height distributions within each site, which is relatively similar to a range of median data observed in airborne LiDAR data (Tab. 3).

The standard deviation values for height measurements from stereo images range from 5.20 meters (Site 1) to 10.34 meters (Site 3). These standard deviation values generally align with the airborne LiDAR-based findings, indicating similar patterns of height variability in the forest stands. As in Table 3, Site 3 displays the highest standard deviation value, indicating a greater diversity in height values compared to the other sites. The $CV$ values obtained from stereo images analysis also exhibit a similar trend to the airborne LiDAR-derived $CV$ values, reflecting the relative variability in height measurements across the sites. Site 4 demonstrates the highest $CV$ value of 167.19%, which can indicate significant variation compared to the mean height, while Site 2 and Site 1 also display notable variations with $CV$ values of 73.62% and 111.66%, respectively. Site 3 exhibits a relatively lower $CV$ value of 101.03%, aligning with its lower variability observed in the airborne LiDAR data. Kurtosis values from stereo images analysis also relatively match with the airborne LiDAR results, revealing the shape of the height distributions within
each site. More specifically, Site 4 exhibits the lowest kurtosis value of -1.43, suggesting a relatively flat distribution of height measurements, while Site 3 displays a kurtosis value of -1.36. Similar to Table 3, Site 2 and Site 1 exhibit kurtosis values of -1.38 and -1.38, respectively, reflecting slightly peaked distributions. Regarding skewness values, stereo images analysis, and airborne LiDAR data show consistency in the symmetry of the height distributions, as all values are approximately close to zero, implying slightly asymmetric distributions by 0.04, -0.01, 0.01, and 0.02 in Site 1 to Site 4 respectively.

Table 4. Forest height measurements using stereo images for each site in meter units. The SD refers to standard division and the CV refers to the coefficient of variation of height measurements.

<table>
<thead>
<tr>
<th>Site</th>
<th>Mean (m)</th>
<th>Max (m)</th>
<th>Min (m)</th>
<th>Median (m)</th>
<th>SD</th>
<th>CV (%)</th>
<th>Kurtosis</th>
<th>Skewness</th>
</tr>
</thead>
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<tr>
<td>Site 1</td>
<td>4.66</td>
<td>31.91</td>
<td>0</td>
<td>1.62</td>
<td>5.20</td>
<td>111.66</td>
<td>-1.38</td>
<td>0.04</td>
</tr>
<tr>
<td>Site 2</td>
<td>10.14</td>
<td>31.04</td>
<td>0</td>
<td>12.66</td>
<td>7.47</td>
<td>73.62</td>
<td>-1.38</td>
<td>-0.01</td>
</tr>
<tr>
<td>Site 3</td>
<td>10.23</td>
<td>31.99</td>
<td>0</td>
<td>6.21</td>
<td>10.34</td>
<td>101.03</td>
<td>-1.36</td>
<td>0.01</td>
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<tr>
<td>Site 4</td>
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<td>31.99</td>
<td>0</td>
<td>1.25</td>
<td>8.97</td>
<td>167.19</td>
<td>-1.43</td>
<td>0.02</td>
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Figure 3. Spatial variability of height map measurements using airborne LiDAR data in meter units. A and B, which are Sites 1 and 2, are in Finland, and C and D, which are Sites 3 and 4, are in Switzerland. The layer has a one-meter spatial resolution and is georeferenced using the UTM (Universal Transverse Mercator) coordinate reference system.
Figure 4. Spatial variability of height map measurements using Stereo images data in meter units. A and B, which are Sites 1 and 2, are in Finland, and C and D, which are Sites 3 and 4, are in Switzerland. The layer has a one-meter spatial resolution and is georeferenced using the UTM (Universal Transverse Mercator) coordinate reference system.

3.2. Land Cover, NDVI, and Rumple Index

In this section, detailed information about the land cover type, NDVI, and Rumple Index for each study site has been provided (Tab. 5, Fig. 5, and Fig. 4A of Supplementary material). For Site 1, the land cover analysis revealed a predominant presence of forest. The calculated mean NDVI value of this study site of 0.52 indicated a moderate vegetation density within
the site. The mean Rumple Index value of 5.46 has been obtained for Site 1, which corresponds to the horizontal and vertical variation of the canopy structure. The land cover analysis of Site 2 indicated the dominant presence of forests, similar to Site 1. The slightly higher mean NDVI value of 0.55 suggests a negligibly denser vegetation cover compared to Site 1. The mean Rumple index value of 7.68 is larger compared with Site 1. Site 3 exhibited a mosaic of forest and crop land classes. The land cover analysis revealed a moderate vegetation density, indicated by a mean NDVI value of 0.73. The moderate mean Rumple index value of 3.09 is significantly lower than the mean Rumple index values in Site 1 and 2. Lastly, Site 4 presents a predominance of the forest and shrublands classes. The relatively high mean NDVI value of 0.71 indicates a relatively dense vegetation cover. The mean Rumple Index value of 2.54 is lower than other study sites.
Figure 5. Spatial variability of Rumple index, ranging between 1 to 20, in each study site. The black lines represent the power. A and B, which are Sites 1 and 2, are in Finland, and C and D, which are Sites 3 and 4, are in Switzerland. The layer has a spatial resolution of 20 meters and is georeferenced using the UTM (Universal Transverse Mercator) coordinate reference system.
3.3. The risk of the tree falls using airborne LiDAR data vs. stereo images

Table 5 provides a concise summary of the comparative analysis between airborne LiDAR and stereo-based height estimation. The coefficient of determination ($R^2$) values present the strength of the relationship between height estimation via airborne LiDAR and stereo (Tab. 5 and Fig. 6). The $R^2$ values at Site 1 and Site 2 are 0.30 and 0.37, respectively. In contrast, the $R^2$ values at Site 3 and Site 4 are 0.64 and 0.62, respectively. This may imply there is a better agreement between the results of height measurement between airborne LiDAR data and stereo images in Switzerland, compared with Finland.

In addition to height estimation, the study assesses the mean NDVI and mean Rumple Index. Both Site 3 and Site 4 display higher mean NDVI values (0.73 and 0.71, respectively) compared to Site 1 and Site 2 (0.52 and 0.55, respectively). Regarding Rumple index values, Site 3 and Site 4 exhibit lower mean values (3.09 and 2.54, respectively) compared to Site 1 and Site 2 (5.46 and 7.68, respectively).

Table 5. Summary of comparison between height map obtained from airborne LiDAR and Stereo imaged in meter units, as well as NDVI, and Rumple Index in each study site. The squared refers to the relationship between height estimation via airborne LiDAR and stereo.

<table>
<thead>
<tr>
<th></th>
<th>Mean LiDAR</th>
<th>Mean Stereo</th>
<th>$R^2$</th>
<th>Mean NDVI</th>
<th>Mean Rumple Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site 1</td>
<td>7.71</td>
<td>4.66</td>
<td>0.30</td>
<td>0.52</td>
<td>5.46</td>
</tr>
<tr>
<td>Site 2</td>
<td>9.74</td>
<td>10.14</td>
<td>0.37</td>
<td>0.55</td>
<td>7.68</td>
</tr>
<tr>
<td>Site 3</td>
<td>12.58</td>
<td>10.23</td>
<td>0.64</td>
<td>0.73</td>
<td>3.09</td>
</tr>
<tr>
<td>Site 4</td>
<td>8.42</td>
<td>5.36</td>
<td>0.62</td>
<td>0.71</td>
<td>2.54</td>
</tr>
</tbody>
</table>
Figure 6. Relationship between height map obtained from airborne LiDAR (x-axis) and stereo images (y-axis) in meter units. A and B, which are Sites 1 and 2, are in Finland, and C and D, which are Sites 3 and 4, are in Switzerland. Blue color refers to a lower density of points and red color refers to a higher density of points.

In addition to the quantitative analysis (Tab. 5), a bar plot was constructed to visually represent the relationship between airborne LiDAR measurements of forest height and the corresponding observations derived from stereo data (Fig. 7). The bar plot covers the entire range of airborne LiDAR measurements and
suggests that, on average, stereo observations tend to increase as the height measurements obtained from airborne LiDAR increase. This implies that stereo data might have the ability to capture the overall patterns and variability in estimating forest height. However, for values below 8 meters, significant disagreements between the stereo observations and the corresponding airborne LiDAR measurements become apparent. These deviations are visually represented by notable differences in bar lengths or heights (Fig. 7). It is worth mentioning that there are not enough points in Site 1 for a range of values between 28 to 32 to conclude.

Aiming to identify potential associations between the airborne LiDAR and stereo data and the characteristics of the surface as represented by the Rumple index, further analysis was conducted (Fig. 8). The results revealed interesting findings, suggesting that the best agreements between airborne LiDAR and stereo height measurements were observed within a specific range of the Rumple index, specifically between 1 and 3. Remarkably, Sites 3 and 4, which exhibited superior $R^2$ values also represent lower mean Rumple index values (Fig. 7 and Tab. 5).
Figure 8. Relationship between LiDAR vs stereo-derived height in meter units in different range of Rumple index (each value v on the x-axes stands for the interval (v-1, v+1]; >v means (v-1,∞)). A and B, which are Sites 1 and 2, are in Finland, and C and D, which are Sites 3 and 4, are in Switzerland. The blue color refers to height measurements using airborne LiDAR data and the orange color refers to height measurements using stereo data in different range of the Rumple Index.

To assess the risk of tree falls, the results of cross-tabulation analysis between the detected dangerous trees using stereo images and airborne LiDAR data, categorizing them into five classes ranging from one (very high risk) to five (no risk). Notably, our results demonstrated a significant level of agreement between the classifications derived from stereo images and airborne LiDAR data for the Finnish sites (Site A and B), as depicted in Fig. 6A and 7A. The analysis revealed a remarkable overall agreement between the two data sources, with an estimated quality assurance of nearly 100% for the Finnish sites. The Finnish sites underwent a clear-cutting of trees near the powerlines, explaining the absence of risky trees in the context of
this study based on our measurements. Additionally, Site 3 and Site 4 exhibited an agreement level of 95.16% and 92.14%, respectively. These findings highlight the robustness and effectiveness of our

4. Discussion

We assessed the risk of tree fall-down for monitoring purposes, with a focus on calculating the accuracy of stereo-based height measurement in comparison with airborne LiDAR-based height measurement. The results revealed varying levels of accuracy between the stereo-based height estimations, and airborne LiDAR-based height estimations, where Sites 3 and Site 4 displayed relatively stronger correlations ($R^2 = 0.64$ and 0.62, respectively) compared with Site 1 and Site 2 ($R^2 = 0.30$ and 0.37, respectively) (Tab. 5). The lower mean Rumple index values in Sites 3 and Site 4 (Tab. 5, Fig. 5) implies a relatively simpler and less complex surface compared to Site 1 and Site 2 (Tab. 5). As stereo techniques rely on distinctive features and matching algorithms that perform optimally in less complex environments [23, 56], the reduced complexity in surface, presented by Rumple index in this study, can facilitate the performance of height measurements using optical satellite data. The Rumple Index presents the horizontal and vertical variation of the canopy structure [50, 51]. Previous studies have reported Rumple index can be controlled by forest type, forest structure, and biodiversity [57-59]. It is worth mentioning that our study revealed that when the Rumple Index is approximately two, indicating a relatively simple canopy structure, stereo images yielded higher accuracy results (Fig. 8, Tab. 5). Kane et al. (2008) shows a surface with a Rumple Index around two can be classified as simple canopies.

In comparing stereo-based height estimation results (Section 3.1.) with previous studies (Tab. 3 and Tab. 4), it becomes evident that the error in height estimation using stereo imagery exhibits significant variability. Notably, studies employing stereoscopy with very high-resolution images to measure buildings consistently report low errors, approximately one meter [18, 30, 31, 60]. However, when evaluating forest ecosystems that inherently have more complex surfaces than simple objects such as buildings, comparable accuracy levels to our study have been reported [26-29]. Specifically, in forested areas, the error in height estimation using stereo imagery can increase from 1.23 meters in bare land to 4.24 meters in more intricate ecosystems [26]. It was reported that by excluding outliers, the $R^2$ value for height estimation improved from 0.53 to 0.91 when comparing airborne LiDAR and stereo imagery [26].

Approach in accurately identifying dangerous trees and assessing their risk of falling, particularly for the Finnish sites.

Although removing outliers can significantly improve the $R^2$ values, considering the specific objective of monitoring dangerous trees in this study, every single tree should be counted in the risk assessment. Furthermore, previous studies reported varying $R^2$ values between 0.47 to 0.7 in different forests with different tree species [61, 62], where the $R^2$ value in coniferous forests was higher than in deciduous forests. Needle leaves forests are typically characterized by dense, evergreen trees with needle-like leaves that often have a more uniform appearance compared with deciduous forests [63]. The consistent structure and color of needle leaves forests may make it easier for stereo-matching algorithms to find correspondences between pixels. However, our study reveals contrasting results, with lower $R^2$ values observed in coniferous forests in Finland compared to Switzerland. This discrepancy suggests the presence of additional factors influencing the performance of stereo matching algorithms such as variations in forest structure, canopy complexity, and environmental conditions (Section 2.4.2). This can again emphasize the importance of Rumple index in explaining the performance of stereo-based height measurement.

We initially obtained and analyzed SkySat stereo images as part of our research to generate height maps, which were taken with a spatial resolution of around 0.5 meters. Despite our efforts in refining codes and requesting re-tasking from the Planet company, persistent errors in the images remained unresolved in the year 2021. High uncertainty in the geolocation of the SkySat cameras and inconsistent orientation of individual scenes have been already reported [64, 65], which could potentially explain the issues we encountered. As a result, we decided to exclude these images from the analysis, as their inclusion could introduce uncertainties and potential inaccuracies in our findings. Hence, we conclude the technology used in SkySat images is not still capable of being used in monitoring tree height at least in our study sites.

Regarding the limitation of stereo imagery for height estimation, it should be noted that the algorithm (Section 2.4.2) requires relatively coarse-resolution of input to enable accurate matching of stereo image pairs in all study sites. This requirement arises from the need to identify corresponding features between the images. However, this enhanced resolution can lead to an increased occurrence of missing values in the resulting height calculation, when compared to the more comprehensive airborne LiDAR-based height
measurement (Fig. 3 and Fig. 4). Furthermore, stereo imaging relies on the visibility of distinct features, and when the requirements are not fulfilled, it can result in height values with gaps or missing information. The presence of missing values implies that certain trees may not have their heights accurately estimated using the stereo imagery-based approach. Consequently, these missed trees could potentially pose risks or have the potential to cause damage, as their height and associated hazards may go unnoticed. In addition, the resolution decreases can lead to a loss of detail in the resulting height calculations.

To enhance the accuracy of height estimation based on stereo imagery, several potential avenues warrant exploration. In our research, we made significant progress in this regard by incorporating an artificial neural network (ANN) approach, which resulted in notable improvements in the $R^2$ values. Specifically, our preliminary findings indicate that the $R^2$ values were enhanced to approximately 0.8 through the utilization of ANN techniques (detailed results to be published separately in a forthcoming manuscript). The integration of multi-source data, such as fusing stereo images with airborne LiDAR data or high-resolution optical imagery, holds promise for capturing complementary information and enhancing the accuracy of height mapping using stereo images. For example, the results (Tab. 5) highlight that NDVI can be one strong predictor that can enhance the potential for integrating multi-source data to improve height estimation accuracy. Additionally, advancements in image processing techniques, including improved stereo matching algorithms and robust DSM generation methods, can contribute to better height estimation.

It is important to emphasize that this study primarily focuses on the development of a methodology for measuring the risk of tree falls. However, by assessing forest-related risks, the results can be further refined [66, 67]. For example, slender trees may tend to exhibit a higher susceptibility to falling. In addition, various environmental factors, such as snow or wind, and the type of tree play a pivotal role [68]. Some species may be prone to experiencing crown snapping and some tree species may be prone to experiencing topple over with their root systems. By considering the time of the year [69], forest type, and forest age, more comprehensive information on the risk of tree falls can be obtained. Regarding the limitation of this study, it should be noted that optical satellite data may cause complexities due to georeferencing, cloud, and shadowing effects which limits the application of this study to when the highest quality satellite data are available. In addition, the model used in this study does not consider the line sag curve and assumes the lines are always the same height as powerlines throughout the year.

Despite the advantages of direct height measurement provided by airborne LiDAR, it is important to acknowledge that stereo imagery still offers acceptable accuracy (mean 96.57%) in detecting risky trees, as demonstrated in our study (Section 3.3., Fig. 6A and 7A). These findings align with a previous study that reported 98% accuracy [70]. Our research adds knowledge on understanding stereo-based techniques and their potential for monitoring hazardous trees. By demonstrating the feasibility and effectiveness of stereo imagery along with the limitations in detecting risky trees, our study highlights the value of this approach as a cost-effective and accessible alternative to airborne LiDAR for tree hazard management and ensuring public safety.

5. Conclusion

This study highlights the potential of very high-resolution optical satellite data as a valuable tool for tree fall risk monitoring and vegetation management. By comparing tree height estimations derived from optical satellite data with those obtained from airborne LiDAR, we demonstrate the feasibility of using optical satellite data as a cost-effective alternative for monitoring tree fall hazards. The analysis of four study sites in Finland and Switzerland reveals varying levels of accuracy in height estimations, with stronger correlations observed in sites with lower Rumple Index values. This indicates the importance of considering canopy surface roughness when utilizing stereo-based height measurements to pre-evaluate the efficiency of stereo-based height measurements. Our study also highlights the limitation of the height map obtained from optical satellites including coarse resolution, compared with airborne LiDAR data as well as potential limitations caused by cloud and shadows. By using the capabilities of very high-resolution optical satellite data, stakeholders can enhance the efficiency and effectiveness of vegetation monitoring, leading to improved public safety and the sustainable management of forest ecosystems.
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Figure 1A. 3D visualization of point cloud data of each study site with RGB color palette. A and B, which are Sites 1 and 2, are in Finland, and C and D, which are Sites 3 and 4, are in Switzerland.
Figure 2A. Visualizing the vertical structure of each study site in 2D cross sections for point cloud analysis. **A** and **B**, which are Sites 1 and 2, are in Finland, and **C** and **D**, which are Sites 3 and 4, are in Switzerland.
Figure 3A. Normalized Difference Vegetation Index map of each study site. **A** and **B**, which are Sites 1 and 2, are in Finland, and **C** and **D**, which are Sites 3 and 4, are in Switzerland. The layer has a 10-meters spatial resolution and is georeferenced using the UTM (Universal Transverse Mercator) coordinate reference system.
Figure 4A. Land cover map of each study site. A and B, which are Sites 1 and 2, are in Finland, and C and D, which are Sites 3 and 4, are in Switzerland. The layer has a 10-meter spatial resolution and is georeferenced using the UTM (Universal Transverse Mercator) coordinate reference system.
Figure 5A. Tree segmentation and distance of each tree to the powerline. A and B, which are Sites 1 and 2, are in Finland, and C and D, which are Sites 3 and 4, are in Switzerland. The layer has one-meter spatial resolution and is georeferenced using the UTM (Universal Transverse Mercator) coordinate reference system. The black lines represent powerline.
Dangerous trees detection using airborne LiDAR

Figure 6A. Dangerous tree detection. A and B, which are Sites 1 and 2, are in Finland, and C and D, which are Sites 3 and 4, are in Switzerland. The layer has one-meter spatial resolution and is georeferenced using the UTM (Universal Transverse Mercator) coordinate reference system. The black lines represent powerline. The class one represents very high risk and class five represents no risk.
Figure 7A. Dangerous tree detection. A and B, which are Sites 1 and 2, are in Finland, and C and D, which are Sites 3 and 4, are in Switzerland. The layer has one-meter spatial resolution and is georeferenced using the UTM (Universal Transverse Mercator) coordinate reference system. The black lines represent powerline. Class one represents very high risk and class five represents no risk.