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Technical Note

Suitable LiDAR Platform for Measuring the 3D Structure of Mangrove Forests

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Abstract: Investigating the three-dimensional structure of mangrove forests is critical for their conservation and restoration. However, mangrove forests are difficult to survey in the field, and their 3D structure is poorly understood. Light detection and ranging (LiDAR) is considered an accurate and dependable method of measuring the 3D structure of mangrove forests. This study aimed to find a suitable LiDAR platform for obtaining attributes such as breast height diameter and canopy area, as well as for measuring a digital terrain model (DTM), the base data for hydrological analysis. A mangrove forest near the mouth of the Oura River in Aza-Oura, Nago City, Okinawa Prefecture, Japan, was studied. We used data from terrestrial LiDAR scanning "TLS" and unmanned aerial vehicle (UAV) LiDAR scanning "ULS" as well as data merged from TLS and ULS "Merge". By interpolating point clouds of the ground surface, DTMs of 5 cm × 5 cm were created. DTMs obtained from ULS could not reproduce the heaps of *Thalassina anomala* or forest floor microtopography compared with those obtained from TLS. Considering that ULS had a few point clouds in the forest, automatic trunk identification could not be used to segment trees. TLS could segment trees by automatically identifying trunks, but the number of trees identified roughly doubled that of the visual identification results. The number of tree crowns identified using TLS and ULS was approximately one quarter of those identified visually, and many of them were larger in area than the visually traced crowns. The accuracy of tree segmentation using the canopy height model (CHM) was low. The number of canopy trees identified using Merge produced the best results, accounting for 61% of the visual identification results. Results of tree segmentation by CHM suggest that combining TLS and ULS measurements may improve tree canopy identification. Although ULS is a promising new technology, its applications are clearly limited, at least in mangrove forests such as the Oura River, where *Bruguiera gymnorhiza* is dominant. Depending on the application, using different LiDAR platforms, such as airborne LiDAR scanning, UAV LiDAR scanning, and TLS, is important. Merging 3D point clouds acquired by different platforms, as proposed in this study, is an important option in this case.

Keywords: mangrove forests; LiDAR; UAV

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Citation: Niwa, H.; Ise, H.; Kamada, M. Suitable LiDAR Platform for Measuring the 3D Structure of Mangrove Forests. *Remote Sens.* **2023**, *15*, 1033. https://doi.org/10.3390/rs15041033

Academic Editors: João Miguel Dias, Carina Lurdes Lopes, Luis Pedro Almeida and Renato Mendes

Received: 5 January 2023
Revised: 11 February 2023
Accepted: 12 February 2023
Published: 14 February 2023

1. Introduction

Mangrove forests are found in the intertidal zone of tropical and subtropical coasts, where they provide a variety of ecosystem services to coastal populations [1]. However, mangrove forests are declining worldwide [2–4]. Obtaining information on the structure of mangrove forests is critical for their conservation and restoration [5]. However, given the difficulty of field surveys, mangrove forests are not well characterized in comparison with other forest biomes [2]. Many previous studies were based on small plot survey results, which could be influenced by site selection biases [2]. Remote sensing can provide information on mangrove forest structure, which is less expensive, faster, and more comprehensive than field surveys [2]. An important research agenda is the development of remote sensing methods that can acquire accurate information on mangrove forest structure and monitor its condition over time to assess mangrove forests [6].

Compared with passive optical sensors, light detection and ranging (LiDAR) can penetrate the forest canopy and map the three-dimensional structure of the forest [7]. LiDAR studies have been conducted in various forest biomes worldwide to obtain information on forest 3D structure [8]. LiDAR is considered an accurate and reliable method of measuring a 3D structure [9]. Using LiDAR to obtain information other than tree height (e.g., crown size and breast height diameter [DBH]) can provide a complete picture of the 3D structure of mangrove forests [10]. Furthermore, it can reduce fieldwork and efficiently collect data in difficult-to-access locations such as mangrove forests [6]. Although LiDAR-based 3D structure measurements have been carried out in a variety of forest biomes, few studies on 3D structure measurement have been conducted in mangrove forests [11].

Depending on the platform used, LiDAR can be classified as spaceborne LiDAR scanning, airborne LiDAR scanning (ALS), unmanned aerial vehicle (UAV) LiDAR scanning (ULS), and terrestrial LiDAR scanning (TLS) [12]. In addition to the traditional type of TLS that measures by fixing the device to a tripod, a new type of TLS that measures by carrying the device on one's back (hereinafter referred to as "backpack TLS") has recently emerged. Among these, ULS has been developed, which plays an important role in forestry surveys because it allows for timely and efficient operations [13]. ULS can acquire point clouds with densities several orders of magnitude greater than conventional ALS by flying at low altitudes and relatively low speeds, and its wide scan angle allows it to resolve the structure of individual trees and branches [12]. DBH and tree height are commonly obtained using ULS [12]. Several methods for segmenting individual trees and measuring DBH and tree height have been proposed [11,13]. However, in dense forests with overlapping canopy, measuring the 3D structure of the lower canopy using ALS and ULS is difficult [14]. However, combining ULS and TLS allows for more comprehensive data acquisition and forest inventory extraction, including the 3D structure of the lower canopy [15]. Despite cases of measurements using the combination of ULS and TLS in alpine forests [15] and savannas [16], Wang et al. [5] observed that mangrove forests have a high density of trees and roots, thereby promoting 3D structure reconstruction.

On the contrary, changes in the hydrology of mangrove forests could affect mangrove mortality and reproduction [17]. Field surveys are necessary to measure the topography and currents of the forest floor and to clarify the hydrology of mangrove forests, but mangrove forests are often difficult to access in the field [18,19]. Remote sensing is also important to estimate the hydrology of mangrove forests [20]. However, compared with other forests, remote sensing-based hydrology studies in mangrove forests are uncommon, primarily because of two major challenges: (1) the difficulty of obtaining ecological data and (2) the difficulty of conducting field surveys [5].

This study aimed to find a LiDAR platform suitable for measuring mangrove forests using ULS and TLS, classifying individual trees, obtaining attributes such as DBH and canopy area and measuring a digital terrain model (DTM), which serves as the foundation for hydrologic analysis.

2. Materials and Methods

2.1. Study Location

The research was conducted in a mangrove forest near the mouth of the Oura River in Aza-Oura, Nago City, and Okinawa Prefecture, Japan (Figure 1). The mangrove forest is approximately 4.6 ha in size, and is dominated mostly by *Bruguiera gymnorhiza*, with the shrub *Kandelia obovata* distributed along the mangrove forest edges bordering the stream channel. The mangrove forest of the Oura River is one of the mangrove forests in the northern limit of distribution [21], the largest and healthiest on Okinawa's main island [22]. Evaluating the changes since 2015, no major human alterations were observed except for the construction of a tourist walkway on the west side of the mangrove forest (Figure 2).

There are indications that canopy density has increased. The Oura River mangrove forest has been designated as a natural monument by Nago City and as an important wetland by the Ministry of the Environment, and they are considered an important site for the conservation of mangrove forests on Okinawa's main island.

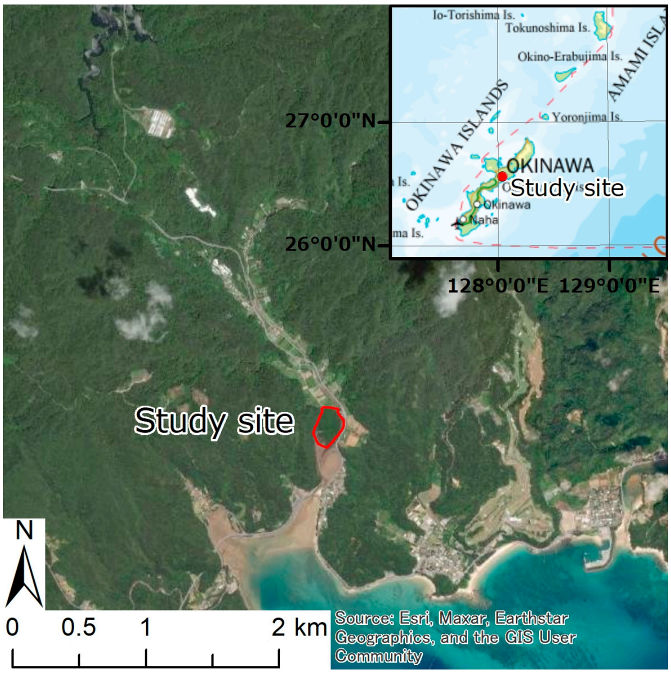

Figure 1. Study location.

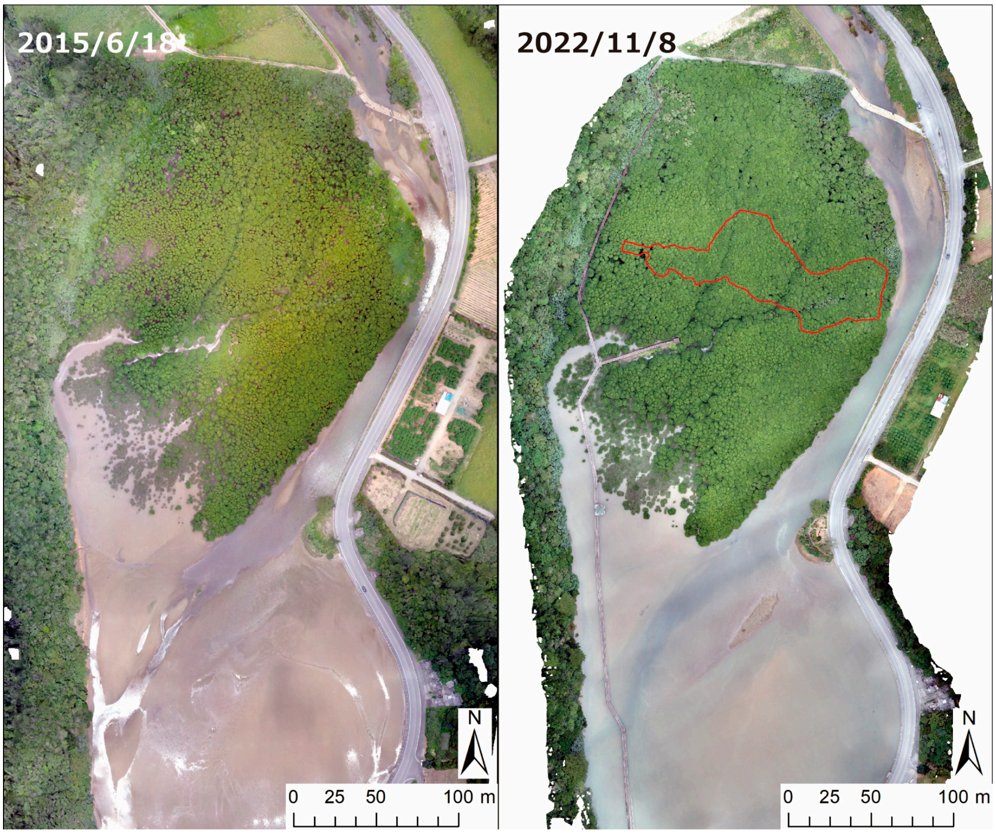

Figure 2. Changes in mangrove forests; comparison of orthomosaic images using UAVs. The red boundary is the validation area (4783 m^2).

2.2. LiDAR Analysis

The GreenValley LiBackpack DGC50 (Demo machine) TLS was used, which is a backpack TLS with two Velodyne VLP-16 laser sensors with a horizontal field of view of 360° and a vertical field of view of 90°. The system accuracy is 3 cm, and the scan rate is 600,000 points per second. DGC50 has an IMU and GNSS module and can measure its position with high accuracy by connecting to a GNSS base station. We trudged across the mangrove forest floor with DGC50 on our backs for approximately 110 min on 12 January 2021, at low tide. GreenValley LiFuser-BP was used to generate 3D point cloud models from the measured data.

ULS used a DJI Matrice 300 RTK with a laser scanner DJI L1. DJI L1 was used in a repetitive scanning pattern, dual return setting. In this case, its horizontal field of view is 70.4°; the vertical field of view is 4.5°; the scan rate is 480,000 points/s, and the system accuracy is 10 cm for horizontal and 5 cm for vertical. Using UgCS (SPH Engineering, Latvia, EU), a flight route was created with a flight altitude of 60 m and a side lap of 70%. The created flight route was imported into DJI Pilot2 and measured at a flight speed of 5 m/s. A DJI D-RTK 2 mobile station was installed at the time of the shooting and real-time kinematic was used to correct positional information. Measurements were taken at low tide on 9 November 2022, over a period of approximately 15 min. The measured data were post-processed by DJI Terra to obtain a 3D point cloud model.

2.3. Data Examination

The following process was conducted on the data measured with TLS (hereafter TLS), data measured with ULS (hereafter ULS), and data merged from TLS and ULS (hereafter Merge) using GreenValley LiDAR360 v5.4.

Tree segmentation requires the DTM to correct the height of the 3D point cloud model from elevation to ground level (=normalized 3D point cloud model) and to create the DTM. The 3D point cloud model outliers were removed and then the ground surface point cloud was classified using default parameters. The surface point clouds were interpolated into a 5 cm × 5 cm DTM using the triangulated irregular network (TIN) method. A simple tide simulation was performed using ULS and Merge's DTM.

Using a normalized 3D point cloud model, individual trees were segmented using the Point Cloud Segmentation from the Seed Points tool of LiDAR360. The Point Cloud Segmentation from the Seed Points tool extracts tree trunk locations from point cloud data at 1.4 m above ground level and uses these data to segment the point cloud data into individual trees. The diameter at breast height (DBH) of each individual tree, tree height, canopy area, and canopy deposition are calculated. Given the lack of point clouds in the forest, the ULS could not be extracted and classified into individual trees. Niwa et al. [23] obtained the location and DBH of individual trees by visual identification of orthomosaic images of the forest floor created by pole photogrammetry in a part of the Oura River mangrove forest (Figure 2). A total of 916 trees were extracted with a density of 1915 trees/ha. Trees extracted from TLS and Merge within that same area were extracted and compared with the distribution of their DBHs.

Using the TIN method, a 5 cm × 5 cm digital surface model (DSM) was created from the 3D point cloud model. The DSM and DTM were used to generate the canopy height model (CHM). The CHM segmentation tool of LiDAR360 was used to segment the canopy of individual trees. Individual tree height and crown area were calculated using the CHM segmentation tool. In the same study area, we used visible light orthomosaic images to generate polygon data by visually tracing the canopy of trees with relatively well-defined canopy. The results of visual identification were compared with the canopy area calculated by TLS, ULS, and Merge.

3. Results

3.1. DTM

TLS, ULS, and Merge-generated DTMs were compared (Figure 3). TLS was used to measure the micro topography of the heaps of *Thalassina anomala* and the forest floor, but it cannot reproduce the topography in some areas, such as the area where the shrub *K. Obovata* was widely dispersed, and it could not be traversed. ULS could measure a larger area, including areas that TLS was unable to traverse, but could not reproduce the microtopography and heaps of *T. anomala*. Merge could generate a broad topographic map, including the heaps of *T. anomala* and microtopography of the forest floor, filling in the gaps left by the TLS. The results of a simple tidal simulation with water levels varying at 10 cm intervals are shown using ULS and Merge's DTM (Figure 4). Merge could replicate the effects of the heaps of *T. anomala* and microtopography of the forest floor. ULS could only reproduce the major trends in tidal fluctuations.

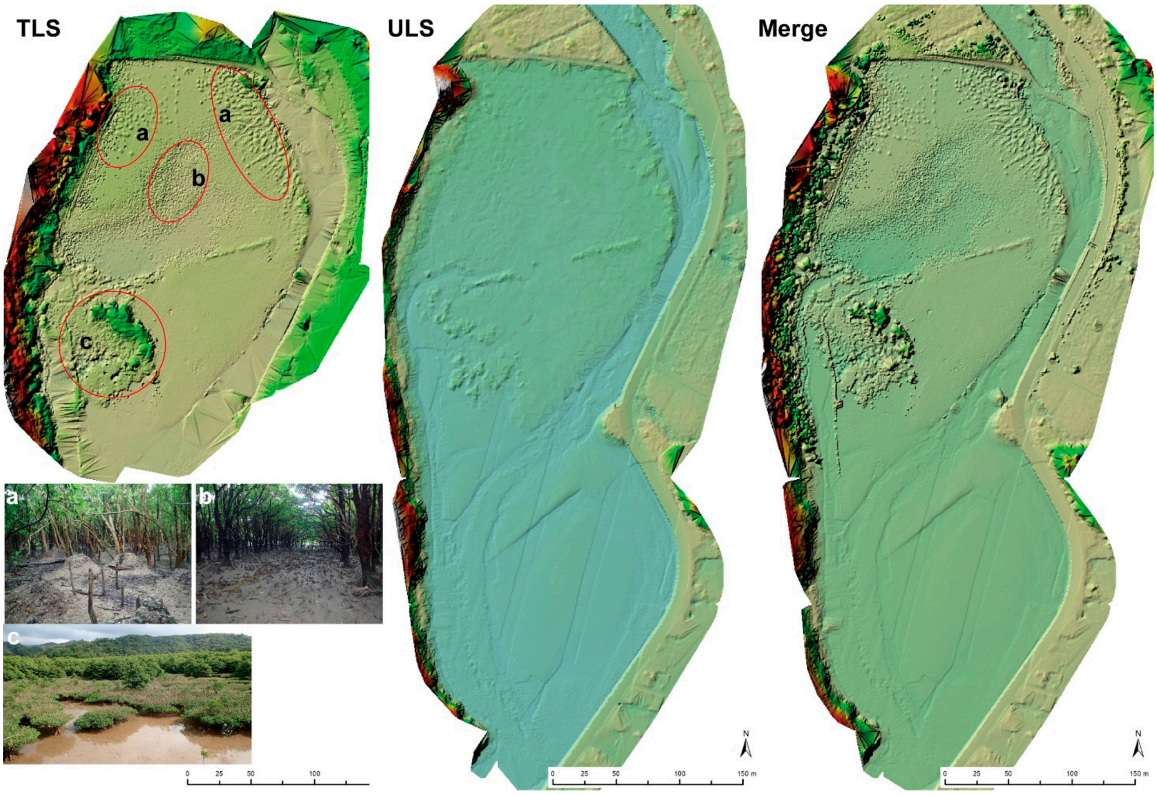

Figure 3. DTM built from 3D point cloud model. (**a**): heaps of *T. anomala*, (**b**): forest floor microtopography, (**c**): area where shrub *K. obovata* was widely dispersed and could not be traversed.

3.2. DBH

In the forest, ULS had few point clouds, and it did not extract tree locations (Figure 5). TLS and Merge had point clouds in the forest and extracted tree locations, but they extracted roughly two times as many trees as visual identification results (Table 1). More trees were extracted at 5–10 cm in the DBH class than in the visual identification results, but the difference was small in the other classes (Figure 6).

3.3. Crown

The number of crowns classified by TLS and ULS was approximately one fourth of the total number of visual identification results, whereas the number of crowns classified by Merge was 61% of the total number visual identification results (Table 1). Merge was most similar to the visual identification distribution of canopy area (Figure 7), whereas TLS and ULS had more canopies with larger area than visual identification (Figure 8).

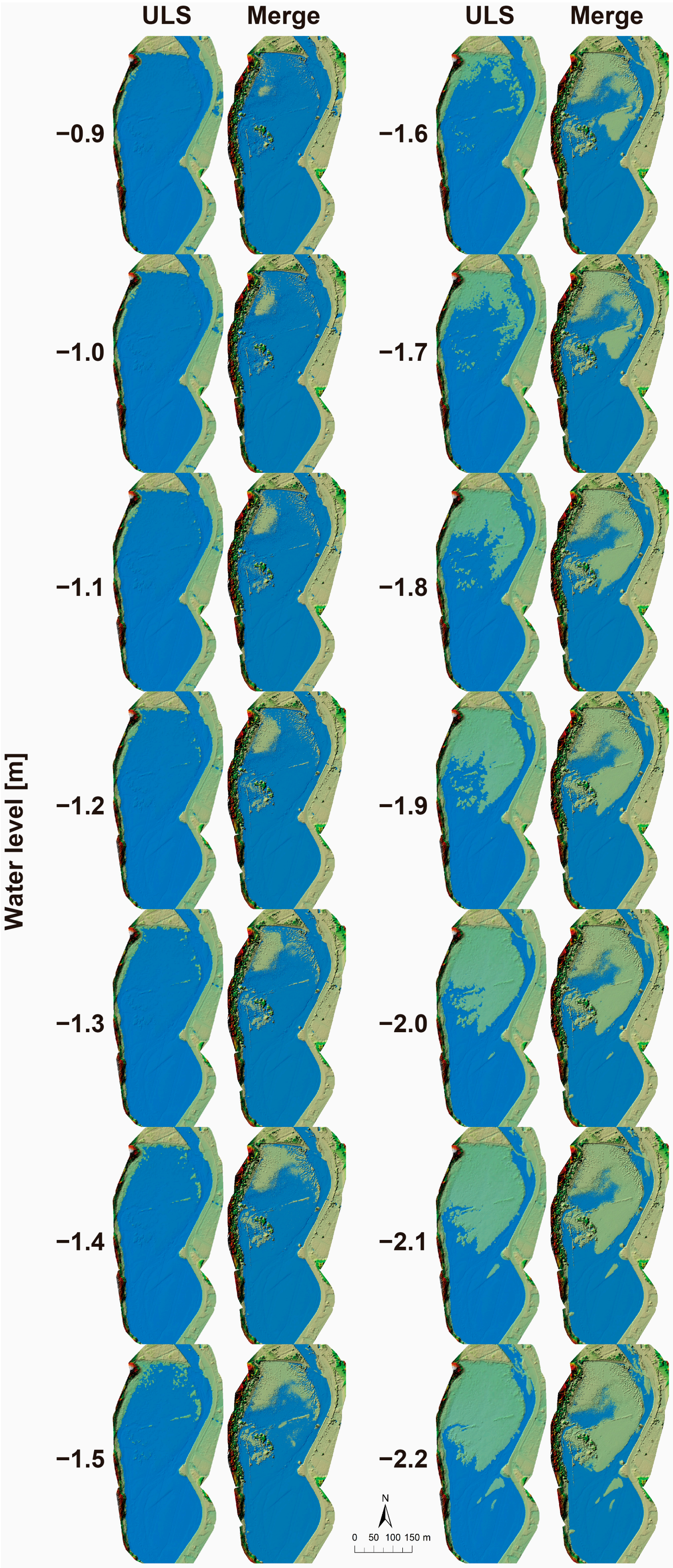

Figure 4. Simple tidal simulation with water levels varying every 10 cm. Blue indicates flooded areas.

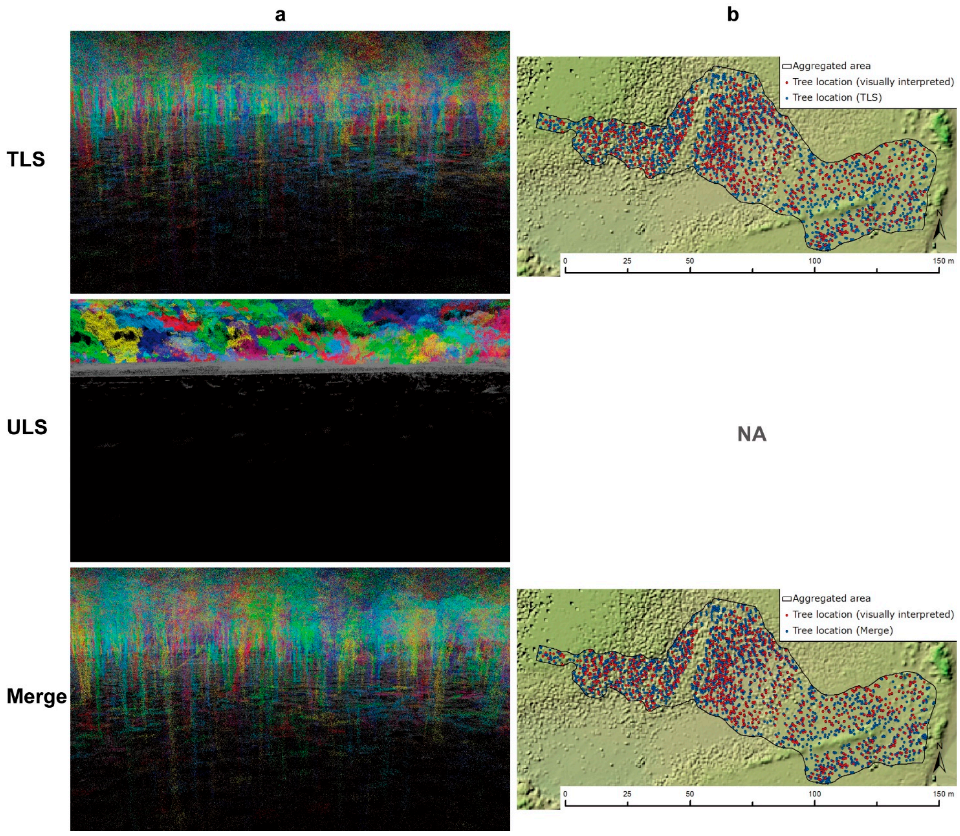

Figure 5. Outcome of tree segmentation. (**a**): A view of the forest point clouds (**b**): The location of identified trees.

Table 1. Count of trees identified through tree segmentation.

	Visual Identification Results	TLS	ULS	Merge
Crown	916	202	229	562
		22%	25%	61%
DBH		1871	NA	1829
		204%		200%

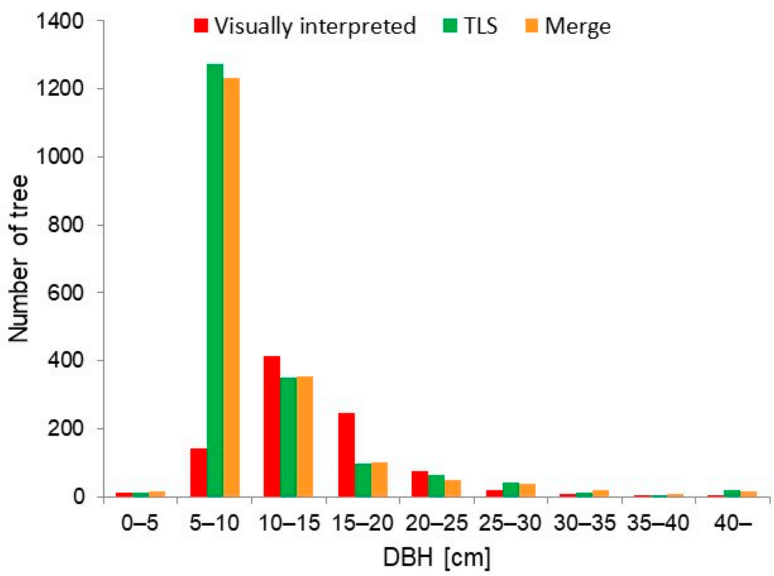

Figure 6. DBH distribution of trees identified through tree segmentation.

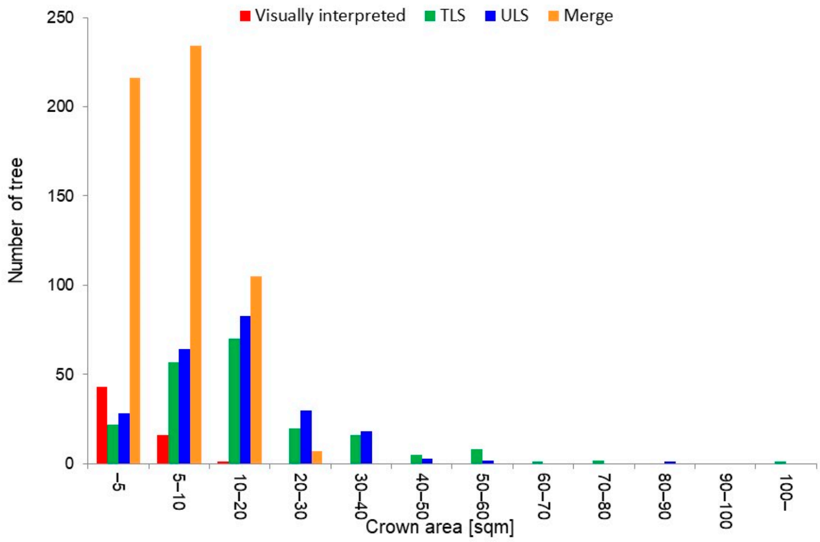

Figure 7. Distribution of canopy area identified through tree segmentation.

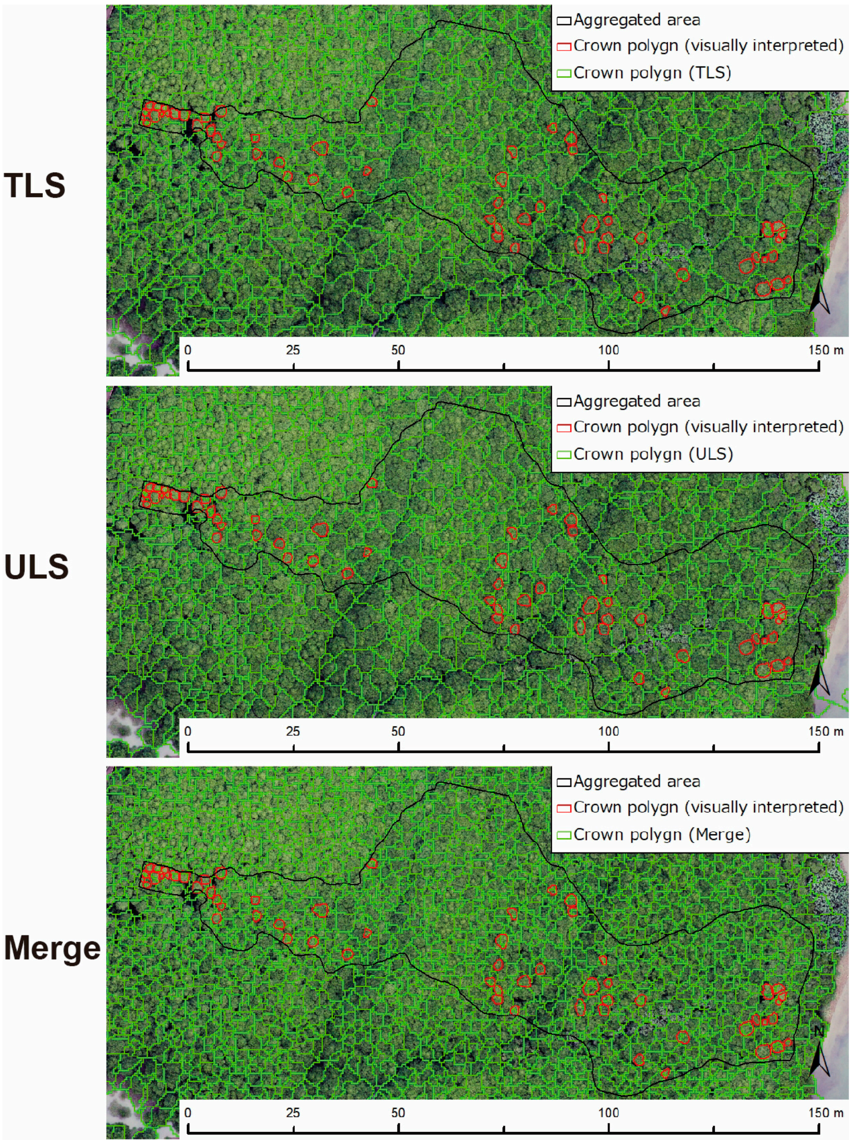

Figure 8. Tree canopies identified through tree segmentation.

4. Discussion

4.1. DTM

The Oura River mangrove forest has a dense canopy, with the majority of the forest area dominated by *B. gymnorhiza*. According to Kellner et al. [12], by flying at low altitudes and relatively low speeds, ULS can obtain point clouds with densities several orders of magnitude greater than conventional ALS, and, similarly to TLS, can clearly represent branch and stem structures. However, in this study, the ULS could not measure the majority of point clouds in the forest. The findings indicate [5] that mapping 3D structures in mangrove forests is difficult because of the high density of trees and roots. The DTM generated from the ULS cannot reproduce the heaps of *T. anomala* because of the lack of point clouds in the forest. By contrast, the TLS generated a highly accurate DTM that reproduced the heaps of *T. anomala* and microtopography of the forest floor. Changes in mangrove forest hydrology affect mangrove mortality and reproduction [17]. Although this study only presented a simple tidal simulation, the highly accurate DTM generated by the backpack TLS can provide a detailed analysis of mangrove hydrology. Although research on remote sensing-based hydrology in mangrove forests has stalled because of data acquisition challenges [5], the high-precision DTM created with backpack TLS can expand data acquisition possibilities and advance the study of mangrove forest hydrology. However, data collection requires walking on the mangrove forest floor, making measurements impossible in areas where access is difficult, and invasiveness is a problem. ULS compensates for difficult-to-access measurements, and it can measure a larger area with less effort than TLS. When field surveys are possible in mangrove forests, backpack TLS and ULS measurements, such as the Merge shown in this study, are combined.

4.2. Segmentation of a Tree

Considering that ULS did not measure the majority of the point clouds in the forest, automatic trunk recognition could not be used to segment trees. The findings support the suggestion [5] that mapping 3D structures in mangrove forests is difficult because of the high density of trees and roots. TLS could perform tree segmentation by recognizing trunks automatically, but the number of trees recognized roughly doubled that of the visual identification results. The DBH class 5–10 cm extracted significantly more than the visual identification results, but the difference was small in the other classes. Levick et al. [16] found that backpack TLS identified more trees than real trees because of the large amount of noise around tree trunks, and many of the misidentified trees had small DBHs. This study also misidentified trunks with small DBH for the same reason. The default parameters for automatic trunk identification were used in this study, but the misidentification rate could be reduced by adjusting the parameters. The small difference between TLS and Merge suggests that the effect of TLS and ULS combined measurement in tree segmentation by automatic trunk recognition is limited. However, this study simply merged data measured by TLS and ULS, and it could be effective if the data merging method were examined as in Wezyk et al. [24] and Liu et al. [15].

The accuracy of tree segmentation by CHM was low because the number of tree crowns classified by TLS and ULS was about one fourth of those classified by visual identification, and many of the tree crowns were larger in area than those classified by visual identification. In forests with similar tree height and density distribution, multiple tree canopies can be erroneously detected as one canopy [25]. The mangrove forests in the Oura River have similar tree height and density distribution, which may have resulted in the misidentification of multiple canopies as a single canopy, resulting in fewer canopies and a larger canopy area. The findings support the suggestion made by Qin et al. [26], that is, automatic tree segmentation in densely forested areas is difficult. In this study, automatic tree canopy identification was performed with default parameters, but the results could be improved by adjusting the parameters. However, in mangrove forests dominated by *B. gymnorhiza*, such as the Oura River, the canopy of *B. gymnorhiza* is difficult to visually decipher. Therefore, the improvement by adjusting the parameters was considered limited.

Merge obtained the most canopy trees, accounting for 61 % of the visual interpretation results. Wezyk et al. [24] obtained forest inventory attributes related to tree canopy with higher accuracy by integrating ALS and TLS data. The results of this study also suggest that combining TLS and ULS measurements may improve tree crown identification results in tree segmentation by CHM.

5. Conclusions

Although ULS is a promising new technology, its applications are clearly limited, at least in mangrove forests dominated by *B. gymnorhiza* such as the Oura River. TLS can measure point clouds in the forest, but not in areas with difficult access, and its invasiveness is a concern. As Kellner et al. [12] point out, the use of different LiDAR platform applications is important, such as ALS, ULS, and TLS. Merging 3D point cloud data acquired by different platforms, as proposed in this study, is an important option in this case.

Author Contributions: Conceptualization, H.N. and M.K.; methodology, H.N.; software, H.N.; validation, H.N.; formal analysis, H.N.; investigation, H.N., H.I. and M.K.; resources, H.N. and M.K.; data curation, H.N.; writing—original draft preparation, H.N.; writing—review and editing, H.N.; visualization, H.N.; supervision, H.N. and M.K.; project administration, H.N. and M.K.; funding acquisition, H.N. and M.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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