Received: 20 September 2024 | Accepted: 23 September 2024

DOI: 10.1002/2688-8319.12399

Ecological Solutions and Evidence

PRACTICE INSIGHTS

Innovation in Practice

Utilising LiDAR-equipped iPhone in forestry: Constructing 3D models and measuring tree sizes in a planting site

Nozomi Oikawa[1] | Yuji Nakagawa[1] | Toshiaki Owari[1] | Shinichi Tatsumi[2,3] | Satoshi N. Suzuki[1,4]

[1]The University of Tokyo Hokkaido Forest, Graduate School of Agricultural and Life Sciences, The University of Tokyo, Furano, Hokkaido, Japan

[2]Hokkaido Research Center, Forestry and Forest Products Research Institute, Sapporo, Hokkaido, Japan

[3]Graduate School of Agriculture, Kyoto University, Kyoto, Japan

[4]Field Science Center for Northern Biosphere, Hokkaido University, Otoineppu, Hokkaido, Japan

Correspondence
Nozomi Oikawa
Email: nozomi2575@g.ecc.u-tokyo.ac.jp

Funding information
The University of Tokyo; Oji Forest & Products Co., Ltd

Handling Editor: Ryan Blackburn

Abstract

1. The LiDAR-equipped iPhone (iPhone-LiDAR) is highly portable for outdoor use and significantly more cost-effective compared with other LiDAR-equipped devices, such as uncrewed aerial vehicles (UAVs) or ground-based LiDAR.
2. This method holds practical promise for small-scale forest measurements.
3. In this study, we conducted terrain mapping and positioning of newly planted small areas in northern Japan, along with tree height measurements, using iPhone-LiDAR.
4. The iPhone-LiDAR generated highly accurate 3D models, allowing for detailed terrain measurements of the planted areas.
5. Despite detecting many false-positive points in identifying tree positions, manual removal of these points enabled the creation of an accurate tree position map, which is expected to significantly reduce the workload compared with traditional survey methods.
6. LiDAR-estimated seedling heights were underestimated due to some inevitable noise in the point cloud.
7. *Solution*: Improvements in software, scanning, and analytical methodologies will expand future possibilities for iPhone-LiDAR applications in forestry practices.

KEYWORDS

3D point clouds, forestry practice, plantation, simultaneous localisation and mapping (SLAM), smartphone

1 | INTRODUCTION

Ground-based Light Detection and Ranging (LiDAR) technology is gaining popularity in forestry and forest sciences (Bauwens et al., 2016; Liang et al., 2016; Tatsumi et al., 2023). The use of LiDAR enables rapid measurements of tree size and spatial coordinates which are essential for effective forest management. Three-dimensional (3D) models generated from LiDAR point clouds can facilitate knowledge sharing amongstpractitioners without the need to access actual stands. However, LiDAR devices are often expensive and/or labour-intensive for field use. These limitations have hindered their widespread use in forestry.

In 2020, Apple Inc. (Cupertino, CA, USA) introduced LiDAR sensors in iPhone Pro and iPad Pro models, bringing consumer-level, low-cost LiDAR devices to the market. Multiple iOS applications have been developed to obtain and analyse LiDAR-derived point clouds (Gollob et al., 2021), including applications dedicated to measuring tree metrics such as trunk diameters and spatial coordinates (Tatsumi et al., 2023). These technologies are now starting to be used by forest ecologists and practitioners to measure forest 3D structure and have been found to attain accuracies well enough for practical applications (e.g. diameter measurement error ≈2 cm; Bobrowski et al., 2023; Gollob et al., 2021; Gülci et al., 2023; Mokroš et al., 2021; Ucar et al., 2021).

Previous studies based on LiDAR-equipped iPhones and iPads have primarily focused on moderately large trees, typically those taller than breast height (1.3 m; Bobrowski et al., 2023; Gollob et al., 2021; Mokroš et al., 2021; Wang et al., 2021). Nevertheless, in forestry, information about the size and spatial coordinates of newly planted tree seedlings, which are often just a few tens of centimetres in height, is also valuable for predicting future tree growth and developing density management plans. In addition, in forest management, topographic data holds valuable information that can enhance work efficiency and safety. LiDAR technology can potentially provide an efficient means to measure seedling heights and topography. To the best of our knowledge, however, no study has verified the ability of LiDAR-equipped iPhones and iPads for such purposes.

In this study, we evaluated the ability of LiDAR-equipped iPhones (hereinafter referred to as iPhone-LiDAR) to map and measure tree seedlings in a newly planted site. In our previous study, we measured the area of a clear-cut site using iPhone-LiDAR (Oikawa et al., 2023). Building on this study, we addressed three research questions: (1) Can iPhone-LiDAR construct a 3D model of a planted site, allowing the estimation of its area shape and terrain? (2) Are iPhone-LiDAR capable of detecting and mapping planted seedlings? (3) How accurately can iPhone-LiDAR measure seedling heights? By addressing these questions, we aimed to highlight the potential benefits and challenges associated with the use of iPhone-LiDAR in forestry.

2 | METHODS

2.1 | Study site

We conducted this study in Compartment 32 within the University of Tokyo Hokkaido Forest (UTHF) (43°17′ N, 142°28′ E, 426–442 m elevation). The study site covered an area of 0.11 ha with slopes ranging from 0 to 12°, facing east to southeast. Before clearcutting, the site was covered by a sparse forest dominated by Sakhalin fir, *Abies sachalinensis* and Japanese lime, *Tilia japonica*. The forest floor is densely covered by the dwarf bamboo *Sasa senanensis*.

The study site was cleared by 2020. In July 2022, the forest floor was sacrificed using a bulldozer for site preparation. In October 2022, we planted 6-year-old seedlings with a mixture of three conifer species: Sakhalin fir (N = 85), Yezo spruce (*Picea jezoensis*) (N = 86), and Sakhalin spruce (*Picea glehnii*) (N = 85; Figure 1). We divided the target area into six plots with roughly equal sizes and planted Sakhalin fir, Yezo spruce, and Sakhalin spruce with two replicates of plots. Seedlings were planted in grids with 2 × 2 m spacing. The

FIGURE 1 The study site (a) before planting, (b) after scarification, and (c) after planting.

height of the seedlings was measured immediately after planting using steel measurement tape.

2.2 | Field survey

A field survey was conducted between July and August 2023. We assumed that there were minimal changes in seedling heights since planting, given that seedlings were planted just before dormancy, and that the field survey was conducted right after bud breaks before stem growths. First, 34 ground markers were placed at the outer edges of the study site. Markers designed by the Mobile Scan Association (MSA; https://mobilescan.jp/) were used. The spatial coordinates of all markers were measured using a high-precision global navigation satellite system (GNSS) receiver, RWX.DC (BizStation Corp., Japan), assisted by the Centimetre-Level Augmentation Service (CLAS) provided by the Quasi-Zenith Satellite System (QZSS).

We conducted a LiDAR scan over the study site, including planted seedlings and markers, using an iPhone 13 Pro (Apple Inc., USA) and the free application 'Scaniverse' (Niantec Inc., USA). We used 'mesh simplification mode' in Scaniverse, which simplifies the 3D model by reducing the redundant data whilst preserving full detail in complex regions (Ito, 2021). Using this simplification process, the irregular points can be removed from a 3D point cloud. We followed the scanning procedure proposed by the MSA. Specifically, we scanned the ground surface by walking slowly (1.5–2.0 km per hour on average) in a direction perpendicular to the narrower dimensions of the target area along the centreline between the planted rows (Figure 2) and scanned the seedlings from all directions by moving around them. The walking distance totalled 690 m. Owing to the limitations of memory and specifications of the application, the target area was divided into six sub-areas and scanned separately (Figure 2).

FIGURE 2 Scanning routes in the study site. We walked between the rows of plantings spaced 2 m apart.

We did not need any permission to carry out the field survey at the study site.

2.3 | Data processing

The 3D point cloud output from Scaniverse in the *las* format was analysed by a freely available software, CloudCompare ver. 2.12.1 (https://www.cloudcompare.org/). The point clouds from the six scans were merged in CloudCompare and georeferenced using five markers as ground control points (GCPs). The orthoimage, Digital Terrain Model (DTM), and Digital Surface Model (DSM) of the target area were generated using a merged 3D point cloud. We used the rasterisation tool in CloudCompare, setting the Z direction projection to 'Minimum' for DEM and 'Maximum' for DSM, then processed and outputted the data. DEM and DSM were imported into ArcGIS (ESRI Inc., CA, USA), and the Digital Canopy Height Model (DCHM) was created as the height difference between the DSM and DTM.

The positions and heights of the seedlings were also estimated using DCHM. The local maximum points of the DCHM were extracted using ArcGIS as the apex points of the seedlings. The range of 'local' was 1 m. Local maximum points lower than 0.1 m and higher than 10 m were removed because the planted seedlings ranged from 20.8 to 72.4 cm in height. The remaining non-seedling points (false-positives) were manually removed. We visually assessed the orthoimage by displaying it with transparency and overlaying it onto the point cloud. The DCHM values at the apex of the seedlings were used as the estimated height of the seedlings.

The horizontal and vertical errors of the markers were calculated as the horizontal and vertical distances between the GNSS-recorded positions and those in the georeferenced 3D model, respectively. Markers used as GCPs were not used to calculate the average horizontal error.

The accuracy of the estimated seedling heights was evaluated by comparison with the seedling heights measured in the field (observed seedling heights). For comparison, we selected 10 trees around the centre of each plot, resulting in 20 individuals for each species. The size of the estimated heights relative to the observed heights was calculated as a summary statistic of the estimation accuracy. We also calculated the root mean squared error (RMSE) of the seedling heights. The relationship between the estimated and observed heights was analysed using a linear model in which the observed heights and species were used as explanatory variables. Statistical analyses were performed using the R ver. 4.3.1 (R Core Team, 2023).

3 | RESULTS

3.1 | Land survey

We successfully obtained a 3D model of the 0.11-ha study site (Figure 3). The point cloud comprised a total of 841,414 points. The average point density was 764.9 points per m^2. The point density was

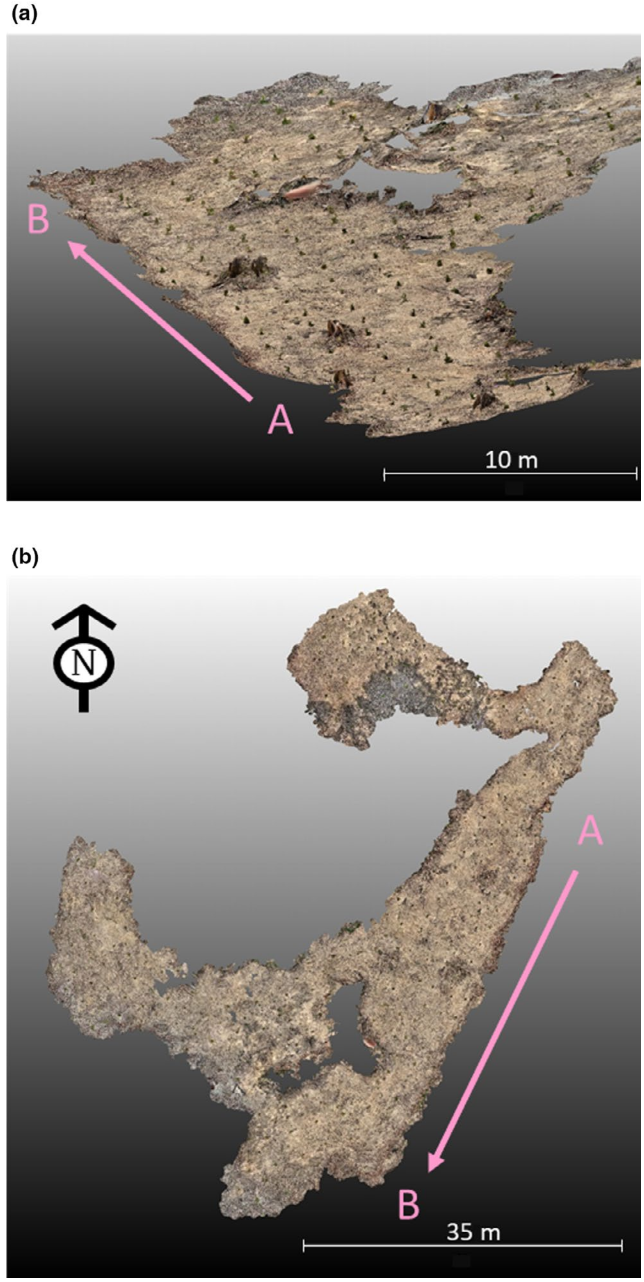

FIGURE 3 (a) A 3D point cloud, and (b) an orthoimage of the study site. A and B in both panels match each other.

particularly high around the seedlings which appeared as 'humps' on the ground surface (Figure 4). Scanning took ~3 h.

The shapes of the study site measured by the iPhone-LiDAR and high-precision GNSS receiver matched well (Figure 5). Horizontal errors of the ground markers (excluding those that were used as GCPs) were 0.46 m on average and ranged from 0.03 to 1.26 m ($N=29$; Table S1). The horizontal errors were smaller than 0.50 m for 12 points. The points with horizontal error >0.50 m were mostly located in the southern parts of the study site. The average vertical errors of the ground markers were 0.23 (Table S1).

3.2 | Seedling detection

In total, 981 local maximum points were automatically detected, of which 775 were not the apexes of the planted seedlings (Figure 6). Upon removal of these false-positive points, 206 points (Sakhalin fir: 69 points, Yezo spruce: 65 points, Sakhalin spruce: 72 points) remained as apexes of planted seedlings, accounting for 80.5% of the total planted seedlings ($N=256$). Additionally, 3D models of 29 seedlings (Sakhalin fir: 6 points, Yezo spruce: 16 points, Sakhalin spruce: 7 points) were generated but went undetected because their heights were less than 10 cm. 3D models could not be generated for the remaining 21 seedlings (Sakhalin fir: 10 points, Yezo spruce: 5 points, Sakhalin spruce: 6 points).

Owing to limitations in the iPhone's internal memory capacity, the LiDAR application crashed and unexpectedly restarted when we scanned the 0.11-ha study site at once. Consequently, we divided the sites into six components (Figure 2). This resulted in increased surface roughness in the merged 3D model, leading to false-positive detection of the apex points (Figure 6). When we used each of the six areas separately to detect the apex points, the number of false-positives significantly decreased (Figure S3).

3.3 | Seedling height measurement

The seedling heights estimated using the iPhone-LiDAR were, on average, 51.2% (Sakhalin fir: 48.8%, Yezo spruce: 54.8%, Sakhalin spruce: 50.0%) of the heights directly measured in the field although they were significantly ($p<0.05$) correlated with the directly measured height (Figure 7, slope: 0.24, intercept for Sakhalin fir: 16.98, Yezo spruce: 9.74, Sakhalin spruce: 10.69). The heights of all the seedlings were underestimated by ~6–38 cm. The mean absolute errors between the estimated and observed heights were 23.7 cm for Sakhalin fir, 21.6 cm for Yezo spruce, and 19.7 cm for Sakhalin spruce. The RMSEs were 24.6 cm (60% of the observed height) for Sakhalin fir, 23.0 cm (43.6%) for Yezo spruce, 40.1 cm (53.1%) for Sakhalin spruce.

4 | DISCUSSION

4.1 | Land survey

The topographic shapes of the study site measured by the iPhone-LiDAR and high-precision GNSS showed good agreement (Figure 5). The points with relatively large horizontal errors (>0.50 m) were mostly found in the southern parts of the study site. The presence of dense litter layers covering the ground surface in the southern area may have added noise to the point cloud, leading to larger horizontal errors. The average vertical errors of the ground markers were 0.23 m (Table S1), suggesting that the elevational variation within the study site was also successfully modelled (Figure S1). The accuracy of our

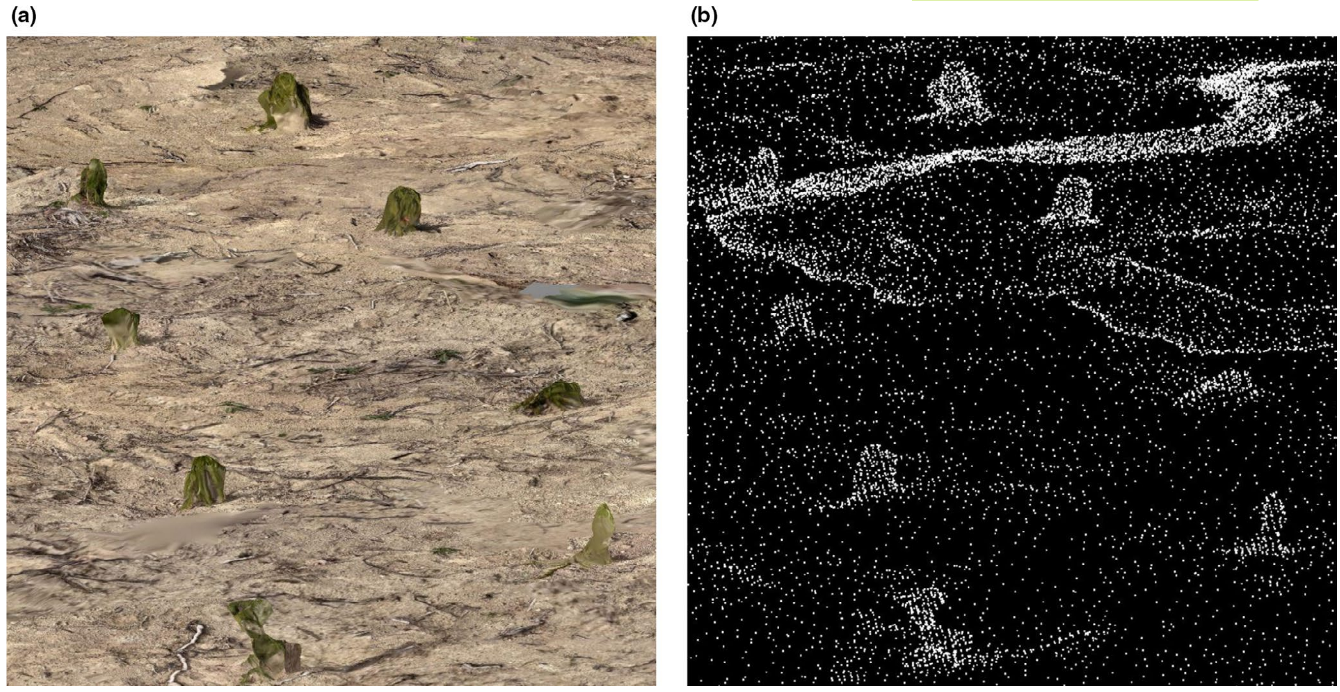

FIGURE 4 (a) A 3D model coloured by RGB information, and (b) a point cloud of seedlings. Note that you can recognise the planting seedlings as mounds in the point clouds.

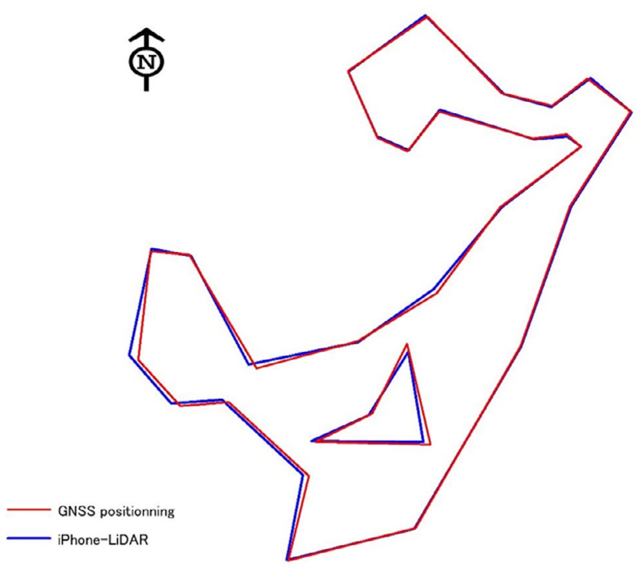

FIGURE 5 The shapes of the target area were measured with high-precision GNSS (red line) and that derived from the 3D cloud generated by iPhone-LiDAR (georeferenced with 5 GCPs, blue line). The boundary lines were drawn by connecting the markers.

survey was comparable to that of a previous study, which surveyed the topography of a coastal cliff using iPhone-LiDAR and found that the vertical error was smaller than 0.30 m for the majority (92%) of points in the point cloud (Luetzenburg et al., 2021). Our results also align with a previous finding that the vertical error of iPhone-LiDAR increases by ~0.11 m for every 30 m of survey (Tamimi, 2022). Our results demonstrate the effectiveness of iPhone-LiDAR as a tool for topographic surveys.

4.2 | Seedling detection

In total, 981 local maximum points were automatically detected in the point cloud. Out of these, 206 points were actual seedlings. The 775 false-positive points were primarily concentrated around tree stumps, boundaries of the target area, and junctions of multiple scans. The alignment of 3D models introduced artificial irregularities into the merged model, which were subsequently identified as false-positive points. There were cases where 3D models of the seedlings were generated but not detected, or where 3D models were not generated at all. These errors can be attributed to the 'simplification process' employed during the generation of 3D models in Scaniverse. Because of the limited capability of iPhone-LiDAR to distinguish objects of only a few centimetres in size or those with irregular shapes (Vogt et al., 2021), some seedlings could have failed to return an adequate number of return points and are consequently filtered out during the simplification process. In this study, we tested only one application, 'Scaniverse' with 'mesh simplification mode'. Future research should investigate the effectiveness of other settings or applications, especially those that allow users to choose point densities during surveys (e.g. 'ForestScanner'; Tatsumi et al., 2023), which can impact the maximum possible survey area. Additionally, whilst we utilised the apex within the point clouds to detect seedlings, developing artificial intelligence that considers not only 3D structures but also RGB information may reduce the number of false-positives.

4.3 | Seedling height measurement

The accuracy of height estimation in this study is relatively low compared with previous research, which used UAV-LiDAR to

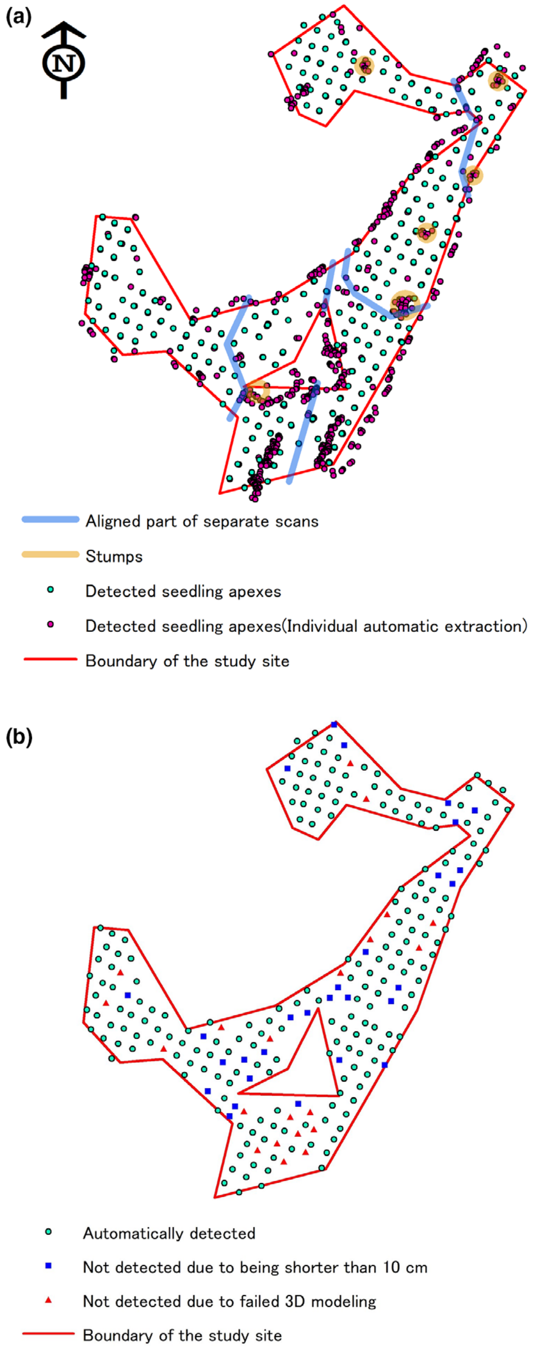

FIGURE 6 (a) Detected local maximum points, and (b) the position map of the planted seedlings.

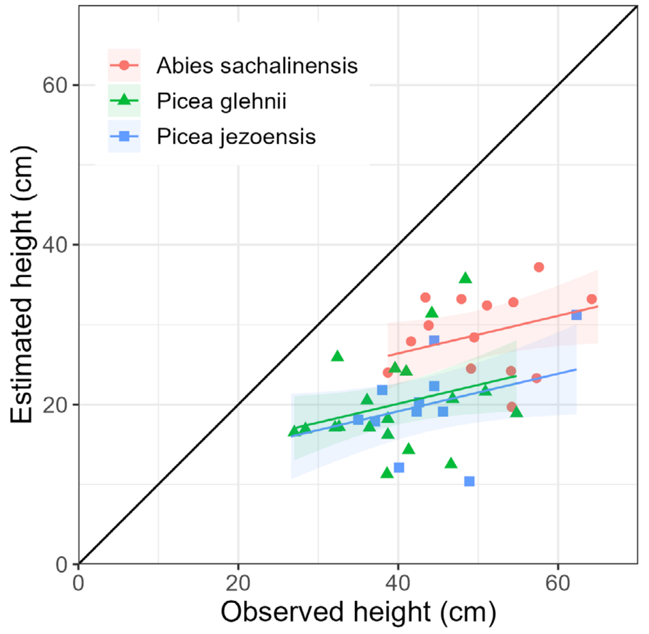

FIGURE 7 The relationship between observed and LiDAR-estimated heights of tree seedlings. The regression lines were estimated by the linear model. The solid black line has a slope of 1 and an intercept of 0, where every point has the same value for both the *X* and *Y* coordinates.

estimate the height of crops such as maize (Luo et al., 2021, RMSE = 23.7 cm, Gao et al., 2022, RMSE = 3.04–4.55), potato (RMSE = 12 cm), sugar beet (RMSE = 7.4 cm), and winter wheat (RMSE = 3.4 cm; Ten Harkel et al., 2019). In particular, the seedling heights estimated using the iPhone-LiDAR were, on average, only 51.2% (Sakhalin fir: 48.8%, Yezo spruce: 54.8%, Sakhalin spruce: 50.0%) of the heights directly measured in the field (Figure 7). This underestimation is likely due to the low reflectance of the leader shoots and the simplification process in Scaniverse, as suggested by the fact that the seedlings were only captured as humps, lacking a detailed structure in the point clouds (Figure 4). This underestimation resulted in the misidentification of some seedlings, as apex points shorter than 10 cm were filtered out during data processing. Our results highlight the need for future improvements in scanning methodologies, including employing slower scanning movements to capture denser point clouds and adjusting application settings to detect seedlings.

4.4 | Implications for forestry practices

Terrestrial LiDAR has gained increased attention as an innovative tool for tree monitoring and land surveying in forestry (Gollob et al., 2021; Mokroš et al., 2021; Oikawa et al., 2023; Tatsumi et al., 2023; Ucar et al., 2021). In this study, we showed that iPhone-LiDAR can create a highly precise 3D model of a planting site and have the potential to map planted tree seedlings (Figures 3–5). Such digital field data can be utilised to assist the autonomous navigation of mechanical weeding (Westwood et al., 2018), predict microtopographic impacts on seedling growth (Tatsumi et al., 2014), and develop future management plans. Currently, the accuracy of tree height measurements using iPhone-LiDAR is insufficient, but it is expected that improvements in measurement techniques and estimation methods will overcome this limitation. Whilst most LiDAR devices in the market remain beyond the reach of numerous forestry organisations (Eitel et al., 2013; Tatsumi et al., 2023), our results indicate that iPhones offer a new opportunity for practitioners to embrace LiDAR technology, thereby improving the collection of digital field data essential for effective forest management.

AUTHOR CONTRIBUTIONS

Nozomi Oikawa is a practitioner of forest management at UTHF. Nozomi Oikawa and Satoshi N. Suzuki designed this study. Nozomi Oikawa conducted the field survey and analysed the data with the support of Yuji Nakagawa and Satoshi N. Suzuki. Nozomi Oikawa drafted the manuscript in Japanese. Satoshi N. Suzuki and Shinichi Tatsumi edited and translated the manuscript into English. Toshiaki Owari provided critical comments regarding the manuscript. All the authors discussed the results and contributed to the final version of the manuscript.

ACKNOWLEDGEMENTS

Funding was provided by a grant for joint research between The University of Tokyo Hokkaido Forest and Oji Forest & Products Co., Ltd. We thank Noriyuki Kimura, Toma Hanezuka, and other staff members of the UTHF for their help with the field survey and for their efforts in managing the study site.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest. Shinichi Tatsumi is an Associate Editor of *Ecological Solutions and Evidence* but took no part in the peer review and decision-making processes for this article.

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1002/2688-8319.12399.

DATA AVAILABILITY STATEMENT

The seedling height data obtained by iPhone-LiDAR and a measuring tape are available at FigShare (Oikawa, 2024).

ORCID

Nozomi Oikawa https://orcid.org/0009-0001-0375-5017
Shinichi Tatsumi https://orcid.org/0000-0002-1789-1685
Satoshi N. Suzuki https://orcid.org/0000-0003-4225-4132

REFERENCES

Bauwens, S., Bartholomeus, H., Calders, K., & Lejeune, P. (2016). Forest inventory with terrestrial LiDAR: A comparison of static and hand-held Mobile laser scanning. *Forests*, *7*(6), 127. https://doi.org/10.3390/f7060127

Bobrowski, R., Winczek, M., Zięba-Kulawik, K., & Wężyk, P. (2023). Best practices to use the iPad Pro LiDAR for some procedures of data acquisition in the urban forest. *Urban Forestry & Urban Greening*, *79*, 127815. https://doi.org/10.1016/j.ufug.2022.127815

Eitel, J. U. H., Vierling, L. A., & Magney, T. S. (2013). A lightweight, low cost autonomously operating terrestrial laser scanner for quantifying and monitoring ecosystem structural dynamics. *Agricultural and Forest Meteorology*, *180*, 86–96. https://doi.org/10.1016/j.agrformet.2013.05.012

Gao, M., Yang, F., Wei, H., & Liu, X. (2022). Individual maize location and height estimation in field from UAV-borne LiDAR and RGB images. *Remote Sensing*, *14*(10), 2292. https://doi.org/10.3390/rs14102292

Gollob, C., Ritter, T., Kraßnitzer, R., Tockner, A., & Nothdurft, A. (2021). Measurement of forest inventory parameters with Apple iPad Pro and Integrated LiDAR technology. *Remote Sensing*, *13*, 3129. https://doi.org/10.3390/rs13163129

Gülci, S., Yurtseven, H., Akay, A. O., & Akgul, M. (2023). Measuring tree diameter using a LiDAR-equipped smartphone: A comparison of smartphone- and caliper-based DBH. *Environmental Monitoring and Assessment*, *195*, 678. https://doi.org/10.1007/s10661-023-11366-8

Ito, K. (2021). *Mesh simplification in Scaniverse*. https://blog.scaniverse.com/mesh-simplification-in-scaniverse-981ca6564340

Liang, X., Kankare, V., Hyyppä, J., Wang, Y., Kukko, A., Haggrén, H., Yu, X., Kaartinen, H., Jaakkola, A., Guan, F., Holopainen, M., & Vastaranta, M. (2016). Terrestrial laser scanning in forest inventories. *ISPRS Journal of Photogrammetry and Remote Sensing*, *115*, 63–77. https://doi.org/10.1016/j.isprsjprs.2016.01.006

Luetzenburg, G., Kroon, A., & Bjørk, A. A. (2021). Evaluation of the apple iPhone 12 Pro LiDAR for an application in geosciences. *Scientific Reports*, *11*, 22221.

Luo, S., Liu, W., Zhang, Y., Wang, C., Xi, X., Nie, S., Ma, D., Lin, Y., & Zhou, G. (2021). Maize and soybean heights estimation from unmanned aerial vehicle (UAV) LiDAR data. *Computers and Electronics in Agriculture*, *182*, 106005.

Mokroš, M., Mikita, T., Singh, A., Tomaštík, J., Chudá, J., Wężyk, P., Kuželka, K., Surový, P., Klimánek, M., Zięba-Kulawik, K., Bobrowski, R., & Liang, X. (2021). Novel low-cost mobile mapping systems for forest inventories as terrestrial laser scanning alternatives. *International Journal of Applied Earth Observation and Geoinformation*, *104*, 102512. https://doi.org/10.1016/j.jag.2021.102512

Oikawa, N. (2024). iPhoneLiDAR_measurement data20241003.csv [Dataset]. FigShare. https://doi.org/10.6084/m9.figshare.27157602

Oikawa, N., Kimura, N., Hanezuka, T., & Suzuki, S. (2023). Test application of iPhone LiDAR in forestry: Example of calculating the size of preplanned planting area from land survey. *Boreal Forest Research*, *71*, 31–34 (in Japanese). https://doi.org/10.24494/jfsh.71.0_31

R Core Team. (2023). *R: A language and environment for statistical Computing_*. R Foundation for Statistical Computing. https://www.R-project.org/

Tamimi, R. (2022). *Relative accuracy found within iPhone data collection* (pp. 303–308). The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLIII-B2-2022. https://doi.org/10.5194/isprs-archives-XLIII-B2-2022-303-2022

Tatsumi, S., Owari, T., Yin, M., & Ning, L. (2014). Neighborhood analysis of underplanted Korean pine demography in larch plantations: Implications for uneven-aged management in northeast China. *Forest Ecology and Management*, *322*, 10–18. https://doi.org/10.1016/j.foreco.2014.03.022

Tatsumi, S., Yamaguchi, K., & Furuya, N. (2023). ForestScanner: A mobile application for measuring and mapping trees with LiDAR-equipped iPhone and iPad. *Methods in Ecology and Evolution*, *14*, 1603–1609. https://doi.org/10.1111/2041-210X.13900

Ten Harkel, J., Bartholomeus, H., & Kooistra, L. (2019). Biomass and crop height estimation of different crops using UAV-based Lidar. *Remote Sensing*, *12*, 17.

Ucar, Z., Değermenci, A. S., Zengin, H., & Bettinger, P. (2021). Evaluating the accuracy of remote dendrometers in tree diameter measurements at breast height. *Croatian Journal of Forest Engineering*, *43*, 185–197. https://doi.org/10.5552/crojfe.2022.1016

Vogt, M., Rips, A., & Emmelmann, C. (2021). Comparison of iPad pro®'s LiDAR and TrueDepth capabilities with an industrial 3D scanning solution. *Technologies*, *9*, 25. https://doi.org/10.3390/technologies9020025

Wang, X., Singh, A., Pervysheva, Y., Lamatungga, K. E., Murtinová, V., Mukarram, M., Zhu, Q., Song, K., Surový, P., & Mokroš, M. (2021). Evaluation of iPad Pro 2020 LiDAR for estimating tree diameters in urban forest. ISPRS annals of the photogrammetry. *Remote Sensing and Spatial Information Sciences*, *VIII-4*, 105–110. https://doi.org/10.5194/isprs-annals-viii-4-w1-2021-105-2021

Westwood, J., Charudattan, R., Duke, S., Fennimore, S., Marrone, P., Slaughter, D., Swanton, C., & Zollinger, R. (2018). Weed management in 2050: Perspectives on the future of weed science. *Weed Science*, *66*(3), 275–285. https://doi.org/10.1017/wsc.2017.78

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Table S1. Horizontal and vertical accuracy of the markers in the 3D clouds.

Figure S1. The digital elevation model (DEM) derived from the 3D model.

Figure S2. The digital canopy height model (DCHM) calculated from the DSM and DTM.

Figure S3. Detected local maximum points using DCHM generated from each point cloud of separate scans.

How to cite this article: Oikawa, N., Nakagawa, Y., Owari, T., Tatsumi, S., & Suzuki, S. N. (2025). Utilising LiDAR-equipped iPhone in forestry: Constructing 3D models and measuring tree sizes in a planting site. *Ecological Solutions and Evidence*, *6*, e12399. https://doi.org/10.1002/2688-8319.12399