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The journey of finding the tallest tree in Formosa Taiwan

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Introduction: Giant trees are ecologically critical ancient organisms, and Taiwan is a key location for those exceeding 80 m in height. This study aimed to identify the tallest tree in Taiwan using a novel, multi-stage approach.

Methods: An island-wide Canopy Height Model (CHM) derived from Airborne Laser Scanning (ALS) initially identified 57,065 local maxima. To account for height overestimations caused by steep topography, tree profile images were evaluated by 372 crowdsourced volunteers, reducing the dataset to 4,736 candidates. These were further refined through expert 3D point cloud analysis, resulting in a verified map of 941 trees taller than 65 m. Final validation involved in-situ tape-drop measurements via tree climbing.

Results: Fieldwork in 2023 confirmed a *Taiwania cryptomerioides* in the Sheshan range as the tallest tree in Taiwan. With a verified height of 84.1 m, this specimen is recognized as the tallest known tree in East Asia. The study successfully cataloged 941 giant trees across the island.

Discussion: The integration of ALS data, crowdsourced visual inspection, and expert point cloud analysis effectively mitigates terrain-induced errors in tree height estimation. This comprehensive inventory provides a vital baseline for the monitoring and conservation of ancient forest ecosystems in topographically complex regions.

KEYWORDS
airborne LiDAR, crowdsourcing task, forest carbon density, Taiwan giant tree map, tree height measurement

Introduction

Ancient trees are often the longest-living organisms in a forest and play a key role in ecosystem function through their influence on hydrological regimes, carbon storage, and biodiversity (Bialic-Murphy et al., 2024). Accurately determining the age of these trees has inherent difficulties. Consequently, it's often suggested that old trees be defined by their relative size, such as the top 5% by diameter for a given species (Cannon et al., 2022). In addition to diameter, tree height is another effective indicator of age, as the tallest trees are often 10–20 times older than the surrounding tree community (Cannon et al., 2022). A positive relationship exists between a tree's diameter and its height, and canopy height is a strong predictor of forest carbon density (Franklin and Dyrness, 1972; Takagi et al., 2024).

Astride the Tropic of Cancer, Taiwan is a mountainous island transitioning from tropical to subtropical latitudes. This habitat heterogeneity creates diverse vegetation types, from alpine tundra to tropical rainforests, and its floristic diversity is exceptionally high,

with over 4,000 vascular plant species, including high concentration of coniferous species in its mountain areas. Several of these species are known for their great stature, including *Taiwania cryptomerioides*, *Cunninghamia lanceolata* var. *konishii*, *Picea morrisonicola*, *Pinus armandii* var. *masteriana*, *Chamaecyparis obtusa* var. *formosana*, and *Chamaecyparis formosensis*, all of which can exceed 50 m in height. Among these, *Taiwania*, *Cunninghamia*, and *Picea* often grow taller than 60 m. The genus *Taiwania* was once widespread across the Northern Hemisphere, with fossils dating back 100 million years (LePage, 2009). Today, its distribution is disjunct, with remnant populations in southwestern China, Myanmar, Vietnam, and Taiwan. This conifer was believed to be one of the tallest tree species in Asia.

Accurately measuring tree height is inherently difficult, particularly for the tallest trees in dense, old-growth forests. Traditional triangulation-based techniques are often inapplicable in these environments because a clear line of sight to the treetop is frequently obstructed and the forest floor lacks sufficient open space for precise measurement. Over the past two decades, Airborne Laser Scanning (ALS) has emerged as a revolutionary tool for overcoming these limitations (Ayrey et al., 2019; Goodbody et al., 2024). ALS is an active remote sensing technique that acquires spatially explicit 3D data by transmitting laser pulses from an airborne platform, such as an airplane, helicopter or drones (Wehr and Lohr, 1999). The primary advantage of ALS is its ability to characterize key forest attributes—such as canopy height, stem density, and above-ground biomass—over vast geographical areas with minimal fieldwork. Consequently, the integration of ALS data into forest ecosystem management has become increasingly widespread (Abbas et al., 2020). Furthermore, ALS has enabled the discovery of exceptionally tall trees in remote, previously unsurveyed forested regions around the world (Gorgens et al., 2019; Jackson et al., 2019; Shenkin et al., 2019).

Deriving accurate tree height parameters from ALS data is constrained by two primary acquisition factors. First, LiDAR pulse density represents a trade-off between operational cost and sampling resolution. While low pulse densities risk under-sampling the canopy apex, resulting in height underestimation, previous studies demonstrate that densities exceeding 0.5–1 pulses/m^2 are sufficient to yield statistically robust height estimates (Hansen et al., 2015; Jakubowski et al., 2013; Treitz et al., 2012). Second, the laser penetration index (LPI), defined as the ratio of ground returns to total emitted pulses, is a critical determinant of Digital Elevation Model (DEM) accuracy. Adequate ground sampling is essential to resolve sub-canopy topography; insufficient penetration introduces DEM interpolation errors that directly propagate into Canopy Height Model (CHM) biases. Under constant pulse density, penetration is modulated by flight configuration, including altitude, pulse repetition frequency (PRF), and field of view (FOV) (Hopkinson, 2007; Lee and Wang, 2018a; Liu et al., 2018). Therefore, in regions with complex terrain, optimizing these acquisition parameters to maximize LPI is required.

This study aimed to locate and verify the tallest tree in Taiwan. A systematic, island-wide survey was conducted using newly available ALS data to create a national CHM. To overcome rugged terrain of the island that reduces CHM accuracy, we applied 3D visualization of tree profiles for precise identification of tree bases and accurate height measurement. We then introduced a web-based crowdsourcing platform to accelerate the verification phases. Finally, the highest-ranking candidates were selected for *in situ* verification, which involved specialized tree climbing and direct tape-drop measurements to confirm absolute heights.

Materials and methods

Study area

Taiwan is a mountainous island in the southwest Pacific (21°45'–25°56'N, 119°18'–124°34'E) with an area of approximately 36,000 km^2. Active orogenesis has created an extensive mountain system, including 258 peaks over 3,000 m and a highest point of 3,952 m. Over one-third of the island's land area is above 1,000 m, contributing to an overall average slope of 14.2°. The island receives abundant rainfall year-round, with regional precipitation ranging from 1,000 to over 6,000 mm annually. This moisture, combined with a warm climate, promotes exceptional tree species richness and growth. The dramatic topography supports a wide range of forest types, from temperate coniferous forests to tropical rainforests. While extensive logging from 1912 to 1991 significantly reduced the island's primary forests, the rugged terrain has also preserved significant tracts of old-growth forest. Today, approximately 60% of the island is forested, containing over 950 million trees (Forestry Bureau, 2016). However, this same terrain complexity introduces significant challenges; the steep slopes can reduce the accuracy of canopy height models derived from ALS data and hinder ground-based field investigations. A primary focus of this study, therefore, was to develop methods to overcome these topographical challenges.

ALS data pre-process

The island-wide ALS dataset was acquired between 2010 and 2016 through a government-funded initiative commissioned to multiple private surveying firms. Data collection employed sensors from Optech, Leica, and Riegl. Flight missions were designed with specific pulse density requirements: a minimum of two pulses/m^2 for elevations below 800 m, and at least 1.5 pulses/m^2 for regions above 800 m. To ensure data quality, flight strip side laps were maintained at over 50%, with the FOV restricted to ±20°. Vertical accuracy was validated using e-GPS checkpoints, requiring a vertical error of less than 0.15 m. Furthermore, the raw point clouds were classified into ground and non-ground points through a rigorous combination of automated algorithms and manual verification using Terrasolid software. Leveraging this validated dataset, a preliminary island-wide tall tree map was generated from airborne laser scanning (ALS) data using a multi-stage filtering protocol (Figure 1, first four steps). A 1-m resolution Digital Elevation Model (DEM), representing the bare earth topography, was produced by interpolating classified ground points using kriging (Habib, 2021). A corresponding Digital Surface Model (DSM), capturing the uppermost canopy surface, was derived from the highest-elevation laser returns (Khosravipour et al., 2016). A CHM, which depicts the absolute height of vegetation above the ground, was then calculated by subtracting the

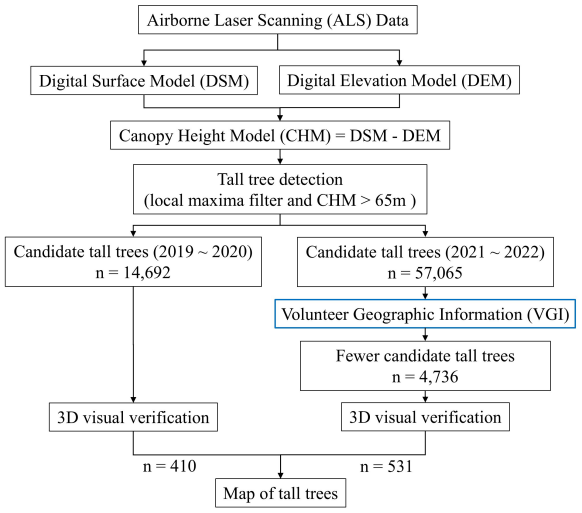


FIGURE 1
A flowchart of the multi-stage process used to generate the national tall tree map from airborne laser scanning (ALS) data. The initial stages describe the generation of the Canopy Height Model (CHM) from raw ALS data (DSMDEM) and the application of a local maxima filter (CHM > 65 m) to identify potential candidates. The verification process followed two distinct paths: 2019–2020 (Left path): verification was conducted entirely by expert analysts through 3D visual assessment of ALS profiles. 2021–2022 (Right path): a Volunteered Geographic Information (VGI) approach was implemented. The sample size of trees at each filtering stage is denoted by *n*.

DEM from the DSM (Lee and Wang, 2018b). The initial filtering step involved applying a 19 × 19 m local maximum filter to this CHM to identify candidate tall trees (>65 m) for further analysis (Popescu et al., 2002; Park et al., 2011). This entire processing workflow was implemented using scripts written in MATLAB R2020.

Tree verification using ALS profile images

Following the initial filtering, each tall tree candidate required verification to eliminate false positives, which frequently occur in mountainous regions with steep terrain. Although ALS data are inherently 3D, navigating and interpreting complex point clouds on a 2D monitor is challenging. To address this, we generated 2D cross-sections, or ALS profile images, for each candidate using GeoCue LP360. This was achieved by subsetting the point cloud data within a rectangular area (Figure 2a) and visualizing the points from a vertical, side-on perspective.

Figure 2 illustrates a typical false positive, where a tree shorter than 25 m was initially identified as having a CHM value of 90 m. The ALS profile image (Figure 2c) clearly reveals that this erroneous height was caused by the tree growing on top of a steep cliff, an artifact also suggested by the deep terrain shadows in the aerial photograph (Figure 2b). Systematically generating these profile images provided essential information, allowing us to effectively screen out terrain-induced errors and create a more accurate candidate list for field investigation. Between 2019 and 2020, a total of 14,692 candidate tall trees were manually inspected using this approach, representing only 20% of the total candidates across Taiwan.

Crowdsourcing for rapid verification of tall tree candidates

Although visual verification using ALS profiles is a reliable method, it is exceptionally labor-intensive. Manually manipulating the 3D data to find an optimal viewing perspective—one that clearly reveals both the tree top and base—can take an operator an average of 20 min per candidate. The importance of the viewing angle is illustrated in Figure 3. An ideal perspective (Figure 3a) shows ground points forming a coherent surface from which the tree base can be inferred. In contrast, a suboptimal perspective of the same tree (Figure 3b) can show scattered ground points that completely obscure the base, making accurate height measurement impossible.

To overcome this bottleneck, we first developed an algorithm that automatically generates an optimal ALS profile for each candidate by identifying the viewing angle that minimizes the dispersion of ground points (for technical details, see Liu, 2021). In 2020, this algorithm was used to generate 57,065 optimal profiles. Given this large volume of images, we then developed a web-based crowdsourcing platform to enlist online volunteers. The platform was designed for non-experts, who were instructed to identify and click on the tree top and base in each pre-generated profile.

Each profile was independently assessed by three volunteers. Candidates that were successfully verified by at least two volunteers and had a calculated height exceeding 65 m were passed to expert operators for a final examination in the full 3D point cloud using GeoCue LP360. This final check was completed before a tree was added to the national tall tree map (Figure 1).

Results

The giant-tree map

The national giant tree map was constructed in phases. In 2019, a survey of 180 map sheets in the Chilan and Danda regions identified 272 tall trees (Figure 4a, blue dots). In 2020, the search was expanded to 229 map sheets across five mountain regions, locating an additional 138 trees (Figure 4a, cyan dots). The remainder of Taiwan was surveyed in 2022 with the assistance of 372 online volunteers. They examined 57,065 ALS profiles, reducing the list to 4,736 final candidates and eliminating 92% of the manual verification workload. From this candidate list, we identified a final 531 tall trees (Figure 4a, magenta dots). In total, 941 tall trees were mapped island-wide. The interactive map, tree metadata, and point cloud figures are available via our public portal: https://no1tree.tw/.

Analysis of the 941 mapped trees reveals that their heights range from 65 to 83.2 m (mean = 68.2 m). They typically occur on very steep slopes (mean = 40°) at an average elevation of 2,087 m, a distribution attributed to their association with montane cloud forest ecosystems. The trees exhibit a spatially clustered distribution across the island, with several high-density hot spots, including the Chilan Conservation Area (Figure 4b) and Benyeshan (Figure 4c).

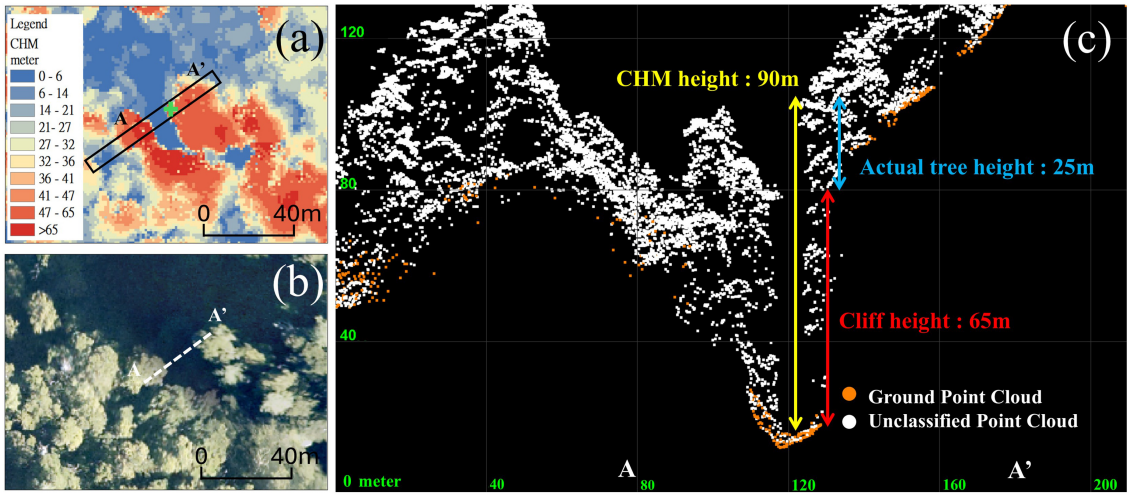


FIGURE 2
An example of using visual verification to screen out a terrain-induced artifact from the tall tree candidate list. **(a)** A candidate, marked with a green cross, is shown on the Canopy Height Model (CHM). **(b)** An aerial photograph of the same location. **(c)** The vertical ALS point cloud profile for the area outlined in panel **(a)**. The profile clearly demonstrates that the candidate is a relatively short tree located on a steep cliff, which caused an erroneously high CHM value.

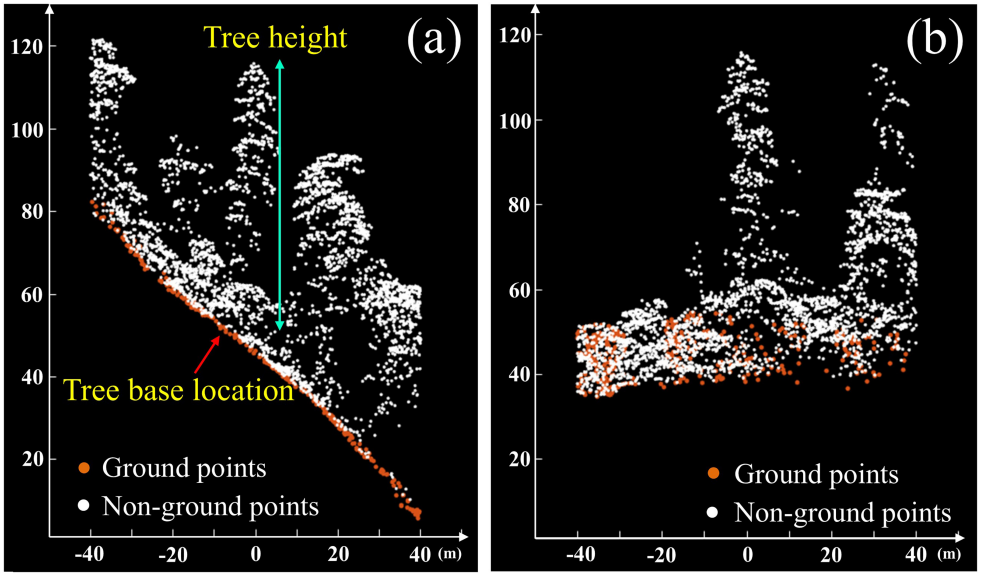


FIGURE 3
Comparison of two ALS profile perspectives. **(a)** Tightly aligned ground points (orange) form an interpretable terrain slope. **(b)** In a different view of the same tree, the scattered ground points fail to form a clear surface, making the tree base impossible to identify.

Field verification of CHM

Since 2014, a total of 22 trees exceeding 40 m in height were located, climbed, and measured via tape-drop across Taiwan. Most of the measured trees (19) were Taiwania fir (*Taiwania cryptomerioides*), with the remainder comprising two *Picea morrisonicola* and one *Cunninghamia lanceolata* var. *konishii*. The absolute heights of two trees were determined using a hybrid methodology, integrating a direct physical measurement via a climber's pole extension to the apex with drone-based photogrammetry that used the pole as an *in situ* scale reference. A significant correlation was found between heights estimated by the Canopy Height Model (CHM) and the field-measured heights (regression analysis, $p < 0.001$), with a Root Mean Square Error (RMSE) of 4.55 m (Figure 5).

Among the verified trees, nine exceeded 70 m in height, all of which were *Taiwania* (Table 1). The estimated age for a 70-m *Taiwania* is approximately 800 to 1,000 years (Wright et al., 2015, pers. comm.). Mature trees typically have a diameter at breast height (DBH) of 2.5 to 3 m; individuals with a DBH exceeding 3 m were often observed to have broken tops. A typical mature *Taiwania* possesses approximately 40 major branches, with the lowest emerging at a height of around 30 m. This fieldwork culminated in the 2023 confirmation of Taiwan's tallest tree, a *Taiwania* individual

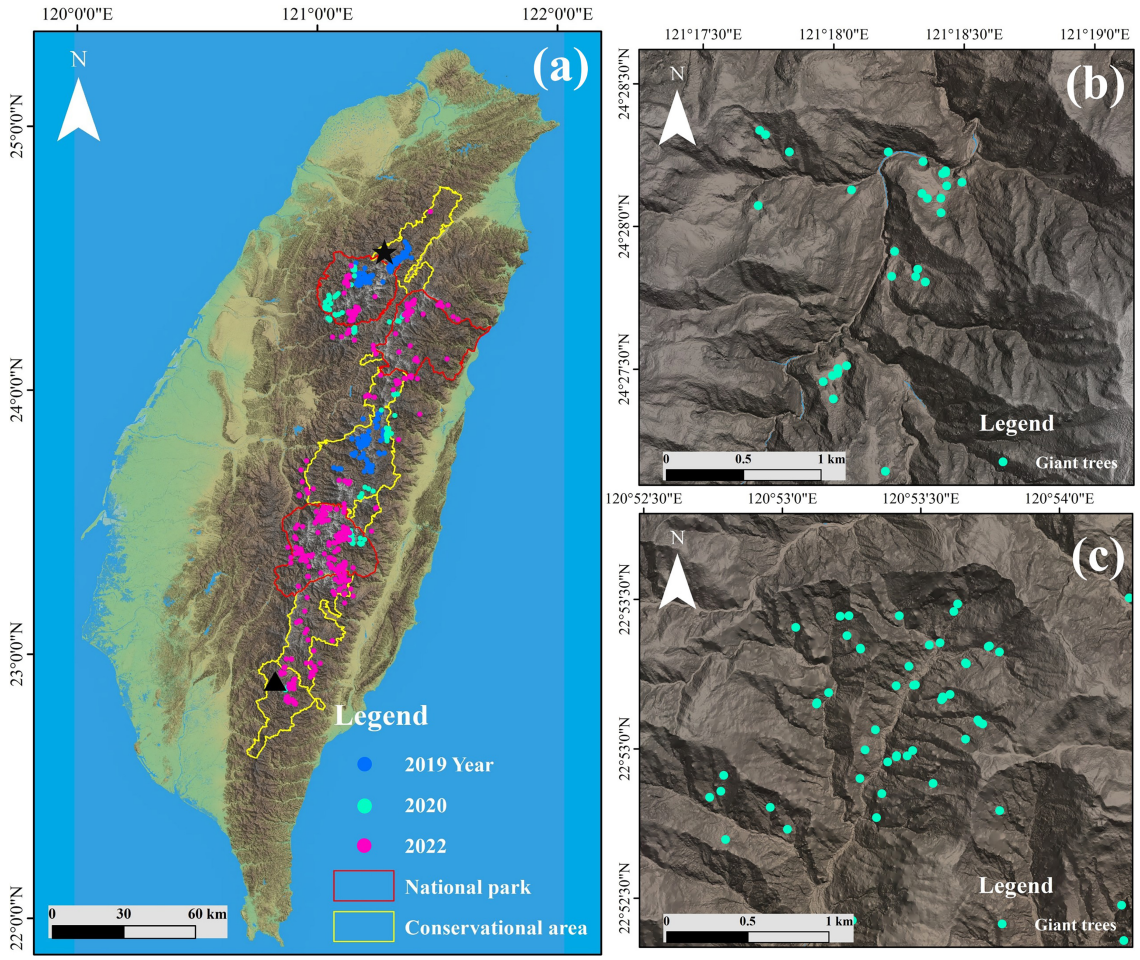


FIGURE 4
The spatial distribution of 941 verified giant trees (>65 m) across Taiwan. **(a)** The overall map shows the locations of trees discovered in 2019 (blue), 2020 (cyan), and 2022 (magenta). **(b,c)** are magnified views showing dense clusters of giant trees within the Chilan Conservation Area and Benyeshan, respectively. The locations of these inset maps are indicated by the star and triangle symbols in panel **(a)**.

in the Sheshan range with a direct measurement of 84.1 m (CHM-estimated height: 79.5 m, Supplementary Figure 2). This individual is now recognized as the tallest known tree in East Asia.

Discussion

The island-wide distribution of giant trees

The strong correlation between CHM and field-measured heights validates the reliability of the resulting giant tree map. The map reveals three primary hot spots for giant trees in Taiwan: The Sheshan Range in the north, the Danda region in the center, and the eastern portion of Yushan National Park (Figure 4). These trees are predominantly located in the steep, mountainous upper reaches of major watersheds, such as those of the Daan, Jhuoshuei, and Siouguluan Rivers. The Luye River watershed, for example, contains the largest known stands of pure *Taiwania* forest; however, this area was severely impacted by the destructive Typhoon Morakot in 2009. While the deep valleys of these upper streams may offer protection from the strong winds of tropical cyclones, the associated storm-induced floods pose a significant threat to the trees' survival.

Ecologically, Taiwan's giant trees are concentrated at mid-elevations (1,500–2,500 m), an environment characterized by the presence of montane cloud forests (Hamilton et al., 1995). Previous studies suggest that the stable microclimates and consistently high air humidity of cloud forests are particularly favorable for tree height growth, providing an ideal environment for the island's giants (Larjavaara, 2014). Taller trees must overcome the increased hydraulic resistance associated with longer xylem pathways (Ryan and Yoder, 1997). Physiologically, a tree's maximum height is constrained by hydraulic limits related to water transport over long distances (Koch et al., 2004). Ecologically, exceptionally tall trees tend to grow in thermally similar climates, with an optimal temperature regime for biomass accumulation characterized by low seasonal variation (10 °C) and a cool temperate climate (annual mean 11 °C –16 °C) (Keith et al., 2009; Larjavaara and Muller-Landau, 2012). However, species that exceed 80 m in height are rare and restricted to specific environmental envelopes (Figure 6 and Supplementary Table 1). These "mega-trees" are primarily located in maritime temperate climate zones. It's believed that these

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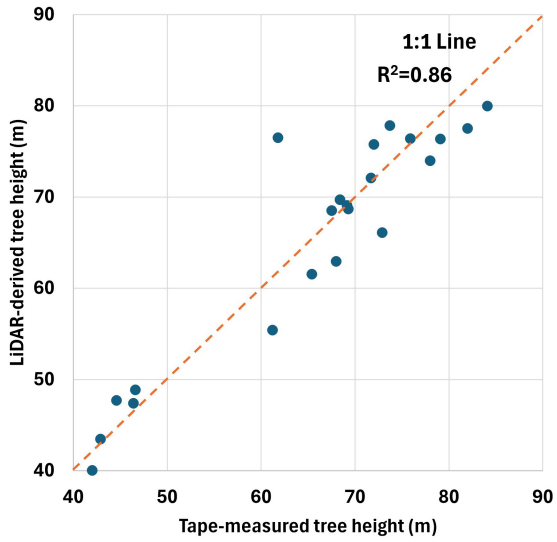


FIGURE 5
Correlation between tree heights estimated from the LiDAR point clouds and those measured directly in the field via tape-drop (n = 22, RMSE is 4.55 m).

mild, oceanic climates served as crucial forest refugia during post-glacial eras (Johnson, 2011). Taiwan was a glacial refuge during the Late Quaternary, which explains this study recording a *Taiwania* individual over 80 m tall.

Giant tree conservation

Large, old trees play a disproportionately significant role in forest ecosystems. They are massive carbon stores; a single giant tree can sequester an amount of carbon equivalent to an entire stand of mid-sized trees (Stephenson et al., 2014). They also provide critical, irreplaceable habitats and alter microclimates, thereby supporting forest biodiversity (Lindenmayer and Laurance, 2016; Gorgens et al., 2019).

Despite their size, these giants are uniquely vulnerable to climate change. Taller trees are more susceptible to hydraulic failure from embolism during drought or freezing events (Olson et al., 2018). Studies have shown that large trees exhibit greater sensitivity to drought, with mortality increasing with tree size, particularly when combined with secondary pressures like bark beetle attacks (Bennett et al., 2015). Furthermore, climate projections indicate a lifting of the cloud base in montane forests, which would decrease the frequency of fog immersion. This is a direct threat to the survival of giant trees that rely on foliar water uptake in these cloud forest environments (Still et al., 1999). A recent trend of reduced low-cloud events has already been noted in the Chilan cloud forest of northeastern Taiwan (Hsu et al., 2024).

In addition to the gradual pressures of climate change, giant trees face threats from increasingly frequent and intense extreme weather events. In 2009, Typhoon Morakot brought over 3,000 mm of rainfall in 72 h, causing massive landslides that destroyed vast areas of primary forest (Tsai et al., 2010). Analyses suggest that typhoons hitting Taiwan have increased 35% in strength over the past four decades (Pandey and Liou, 2022). As most giant trees are

TABLE 1 Characteristics of the ten giants *Taiwania cryptomerioides* trees over 70 m discovered in this study.

No.	Given name	Chinese name	Discovery year	Height (m)	CHM height (m)	Girth (m)	Elevation (m)	Slope (°)	Longitude	Latitude
1	Twin towers	雙子星	2016	71.7	73.3	–	1,961	37.4	E120.8953	N22.8891
2	DanShi	丹絲神木	2018	72	74	8.35	2,133	40.7	E121.1800	N23.7982
3	NanKengSi	南坑溪巨木	2019	72.9	66.5	8.25	1,908	48.5	E121.0237	N24.3147
4	The Tao Tree	桃山神木	2020	79.1	76.4	9.4	2,067	12.2	E121.3002	N24.4583
5	ShihTzu	西施	2021	73.7	77.8	7.8	2,127	48.7	E121.0367	N24.3124
6	Kaalang	卡阿郎	2022	82*	77.5	8.2	2,001	44.8	E121.2151	N23.7085
7	Behuy	風之巨木	2022	75.9*	76.4	7.04	1,857	37.8	E121.3319	N24.5044
8	The Heaven Sword	大安溪倚天劍	2023	84.1	80	8.5	1,656	29.6	E121.1142	N24.4164
9	Holas	長老巨木	2024	78*	74.5	9.5	2,023	38.8	E121.1386	N23.4383
10	Balenge Kayngu	巴冷奶奶	2026	76.7	74	12.7	1,941	41	E120.8944	N22.8881

*Height was measured via drone-based photogrammetry, using a climber's pole extension as an *in situ* scale reference near tree tops.

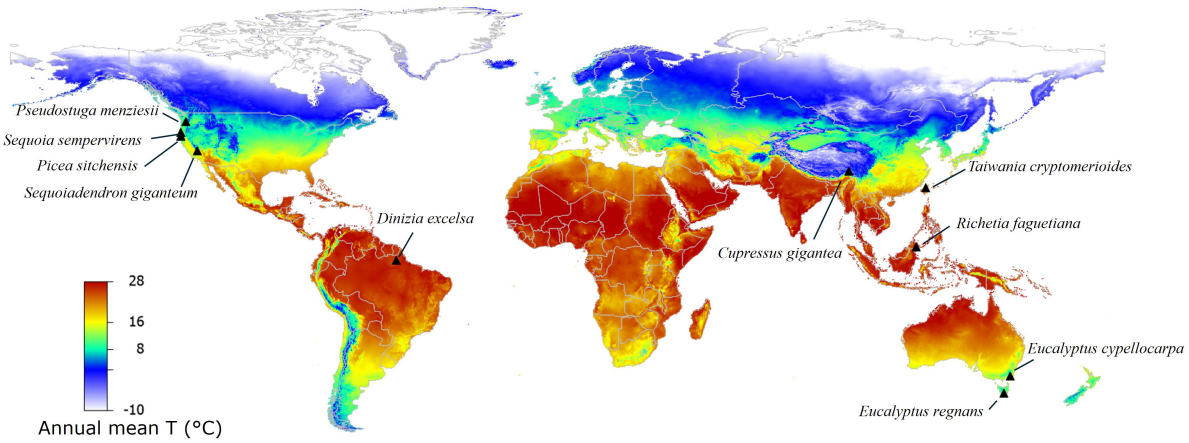


FIGURE 6
Global distribution of the world's tallest known trees. Each point corresponds to a record-holding specimen for a species known to exceed 80 m in height (see Supplementary Table 1 for details). The map's color gradient represents the mean annual temperature, based on WorldClim data (Fick and Hijmans, 2017).

located on steep slopes in the upper reaches of rivers, they are highly vulnerable to these storm-induced floods and landslides.

Direct human activity also remains a threat. Although over 95% of the identified giant trees fall within protected areas, their remote locations make them difficult to monitor. During our ground expeditions, we discovered several cases of illegal poaching of old-growth trees. This highlights that official protection, while essential, is insufficient without broader community vigilance.

The role of citizen science in future conservation

The crowdsourcing approach used in this study represents a powerful model for modern conservation. By transforming citizens from passive information receivers to active data suppliers—a process known as volunteered geographic information (VGI)—we not only reduced the intensive labor of data verification but also fostered greater public awareness through direct participation. Beyond its social impact, the VGI-derived dataset provided a critical foundation for machine learning applications.

Safeguarding the island's ancient trees requires a community-wide effort, as conservation authorities face labor shortages in managing these vast, remote areas. The Taiwan giant tree map created through this collaborative effort serves as a critical baseline for future monitoring. It empowers both scientists and citizens, providing the foundational data needed to protect these irreplaceable natural monuments for generations to come.

Conclusion

This decade-long journey to locate Taiwan's tallest trees began as a simple scientific inquiry but evolved into a complex study that overcame significant methodological and topographical challenges. We have confirmed the existence of trees exceeding 80 m in Taiwan, including the tallest known individual in East Asia. Our findings demonstrate that 3D point cloud visualization is a reliable and precise method for measuring extreme tree heights in complex terrain. Furthermore, by integrating crowdsourcing and volunteer participation, this study not only fostered greater public awareness for forest conservation but also generated a robust dataset for the future development of advanced machine learning models. We hope this study serves as a valuable model for the identification and conservation of ancient giant trees globally.

Data availability statement

The resultant data supporting the findings of this study are publicly available at https://no1tree.tw/.

Ethics statement

Ethical approval was not required for this study involving human participants in accordance with local legislation and institutional requirements. Written informed consent for participation was also not required from the participants or their legal guardians/next of kin, in accordance with national legislation and institutional requirements.

Author contributions

RH: Funding acquisition, Software, Formal analysis, Writing – original draft, Visualization, Project administration, Resources, Methodology, Supervision, Investigation, Validation, Conceptualization, Data curation, Writing – review & editing. C-KW: Conceptualization, Supervision, Methodology, Writing – review & editing, Project administration, Funding acquisition, Data curation, Resources, Validation. C-CL: Visualization, Software,

Conceptualization, Data curation, Writing – review & editing, Formal analysis, Validation, Methodology.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/ffgc.2026.1746112/full#supplementary-material

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