From mobile LiDAR to neural radiance fields: practical pathways for accessible ecological 3D reconstruction

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Data Availability

All data will be made available upon Zenodo at the following link:

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Contributions

HC, SMKM, RSG, and GKT conceived the ideas and designed methodology; HC adn SMKM collected the data; HC and SMKM analysed the data; HC and SMKM led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

Abstract

Ecological monitoring increasingly depends on high resolution three dimensional data, yet many reconstruction workflows remain constrained by the cost and logistical complexity of terrestrial laser scanning (TLS). At the same time, advances in mobile device imaging have enabled accessible three dimensional reconstruction using mobile LiDAR, structure from motion (SfM) photogrammetry, and neural radiance fields (NeRFs). Here, we present an interdisciplinary perspective on mobile phone based reconstruction workflows for ecology and compare their tradeoffs in accessibility, geometric fidelity, realism, and computational demand. Using a case study in Wytham Woods, UK, we compare reconstructions of trees generated using TLS, mobile LiDAR, SfM photogrammetry, app-based NeRFs, and NeRFs. Rather than positioning radiance fields as replacements for TLS or established photogrammetric workflows, we argue that they occupy a complementary niche by combining accessibility, visual realism, and reusable digital scene representations for ecological monitoring. We conclude with practical recommendations for selecting workflows across ecological applications including forest inventories, understory monitoring, and long term ecosystem archives.

1 Introduction

Monitoring ecological systems with high precision is foundational to ecological research and increasingly urgent as ecosystems face accelerating environmental change. As global awareness grows around the need to steward forests, deserts, and other ecosystems [United Nations, Department of Economic and Social Affairs, 2024], so too does the demand for tools capable of monitoring, understanding, and forecasting ecological change across a range of spatial and temporal scales. Vegetation structure is one of the most informative and widely measured properties of ecosystems because it is closely linked to biodiversity, ecosystem functioning, resilience to disturbance, and carbon storage [Storch et al., 2023, Winter et al., 2011, Ozanne et al., 2003, Gao et al., 2014, West et al., 2023]. Unlike many ecological variables, structural properties can also be observed remotely and repeatedly across large spatial extents. Consequently, considerable effort has been devoted to measuring ecosystem structure from airborne and space-borne platforms, enabling routine monitoring of forests and other vegetation at regional to global scales.

These broad-scale observations provide essential information about ecosystem condition and change, but they often lack the spatial resolution required to capture the local processes that drive ecological dynamics. Changes such as seedling establishment, branch loss, understory development, or fine-scale disturbance frequently occur at spatial scales below the resolution of satellite products and can therefore be difficult to observe directly from above [Dietze et al., 2018]. Close-range remote sensing provides a complementary perspective by capturing structural variation at the scale of individual plants, trees, and plots. These observations not only reveal local ecological processes but can also provide the ground-based measurements needed to calibrate and validate larger-scale airborne and satellite observations.

Recent reviews have argued that advances in three-dimensional mapping technologies are beginning to fill a previously under-sampled ecological scale space by enabling rapid and spatially continuous reconstruction of ecosystems [D'Urban Jackson et al., 2020]. This is particularly important for tree- and plot-scale ecology, where many processes of interest, including regeneration, crown development, stem growth, branch loss, and local disturbance, occur at spatial resolutions that are often poorly captured by satellite or airborne observations alone. Close-range three-dimensional sensing therefore provides an important bridge between traditional field measurements and landscape-scale remote sensing.

Within this close-range space, LiDAR has become central because it directly measures three-dimensional structure. However, LiDAR-based ecological reconstruction spans a wide range of instruments rather than a single technology class [Calders et al., 2020]. Systems differ in sensing principle, including time-of-flight and phase-shift approaches, as well as in detectable range, beam divergence, portability, cost, scan geometry, and processing requirements. These differences can lead to substantial variation in point-cloud density, completeness, noise, and metric reliability. At one end of the spectrum, high-end terrestrial laser scanning (TLS) instruments provide benchmark-quality structural data, but they are expensive and logistically demanding. At the other, lower-cost TLS, mobile laser scanning (MLS), and smartphone LiDAR systems are increasingly accessible, but often have shorter ranges, lower point density, or greater sensitivity to capture protocol and vegetation complexity [Výbošťok et al., 2025, Výbošťok et al., 2025, 2026]. We therefore treat LiDAR workflows as a continuum, from reference-grade TLS through mobile and consumer-device LiDAR, rather than assuming that all LiDAR-derived data are directly comparable.

In this paper, we use high-resolution TLS as the reference standard against which more accessible workflows are compared. Our focus is not on specialised low-cost LiDAR instruments, which occupy an important but separate part of this continuum, but on consumer-grade mobile phone technologies that could realistically broaden ecological monitoring. Modern smartphones already provide high-quality RGB cameras, and some recent devices also include integrated LiDAR sensors. At the same time, image-based reconstruction methods, including established structure-from-motion (SfM) photogrammetry and newer radiance-field approaches such as NeRFs Mildenhall et al. [2020], can recover three-dimensional structure from ordinary two-dimensional imagery. These developments raise a practical question for ecology: how much useful structural information can now be recovered using devices already available to many field researchers, and where do these workflows still fall short of TLS?

Here, we compare consumer-grade smartphone LiDAR, SfM, and radiance-field reconstruction against TLS across two contrasting ecological settings: an open urban ecosystem at University Parks, Oxford, and a closed-canopy forest at Wytham Woods. By placing these workflows in direct comparison with TLS, we ask whether recent advances in mobile sensing and AI-enabled reconstruction genuinely expand the capacity for ecological three-dimensional monitoring, or whether their current value is limited to specific vegetation sizes, canopy structures, and ecological questions.

2 A spectrum of mobile 3D reconstruction workflows

2.1 Smartphone LiDAR

Recent generations of mobile phones and tablets equipped with integrated LiDAR sensors have enabled rapid three-dimensional ecological capture using highly portable devices. Applications such as ForestScanner [Tatsumi et al., 2023] allow users to collect metrically scaled point clouds directly in the field using consumer hardware. Compared with TLS, consumer-grade LiDAR workflows substantially reduce equipment costs and acquisition complexity while preserving the ability to recover useful structural measurements such as stem diameter and tree position.

However, smartphone LiDAR systems generally operate at lower spatial resolution and shorter sensing range (~ 5 m) than dedicated terrestrial laser scanners. Fine branches, canopy structure, and understory vegetation will therefore be under-sampled or noisy, particularly in cluttered environments. Nevertheless, these LiDAR systems provide one of the most accessible routes to rapid metric ecological reconstruction and occupies an important middle ground between highly accurate TLS workflows and purely image-based methods Mokroš et al. [2021].

2.2 Classical SfM photogrammetry

Structure-from-motion (SfM) photogrammetry reconstructs scene geometry by identifying and matching visual features across overlapping images [Schönberger and Frahm, 2016]. Over the past decade, SfM has become one of the most widely used low-cost approaches for ecological three-dimensional reconstruction because it requires only standard RGB imagery and can be implemented using both open-source (e.g. COLMAP Schönberger and Frahm [2016], Schönberger et al. [2016]) and commercial software pipelines (e.g. Pix4DMapper Pix4D SA [2026]). In practice, the SfM step estimates camera positions and produces a sparse reconstruction, while ecologically useful structural outputs usually require subsequent dense multi-view stereo reconstruction Wang et al. [2025] to generate a sufficiently detailed point cloud or mesh. This makes SfM attractive as an accessible image-based capture workflow, but the processing needed for dense geometric reconstruction is still computationally demanding and needs GPU-equipped desktop hardware with a dataset of 50-150 images taking one to three hours to train on a modern GPU.

A major advantage of SfM is its transparency and reproducibility. Camera poses, sparse reconstructions, dense point clouds, and meshes can all be inspected directly, making the workflow reproducible and scientifically accessible. SfM has been applied successfully across forest ecology, vegetation monitoring, and biomass estimation [Marlow et al., 2024]. However, because reconstruction depends on reliable feature matching across views, SfM can struggle in scenes with low texture, strong occlusion, repetitive vegetation structure, or inconsistent lighting. The resulting reconstructions may therefore contain gaps, incomplete crowns, or poorly reconstructed thin structures, particularly where dense image overlap and viewing geometry are insufficient.

2.3 Radiance field methods

Radiance-field reconstruction represents a newer class of image-based three-dimensional reconstruction methods, driven by rapid advances in AI-enabled computer vision. A radiance field encodes a scene as a function that relates 3D position and viewing direction to colour and density, allowing the scene to be rendered from novel viewpoints (see Box 1 for a glossary of key terms). In practice, these methods use multiple overlapping images of a target object or scene to estimate both geometry and appearance. Neural Radiance Fields (NeRFs) represent the scene as a continuous volumetric function learned by a neural network [Mildenhall et al., 2020], whereas Gaussian splatting represents the scene using many overlapping 3D Gaussians, each with its own position, shape, colour, and opacity [Kerbl et al., 2023]. Both approaches differ from classical SfM in that they are designed not only to recover geometry, but also to produce view-consistent, photorealistic renderings of the scene.

Most radiance-field workflows still rely on accurate camera poses, which are commonly estimated from overlapping imagery using SfM-based methods such as COLMAP [Schönberger and Frahm, 2016]. Once camera poses are available, the radiance-field model is optimised so that rendered views match the input photographs. The resulting representation can then be used to generate novel views, visual fly-throughs, meshes, or dense point clouds, depending on the software pipeline. For ecological applications, this is attractive because the same image set can potentially support both visual archiving and later structural analysis, provided that the original images, metadata, and scale references are retained.

2.3.1 Off-the-shelf radiance-field applications

These workflows can now be processed through two broad routes. The first is an app-based route, using platforms such as Luma AI, Polycam, or Kiri Engine, where image capture, cloud processing, and output generation are largely automated. These tools have made dense 3D reconstruction accessible to non-specialists using only a mobile phone, often without requiring local computing resources or commercial photogrammetry software. However, they are also partly black-box systems: model versions, reconstruction settings, optimisation procedures, and post-processing steps may not be fully documented or stable through time. Their outputs may therefore be useful for rapid visualisation and exploratory ecological capture, but less reliable as reproducible scientific pipelines unless the raw imagery and associated metadata are carefully archived.

2.3.2 Research-grade radiance-field workflows

The second route is to process radiance-field models locally using desktop or research-grade software. Unlike cloud-based applications, these workflows run on the user's own hardware, require a capable GPU (similarly to large SfM workflows), and provide full control over model parameters and intermediate outputs. Open frameworks such as Nerfstudio [Tancik et al., 2023] have become the most widely used research platform for this approach. These workflows allow users to process the same image sets with greater control, inspect intermediate outputs, compare NeRF and Gaussian splatting approaches, and document parameters for reproducibility. This makes them more suitable for scientific benchmarking against reference data such as TLS. The tradeoff is that they require greater technical expertise and are usually GPU-intensive, limiting their accessibility relative to app-based workflows. Thus, radiance-field methods occupy a useful but heterogeneous position in ecological 3D reconstruction: app-based tools provide low-barrier access to visually coherent reconstructions, while open desktop workflows provide greater transparency and reproducibility for quantitative comparison.

3 Benchmarking mobile workflows in the wild

To move beyond a purely conceptual comparison of accessible 3D reconstruction workflows, we evaluated a small benchmark dataset collected in both a closed canopy (Wytham Woods, UK) and open environment (University Parks, Oxford) using three trees each spanning a range of sizes: one small (up to 2 m), one medium (2-10 m), and one large individual (greater than 10 m). University Parks provides a proxy for the open-canopy end of the gradient, where individual trees are accessible from multiple viewpoints and occlusion is relatively limited. Wytham Woods represents the more closed-canopy case, where the same workflows are challenged by overlapping vegetation, lower light, and restricted capture geometry, but may still provide useful information on lower-stem and understory structure. Our goal was not to identify a single universally superior method, but rather to compare how different mobile capture reconstruction workflows perform under the same ecological conditions, using terrestrial laser scanning (TLS) as the ground truth reference. We therefore compared five approaches: TLS; smartphone LiDAR using ForestScanner (missing for the open environment); a consumer phone-based radiance field workflow using Luma; a desktop structure-from-motion (SfM) photogrammetric workflow; and a Nerfstudio NeRF workflow. The latter two methods require a GPU-equipped desktop while still using a mobile phone as the in-the-field data capture device.

This comparison allows the demonstration of each techniques' strength and weakness, namely which workflow is most appropriate for a given ecological task, scale of vegetation, and level of processing capacity. In keeping with the broader theme of this paper, we treat the different methods as points on a spectrum rather than as competing replacements. TLS remains the most complete and metrically grounded reference, but it is also the most resource-intensive. Smartphone LiDAR reduces the hardware barrier substantially and offers rapid metric capture, while SfM remains a reliable and interpretable image-based baseline when image overlap and lighting are adequate. Radiance field methods, by contrast, offer the strongest visual continuity and the most flexible rendering outputs, especially when the scene is sufficiently well sampled.

Across both ecosystems, clear differences emerged in reconstruction completeness, visual coherence, and practical usability. Mobile LiDAR primarily captured lower-stem geometry, with useful information largely restricted to DBH-scale measurements, and did not recover higher-order branching or canopy structure. Image-based methods performed best in the open ecosystem, where both conventional SfM and radiance-field approaches reconstructed short and medium-sized trees relatively well and captured partial crown structure in taller individuals. In the closed-canopy forest, however, all passive image-based methods were more strongly constrained by occlusion and limited viewing geometry. SfM and radiance-field reconstructions were reasonably complete for the smallest tree, but became less reliable for medium and tall trees, where crown structure and fine woody architecture were only partially recovered. SfM often retained more explicit point-level detail, but also produced noisier and more fragmented point clouds, whereas the radiance-field outputs were generally smoother and visually more coherent (see Figure 2).

The comparison between Nerfstudio and Luma is particularly informative. Nerfstudio represents a more transparent and configurable research-grade workflow, allowing greater control over processing and clearer documentation of reconstruction parameters. Luma, by contrast, represents a low-barrier app-based route in which capture and cloud processing are largely automated. Despite this difference, Luma produced reconstructions with visual realism broadly comparable to the Nerfstudio radiance-field outputs in several cases, especially for open-grown trees. This is an important opportunity for ecological monitoring: app-based radiance-field tools may allow researchers to generate visually rich, re-renderable 3D records of trees and vegetation patches using only consumer phones and minimal technical expertise. At the same time, these outputs should be interpreted cautiously for quantitative measurement because app-based workflows are less transparent, may change through time, and require careful archiving of the original imagery, metadata, and scale references to support reproducibility.

These comparisons reinforce the central argument of this paper: accessible 3D ecological reconstruction should be viewed as a continuum of complementary workflows rather than as a set of direct replacements for TLS. TLS remains the benchmark for metric accuracy and structural completeness where high-quality measurements are required. Smartphone LiDAR offers a rapid and accessible route to lower-stem measurements, but its value is currently limited for crown-scale or whole-tree reconstruction. SfM remains a transparent and relatively low-cost photogrammetric workflow, particularly in open environments where sufficient image overlap and viewpoint coverage can be achieved, although dense reconstruction can be computationally demanding and outputs may be noisy. Radiance-field methods occupy a related image-based space: desktop workflows such as Nerfstudio provide transparency and reproducibility, while app-based workflows such as Luma substantially lower the barrier to visually realistic ecological 3D capture. Consequently, the most appropriate reconstruction workflow is determined less by the technology alone than by the balance between measurement precision, vegetation size, canopy openness, available resources, and the intended ecological application.

4 Ecological suitability across biome structure

Accessible close-range 3D reconstruction workflows are unlikely to be equally useful across all biomes, because their value depends strongly on vegetation height, structural complexity, tree cover, and occlusion. Placed against the Whittaker biome space Whittaker [1975], treeless or near-treeless systems such as tundra, subtropical deserts, and temperate grassland/desert occupy environments where close-range tree reconstruction is often of limited general value, except for localised applications such as shrubs, biological soil crusts, erosion features, or small restoration plots. In these open systems, UAV-based SfM or aerial LiDAR may often provide a more scalable route to ecosystem structure. By contrast, open-canopy wooded systems, including woodland/shrubland, savannas, and sparse tropical seasonal forests, may represent the strongest ecological niche for SfM and radiance-field methods. Here, individual trees or shrubs are often sufficiently separated to reduce occlusion, while still being structurally complex enough that ground-based 3D capture adds information not easily recovered from nadir aerial imagery alone. In such settings, phone-based workflows could provide detailed ground references for tree architecture, crown form, regeneration, or fuel structure, which can then be linked to UAV or satellite products for landscape-scale inference. Closed-canopy forests, including temperate seasonal forests, temperate rain forests, boreal forests, and especially tropical rain forests, present a different use case. Dense canopies, overlapping crowns, and understory clutter increase occlusion and make complete reconstruction of large trees difficult using mobile image-based methods alone. However, these systems are precisely where fine-scale ecological structure is most important and least visible from above. In dense forests, accessible close-range workflows may therefore be most useful for targeted reconstruction of saplings, small trees (2 — 5m depending on neighboring vegetation), lower stems (especially buttresses), understory vegetation and coarse woody debris, rather than for complete stand-level reconstruction. This suggests that the ecological role of mobile 3D reconstruction shifts across the biome space: from limited or specialised use in treeless systems, to high suitability for individual-tree and shrub reconstruction in open wooded systems, to targeted fine-scale structural sampling in closed-canopy forests (see Figure 1 for a decision framework across ecological contexts).

5 Practical guidance for ecologists

Beyond ecosystem type, workflow selection should be guided by the ecological measurement of interest. Many ecological processes occur at spatial scales that are too fine to be resolved consistently by airborne or satellite remote sensing, but too spatially extensive or frequently changing to justify repeated TLS campaigns. Examples include sapling recruitment, understory regeneration, coarse woody debris decomposition, cavity formation, epiphyte colonisation, branch loss after storms, and the spread of climbing plants. These processes often require repeated observations of individual plants, tree parts, or small plots over months to years. Accessible mobile reconstruction workflows are useful in this context because they can provide repeatable three-dimensional records that complement traditional field measurements and help bridge the gap between detailed plot ecology and landscape-scale remote sensing.

A practical way to select among workflows is to begin with the target metric. If the aim is rapid lower-stem measurement, particularly DBH or coarse stem form, smartphone LiDAR may offer the best balance between speed and field accessibility, although its value for crown-scale reconstruction remains limited. If the aim is to estimate whole-tree metrics such as height, crown area, or crown form from image data, both SfM and radiance-field workflows can be suitable when the tree is sufficiently visible and image coverage is adequate. In our examples, these image-based methods performed best for open-grown trees and became less reliable as canopy closure, occlusion, and vegetation size increased. For many coarse structural metrics, therefore, the choice between SfM and Nerfstudio-style radiance-field processing may matter less than the quality of the capture protocol, the degree of occlusion, and the availability of a reliable scale reference.

The distinction between SfM and radiance-field methods becomes more important when the ecological target is finer structural detail (see Figures 1 and 2). SfM can recover substantial geometric information, but its dense point clouds may be noisy, fragmented, and sensitive to feature matching errors, especially in complex vegetation. Radiance-field methods, including NeRF and Gaussian splatting workflows, can produce smoother and more visually coherent reconstructions from similar image sets, and may be preferable when the goal is to preserve branch continuity, crown morphology, branching topology, or a re-renderable visual record of the scene. App-based tools such as Luma lower the barrier to this kind of capture and can produce visually realistic outputs with minimal technical expertise. More configurable desktop workflows such as Nerfstudio are better suited when the same imagery needs to be processed transparently, compared across algorithms, or benchmarked against TLS, but they require greater expertise and GPU-enabled computing.

Beyond geometry alone, radiance field methods also preserve aspects of scene appearance that are often lost in point-cloud-only representations, including canopy shading, glossiness, translucency, and view-dependent reflectance effects. These optical properties are ecologically relevant because they relate directly to physiological processes, stress responses, and phenological change [Li et al., 2023]. As a result, radiance field approaches may support analyses beyond surface reconstruction, including standardized re-rendering, volumetric slicing, and future reanalysis as spectral and biophysical inference methods improve [Zhang et al., 2025]. At present, however, radiance field methods should be viewed as complementary additions to existing ecological reconstruction workflows rather than direct replacements for TLS or classical photogrammetry. Their primary strengths lie in visual realism, flexible rendering, and the ability to generate reusable image-based scene representations from relatively lightweight capture workflows [Li et al., 2025].

For most ecological applications, capture protocol matters as much as the reconstruction algorithm. Image-based methods require high overlap, smooth camera motion, adequate coverage from multiple viewpoints, and, where possible, multiple viewing heights. Diffuse lighting is preferable because glare, hard shadows, and changing exposure can degrade both SfM and radiance-field reconstructions. A known-scale reference should be included whenever quantitative measurements such as DBH, height, or crown area are required. The original images, metadata, and scale information should also be retained so that datasets can be reprocessed as algorithms improve or compared across pipelines. This is particularly important in ecology, where field campaigns are often difficult, expensive, or impossible to repeat.

These considerations reinforce the central point that accessible 3D reconstruction methods are complementary rather than interchangeable. TLS remains the benchmark where high metric fidelity and structural completeness are required, although TLS itself spans a wide range of instruments with different ranges, point densities, and canopy penetration capabilities. Smartphone LiDAR is useful for fast, accessible lower-stem measurements, but not for complete tree reconstruction. SfM and radiance-field workflows both offer practical routes to image-based reconstruction of visible tree structure, especially in open systems. Radiance-field methods may be especially valuable when visual coherence, branch continuity, and fine structural representation are important, while SfM remains useful where an inspectable photogrammetric workflow is sufficient. The appropriate workflow is therefore determined by the combination of measurement objective, vegetation size, canopy openness, available expertise, processing resources, and the level of uncertainty that can be tolerated.

6 Current limitations and future opportunities

Although mobile 3D reconstruction is becoming substantially more accessible, several limitations remain. First, occlusion continues to constrain all close-range reconstruction workflows. Dense foliage, overlapping branches, and shadowed understory vegetation introduce missing volumes that cannot be recovered reliably from insufficient viewpoints. This limitation is shared across SfM, radiance-field methods, and some LiDAR workflows, although it manifests differently in each case. In practice, reconstruction completeness depends not only on the algorithm, but also on vegetation structure, viewpoint coverage, lighting, and capture protocol.

Second, scale remains an important issue for image-based methods. Even where the reconstructed shape is visually convincing, quantitative ecological use requires metric consistency. This is one reason why TLS remains a valuable benchmark and why mobile image-based workflows should be interpreted cautiously when the task depends on absolute dimensions. Including known scale objects, using device-based pose information, or integrating range data from mobile LiDAR can reduce this problem, but scale ambiguity remains a core challenge for image-only pipelines.

Third, the most user-friendly systems are not always the most scientifically transparent. Consumer apps often emphasise polished renderings and automated processing, but this can obscure the details of the reconstruction pipeline and make it harder to diagnose errors or compare outputs across studies. By contrast, open workflows such as COLMAP and Nerfstudio require more expertise, but offer greater control, reproducibility, and opportunities for calibration. For ecological applications, the tradeoff between convenience and transparency needs to be considered carefully, especially when reconstructions are used for quantitative measurement rather than visual documentation.

These limitations also point toward important future opportunities. Improvements in pose estimation, scale recovery, sensor fusion, and uncertainty quantification could make mobile workflows substantially more useful for ecological monitoring. Better integration of RGB imagery with LiDAR, inertial data, or automated scale references may help bridge the gap between accessibility and metric reliability. In parallel, ecological benchmark datasets that compare methods against shared reference data would help move the field from anecdotal demonstrations toward systematic evaluation. Such benchmarks should report not only rendering quality, but also ecologically relevant metrics such as DBH, height, crown area, reconstruction completeness, and the recovery of fine structures such as branches, saplings, buttresses, and coarse woody debris.

A further opportunity lies in broadening participation in ecological monitoring. Citizen science initiatives such as eBird have demonstrated the value of distributed ecological observation networks [Sullivan et al., 2009], and mobile recording technologies have similarly expanded participation in biodiversity monitoring [Dickinson et al., 2010]. As consumer phones increasingly support high-quality imaging, LiDAR sensing, and app-based 3D reconstruction, mobile workflows could enable richer forms of ecological documentation by researchers, students, conservation practitioners, and local communities. This is particularly important for ecosystems where repeated high-end TLS surveys are impractical because of cost, remoteness, or limited infrastructure. To realise this potential, however, citizen-contributed 3D data would need simple capture protocols, standardised metadata, scale references, quality checks, and clear guidance on which ecological measurements can and cannot be inferred reliably.

The long-term opportunity is therefore not to replace established ecological sensing methods, but to expand the range of situations in which useful 3D data can be collected. Smartphone LiDAR, SfM and radiance fields each contribute to a broader shift toward accessible ecological reconstruction, but their value depends on matching the workflow to the ecological question and the required level of measurement confidence. As hardware improves and software becomes more interoperable, the most important development may be the emergence of a flexible ecosystem of methods rather than any single dominant technique. Such a shift would not eliminate the need for TLS or other high-end instruments, but it could make detailed ecological 3D observation more widely available, more repeatable, and easier to integrate into routine field practice.

7 Conclusion

Mobile sensing and image-based reconstruction are rapidly expanding the range of practical workflows available for ecological three-dimensional reconstruction. Rather than converging on a single dominant approach, ecology is instead gaining access to a flexible ecosystem of methods spanning terrestrial laser scanning, smartphone LiDAR, classical photogrammetry, neural radiance fields, and Gaussian splatting. Each workflow carries distinct tradeoffs in accessibility, metric fidelity, computational demand, and visual realism.

Our comparison in Wytham Woods demonstrates that useful ecological three-dimensional data can now be collected using consumer mobile devices, although the suitability of each workflow depends strongly on the ecological question, scene structure, and desired outputs. TLS remains the benchmark standard for quantitative reconstruction, while mobile workflows substantially reduce barriers to capture and broaden the range of environments in which three-dimensional ecological data can realistically be collected.

The most important development may therefore not be any individual reconstruction algorithm, but the emergence of accessible and reusable three-dimensional ecological observation using devices already carried by many field researchers.

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Glossary of 3D Reconstruction Terms for Ecologists

Continuous Representation – A scene representation that stores geometry and appearance as a mathematical function rather than a discrete point cloud, allowing resampling and re-rendering from arbitrary viewpoints.

Gaussian Splatting – A radiance-field reconstruction approach that represents surfaces as overlapping 3D Gaussians ("splats"), enabling fast rendering and visually smooth reconstructions.

Mobile LiDAR – Three-dimensional sensing using integrated LiDAR sensors within consumer mobile devices such as phones or tablets.

Neural Radiance Field (NeRF) – A neural-network-based radiance field representation learned from overlapping photographs, capable of rendering novel viewpoints of a scene.

Photogrammetry – The reconstruction of three-dimensional structure from overlapping photographs.

Point Cloud – A set of three-dimensional points representing sampled surface geometry within a scene.

Radiance – The colour or intensity of light leaving a point in a given direction.

Radiance Field – A continuous function mapping spatial position and viewing direction to colour and density values, describing how light interacts with a scene.

Structure-from-Motion (SfM) – A photogrammetric workflow that estimates camera poses and scene geometry from overlapping images.

Terrestrial Laser Scanning (TLS) – A LiDAR-based reconstruction technique that measures distance directly using emitted laser pulses to produce dense and metrically grounded point clouds.

View-dependent Effects – Changes in scene appearance caused by viewing angle, such as glossiness or specular reflection.

Box 1: Glossary summarizing common terms used in mobile ecological three-dimensional reconstruction workflows.

Practical Guidance for Mobile Ecological 3D Reconstruction

Capture Path: Maintain consistent motion and sufficient overlap while moving around the target object or stand. Include views from multiple elevations where possible.

Capture Device: Modern smartphones or tablets equipped with high-quality RGB cameras and, where available, integrated LiDAR sensors.

Environment: Prefer diffuse lighting conditions (overcast skies or shaded environments) to reduce glare, hard shadows, and inconsistent exposure across images.

Image Overlap: Ensure substantial overlap between successive images or video frames to support reliable pose estimation and reconstruction.

Scale Reference: Include a known-size object or metric reference when quantitative measurements such as DBH or canopy height are required.

Data Retention: Preserve original photographs or video whenever possible so that datasets can be reprocessed later using improved reconstruction workflows.

Workflow Selection: Match the reconstruction workflow to the ecological question. Mobile LiDAR may be preferable for rapid metric measurements, SfM for transparent low-cost reconstruction, and radiance fields for photorealistic visualization and re-rendering.

Processing: Mobile applications such as ForestScanner, Luma AI, Polycam, and RealityScan offer accessible capture and reconstruction pipelines, while open-source workflows such as COLMAP and Nerfstudio provide greater control and reproducibility.

Validation: Compare reconstructed outputs against field measurements or TLS references whenever quantitative ecological interpretation is required.

Box 2: Practical recommendations for collecting and processing mobile ecological three-dimensional reconstruction data.

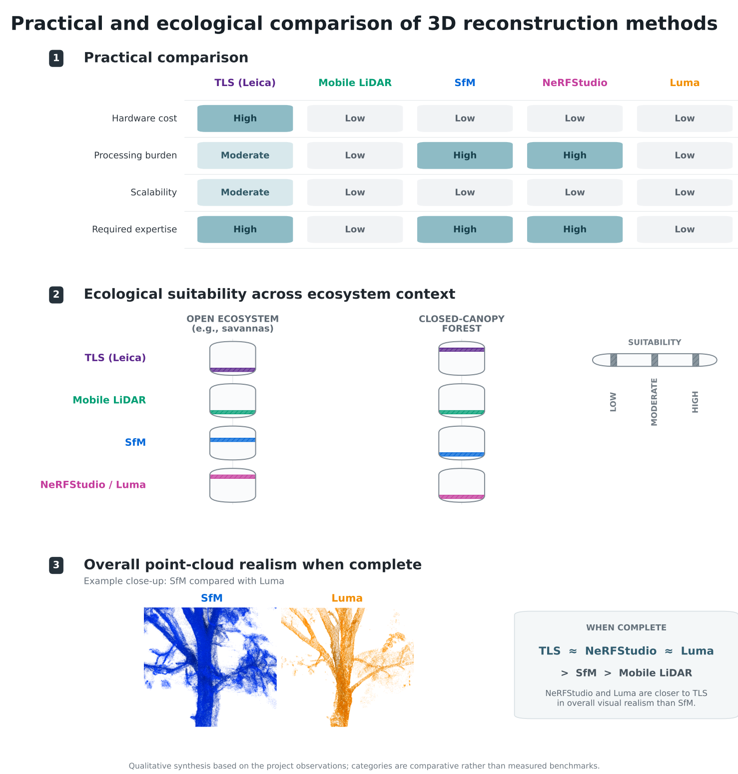

Figure 1: Practical and ecological comparison of 3D reconstruction methods. **(1)** Qualitative comparison of the practical trade-offs associated with terrestrial laser scanning (TLS), mobile LiDAR, Structure-from-Motion (SfM), NeRFStudio, and Luma, including hardware cost, processing burden, scalability, and required user expertise. **(2)** Relative suitability of each method across open, semi-open, and closed-canopy ecosystems, summarising their expected performance under increasing vegetation complexity. **(3)** Visual comparison of point-cloud realism using a representative close-up, highlighting the improved reconstruction fidelity of Luma relative to SfM. When complete reconstructions are obtained, NeRFStudio and Luma produce point clouds that approach the visual realism of TLS and consistently outperform conventional SfM and mobile LiDAR in representing fine woody structure. Rankings are qualitative summaries derived from observations across the study rather than quantitative performance benchmarks.

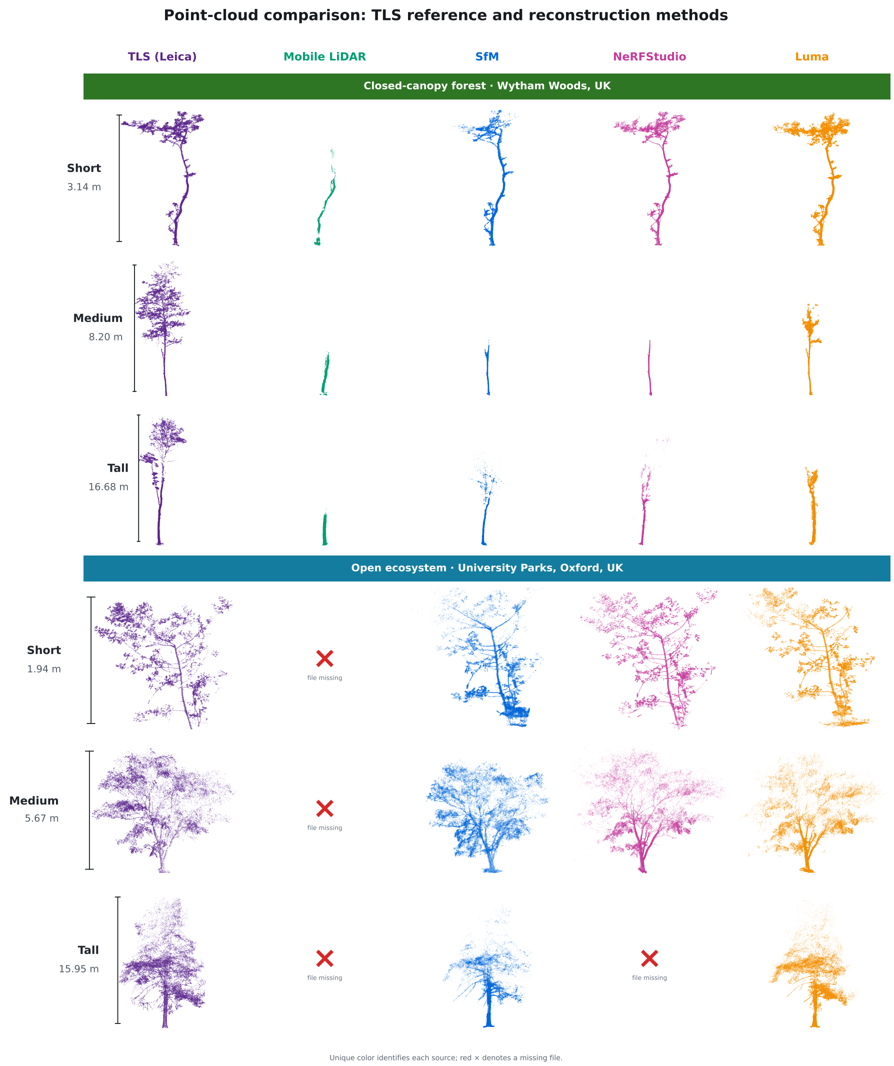

Figure 2: Point-cloud comparison across reconstruction methods. Comparison of representative tree reconstructions generated using terrestrial laser scanning (TLS), mobile LiDAR, Structure-from-Motion (SfM), NeRFStudio, and Luma across two contrasting ecosystems. **Top panel** shows trees from a closed-canopy temperate forest (Wytham Woods, UK), while the **bottom panel** shows trees from an open urban woodland (University Parks, Oxford, UK). Rows span short-, medium-, and tall-stature individuals to illustrate performance across increasing structural complexity. TLS (purple) provides the reference geometry against which alternative methods are visually compared. Mobile LiDAR frequently under-samples fine branching, whereas SfM produces sparse reconstructions with incomplete canopy structure. NeRFStudio and Luma recover more complete crown architecture and branch connectivity, producing point clouds that more closely resemble the TLS reference across both environments. Red crosses indicate datasets that were unavailable for comparison.

A Benchmarking Data Collection

For all areas, terrestrial laser scanning was performed using a Leica RTC360 3D laser scanner and six registration spheres per site. Registration was performed in Leica Cyclone Register 360. Point clouds were then exported for segmentation.

B Mobile-based Data Collection

Mobile-based 3D capture was performed using the Luma Labs 3D Capture application with a Samsung Galaxy M10. The application's user instructions were followed in collecting novel views while walking around trees of interest in each site. Images were then uploaded and processed in Luma and exported as point clouds for evaluation.

C Mobile-based laser scanning

Mobile-based 3D scanning was performed using the ForestScanner application with an iPhone 12 Pro. The application's user instructions were followed in generating a point cloud while walking around trees of interest in each site. Point clouds were then offloaded and processed along with the TLS data.

D Tree segmentation and analysis

NeRF point clouds were exported, aligned, and metric-scaled to the TLS references in CloudCompare using three manually selected tie-points per tree. Vertical point-density profiles were subsequently derived in Python using kernel-density estimators, while stem diameter at breast height (DBH), total height and crown-projection area were extracted with the ITSMe package in R [Terryn et al., 2023].

E Controlling for Scaling

Given that reconstructions exported from Luma do not have a unit associated with them, an object with known size and scale is needed. We utilized a size 5 football to act as a consistent, widely-accessible 3D scale parameter in scans.

We present a demonstration of a field study utilizing an off-the-shelf radiance field reconstruction mobile application. In this study, vertical point-density profiles revealed a systematic downward bias, with NeRF concentrating the majority of points in the lower bole even where TLS showed that most vegetation mass resides in the canopy. For the open-grown (urban) tree, all structural metrics (diameter at breast height [DBH], height, and crown projection area) from NeRF agreed with TLS to within 4%. In the closed-canopy temperate stand, the results from four standing trees showed a mean DBH relative error of 4%, while height and crown area from NeRFs were systematically underestimated by 29% and 75% respectively, closely echoing the errors reported in earlier NeRF–SfM forestry evaluations [Huang et al., 2024]. Thus, NeRF reconstructions deliver research-grade accuracy for isolated trees, but occlusion in dense forest can still limit absolute crown and height estimates. While terrestrial laser scanning (TLS) can capture understory and open-vegetation structures, it is time-consuming and labor-intensive, especially when deployed over large savannas, grasslands, or tundra. Moreover, understory saplings often suffer from low signal-to-noise ratios in TLS or mobile-laser scans (MLS), a problem that only worsens when using lower-cost sensors [Calders et al., 2020].

Despite promising results for open-grown trees, we observe systematic biases under dense canopy caused primarily by occlusion and limited viewpoint coverage. Scale ambiguity in image-only reconstructions requires reliable external references or integrated range sensors for absolute metrics. Current mobile NeRF pipelines are sensitive to lighting and reflective surfaces, and their computational costs (training time, memory) can limit rapid deployment in field campaigns. These limitations suggest priority areas for methodological development (see below).

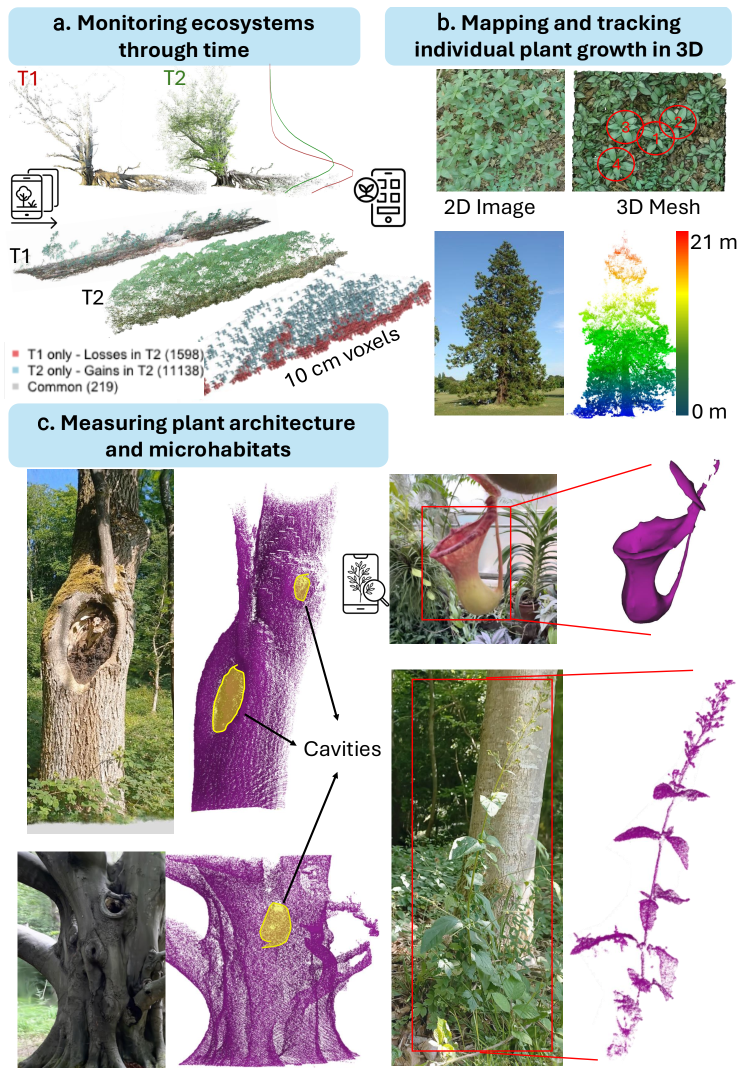

Figure S1: This multi-panel figure showcases NeRF-enabled 3D mapping across scales and through time. **(a)** Monitoring ecosystems through time: Dense point clouds of the same tree reconstructed at two dates (T_1 in red vs. T_2 in green) reveal canopy development, with an overlaid vertical distribution of plant components, and a change-detection map highlighting loss (red), gain (blue), or unchanged (gray) points, emphasizing shifts in understory structure. **(b)** Mapping and tracking plant growth in 3D: the top row presents a ground-level photograph of forest-floor saplings alongside its 3D mesh with individuals mapped in red circles, enabling precise tracking of each seedling's height and form; the bottom row shows a full-tree reconstruction coloured by height (blue at the base to red at the crown), illustrating whole-plant structure. **(c)** Measuring plant architecture and microhabitats: this composite illustrates how NeRF-based 3D reconstruction can capture plant form and function from the micro- to macro-scale. On the left, microhabitat and tree-architecture modelling uses high-resolution photographs of trunk cavities and buttress surfaces converted into dense point clouds, with cavities outlined in yellow. On the right, small-plant architecture in both controlled-lab (top) and in-field (bottom) settings is reconstructed into full-plant point clouds, demonstrating the method's applicability across plant sizes and environments.