Democratizing 3D Ecology: Mobile Radiance Fields for Scalable Ecosystem Monitoring

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Abstract

High-resolution 3D monitoring is vital for understanding ecological dynamics, but methods like terrestrial laser scanning (TLS) are limited by cost and accessibility. We demonstrate that mobile neural radiance fields (NeRF), using consumer smartphones and open-source platforms, can produce vegetation reconstructions comparable to TLS in open environments, though performance decreases under dense canopies. Mobile NeRF methods democratize ecological monitoring by reducing hardware barriers, excelling at capturing understory complexity, and potentially integrating hyperspectral and robotic data for scalable ecosystem surveillance.

Monitoring ecological systems with high precision is foundational to ecological research, and never more urgent than now. As global awareness grows around our responsibility to steward forests, deserts, and other ecosystems [1], so too does the demand for tools and techniques that can monitor, understand, and forecast ecological accurately and at scale. The field has moved beyond manual surveys towards sophisticated 3D techniques like high-resolution photogrammetry and terrestrial laser scanning (TLS hereafter)[2]. These novel methods are vital for accurately evaluating conservation schemes such as REDD, where traditional metrics have often overestimated effectiveness [3]. Yet while these 3D methods increase accuracy and ecological insight [4], they often come with steep costs: specialised, expensive equipment; technical know-how; and intensive post-processing. In short, the bottleneck has started to shift from data collection in the field to computation in the lab. Given the lack of off-the-shelf and inexpensive LiDAR solutions for ecological data collection, photogrammetry

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has been used for the past decade to provide 3D capabilities in ecology. While low-cost Structure-from-Motion (SfM) pipelines can produce accurate sparse or moderately dense 3D reconstructions, they remain fundamentally limited by their discrete, point-matching basis. SfM can leave holes under heavy occlusion (e.g., understory vegetation), fail in challenging lighting, and only reconstruct surfaces actually seen in the input photos [5]. In contrast, neural radiance fields (NeRFs) learn a continuous volumetric function that jointly encodes scene geometry (density) and appearance (radiance) at every 3D location and viewing direction. Because NeRF is trained to render photorealistic novel views from arbitrary camera poses, it can fill in previously unseen angles and thin structures, yielding seamless, gap-free reconstructions. Moreover, by sampling the learned volume at any desired resolution, NeRF automatically produces much denser point clouds than SfM, even in areas with minimal original overlap. This combination of continuous representation, high-fidelity rendering, and arbitrarily dense sampling makes NeRF particularly powerful for capturing fine-scale understory or open-vegetation structure that discrete SfM often misses or cannot interpolate.

A radiance field encodes a scene as a continuous function that maps every 3D point (x, y, z) and viewing direction (θ, ϕ) to a volume density and an RGB radiance. Given a camera pose—i.e. its position and orientation in space—you cast a ray through each image-plane pixel, sample the field along that ray, and composite the density-weighted colours to determine exactly how the scene appears from that viewpoint. The last decade has witnessed the proliferation of AI/ML based tools that leverage radiance fields for 3D reconstruction from 2D views. Among them are NeRFS [6] and Gaussian Splatting [7]. Regardless of reconstruction technique, radiance field methods begin with a sparse 3D point cloud that is created using Structure-from-Motion. NeRF reconstruction employs a deep neural network to learn a continuous volumetric function that, given a 3D coordinate and viewing angle, outputs the corresponding colour and density. This reconstruction is carried out by taking in tens to hundreds of overlapping photographs (views) around a target object, whether a tree crown, root ball, or other natural artifact. The network optimizes a mapping to produce a continuous, consistent 3D volume. The end product thus goes far beyond a typical SfM point cloud, as the learned mapping encodes the nonlinear, high dimensional scene better than a vanilla SfM interpolation. A key advantage of the application of radiance field methods in Ecology is the possibility to monitor volumetric change of complex structures through time. Once trained, radiance field methods allow virtual flythroughs of, for instance, canopy architecture, precise cross-sectional slicing, and accurate computation of volumes and surface areas.

Whereas NeRF represents scene geometry as a continuous field, Gaussian Splatting decomposes surfaces into many small, overlapping “splats”, each defined by a 3D Gaussian with its own position, orientation, colour, and size. Radiance field methods’ ease of use in ecology has increased thanks to freely available, phone-based applications such as Luma AI (lumalabs.ai), Polycam (poly.cam), and RealityScan (realityscan.com). These applications allow for real-time or post-hoc uploading of photos or videos to be processed in a standard AI-based reconstruction pipeline. Given that 53% of people worldwide have access to a camera-capable smartphone [8], we are entering an era where a large proportion of mankind is now capable of capturing scientific quality data of natural artifacts. This workflow can help democratize volumetric data collection, enabling ecologists and citizen scientists to replace days of manual labour or expensive equipment for a brief scan with a device they already carry.

Calls to leverage mobile devices for ecological monitoring are not new. Previous methodologies have demonstrated that the photographic and LiDAR capabilities of most recently released phones and tablets can serve as viable alternatives to specialized equipment [9, 10, 11, 12, 13, 14]. However, radiance field methods have expanded these possibilities further, enabling detailed three-dimensional reconstructions that offer significant advantages over traditional photogrammetry. Although these AI based models do not yet match the accuracy of TLS, they consistently outperform classical photogrammetric methods in reconstructing detailed objects, such as individual trees and forest canopies, while often requiring fewer input images [15]. Beyond forests, NeRF-based methods have demonstrated reliable three-dimensional morphometric measurements for crop structures [16] and have even been integrated into mobile robotic platforms, such as quadrupedal robots, to automate forest inventories [17]. These advances collectively highlight that radiance field methods not only extend existing mobile-based ecological monitoring approaches, but also open entirely new avenues for research, facilitating high-resolution, accessible, and flexible ecological data collection.

While NeRFs produce point clouds that are equivalent (or in some cases less than) to those yielded by TLS and/or classical structure-from-motion approaches [15], the major advancement of these methods lie in their photorealism and small scale accuracy. As we seek to bring monitoring of the environment closer to the current state of citizen science in other fields such as ornithology [18] and aim to understand change on shorter time scales, accessible, high resolution data capture is essential. Much as bioacoustics has transformed ornithology [19], we argue that reliable radiance field reconstruction is poised to do the same for the study of a wide range of ecological systems, bringing current efforts [20] into a much needed, realistic third dimension. The ease of use of these methods also helps to bridge the spatial mismatch of ecosystem monitoring: many of the ecosystems we wish to monitor (in remote areas) are far removed from most of the (sometimes expensive) infrastructure that exists to monitor them (R1 universities) [21]. The additional strength of radiance field methods is the universality of the data input. A set of as few as 20 overlapping photos can be reprocessed and revisited over time and with new, improved methods. If the set point reference images typically recorded of forests, for example, had been taken in this manner, radiance field reconstruction methods could be applied interchangeably. In our field validation trials of an off-the-shelf radiance field reconstruction mobile application, 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 [15]. 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 [2].

In addition to new avenues for capturing small-scale features in ecosystems, parameterization of a scene into radiance fields can be extended to hyperspectral cases, where each point in the scene not only captures RGB colour information but also continuous spectral reflectance data across many narrow spectral bands. Hyperspectral radiance fields offer significant potential opportunities for ecology by enabling detailed 3D analyses of plant biochemistry, early warning signals of ecophysiological stress, species identification, biodiversity mapping, and habitat characterization. Hyperspectral radiance fields can extend the capabilities of hyperspectral imaging in non-invasively monitoring plant health by detecting subtle spectral changes related to biochemical traits like chlorophyll content and water stress [22] and providing fine-resolution insights into ecosystem productivity and responses to environmental change [23]. Additionally, the capacity of hyperspectral radiance fields for detailed 3D habitat reconstructions integrating spectral data supports precise species discrimination and biodiversity mapping in complex ecosystems such as tropical forests [24] and coral reefs [25]. By capturing radiance as a function of viewpoint and wavelength, radiance fields can also enable advanced modelling of ecosystem interactions with solar radiation, informing studies of canopy structure, light penetration, and photosynthesis under varying conditions.

Radiance field methods offer scalable, better democratised, and flexible approaches for ecological monitoring and forecasting. By leveraging widely available mobile technologies, these methods provide a practical means to rapidly capture and reconstruct high-resolution ecological data in remote and understudied areas. Since NeRF reconstructions rely solely on photographic data, existing archived image datasets [26] can be revisited and reprocessed using future advances in reconstruction algorithms, creating rich temporal archives of ecosystem dynamics. The accuracy at small scales, improved accessibility, aligning technological capabilities with ecological needs, and avenues for future integration situate radiance field methods as a paradigm shifting methodology in ecosystem monitoring. While current implementations excel at detailed, small-scale measurements—such as individual tree structure, continuous advancement in AI-driven techniques promises to bridge remaining accuracy gaps at larger scales and in denser vegetation. The democratic nature of these tools allow for widespread adoption which will increase the community's ability to benchmark methodologies across ecosystems and use cases. Further integration with emerging hyperspectral and mobile drone and robotic platforms presents an exciting frontier, enabling increasingly sophisticated ecosystem analyses. Ultimately, the continued convergence of ecological research and cutting-edge computational methods will significantly enhance our capacity to monitor and protect Earth's ecosystems.

References

[1] Martin. Forests, desertification and biodiversity.

[2] Calders, K. *et al.* Terrestrial laser scanning in forest ecology: Expanding the horizon. *Remote Sensing of Environment* **251**, 112102 (2020).

[3] West, T. A. P. *et al.* Action needed to make carbon offsets from forest conservation work for climate change mitigation. *Science* **381**, 873–877 (2023).

[4] Marlow, J., Halpin, J. E. & Wilding, T. A. 3D photogrammetry and deep-learning deliver accurate estimates of epibenthic biomass. *Methods in Ecology and Evolution* **15**, 965–977 (2024).

[5] Mathes, T., Seidel, D., Häberle, K.-H., Pretzsch, H. & Annighöfer, P. What Are We Missing? Occlusion in Laser Scanning Point Clouds and Its Impact on the Detection of Single-Tree Morphologies and Stand Structural Variables. *Remote Sensing* **15**, 450 (2023).

[6] Mildenhall, B. *et al.* NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis (2020). `2003.08934`.

[7] Kerbl, B., Kopanas, G., Leimkuehler, T. & Drettakis, G. 3D Gaussian Splatting for Real-Time Radiance Field Rendering. *ACM Transactions on Graphics* **42**, 1–14 (2023).

[8] GSMA. The state of mobile internet connectivity report 2024. Tech. Rep., GSMA (2024). URL `https://www.gsma.com/r/somic/`. Accessed: 2025-06-03.

[9] Teacher, A. G. F., Griffiths, D. J., Hodgson, D. J. & Inger, R. Smartphones in ecology and evolution: A guide for the app-rehensive. *Ecology and Evolution* **3**, 5268–5278 (2013).

[10] Ahamed, A., Foye, J., Poudel, S., Trieschman, E. & Fike, J. Measuring Tree Diameter with Photogrammetry Using Mobile Phone Cameras. *Forests* **14**, 2027 (2023).

[11] Jeftha, K. J. & Shoko, M. Mobile phone based laser scanning as a low-cost alternative for multidisciplinary data collection. *South African Journal of Science* **120** (2024).

[12] Holcomb, A., Tong, L. & Keshav, S. Robust Single-Image Tree Diameter Estimation with Mobile Phones. *Remote Sensing* **15**, 772 (2023).

[13] Tatsumi, S., Yamaguchi, K. & Furuya, N. ForestScanner: A mobile application for measuring and mapping trees with LiDAR-equipped iPhone and iPad. *Methods in Ecology and Evolution* **14**, 1603–1609 (2023).

[14] Borz, S. A. & Proto, A. R. Low-cost phone-based LiDAR scanning technology provides sub-centimeter accuracy when measuring the main dimensions of motor-manual tree felling cuts. *Ecological Informatics* **85**, 102999 (2025).

[15] Huang, H., Tian, G. & Chen, C. Evaluating the Point Cloud of Individual Trees Generated from Images Based on Neural Radiance Fields (NeRF) Method. *Remote Sensing* **16**, 967 (2024).

[16] Arshad, M. A. *et al.* Evaluating Neural Radiance Fields for 3D Plant Geometry Reconstruction in Field Conditions. *Plant Phenomics* **6**, 0235 (2024).

[17] Korycki, A., Yeaton, C., Gilbert, G. S., Josephson, C. & McGuire, S. NeRF-Accelerated Ecological Monitoring in Mixed-Evergreen Redwood Forest (2024). 2410.07418.

[18] Sullivan, B. L. *et al.* eBird: A citizen-based bird observation network in the biological sciences. *Biological Conservation* **142**, 2282–2292 (2009).

[19] Dickinson, J. L., Zuckerberg, B. & Bonter, D. N. Citizen Science as an Ecological Research Tool: Challenges and Benefits. *Annual Review of Ecology, Evolution, and Systematics* **41**, 149–172 (2010).

[20] Schiller, C., Schmidtlein, S., Boonman, C., Moreno-Martínez, A. & Kattenborn, T. Deep learning and citizen science enable automated plant trait predictions from photographs. *Scientific Reports* **11**, 16395 (2021).

[21] Qi, M. *et al.* Biodiversity research requires more motors in the mud, air and water. *EcoEvoRxiv* (2025).

[22] Qin, J. *et al.* A hyperspectral plant health monitoring system for space crop production. *Frontiers in Plant Science* **14** (2023).

[23] DuBois, S. *et al.* Using imaging spectroscopy to detect variation in terrestrial ecosystem productivity across a water-stressed landscape. *Ecological Applications* **28**, 1313–1324 (2018).

[24] Aguirre-Gutiérrez, J. *et al.* Canopy functional trait variation across Earth's tropical forests. *Nature* **641**, 129–136 (2025).

[25] Mills, M. S. *et al.* Assessment of the utility of underwater hyperspectral imaging for surveying and monitoring coral reef ecosystems. *Scientific Reports* **13**, 21103 (2023).

[26] Depauw, L. *et al.* The use of photos to investigate ecological change. *Journal of Ecology* **110**, 1220–1236 (2022).

[27] Terryn, L. *et al.* Analysing individual 3D tree structure using the R package ITSMe. *Methods in Ecology and Evolution* **14**, 231–241 (2023).

Methods

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.

Mobile-based Data Collection

Phone-based 3D capture was performed using the Luma Labs 3D Capture application with an iPhone 12 Pro. The application's user instructions were followed in collecting novel views while walking around trees of interest in each site. Models were then uploaded and processed in Luma and exported as point clouds for evaluation.

Tree segmentation and analysis

NeRF point clouds were exported, aligned and metric-scaled to the terrestrial-laser-scanning (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 [27].

Controlling for Scaling

Given the scaleless nature of the reconstructions exported from Luma, a scaling object is needed. We utilized a size 5 football to act as a consistent, widely-accessible 3D scale parameter in scans.

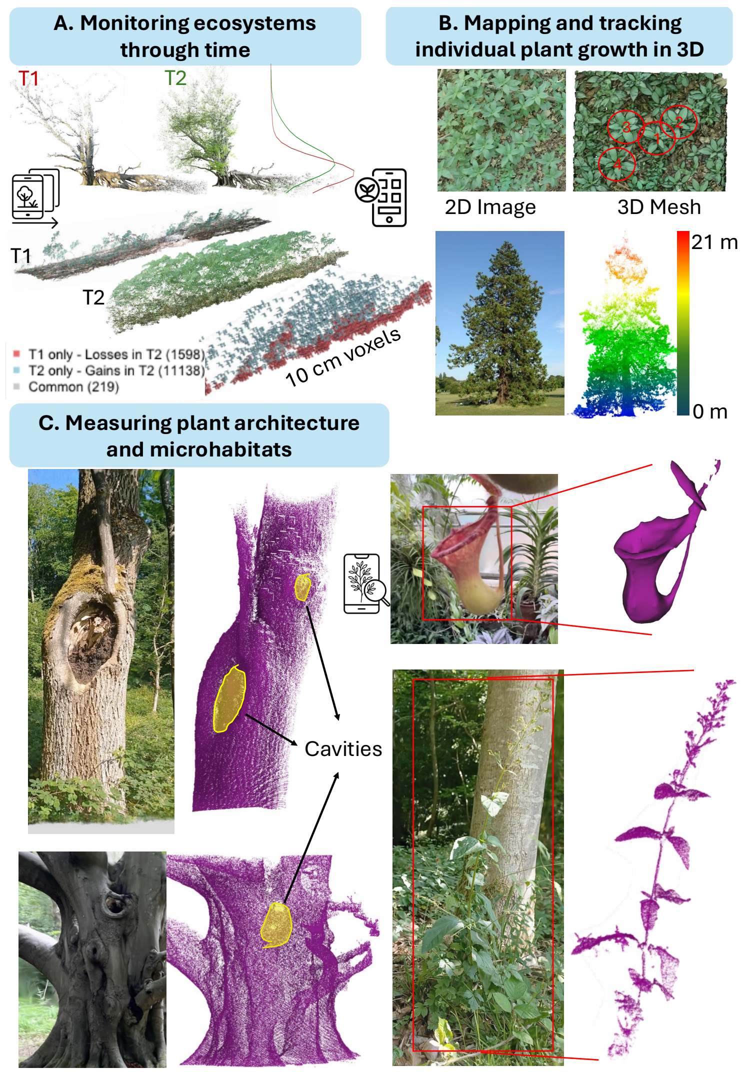

Figure 1: This multi-panel figure showcases NeRF-enabled 3D mapping across scales and through time. **(A)** Monitoring ecosystems through time: Dense point clouds of the same tree reconstructed at two dates (T_1 in red vs. T_2 in green) reveal canopy development, with an overlaid vertical distribution 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.

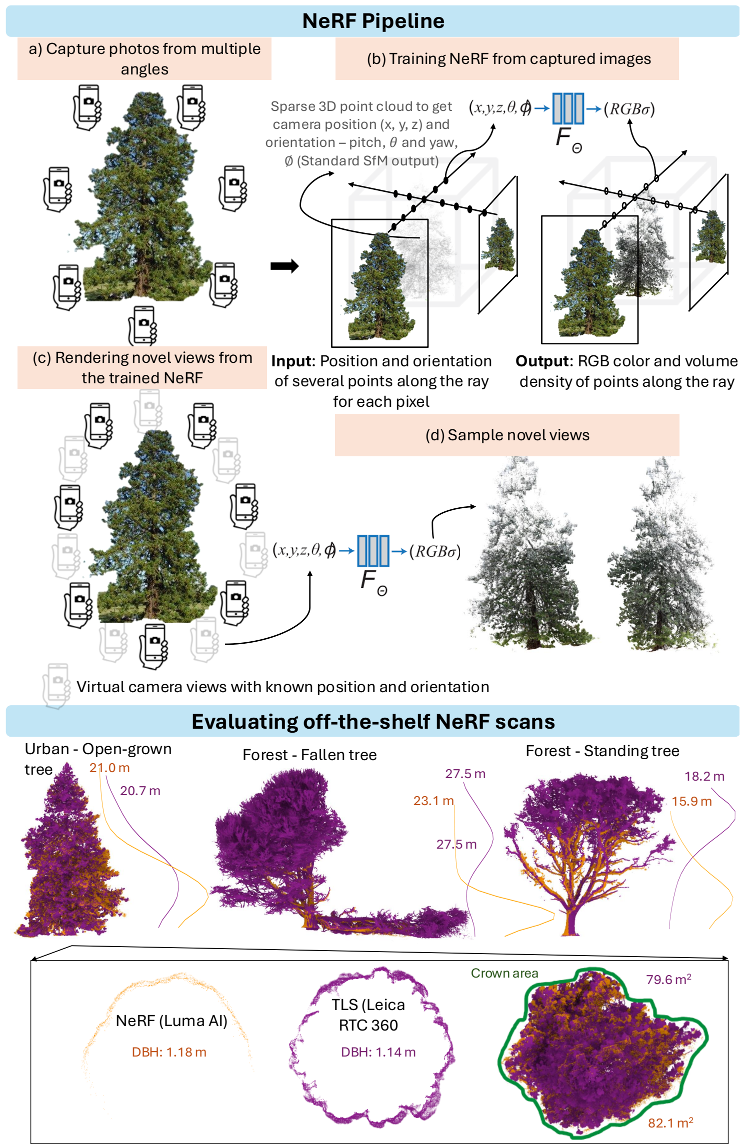

Figure 2: **NeRF Pipeline and Evaluation of Off-the-Shelf Scans. Top row** illustrates the end-to-end NeRF workflow: **(a)** Multiple overlapping photographs are captured around a target tree. **(b)** A standard Structure-from-Motion (SfM) step recovers a sparse 3D point cloud and camera extrinsics (x, y, z, θ, ϕ), which are used to train the neural radiance field F_Θ to predict colour and density (r, g, b, σ) at any 5D query. **(c)** Once trained, F_Θ renders novel views by sampling rays through the learned volume. **(d)** These rendered viewpoints are then re-sampled to produce a dense, coloured 3D point cloud. **Bottom row** compares NeRF-derived reconstructions (orange) against terrestrial laser scanner (TLS) data (purple) for three exemplar trees. To the right of each tree are the vertical point density distributions of the two point clouds. Footprint and cross-section plots at breast height (1.3 m) demonstrate matching stem diameters (DBH: 1.18 m vs. 1.14 m) and near-identical crown area estimates (79.6 m^2 vs. 82.1 m^2).