Radiance field methods as a representational paradigm in ecology

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Data Availability

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

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Abstract

1. High-resolution ecological data are fundamental to understanding the structure, function, and change of ecosystems. Yet, the ways we capture and represent these data have remained largely constrained by expensive instruments and narrowly defined measurement paradigms. Here, we propose that radiance fields, representations that encode the color and density of points in a system, offer a powerful and general additional to any existing ecological observation framework. Radiance field models preserve not only geometry but also texture, reflectance, and viewpoint-dependent properties of ecosystems, enabling reusable and reinterpretable datasets as analytical methods advance.

2. We illustrate the democratizing potential of this technology using mobile implementations of neural radiance fields (NeRFs) captured with consumer-grade smartphones across open-grown and forested environments. Despite operating without specialized sensors, these reconstructions reproduce key structural metrics with high fidelity relative to terrestrial laser scanning (TLS), while providing photorealistic, fine-scale renderings of vegetation. Beyond structural measurement, the same radiance field parameterization enables new analyses, volumetric slicing, virtual flythroughs, and temporal change detection, derived entirely from image data.

3. Drawing on ecological and computational literature, we also outline areas in which radiance field methods should improve to better serve the ecological community. We highlight five key areas for increased collaboration and focus: addressing occlusions, pieces of the canopy obscured due to vegetation; scale ambiguity; interpretability; computational efficiency; and benchmark alignment.

4. By reframing radiance fields as a novel way to represent ecological data rather than as simply a reconstruction tool, we outline a path toward more democratized, flexible, and enduring modes of environmental monitoring. We show that, not only do radiance field methods represent a standalone mode of monitoring an ecological system, but fill a need in existing monitoring methodologies. As radiance field methods continue to evolve, they promise to make ecological datasets both more accessible and more expressive, supporting a shift from static measurement to dynamic, light-based understanding of ecosystems.

1 Introduction - from measurement to representation

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 [United Nations, Department of Economic and Social Affairs, 2024], so too does the demand for tools and techniques that can monitor, understand, and forecast ecological change across a range of spatial and temporal scales. Vegetation structure is a key indicator of biodiversity [Storch et al., 2023, Winter et al., 2011, Ozanne et al., 2003, Gao et al., 2014]. Along with structure, there is a need for additional data when measuring biodiversity and ecosystem change [Purvis and Hector, 2000]. For decades, fixed-point photos have been used as a measure of environmental change [UK Environmental Change Network, 2024]. Additionally, a key link between biodiversity and climate is the measurement of carbon storage which fundamentally relates to measurement of structure [West et al., 2023]. Optical and laser scanners operated from spaceborne and/or airborne platforms offer broad coverage and important context. However, resolving the small-scale, fast-moving ecological processes that drive local ecosystem change like seedling growth, branch loss, etc. requires near-range remote sensing with finer spatial and temporal resolution [Dietze et al., 2018].

Recent innovations in close-range remote sensing technologies (unmanned aerial vehicles (UAVs) - LiDAR and structure-from-motion (SfM hereafter) from images, terrestrial laser scanning (TLS hereafter), mobile laser scanning (MLS hereafter)) have made tree- and plot-scale monitoring practical and far more detailed than satellite products. However, trade-offs remain: UAVs can cover large areas cheaply but struggle with fine, occluded structures and view-dependent appearance [Maboudi et al., 2023, Dainelli et al., 2021]. TLS and MLS can deliver 3D data at high spatial resolution yet are costly to deploy, generate large data volumes, and can miss small understory vegetation due to line-of-sight and signal-to-noise limits [Calders et al., 2020]. These cost, logistical, and processing burdens limit re-survey frequency and the capture of the finest spatial detail (branch- and sapling-scale) [Boucher et al., 2021, Verhelst et al., 2024].

Here, we introduce radiance fields as a means of filling the gap in extant ecological pipelines. By learning a continuous, view-dependent light field from a set of overlapping images, radiance fields can produce photorealistic, metrically useful 3D reconstructions from consumer-grade cameras or drone imagery. This makes them uniquely well suited to high-frequency, fine-scale monitoring. We focus on radiance fields not merely as reconstruction methods but as long-lasting, light-based ecological data representations: compact, re-visitable parameterizations that preserve geometry, appearance, and viewpoint-dependent effects, that can be reprocessed as algorithms and sensors evolve. We argue that these improvements allow for new opportunities for ecological study from light penetration studies [Koop and Sterck, 1994] to fine-scale vegetation structure [Nuijten et al., 2024] to viewshed analysis [Aben et al., 2018]. The recent innovations in 3D computer vision, *i.e.* radiance field methods, now enables 1) the capturing of high resolution 3D data at an unprecedented spatial and temporal resolution 2) the capturing of functional signals beyond structure 3) the democratization of 3D data collection and processing by leveraging consumer-grade imaging hardware 4) the creation of reusable data archives. Within these arguments, we provide a guide for ecologists asking how radiance field methodologies integrate into their existing data collection methods.

2 What are radiance fields and why care?

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, a ray is marched through each image-plane pixel, sampling the field along that ray, and compositing 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 [Rabby and Zhang, 2024]. Among them are Neural Radiance Fields (NeRFs) [Mildenhall et al., 2020] and Gaussian Splatting [Kerbl et al., 2023] (*c.f.* Box 1). Regardless of reconstruction technique, radiance field methods begin with a sparse 3D point cloud that is created using a Structure-from-Motion technique such as COLMAP [Schönberger and Frahm, 2016]. 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 (*c.f.* Figure 2). 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. 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 [GSMA, 2024], 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 complement and future-proof days of manual labour or expensive equipment for a brief scan with a device they already carry. Additionally, unlike large LiDAR point clouds, which pose a problem for data storage and retention [Béjar-Martos et al., 2022], radiance field models by definition require only storage of the images. This image-only property allows for not only lighter weight data storage requirements for long term projects but the ability to revisit data as reconstruction techniques improve. Unlike with point clouds which are fixed to the current technological state-of-the-art during capture. Furthermore, fewer images will be necessary for photorealistic 3D reconstruction of objects as reconstruction algorithms evolve. Previous work has shown that phone photographic and LiDAR capabilities can be viable alternatives to specialized equipment [Teacher et al., 2013, Ahamed et al., 2023, Jeftha and Shoko, 2024]. Radiance field methods expand these possibilities further, often outperforming classical photogrammetric methods in reconstructing individual trees and forest canopies while sometimes requiring fewer input images [Huang et al., 2024]. NeRF-based methods have also been applied to crops [Arshad et al., 2024] and integrated into mobile robotic platforms for automated inventories [Korycki et al., 2024].

This representational reframing matters because it changes what aspects of an ecosystem we are able to preserve and interrogate. Traditional point clouds primarily store where surfaces exist [Xia et al., 2020], producing geometry that is indispensable for many ecological measurements, but fundamentally divorced from how vegetation interacts with light [Xia et al., 2020]. By contrast, radiance-field representations capture both geometry and the directional flow of light through a scene, allowing appearance, reflectance, and view-dependent effects to be modeled explicitly rather than treated as noise [Freeman et al., 2025]. Importantly, the encoding of light into surfaces does not mean that radiance fields force ecological analyses to depend on lighting. Because illumination and intrinsic reflectance are modeled separately, radiance fields have the potential to be relit or normalized after capture. This seperation potentially enables ecologists to extract standard, light-independent structural metrics comparable across sites, seasons, and sensors with the proper calibration steps [Rudnev et al., 2021].

At the same time, many questions in plant ecology rely on more than geometry alone. Optical cues such as leaf translucency, pigment-related reflectance, glossiness, and canopy shading patterns directly inform physiological processes, stress responses, and phenological change, yet these are lost in point-cloud–only representations [Li et al., 2023]. By preserving this richer information, radiance fields make it possible to recover traits relevant to plant function (*e.g.*, directional reflectance, early color change, spectral behavior), perform analyses beyond surface geometry (*e.g.*, re-rendering under standardized light, volumetric slicing), and revisit datasets as improved spectral or biophysical inference methods emerge [Zhang et al., 2025]. Thus, rather than replacing existing structural approaches, radiance fields provide a light-aware, calibration-ready, and future-proof representation that preserves both the physical structure and the ecological optical signals needed to address a broader class of ecological questions [Li et al., 2025].

3 Integrating radiance field methods into current workflows

There has been great progress in the 3D monitoring technologies for monitoring forests in the past two decades [Calders et al., 2020]. The field has moved beyond manual surveys towards sophisticated 3D techniques like high-resolution photogrammetry and terrestrial laser scanning [Calders et al., 2020]. These novel methods are vital for accurately evaluating conservation schemes such as REDD, where traditional metrics have often overestimated effectiveness [West et al., 2023]. Yet, while these 3D methods increase accuracy and ecological insight [Marlow et al., 2024], they often come with steep costs: specialised, expensive equipment; technical know-how; and intensive post-processing [Calders et al., 2020, Maeda et al., 2025, Mokroš et al., 2021]. In short, the bottleneck has started to shift from data collection in the field to computational time and efficiency in the lab. Although there have been recent advances in inexpensive LiDAR solutions for ecological data collection [Výboštok et al., 2025], photogrammetry has provided a low-cost alternative to LiDAR over 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 [Mathes et al., 2023, Kükenbrink et al., 2025]. Likewise, radiance field methods also struggle in settings where there are high degrees of occlusion [Tian et al., 2024]. However, as radiance field methods learn a continuous volume encoding scene geometry (density) and appearance (radiance) at every 3D location and viewing direction, they outperform SfM in several areas. Because radiance field methods are trained to render photorealistic novel views from arbitrary camera poses, these methods can fill in previously unseen angles and thin structures, yielding seamless, gap-free reconstructions. Moreover, by sampling the learned volume at any desired resolution, radiance field methods automatically produce denser point clouds than SfM, even in areas with minimal original overlap [Wang et al., 2023]. While radiance-field reconstructions can produce point clouds comparable to, or in some cases less detailed than, those obtained from TLS or classical structure-from-motion [Huang et al., 2024], their relative performance is strongly ecosystem- and scale-dependent. As illustrated in Figure 1 and confirmed by our results in Figure 2, radiance fields are outperform TLS for fine-scale structures such as saplings or small understory vegetation, achieve TLS-comparable accuracy in open ecosystems where full object coverage is possible, and underperform TLS in closed-canopy environments where occlusion limits capture completeness. Their main advantages, photorealistic rendering, fine-structure recovery, and view-consistent appearance modelling, are therefore best realised in settings where sufficient multi-view overlap is achievable.

This combination of continuous representation, high-fidelity rendering, and arbitrarily dense sampling makes radiance field methods particularly powerful for capturing fine-scale understory or open-vegetation structure that discrete SfM often misses or cannot interpolate. 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.

High resolution data are needed not only to understand change on shorter time scales, but also to bring monitoring of the environment closer to the current state of citizen science in other fields, *e.g.* ornithology [Sullivan et al., 2009].

Much as bioacoustics has transformed ornithology [Dickinson et al., 2010], 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 [Schiller et al., 2021] into a much needed, realistic third dimension.

4 The democratizing potential of mobile radiance fields

The ease of use of radiance field 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) [Qi et al., 2025]. 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 as demonstrated in Figure 2. 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 (*c.f.* Box 2).

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 [Teacher et al., 2013, Ahamed et al., 2023, Jeftha and Shoko, 2024, Holcomb et al., 2023, Tatsumi et al., 2023, Borz and Proto, 2025]. 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 [Huang et al., 2024]. Beyond forests, NeRF-based methods have demonstrated reliable three-dimensional morphometric measurements for crop structures [Arshad et al., 2024] and have even been integrated into mobile robotic platforms, such as quadrupedal robots, to automate forest inventories [Korycki et al., 2024]. 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.

5 Limitations

We emphasize several practical and conceptual limitations that must be addressed for radiance field methods to mature as reliable ecological tools.

First, image-only radiance field reconstructions remain highly susceptible to occlusion. Dense canopies, overlapping foliage, and shadowed understories introduce large unobserved volumes that bias structural estimates and reduce reconstruction completeness. While there has been some research in this area [Liu and Kong, 2025], occlusion still marks a serious problem for ecologists [Kükenbrink et al., 2025]. Unlike active-sensing methods such as terrestrial or mobile laser scanning, which directly measure range [Calders et al., 2020], radiance field approaches must infer geometry from visible features in the images alone. This feature makes them particularly sensitive to missing viewpoints or under-sampled regions [Tao et al., 2025]. Potential solutions include active-view planning and adaptive capture protocols that guide users toward underrepresented angles, as well as fusing imagery across multiple temporal captures or mobile agents to fill occluded volumes.

Second, scale ambiguity remains a central challenge. Radiance field reconstructions trained purely on images lack an intrinsic metric reference, meaning that dimensions such as stem diameter or canopy height can only be recovered if a known scale object or external calibration is provided [Mildenhall et al., 2020]. For ecological applications—where size and volume underpin most functional metrics—this limitation constrains quantitative comparability across studies. Achieving metric consistency will require either automatic fiducial detection within images (recognizing objects of known scale), joint optimization with embedded depth priors, utilizing IMU data from a capture device, or adoption of metrically grounded architectures. Recent advances in metrically consistent 3D reconstruction demonstrate that scale alignment is achievable through learned geometric priors and joint optimization with real-world coordinate frames [Keetha et al., 2025]. Implementing these approaches in ecological pipelines would allow radiance field data to integrate directly with existing LiDAR and photogrammetric datasets, enabling more robust cross-ecosystem comparisons.

Third, current mobile pipelines trade off between photorealism and metric fidelity. Applications optimized for consumer use often prioritize visually pleasing reconstructions over geometric accuracy, applying aggressive regularization and mesh smoothing that can obscure fine structural details such as small branches or leaf clusters. For ecological purposes where these fine structures influence light interception, transpiration, and habitat microstructure—preserving geometric detail is essential. Open-source and research-grade NeRF frameworks, in contrast, enable tuning of model parameters to balance visual quality with quantitative accuracy. Developing standardized ecological benchmarks that assess not only visual fidelity but also structural realism will be key to ensuring reproducibility and comparability across studies.

Fourth, computational efficiency and accessibility remain limiting factors. Training radiance field models typically requires specialized hardware (GPUs) and substantial processing time or the use of blackbox server processing in a free-to-use mobile app, constraining large-scale or real-time deployment. Alternatives such as Gaussian Splatting, point-based radiance fields, and model compression offer promising routes in terms of either rendering or computation efficiency which point toward on-device inference and field-ready workflows [Chen et al., 2023]. Future development should aim for portable, efficient architectures that can be executed on smartphones, edge devices, or autonomous platforms without cloud dependence.

Finally, there is a need for clearer alignment between ecological requirements and computer-vision benchmarks. Ecologists typically prioritize metrics such as small-scale measurement accuracy, reproducibility, and interpretability, whereas radiance field research often focuses on visual fidelity, rendering speed, and generalization performance [Tao et al., 2025, Wang et al., 2024]. Bridging this gap will require shared benchmark datasets that include both radiometric and biological ground truth, along with standardized metrics linking ecological relevance to computational performance. Collaborative efforts between ecologists and computer scientists could define evaluation protocols where, for example, canopy height accuracy or crown area estimation errors are considered alongside photorealism and rendering efficiency. Establishing such interdisciplinary standards would allow radiance field methods to evolve toward tools that are not only visually impressive but ecologically meaningful.

In summary, addressing occlusion, scale, fidelity, and benchmarking challenges will determine how radiance field methods transition from demonstration to dependable ecological instrumentation. As metrically consistent and hybrid models emerge, and as ecological benchmarks begin to influence model design, radiance field methods are poised to become central to a new generation of ecological monitoring—one that captures the complexity of living systems in both form and light.

6 Future directions

6.1 Short-term improvements for radiance fields in ecology

To realize the full potential of radiance field methods as ecological data representations, their future evolution must balance algorithmic sophistication with ecological relevance. This goal will require closer collaboration between computer vision researchers developing new architectures and ecologists defining what constitutes meaningful environmental information. We outline several directions that are both technically feasible and ecologically impactful.

6.1.1 Toward metrically consistent and uncertainty-aware models

Ecological measurements depend on reliable scale and quantified errors. Next-generation radiance field models should embed explicit metric priors, through integrated depth cues, calibration tag detection, utilize inbuilt IMU in the capture device, or co-registration with low-cost LiDAR, to ensure that reconstructions are expressed in real-world units. Utilizing LiDAR maps has shown promise in achieving metric consistency such as previous work by Chang et al. [2023]. Beyond absolute scale, uncertainty quantification is crucial: probabilistic radiance fields that propagate confidence through volumetric sampling would allow ecologists to assess where reconstructions are reliable and where occlusion or noise dominate. These developments would transform radiance fields from aesthetic reconstructions into quantitative instruments suitable for long-term ecological monitoring.

6.1.2 Expanding beyond RGB to spectral and multimodal representations

Most current radiance field models operate on standard RGB imagery, yet many ecological traits, such as chlorophyll concentration, water stress, or species identity, are expressed in non-visible spectral bands [Zhao et al., 2021]. Integrating hyperspectral or multispectral data into radiance field parameterizations would allow joint inference of structural and biochemical properties. These "spectral radiance fields" could unify geometry, reflectance, and physiology, enabling analyses that connect structure to function. Lightweight multisensor rigs (*e.g.*, RGB plus near-infrared) or drone-based imaging platforms could serve as early testbeds for these hybrid ecological models.

6.1.3 Democratizing capture and computation

For radiance field methods to become genuinely transformative, they must be deployable by non-specialists using accessible hardware. Progress in Gaussian Splatting [Kerbl et al., 2023] and point-based radiance fields [Xu et al., 2023] now allows near real-time training and/or rendering on consumer devices. Embedding simplified capture guidance and automated quality checks within mobile applications could make 3D ecological documentation as straightforward as taking a panorama photograph. Combined with standardized metadata capture—GPS, time, illumination—such workflows could enable crowdsourced, globally distributed ecological monitoring networks.

6.1.4 Building shared benchmarks and ecological standards

A central step toward the ecological adoption of these technologies is the creation of open benchmark datasets that couple radiance fields with verified ground truth. These datasets should include diverse habitats (forests, grasslands, coral reefs, urban vegetation) and annotate both geometric and functional attributes. Evaluation protocols should report not only rendering fidelity and reconstruction completeness, but also ecologically relevant metrics such as canopy height error, crown volume bias, and species-level segmentation accuracy. By defining such standards, the ecological community will be able to guide machine-learning development toward tools that serve specific research and conservation goals.

6.1.5 Integration with autonomous and temporal sensing

Finally, future ecological radiance fields should incorporate temporal dynamics and mobility. Radiance-field-based mapping from drones, quadrupedal robots, or fixed stations could track ecosystem change over days to years, providing volumetric time series of vegetation growth, senescence, and resilience. Temporal radiance fields, which treat time as an additional input dimension, have already been demonstrated in controlled settings and could form the foundation for continuous ecosystem monitoring frameworks [Park et al., 2023]. There is also a rich literature on using radiance fields for change detection, which shows promise in application to ecological monitoring and conservation [Huang et al., 2023, Lu et al., 2025].

6.1.6 Protocol standardization

Collectively, these developments point toward a mature framework in which radiance fields are not simply visualizations of nature, but scientific data objects: metrically grounded, spectrally rich, temporally aware, and globally shareable. Achieving this vision will require interdisciplinary coordination and shared infrastructure, but the outcome, a universally interpretable, light-based representation of ecosystems, would mark a profound advance in how ecology perceives, archives, and understands the living world.

6.2 Long-term vision

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 [Storch et al., 2023], species identification [Zhao et al., 2021], biodiversity mapping [Qi et al., 2025], and habitat characterization [Dietze et al., 2018]. 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 [Qin et al., 2023] and providing fine-resolution insights into ecosystem productivity and responses to environmental change [DuBois et al., 2018]. 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 [Aguirre-Gutiérrez et al., 2025] and coral reefs [Mills et al., 2023]. 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. Recent advances in radiance field methods such as neural exposure field [Niemeyer et al., 2025] also offer increased understanding of the light environment of a scene, a benefit that may pose significant interest to ecologists interested in growth dynamics.

Radiance field methods offer scalable 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 [Depauw et al., 2022] 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. 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.

Equally important is the democratizing potential of these methods. Because radiance field capture relies only on cameras, citizen scientists, local communities, and researchers in resource-limited regions can contribute high-quality 3D ecological data at large spatial scales Qi et al. [2025]. Standardized mobile workflows and open repositories could create global archives of radiance field data, comparable to eBird or iNaturalist, but in 3D. To realize this vision, collaboration is needed between ecologists and computer vision researchers to refine benchmarks, address challenges like scale calibration and occlusion, and extend radiance field models to multispectral and temporal domains. The convergence of ecological and computational paradigms may thus redefine not only how we measure ecosystems, but how we see them.

7 Conclusion

Radiance fields represent a fundamental advance in how ecological systems can be captured, monitored, represented, understood, and managed. By encoding both geometry and radiance, these approaches transform scenes into living datasets which are continuously interpretable, visually expressive, and adaptable to new analytic techniques. Their compatibility with everyday hardware and their openness to reprocessing make them uniquely suited to democratize ecological monitoring. As these methods mature, they may usher in a new era of ecological observation wherein the world's ecosystems are represented not as static collections of points, but as dynamic fields of light and life.

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Glossary of Radiance Field Terms for Ecologists

Continuous Representation – Unlike discrete point clouds, radiance fields store scenes as mathematical functions, allowing resampling, re-rendering, and reanalysis at arbitrary resolutions.

Density / Opacity (σ) – A measure of how much light is absorbed or scattered at a point in space; directly related to material presence.

Gaussian Splatting – A radiance-field variant that represents surfaces as overlapping 3D Gaussians ("splats") rather than as a dense voxel grid, allowing fast and visually smooth reconstructions.

Neural Radiance Field (NeRF) – A neural network implementation of a radiance field that learns this mapping from overlapping 2D photographs, enabling rendering from novel viewpoints.

Rendering Equation – The physical equation that describes how light is emitted, absorbed, and scattered in a scene; NeRFs learn an approximation of this process.

Radiance (r, g, b) – The color or intensity of light leaving a point in a given direction.

View-dependent Effects – Changes in appearance (*e.g.*, specular reflection) that depend on camera angle; preserved by radiance-field methods but not by traditional point clouds.

Radiance Field – A continuous function that maps every 3D point (x, y, z) and viewing direction (θ, ϕ) to color and density values, describing how light interacts with a scene.

Structure-from-Motion (SfM) – A classical photogrammetric approach that reconstructs geometry by matching points across multiple overlapping photographs.

Terrestrial Laser Scanning (TLS) – A LiDAR-based technique producing precise 3D point clouds by measuring the return time of emitted laser pulses.

Box 1: Conceptual glossary summarizing key radiance-field terminology and their relevance for ecological monitoring.

Practical Guidance for Mobile Radiance Field Capture

Camera Path: Maintain constant distance and speed; encircle the target while varying elevation slightly to capture top and side views.

Capture Device: Modern smartphones (iPhone 12 Pro or later; Android equivalents with multi-lens cameras).

Data Management: Record GPS location, lighting conditions, and device metadata to support reproducibility and ecological interpretation.

Environment: Prefer diffuse lighting (overcast or shaded) to avoid glare and hard shadows that degrade reconstructions.

Image Count: 20–200 (depending on complexity) overlapping photographs or a smooth 10–20 s video orbit around the subject.

Output: Save both the rendered 3D model and the learned radiance-field parameters for future reprocessing as algorithms evolve.

Processing: Upload imagery to NeRF-based mobile applications (*e.g.*, Luma AI, Polycam, RealityScan) or open-source pipelines for local reconstruction.

Scale Reference: Include a known-size object (*e.g.*, a football or calibration pole) visible from multiple angles for metric scaling.

Validation: Compare derived point clouds or volumetric renders against known field measurements (*e.g.*, DBH, tree height).

Box 2: Step-by-step best practices for capturing ecological radiance-field data with consumer-grade devices.

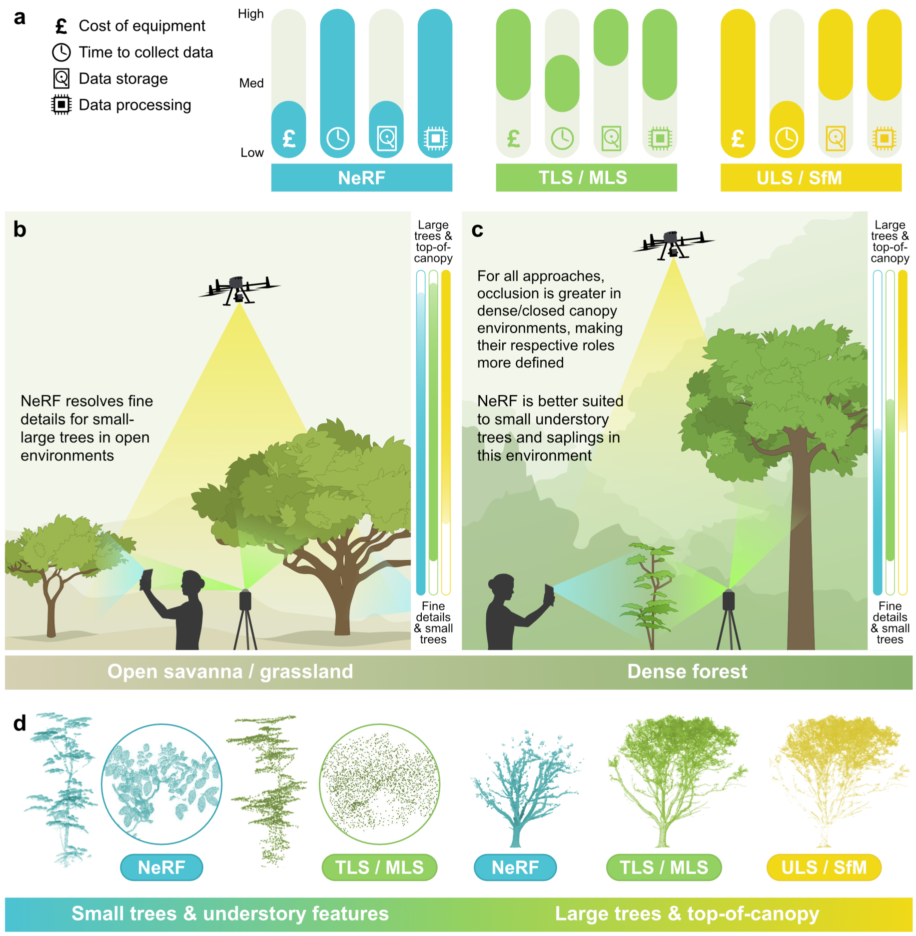

Figure 1: Comparison of neural radiance fields (NeRF), terrestrial laser scanning/mobile laser scanning (TLS/MLS), and unmanned aerial vehicle scanning/structure-from-mtoin (ULS/SfM) approaches for ecological 3D reconstruction across environments. (a) Relative cost, time, storage, and processing demands for mobile NeRF capture, terrestrial/mobile laser scanning (TLS/MLS), and UAV-based LiDAR or structure-from-motion (ULS/SfM). Consumer-grade NeRF methods have low equipment cost and data volumes but higher processing demands, whereas TLS/MLS requires expensive instruments and generates heavy datasets. (b) In open savanna and grassland systems, NeRF resolves fine structural details of small and large trees due to reduced occlusion, while TLS/MLS provides detailed geometry from ground level. (c) In dense or closed-canopy forests, occlusion affects all methods, but NeRF excels at reconstructing understory vegetation, saplings, and small-diameter structures, while TLS/MLS and ULS/SfM are more effective for larger stems and upper canopy structure. (d) Summary of method suitability across structural scales: NeRF best captures small trees and understory features; TLS/MLS excels at mid- to large-scale geometry; ULS/SfM is optimal for large trees and top-of-canopy structure.

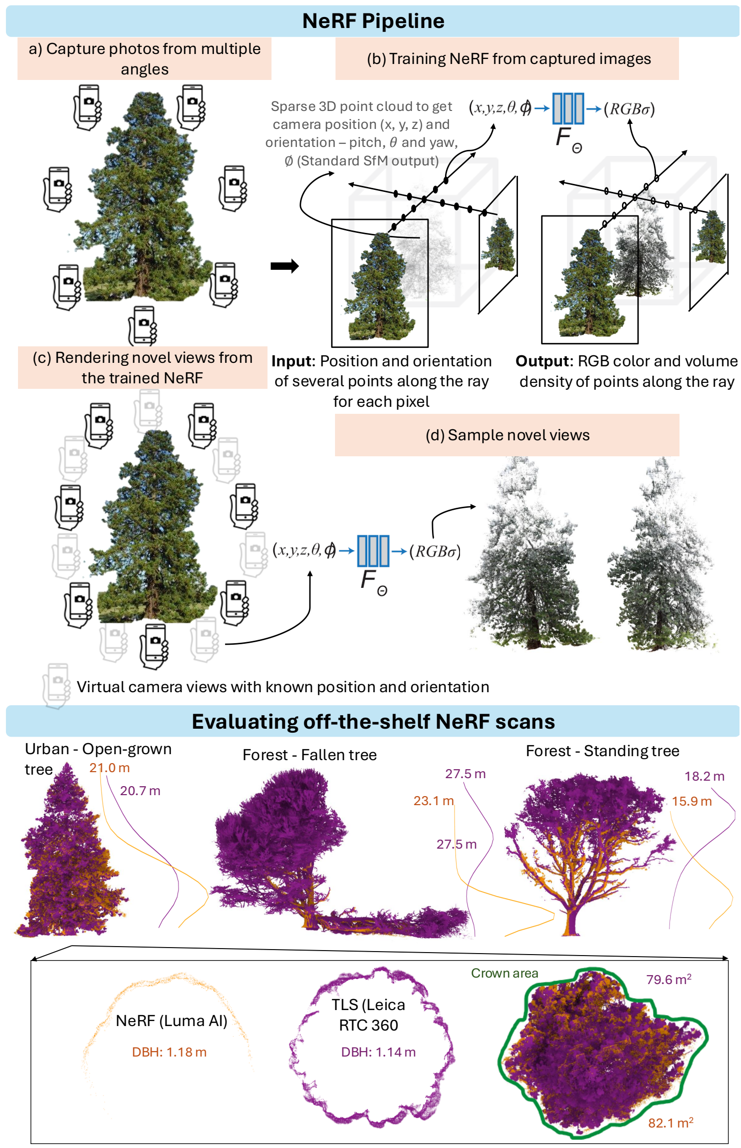

Figure 2: NeRF pipeline and evaluation of off-the-shelf scans. The top row illustrates the end-to-end NeRF workflow: **(a)** Multiple overlapping photographs are captured around a target tree. **(b)** A standard Structure-from-Motion (SfM) step recovers a sparse 3D point cloud and camera extrinsics (x, 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).

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

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. Images were then uploaded and processed in Luma and exported as point clouds for evaluation.

C 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].

D 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).

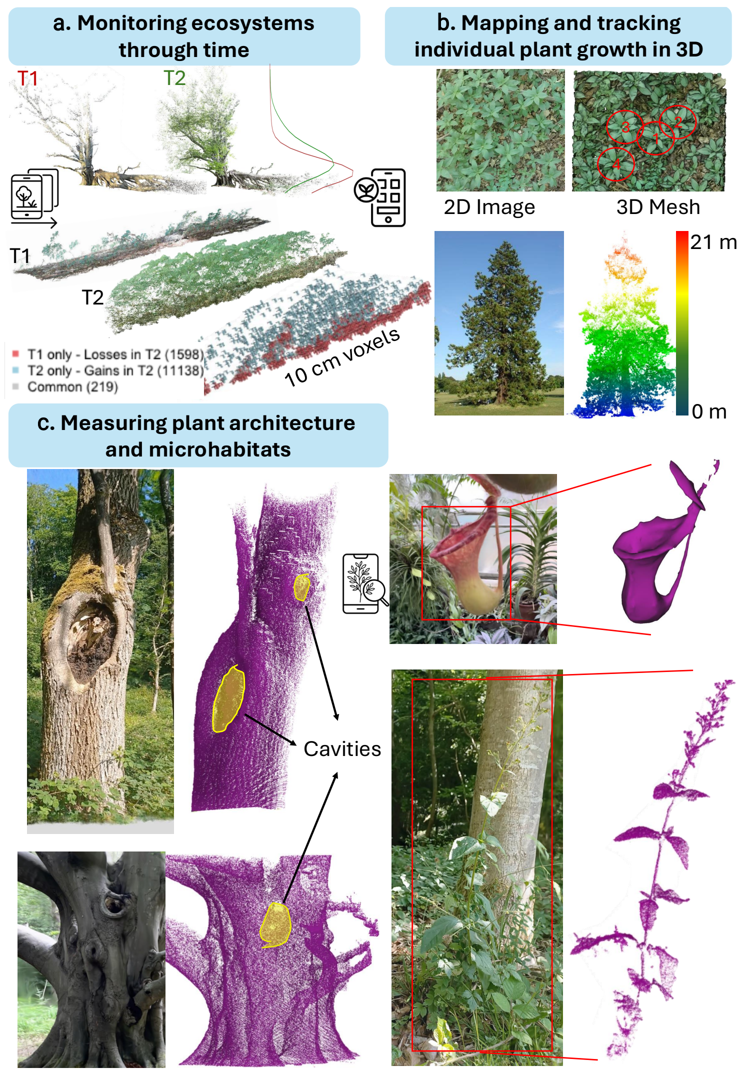

Figure S1: This multi-panel figure showcases NeRF-enabled 3D mapping across scales and through time. **(a)** Monitoring ecosystems through time: Dense point clouds of the same tree reconstructed at two dates (T_1 in red vs. T_2 in green) reveal canopy development, with an overlaid vertical distribution 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.