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RESEARCH ARTICLE

Advancing plant biomass measurements: Integrating smartphone-based 3D scanning techniques for enhanced ecosystem monitoring

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Abstract

1. New technological developments open novel possibilities for widely applicable methods of ecosystem analyses. We investigated a novel approach using smartphone-based 3D scanning for non-destructive, high-resolution monitoring of above-ground plant biomass.
2. This method leverages Structure from Motion (SfM) techniques with widely accessible smartphone apps and subsequent computing to generate detailed ecological data. By implementing a streamlined pipeline for point cloud processing and voxel-based analysis, we enable frequent, cost-effective and accessible monitoring of vegetation structure and plant community biomass.
3. Conducted in long-term experimental grasslands, our study reveals a high correlation (R^2 up to 0.9) between traditional biomass harvesting and 3D volume estimates derived from smartphone-generated point clouds, validating the method's accuracy and reliability. Additionally, results indicate significant effects of plant species richness and fertilization on biomass production and volume estimates, underscoring the potential for high-resolution temporal and spatial analyses of vegetation dynamics.
4. This method's innovation extends beyond traditional practices with implications for future integration of AI to automate species segmentation, ecological trait extraction and predictive modelling. The simplicity and accessibility of the smartphone-based approach facilitate broader engagement in ecosystem monitoring, encouraging citizen science participation and enhancing data

Peter Dietrich and Melanie Elias shared first authorship.

collection efforts. Future research will make it possible to refine the accuracy of point cloud processing, expand applications across diverse vegetation types and explore new possibilities in ecological monitoring, modelling and its application in ecosystem analyses and biodiversity research.

KEYWORDS
biodiversity, photogrammetry, Scaniverse, vegetation height, vegetation structure

1 | INTRODUCTION

Biodiversity is declining dramatically due to the effects of global change, with unknown consequences for human life on Earth (Cardinale et al., 2012; Habibullah et al., 2022; Keesing & Ostfeld, 2021). In recent years, more and more research has been carried out on this topic in order to better predict the consequences of global change and to understand its underlying processes. Flagships of such research are biodiversity experiments, such as Cedar Creek (Tilman et al., 1997) and the Jena Experiment (Weisser et al., 2017), globally distributed experimental studies in natural grasslands, such as Drought Network (Smith et al., 2024) or the Nutrient Network (Borer et al., 2014), and research infrastructures along natural diversity or land-use gradients such as the Biodiversity Exploratories (Fischer et al., 2010) or TERENO in Germany (Zacharias et al., 2024) and eLTER in Europe (Mollenhauer et al., 2018; Ohnemus et al., 2024). All of these platforms share a common focus on conducting long-term research on fundamental ecological and ecosystem processes, as well as the impacts of global environmental change. This research is crucial for improving our understanding of how the environment is changing and how our life on Earth may be affected in the near future. A common variable studied in these research facilities is above-ground plant biomass, serving as a proxy for plant productivity, which is a fundamental component of ecosystem functioning. The most frequent method to determine above-ground biomass is to harvest the plants at ground level on a defined area, followed by drying and weighing (there are also alternative non-destructive methods (López-Díaz et al., 2011), which are, however, used comparatively rarely).

Despite its simplicity and relatively low cost, the harvest method has notable limitations: Repeated destructive biomass harvest can change plant growth and can therefore not be repeated in short time intervals on permanent plots. Estimating actual productivity, which entails measuring rates of biomass change rather than just the standing stock, however, requires long-term series of biomass data over multiple seasons. Furthermore, destructive sampling offers only a coarse temporal and spatial resolution, limiting the ability to capture detailed variation in vegetation structure.

In recent years, advanced and modern techniques for measuring plant productivity have emerged, allowing for higher resolution temporal and spatial measurements through 3D scanning and computational analysis of resulting digital point clouds (Kolhar & Jagtap, 2023; Lausch et al., 2020). Active sensing methods are often summarized as 'LiDAR' (Light Detection And Ranging) and include among others airborne (ALS), mobile (MLS) and terrestrial laser scanning (TLS), which have become well-established for high-precision 3D vegetation mapping, especially in forestry applications (Bienert et al., 2021, 2024; Demol et al., 2022; Richter & Maas, 2022). However, laser scanning has one decisive disadvantage: The required equipment and software are prohibitively expensive and often inaccessible to many researchers. Passive/optical sensing methods using cameras are of particular interest in today's on-site crop growth monitoring. Alternative optical methods include the light-field measurement approach (Hu et al., 2023; Schima et al., 2016), which, while innovative, currently lacks commercially available cameras suitable for this purpose. Another approach is stereoscopy, which derives structural vegetation properties, although it requires calibrated permanent installations and continuous power supply (Dandrifosse et al., 2020; Kobe et al., 2024).

An additional promising method is Structure from Motion (SfM), which uses standard cameras to derive the structural properties of plant communities (Cooper et al., 2017; Enterkine et al., 2025; Kröhnert et al., 2018). This technique holds significant potential for extracting structural features of plant communities at the plot level (Enterkine et al., 2025). There are already some approaches using this technique for ecosystem monitoring, but they usually involve expensive cameras (e.g. DSLR cameras) and rather complex processing methods (Enterkine et al., 2025). Here, we present a new approach that makes the SfM method easily accessible (i.e. inexpensive and simple to implement) to everyone (e.g. researchers with limited funding, graduate workers, citizen scientists and farmers) by using a smartphone and freely available 3D scanning apps. Given that nearly everyone owns a smartphone, and that smartphone camera technology has seen rapid advancements in recent years, we see huge potential for ecosystem monitoring. Modern smartphones come with features such as multiple lenses, image stabilization, autofocus and cameras with at least 40 megapixels, capable of producing high-resolution images comparable to those taken with SLR cameras.

Modern smartphone cameras enable photogrammetric image processing, such as SfM, widely applied in geosciences. Even low-resolution smartphones (e.g. 5 MP) can achieve centimetre-precision terrain models, particularly in small-scale applications (Micheletti et al., 2015). Higher resolution cameras and post-processing enhance accuracy, making smartphones viable for close-range surveying. The integration of LiDAR sensors in consumer smartphones, such as the iPhone 12 Pro, has improved topographic surveying, enabling ±1-cm accuracy for small objects and ±10 cm for larger structures (Luetzenburg et al., 2021). While LiDAR enhances depth perception, smartphones without it still achieve accurate 3D reconstructions via image-based depth estimation. Chiappini et al. (2024) compared smartphone-based SfM, LiDAR and Neural Radiance Fields (NeRF) to professional MLS, analysing tree height, canopy base height and canopy volume. Smartphone-based methods underestimated larger trees due to MLS's greater acquisition range, though this limitation may be less relevant for small-scale plant monitoring. Despite these constraints, smartphone-based techniques remain cost-effective alternatives for urban tree assessments, balancing accessibility and accuracy.

Beyond the hardware, the software side has also evolved significantly. Freely available apps such as Scaniverse (Niantic Inc., San Francisco, CA, US) or Polycam (Polycam, San Francisco, CA, USA) now enable users to perform 3D scans of above-ground vegetation. The process is straightforward: users simply open the app, scan the vegetation and the app processes the captured images (which takes about 1–2 min) before generating a point cloud. This point cloud can then be used to estimate vegetation variables, such as growth height and biomass production. This approach allows for repeated, low-cost and non-invasive data collection at daily, weekly or monthly intervals, providing a more accurate and detailed monitoring of plant communities. This can be, for example,

- temporal dynamics—regular or even automated sampling enables estimates of biomass production rates and growth strategies over time,
- vegetation structure and spatial variation—3D point clouds enable a detailed analysis of vegetation structure, including spatial heterogeneity,
- phenological patterns—by capturing changes in colour, greening and flowering phenology can be quantified.

Moreover, the ability to scan plants with smartphones opens up numerous possibilities for citizen science, since people can collect data and provide important additional quantitative and qualitative information (Koedel et al., 2022; von Gönner et al., 2023). Other conceivable uses would be the investigation of protected or sensitive plant communities through time (Tirrell et al., 2023) where harvesting is not permitted or possible, or for teaching, in order to better explain structural interrelationships.

In the present work, we tested whether 3D scans with smartphones generally produce similar results to those of traditional biomass harvesting in a long-term grassland experiment. As part of this research, we aim to provide initial guidance on optimal ways to scan vegetation with a smartphone and, in particular, how to subsequently process the resulting point clouds to generate biomass-like data.

2 | MATERIALS AND METHODS

In the following, we analyse vegetation structure and biomass production in the DivResource Experiment (Bad Lauchstädt, Germany) as a case study to outline our use of consumer-grade 3D scanning via Scaniverse for scaled vegetation modelling, forming our basis for biomass quantification.

2.1 | Study site

The study was conducted in experimental grasslands (DivResource Experiment) established at the Feld Station of the Helmholtz Centre for Environmental Research (UFZ) in Bad Lauchstädt, Germany (51°23′38″ N, 11°52′45″ E, 118 m a.s.l.) in 2011 (Siebenkäs et al., 2016). The site has an average annual temperature of 9.5°C and 492 mm of precipitation (1981–2010). Eight perennial plant species (four forbs, four grasses), typical of Central European mesophilic grasslands, were selected and divided into two independent species pools. Sown species richness levels are 1, 2 and 4 with paired fertilized and unfertilized experimental plots, respectively. Plots of 2 × 2 m area (later reduced to 1 × 1 m) and arranged in four experimental blocks were weeded three times per year to maintain the sown species combinations. The experiment was mown twice annually (early June, September), and the mown biomass was removed. Fertilization (NPK as pellets, 120:52:100 kg ha^{-1} year^{-1}) was applied distributed with two even doses (March and June after first mowing) from 2012 to 2023. Permission for fieldwork was not required.

2.2 | 3D scans and biomass sampling

On 4 September 2024, we scanned the vegetation in the monocultures and four-species plots from a single species pool, that is two monoculture plots of *Lolium perenne* L., *Dactylis glomerata* L., *Prunella vulgaris* L. and *Knautia arvensis* (L.) Coulter, respectively, and four plots containing all four species (Siebenkäs et al., 2016). To do this, we used a wooden frame with a 0.3 × 0.3 m inner surface (made of 0.25-m-wide planks; Figure 1a) to define a specific sub-area per plot (position was randomly chosen in the plot with a sufficient distance from the plot margin). We then used an iPhone 15 Pro and the app Scaniverse to scan the defined area. The Scaniverse app, which is available for free download from the Apple Store and Google Play Store, was chosen over alternatives due to ease of use, fast scanning speed and high-quality results. Scaniverse leverages the advantages of LiDAR on compatible devices such as iPhones, while also being fully functional on Android devices without LiDAR, utilizing alternative onboard sensors. This flexibility makes it broadly accessible across different smartphone models, and the technical distinctions are explored in detail in the following section.

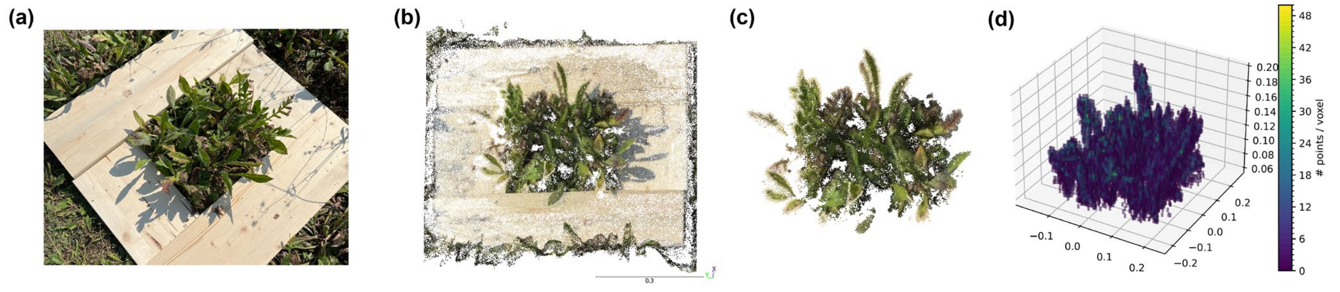

FIGURE 1 Vegetation in the field with the wooden frame around (a), original point cloud from Scaniverse (b), clipped point cloud (c) used for voxel space calculation (d). Illustrated is a fertilised 4-species mixture plot (voxel size 5 mm).

2.2.1 | Technical architecture of Scaniverse

Scaniverse enables users to create high-quality 3D scans of environments and objects using modern smartphones, including iPhones with LiDAR and Android devices capable of real-time multi-view stereo (MVS) processing. It captures RGB images and depth data, reconstructing 3D geometry via MVS techniques, which compute a dense point cloud or triangulated mesh from multiple viewpoints (Sayed et al., 2022, 2024; Van Brummelen et al., 2024).

Simultaneous Localization and Mapping (SLAM) ensures spatial coherence and device tracking (e.g. Davison, 2003), possibly leveraging Niantic's Lightship ARDK for pose estimation (Niantic Inc, 2023). Real-time visual feedback, such as rendered meshes and feature overlays, improves usability and scan completeness (Numan et al., 2025). Scaniverse integrates efficient mobile processing, including sparse inference to reduce computational load and lightweight neural networks, allowing initial scene understanding with minimal manual input (Van Brummelen et al., 2024). Advances such as *SimpleRecon* enhance high-fidelity 3D reconstruction using optimized metadata and cost volume computation, avoiding heavy 3D convolutions (Sayed et al., 2022).

2.2.2 | Scan modes and processing

Scaniverse offers two scan modes: 'Splat' and 'Mesh'. The 'Splat' mode likely applies Gaussian splatting, representing 3D space with modifiable splats containing colour and depth attributes, but lacks measurable 3D data. Mesh-based scans, however, define geometry explicitly using points, edges and surfaces, ensuring higher point density.

For scanning, we used 'Mesh' mode with 'Small Object', predefined for objects such as flowers, toys and pets. The vegetation was scanned from multiple angles until no red-marked areas remained (visual feedback). Each plot was scanned three times, taking 1–2 min depending on density.

In 'Detail' processing mode, the workflow follows a SfM + MVS workflow, as indicated by the *status messages* displayed during the processing on the device:

1. *Aligning images*: SFM—determining image orientation parameters.
2. *Computing depth*: MVS—dense matching to compute depth information, that is 3D points.
3. *Texturing*: applying image colour information to calculated points.

SfM does not inherently provide scale information. On LiDAR-equipped devices, scale can be derived from the time-of-flight scanning principle, where SLAM incorporates depth data, allowing each image's pose to be estimated within a metric coordinate system. On devices without LiDAR, such as most Android smartphones, scale information is likely obtained from built-in inertial sensors, which can be integrated into SLAM-based pose estimation (e.g. Hamadi and Latoui (2025)). These pose estimations provide an initial guess in SfM, facilitating the determination of image trajectory in a scaled coordinate system, ensuring true-to-scale 3D points. The final 3D point cloud was exported in .ply format via 'Share' (Figure 1b), widely used for 3D visualization.

After scanning, the maximum height of the vegetation in the 0.3 × 0.3 m sub-plot was measured (vegetation height), and finally plants were harvested 3 cm above the ground (i.e. at height of the wooden frame; which is common for harvesting biomass in such grassland experiments). Biomass was weighed before (fresh biomass) and after (dry biomass) drying for 48 h at 60°C.

2.3 | Point cloud and voxel space processing

First, the 3D point clouds were processed using CloudCompare, a free software for visualizing and editing point clouds (CloudCompare (version 2.13.2) [GPL software], 2024, retrieved from http://www.cloudcompare.org/). Each point cloud was manually clipped to focus on the region of interest, specifically removing all 3D points associated with the structure of the wooden frame and all extraneous 3D points (Figure 2). In addition, 3D points with height values below the height of the top board layer were excluded to focus only on 3D points on plant parts at least 3 cm above soil surface consistent with the cutting height of biomass (Figure 1c). Future versions of this process could be automated, possibly using, for example the Python wrapper CloudComPy.

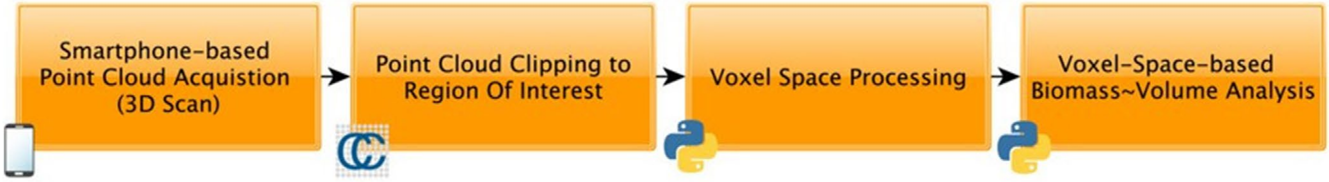

FIGURE 2 Workflow description: After point cloud acquisition via smartphone, point clouds were clipped, voxel space was processed, and finally, relationships between resulting voxel volumes and the harvested biomass were evaluated.

2.4 | Voxel data analyses

To quantify spatial distributions and characteristics within 3D point clouds, we implemented a voxel-based analysis using Open3D (version 0.18.0) in Python (version 3.10, Figure 2). Each point cloud was processed into a voxel grid representation at a resolution of 2.5, 5.0, 7.5 and 10.0-mm^3 per voxel (Figure 1d). The voxel size is directly related to derived geometric quantities such as volume and height, which is why different voxel sizes were tested, and the derived statistical parameters were compared with conventional measurements to find the most suitable size (Enterkine et al., 2025). The voxel grid was generated, respectively, by dividing the spatial domain into cubic voxels of the defined size. The number of points contained within each voxel was then calculated and stored, facilitating density analysis across the scanned region.

Voxel-based statistics were computed, including mean, median and standard deviation of the point count per voxel to describe spatial distribution patterns. Estimates of total volume were derived based on the number of occupied voxels (of known volume—volume is the biomass-like variable), while the maximum vertical height of occupied voxels along the *z*-axis within each voxel data set was measured to indicate the height of the structure. For visualization, voxel data that met certain density thresholds were rendered using Python's Matplotlib, with a colour map representing voxel point densities. The approach enabled an efficient analysis of point cloud density and volumetric characteristics, providing insights into spatial heterogeneity within the scanned region. In terms of reliability, we averaged the heights and volumes determined per plot (from the three repeated scans) and voxel size for the statistical analyses. The original image data, the clipped image data, as well as the data processing scripts within a Jupyter Notebook are published under a CC BY 4.0 licence at Elias et al. (2024) and can be reused accordingly.

2.5 | Statistical analyses

First, we tested whether biomass (fresh/dry) and determined volumes (derived from voxel sizes 2.5, 5, 7.5 and 10 mm^3) as well as the measured height and the determined height obtained from the 3D scans show significant positive relationships. To assess these relationships, we applied linear mixed-effects models with block included as a random effect. For the biomass–volume analysis, fresh or dry biomass was used as the response variable, while voxel-based volume (with resolutions of 2.5, 5, 7.5, and 10 mm^3) served as the fixed effect. For plant height, measured height was set as the response variable and height estimated from 3D scans was included as the fixed effect. By visually analysing the regression between measured and determined height, we recognized a potential outlier (one grass monoculture). For this reason, we conducted the height analysis once with and once without this plot. Mixed-effects models were fitted with maximum likelihood (ML), and likelihood ratio tests were used to compare models and assess the significance of the fixed effects.

In a second step, we tested whether species richness and fertilization history have the same effects on sampled biomass (fresh/dry) and on the determined volumes obtained from the 3D scans (with different voxel size). For this, we also used linear mixed-effects models with biomass or volume (derived from voxel sizes 2.5, 5, 7.5 and 10 mm^3) as response variable (in single models), species richness, fertilization history and their interaction as fixed effects and block as random effect. We started with a null model with the random effect only, and then extended the model stepwise by adding the fixed effects (first species richness, then fertilization history and finally the interaction of species richness and fertilization history).

All analyses were performed with the statistical software R (version 3.6.1, R Development Core Team, http://www.R-project.org). The R code along with the data on height, biomass, and volume are provided in Supporting Information (Text S1; Table S1). For linear mixed-effects models, we used the lmer function in the R package lme4 (Bates et al., 2014). To calculate R^2 of regressions, we used the r.squaredGLMM function of the R package MuMIn (Barton & Barton, 2015).

3 | RESULTS

3.1 | Regressions between measured and determined variables

We found highly significant positive linear relationships between biomass (fresh/dry) and volume (Table 1; Figure 3). The coefficient of determination R^2 was higher for fresh biomass (R^2_{mean} = 0.85) than for dry biomass (R^2_{mean} = 0.73; Table 1). R^2 increased with larger voxel size, whereby this was more pronounced for dry biomass (from R^2 = 0.64 to R^2 = 0.79) than for fresh biomass (from R^2 = 0.82 to R^2 = 0.86; Table 1; Figure 3). We also found a significant positive relationship between measured and determined height (Table 1; Figure 4). If we

TABLE 1 Results of mixed-effects model analyses testing for linear relationships between biomass (fresh or dry) and volume obtained from voxel analysis with voxel sizes of 2.5, 5, 7.5, and 10 mm^3, and between vegetation height measured in the field and height obtained from point cloud analysis. Shown are degrees of freedom (df), Chi^2 values (χ^2), p values, and coefficient of determination (R^2).

	df	χ^2	p	R^2
Fresh biomass				
Biomass ~ Volume 2.5	1	19.80	<0.001	0.821
Biomass ~ Volume 5	1	21.81	<0.001	0.850
Biomass ~ Volume 7.5	1	22.01	<0.001	0.852
Biomass ~ Volume 10	1	22.64	<0.001	0.859
Dry biomass				
Biomass ~ Volume 2.5	1	11.65	<0.001	0.641
Biomass ~ Volume 5	1	15.41	<0.001	0.741
Biomass ~ Volume 7.5	1	16.68	<0.001	0.767
Biomass ~ Volume 10	1	17.64	<0.001	0.785
Vegetation height				
Measured height ~ determined height	1	9.89	0.002	0.583
Measured height ~ determined height (without one grass monoculture)	1	17.31	<0.001	0.808

removed one outlier (grass monoculture) from the analysis, R^2 was considerably higher (increase from $R^2=0.58$ to $R^2=0.81$; Table S2; Figure 4). An overview of the biomass, volume, and height characteristics of the individual plant communities is provided in Figure S1. Additional results related to plant species richness and fertilization are also presented in Supporting Information.

4 | DISCUSSION

Our study shows that traditional biomass harvesting and 3D scanning of vegetation with a smartphone produce similar results. Importantly, we found similar results of 3D-derived volume and dried biomass, which is commonly used as an estimate of plant productivity in ecological studies. High proportions of explained variation (R^2 values between 0.7 and 0.9) show a good comparability between volume and dry biomass. The same applies to vegetation height. We conclude from our results that smartphone 3D scanning can be a very useful approach to estimate biomass production and vegetation height in a cheap, fast and almost non-destructive way. The method has several advantages, in particular the simplicity of implementation, the widespread availability of measurement devices (i.e. smartphones) as well as the free apps and analysis software.

From our experience, we can make the following recommendations regarding measurements in the field and the subsequent processing of the point clouds:

- The frame is an important tool. Besides a well-defined area to scan, the frame also has the advantage that nothing has to be cut off around the vegetation for proper scanning—so the method is almost non-destructive. The frame should consist of wide boards so that the vegetation growing around the focus area can be compressed (at least 25 cm wide).
- It is useful to scan the vegetation at least three times in a row because each scan produces slightly different volumes (data not shown). To reduce this variability, multiple scans are recommended.
- The processing of the point clouds is simple and can be realized with freely available software. The corresponding script can be found under Elias et al. (2024). This workflow, in its current form, can be used immediately as a standard protocol in research infrastructures, long-term experiments or in citizen science projects. The only step that is not (yet) automated is the clipping of the point cloud to the region of interest.
- Our case study has shown that R^2 increases with voxel size, indicating that larger voxel sizes lead to more realistic results. However, we found different effects of fertilization history for voxel size 10 mm^3 and fresh biomass. To increase certainty, we recommend using voxel sizes larger than 2.5 mm^3 and smaller than 10 mm^3, similar to previous findings (Enterkine et al., 2025).

4.1 | Outlook

Apart from biomass and height data, which can be reliably estimated with this technique, we see great potential in developing this approach to derive further vegetation-related variables, for example:

- segmentation of species in image data and semantic annotation including AI methods for deriving species to determine the biomass production of individual species or functional groups (e.g. grasses, forbs, legumes) or to determine plant species richness;
- detailed analysis of individual species or specific structures, such as leaves, through 'virtual sampling,' which can yield insights into key ecological traits like leaf distribution and leaf functional traits (e.g. specific leaf area);
- vertical distribution of different plant species or compartments (i.e. biomass allocation) in a plant community; and
- assess the physiological state (e.g. drought response) of a plant community when dealing with global change drivers, e.g. by deriving the proportion of living and dead plant material.

This task will necessitate comprehensive research, including the modelling of the internal structure of point clouds, potentially leveraging artificial intelligence and utilizing high-resolution 3D scans of individuals from various species, encompassing different growth forms and functional groups. Additionally, the data foundation must be expanded. One approach could involve conducting measurements across multiple time points in various long-term experiments, ideally within globally coordinated networks, to capture a diverse range of vegetation types.

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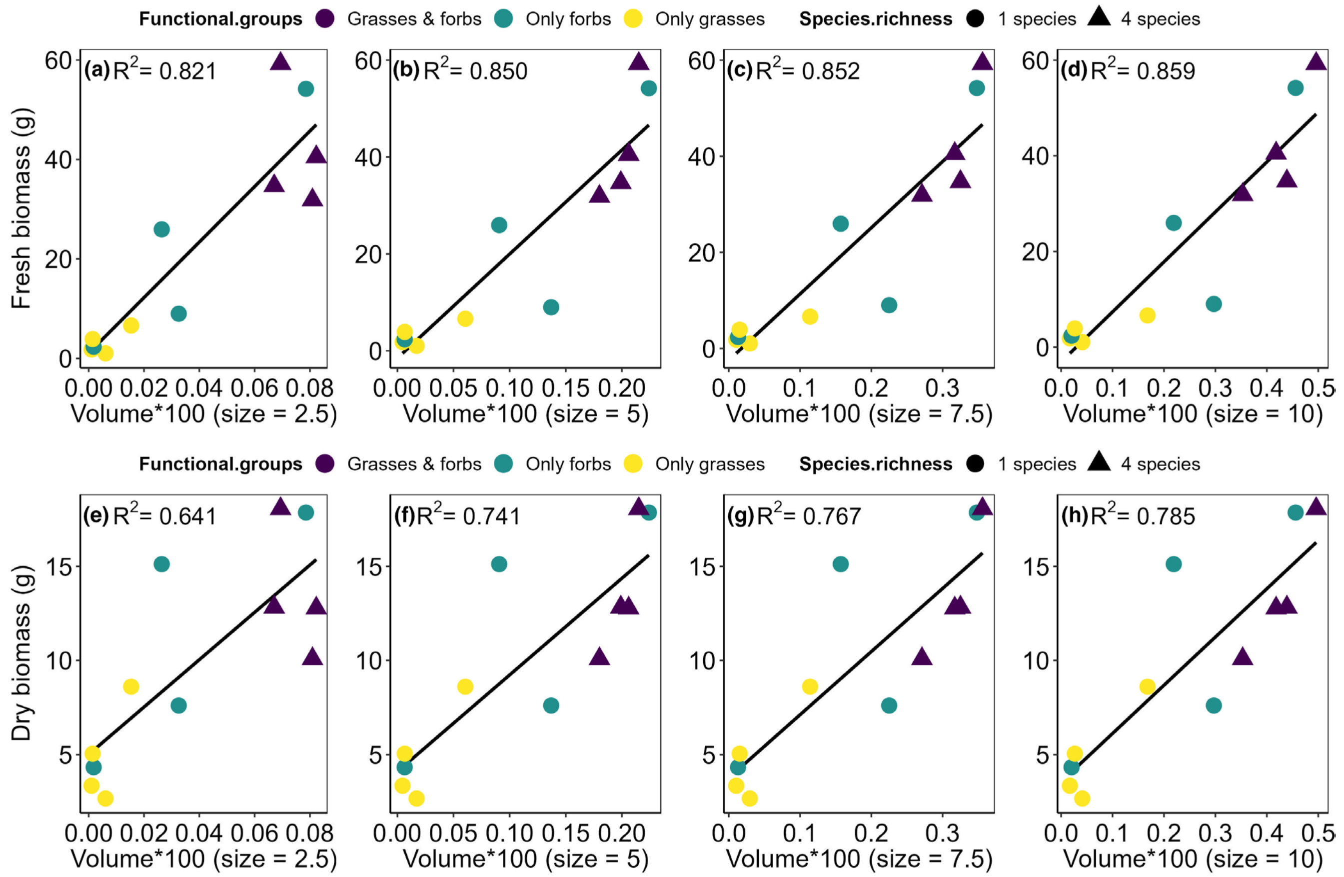

FIGURE 3 Relationship between plant biomass and volume determined from 3D scanning across different voxel sizes. Panels (a–d) show the relationship between fresh biomass (in g) and volume (scaled by 100), while panels (e–h) depict the relationship between dry biomass (in g) and volume. Each column represents a different voxel size (2.5, 5, 7.5, and 10 mm^3, respectively). Dot shape indicates whether the community was a monoculture or a four-species mixture, while dot colour represents the functional composition: Grasses only, forbs only, or a combination of both. Linear regression lines are included in each panel, along with the coefficient of determination (R^2), indicating the strength of the relationship.

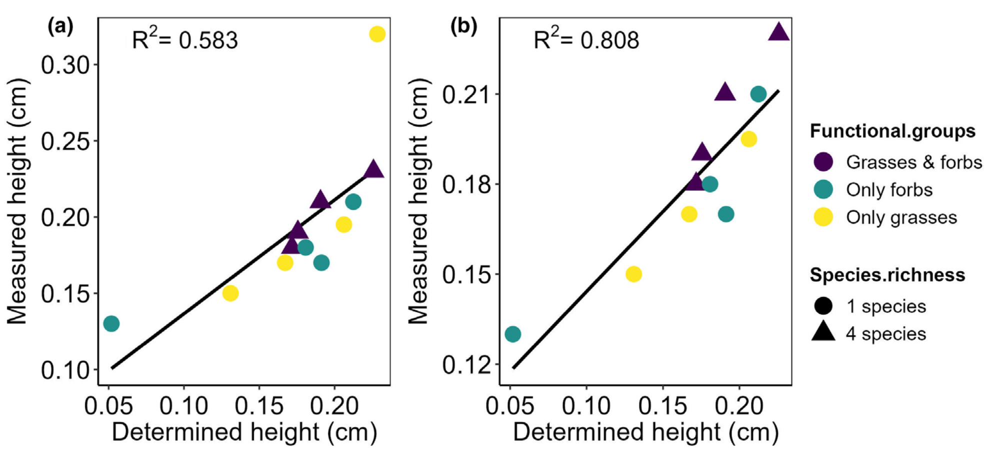

FIGURE 4 Relationship between measured plant height (cm) and estimated plant height derived from 3D scanning ("determined height"). Panel (a) includes all plots, while panel (b) excludes one outlier (grass monoculture). Dot shape indicates whether the community was a monoculture or a four-species mixture, while dot colour represents the functional composition: Grasses only, forbs only, or a combination of both. Linear regression lines are included in each panel, along with the coefficient of determination (R^2), indicating the strength of the relationship.

The direct next steps include further 'ground-truthing' to estimate biomass from 3D point cloud data, and to test reproducibility and comparisons to traditional methods, as well as scaling opportunities to various more remotely sensed imaging methods. Challenges are that the resolution of the 3D scans is not very high and strongly depends on the quality of the used smartphone (camera). Furthermore, the point clouds are quite noisy and require some, for now, manual clipping and outlier removal. A contributing factor to the observed noise and outliers is the limited ability to accurately capture very fine, thin structures, such as grass leaves or inflorescences. Thus, further research and development is needed to improve both the scanning processes and the methods used for the automatic preprocessing and analysis of point cloud. In addition, while it is currently possible to detect effects of experimental treatments using volume data (e.g. differences in species richness or fertilization effect), further more comprehensive studies are needed to determine exact biomass data (if an exact biomass estimate is required for a project), that is to calibrate volume data (Enterkine et al., 2025).

5 | CONCLUSION

Our pilot study demonstrates that the consumer-grade scanning of vegetation with a smartphone is a suitable alternative to conventional biomass harvesting. At the same time, new insights can be gained, for example by measuring biomass production over short time intervals or, in future, non-destructive measurement of vegetation structure or plant functional traits. Because of the growing necessity for more and higher-quality vegetation data, we see harnessing these emerging technologies as an opportunity to meet the challenges of monitoring ecosystems, opening up new questions and novel data to old questions, as well as a way to increase inclusion and access to biodiversity science.

AUTHOR CONTRIBUTIONS

Peter Dietrich (MLU), Melanie Elias, Peter Dietrich (UFZ), Stan Harpole and Jan Bumberger conceived the ideas. Peter Dietrich (MLU), Melanie Elias and Jan Bumberger designed the methodology. Peter Dietrich (MLU) and Christiane Roscher collected the data. Melanie Elias and Peter Dietrich (MLU) analysed the data. Peter Dietrich (MLU), Melanie Elias and Jan Bumberger led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

PEER REVIEW

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DATA AVAILABILITY STATEMENT

The original image data, the clipped image data and the data processing scripts within a Jupyter Notebook are published under an CC BY 4.0 licence and archived at https://doi.org/10.5281/zenodo.14024990 (Elias et al. (2024)).

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SUPPORTING INFORMATION

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

Figure S1. Relationship between plant biomass and volume as well as measured height and determined height (with plot names).

Figure S2. Fresh and dry biomass, and volume values of plant communities with one or four plant species.

Figure S3. Fresh and dry biomass, and volume values of plant communities without or with fertilization history.

Table S1. Overview of plot-level data used for height, biomass and volume analysis.

Table S2. Results of mixed-effects model analyses testing the effects of plant species richness, fertilization history, and their interaction on biomass and volume.

Text S1. R code for data analysis.

Text S2. Effects of plant species richness and fertilization history.

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