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Advancing Plant Biomass Measurements: Integrating Smartphone-based 3D Scanning Techniques for Enhanced Ecosystem Monitoring

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Abstract

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. 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. 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. This method's innovation extends beyond traditional practices with implications for future integration of AI to automate species segmentation, ecological trait extraction, and predictive modeling. The simplicity and accessibility of the smartphone-based approach facilitate broader engagement in ecosystem monitoring, encouraging citizen science participation and enhancing data 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, modeling, and its application in ecosystem analyses and biodiversity research.

Keywords: biodiversity, photogrammetry, Scaniverse, vegetation height, vegetation structure

Introduction

Biodiversity is declining dramatically due to the effects of global change, with unknown consequences for human life on Earth (Cardinale *et al.* 2012; Keesing & Ostfeld 2021; Habibullah *et al.* 2022). 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 like 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).

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, Roca-Fernández & González-Rodríguez 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 have emerged, allowing for higher resolution temporal and spatial measurements through 3D scanning and computational analysis of resulting digital point clouds (Lausch *et al.* 2020; Kolhar & Jagtap 2023). 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; Demol *et al.* 2022; Richter & Maas 2022; Bienert *et al.* 2024). 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 particularly interest in today's on-site crop growth monitoring. Alternative optical methods include the light-field measurement approach (Schima *et al.* 2016; Hu *et al.* 2023), 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; Kröhnert *et al.* 2018; Enterkine *et al.* 2023). This technique holds significant potential for extracting structural features of plant communities at the plot level (Enterkine *et al.* 2023). There are already some approaches using this technique for ecosystem monitoring, but they usually involve expensive photo cameras and rather complex processing methods (Enterkine *et al.* 2023). Here we present a new approach that makes the SfM method easily accessible to everyone (i.e., inexpensive and simple to implement) 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 stabilisation, autofocus, and cameras with at least 40 megapixels, capable of producing high-resolution images comparable to those taken with SLR cameras. The high quality of today's smartphone camera images enables photogrammetric image processing, e.g. using SfM (Micheletti, Chandler & Lane 2015; Vinci *et al.* 2017; Luetzenburg, Kroon & Bjørk 2021). In a recent study by Chiappini *et al.* (2024), the authors compared the accuracy of 3D urban olive tree models generated including SfM models generated from smartphone images against models from professional MLS. While smartphone-based methods underestimated larger trees, they demonstrated potential as cost-effective alternatives for urban tree assessments, despite limitations in accuracy compared to high-end devices.

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, US) 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 minutes) 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, i.e., 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.

Materials and methods

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, Schumacher & Roscher 2016). The site has an average annual temperature of 9.5°C and 492 mm of precipitation (1981-2010). Eight perennial plant species (four herbs, four grasses), typical of Central European mown 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} yr^{-1}) was applied distributed with two even doses (March, and June after first mowing) from 2012 to 2023.

3D scans and biomass sampling

On 4 September 2024, we scanned the vegetation in the monocultures and 4-species plots of one species pool, i.e, 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, Schumacher & Roscher 2016). To do this, we used a frame with a 0.3 × 0.3 m inner surface (made of 0.25 m wide planks; Fig. 1a) to define a specific sub-area per plot (position was randomly chosen in the plot with a sufficient distance from the plot edge). 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 preferred to alternatives such as Polycam due to its easy handling, fast scanning speed and high-quality results.

For scanning, Scaniverse offers two scan modes: 'Splat' and 'Mesh'. It is very likely that the splat option uses a Gaussian splatting approach to generate 3D representations. With Gaussian splatting, only a small number of 3D points need to be generated from images, with each point having a coordinate in 3D space as well as colour and depth information. Using the Gaussian splats, imaginable as a kind of modifiable bubbles, the appearance of the scanned space can be reconstructed from these points by changing the splats depending on the point attributes. By default, no new real 3D information is generated that can be used for measurement purposes. Mesh-based 3D models are explicitly defined by geometric information, i.e., points, edges, and surfaces. A high-quality mesh that also performs well in visualization is therefore associated with a high-quality and dense 3D point cloud. Consequently, it stands to reason that the mesh function would generate a higher point density.

For scanning, we thus first selected the 'Mesh' mode and 'Small Object' (recommended for objects at a size of "pets, toys and flowers" and likely to predefine the measurement volume), and then scanned the area by capturing the vegetation from all possible angles and distances until the app no longer indicated any red-marked areas in the scan. The scanning took one to two minutes, depending on the density of the vegetation. Each plot was scanned three times. After scanning, we used the ‘Detail’ processing mode to generate the point cloud. This mode is recommended to get the most detailed 3D information. During the ‘Detail’ processing stage, various status messages are displayed, i.e., ‘Aligning Images, Computing Depth, Texturing’, which point to the workflow of SfM. First, the image orientation parameters are determined within the sequence. This is followed by dense matching to compute depth information, i.e., 3D points, through depth triangulation. The calculated 3D points are subsequently textured by the image data. It is important to note that SfM does not inherently provide scale information. Scaniverse probably uses some kind of visual odometry to determine the image trajectory in a metrically scaled coordinate system. This information can be used in the SfM process during image orientation to obtain true-to-scale 3D points in subsequent dense matching. The model was then saved and exported in .ply format (Fig. 1b), that is widely used in the 3D community, using the ‘Share’ function.

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 48h at 60°C.

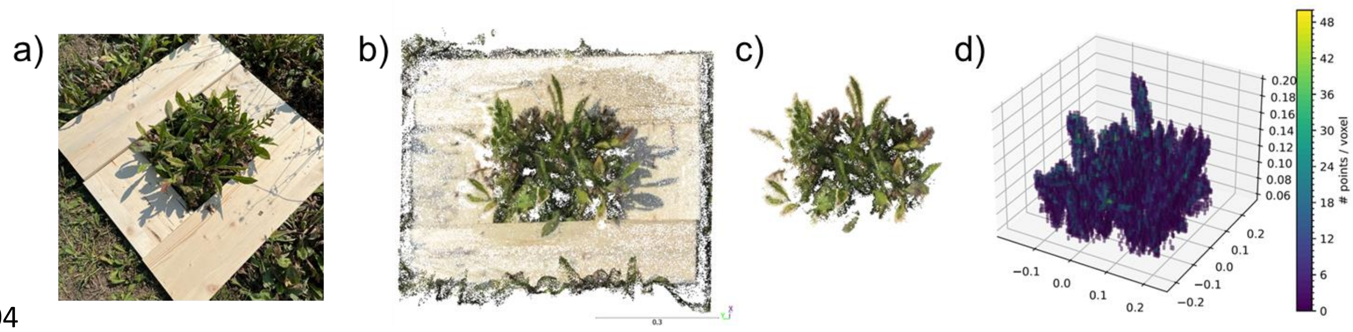

Fig. 1 Vegetation in the field with the wooden frame around (a), original point cloud from Scaniverse (b), clipped point cloud (c) used for voxel space calculation (d). Illustrated is a fertilized 4-species mixture plot (voxel size 5 mm).

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 (Fig. 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 (Fig. 1c). Future versions of this process could be automated, possibly using e.g. the Python wrapper CloudComPy.

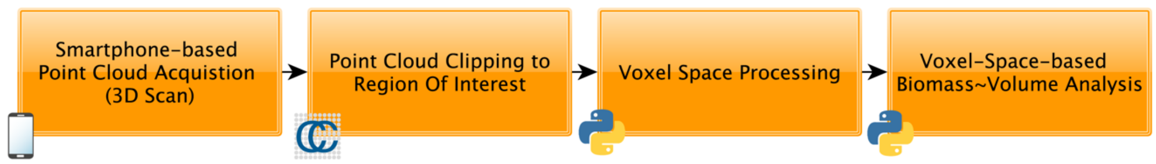

Fig. 2 Workflow description: after point cloud acquisition via smartphone, point clouds were clipped, voxel space was processed, and finally, relationships between resulting voxel volumes and the harvested biomass were evaluated.

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, Fig. 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 (Fig. 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.* 2023). 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 dataset 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 color 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 an CC BY 4.0 license at Elias, Dietrich and Bumberger (2024) and can be reused accordingly.

Statistical analyses

First, we tested whether species richness and fertilisation 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 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, fertilisation 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). 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 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 relationships. For this we used the same mixed effects-model structure as above. For biomass~volume analysis we used fresh or dry biomass as response variable and volume (voxel sizes 2.5, 5, 7.5 and 10 mm^3, respectively) as fixed effect, and for height we used measured height as response variable and determined height from 3D scans as fixed effect. By visually analysing the regression between measured and determined height, we recognised a potential outlier (one grass monoculture). For this reason, we conducted the height analysis once with and once without this plot.

All analyses were performed with the statistical software R (version 3.6.1, R Development Core Team, http://www.R-project.org). 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 R package MuMIn (Barton & Barton 2015).

Results

Effects of plant species richness and fertilization history

We found an overall positive effect of plant species richness on aboveground biomass, i.e., four-species mixtures produced more biomass than monocultures (Table 1; Fig. 3a, b). Fertilization history also showed a tendency to increase biomass (Fig 4a, b), while this effect was only marginally significant for dry biomass (Table 1). The interaction between species richness and fertilization history did not have any influence (Table 1). We found similar effects of species richness and fertilization history on the determined volumes obtained from the 3D scans (Table 1; Fig. 3c-f, 4c-f).

Table 1 Results of mixed-effects model analyses testing the effects of plant species richness (SR), fertilization history (Fert.), and their interaction on biomass (fresh and dry) and volume measurements (voxel size: 2.5, 5, 7.5 and 10 mm^3). Shown are degrees of freedom (DF), Chi^2 values (χ^2) and P values.

		Fresh biomass		Dry biomass	
	DF	χ^2	P	χ^2	P
Plant species richness (SR)	1	6.80	**0.009**	3.78	*0.052*
Fertilization history (Fert.)	1	2.25	0.133	2.70	*0.100*
SR x Fert.	1	0.68	0.410	0.24	0.627
		Volume 2.5		Volume 5	
	DF	χ^2	P	χ^2	P
Plant species richness (SR)	1	6.50	**0.011**	5.62	**0.018**
Fertilization history (Fert.)	1	2.78	*0.096*	3.22	*0.073*
SR x Fert.	1	0.13	0.715	0.22	0.640
		Volume 7.5		Volume 10	
	DF	χ^2	P	χ^2	P
Plant species richness (SR)	1	5.50	**0.019**	5.57	**0.018**
Fertilization history (Fert.)	1	3.67	*0.055*	4.05	**0.044**
SR x Fert.	1	0.22	0.642	0.23	0.628

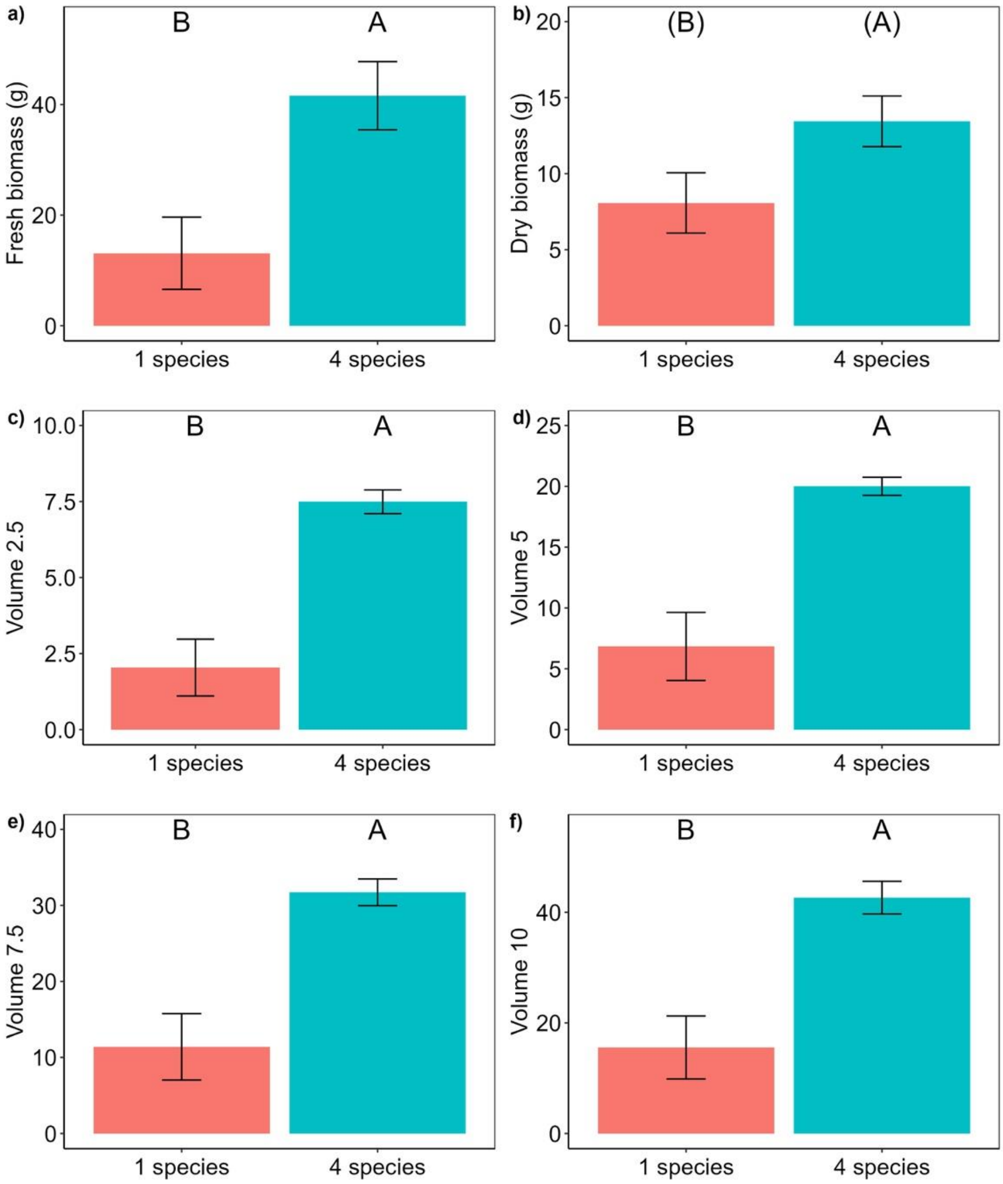

Fig. 3 Fresh and dry biomass (a, b), and volume values obtained from voxel analysis with voxel sizes of 2.5 (c), 5 (d), 7.5 (e) and 10 (f) of plant communities with one (red) or four (blue) plant species (N_{one} = 8 plots, N_{four} = 4 plots). Bars show mean values (± 1 standard error); letters above bars indicate significant ($P < 0.05$) differences among treatments, letters in brackets indicate marginal significant ($0.05 < P < 0.1$) differences (Tukey's HSD test).

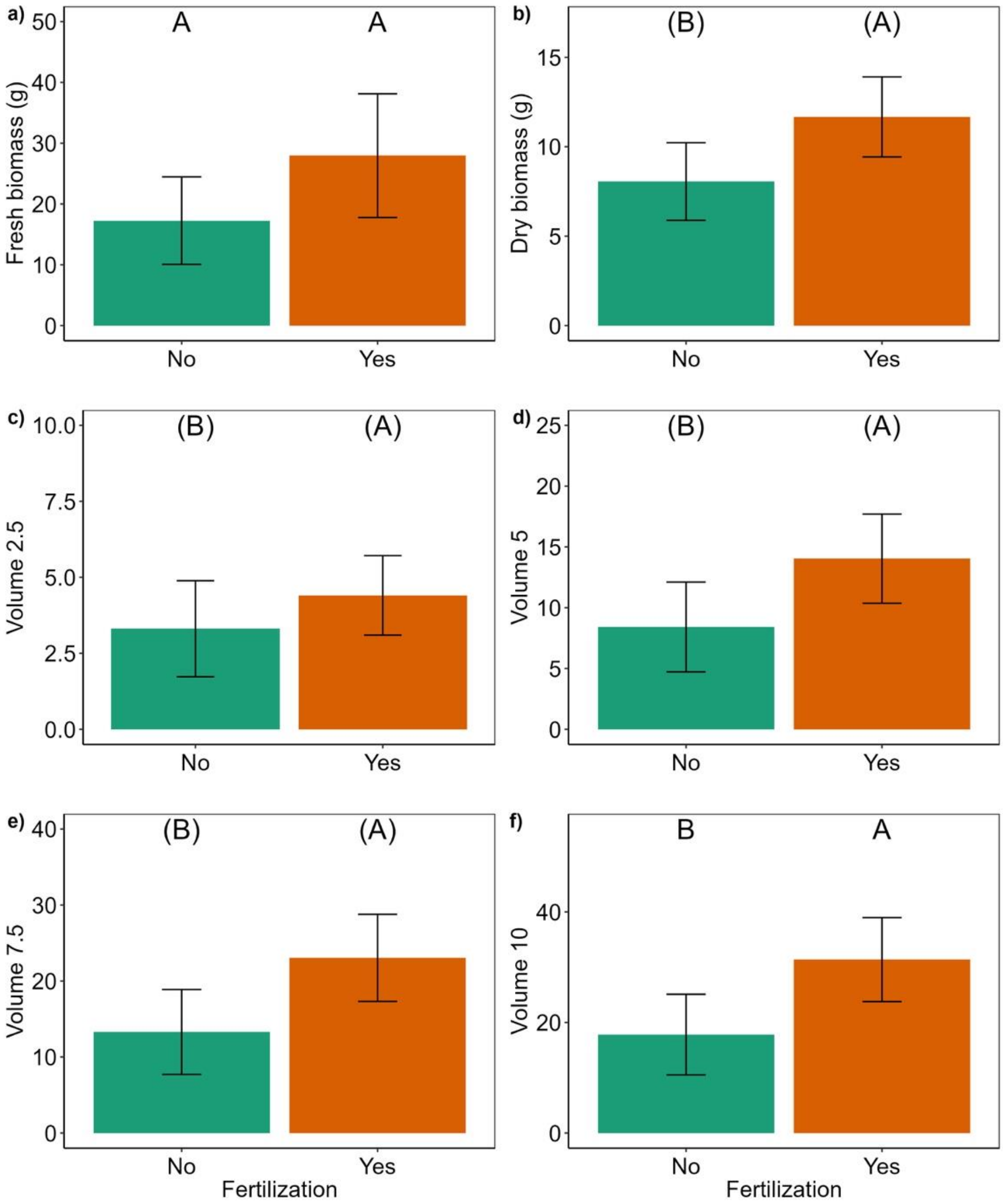

Fig. 4 Fresh and dry biomass (a, b), and volume values obtained from voxel analysis with voxel sizes of 2.5 (c), 5 (d), 7.5 (e) and 10 (f) of plant communities without (green) or with (red) fertilization history (six plots, respectively). Bars show mean values (± 1 standard error); letters above bars indicate significant ($P < 0.05$) differences among treatments, letters in brackets indicate marginal significant ($0.05 < P < 0.1$) differences (Tukey's HSD test).

Regressions between measured and determined variables

We found highly significant positive linear relationships between biomass (fresh/dry) and volume (Table 2). 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 2). R^2 increased with larger voxel size, whereby this was more pronounced for dry biomass (R^2 = 0.64-0.79) than for fresh biomass (R^2 = 0.82-0.86; Table 2). We also found a significant positive relationship between measured and determined height (Table 2). If we 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 2).

Table 2 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 B8A88)	1	17.31	**<0.001**	0.808

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 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 realised with freely available software. The corresponding script can be found under Elias, Dietrich and Bumberger (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 fertilisation 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.* 2023).

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, herbs, 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
- 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.

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. Thus, it is necessary to further develop the methods used to automatically preprocess and analyse the point clouds. In addition, while it is currently possible to detect effects of experimental treatments using volume data (e.g., differences in species richness or fertilisation effect), further more comprehensive studies are needed to determine exact biomass data (if an exact biomass estimate is required for a project), i.e. to calibrate volume data (Enterkine *et al.* 2023).

Conclusion

Our pilot study demonstrates that scanning 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 the 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 that 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.

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Data availability

The original image data, the clipped image data, as well as the data processing scripts within a Jupyter Notebook are published under an CC BY 4.0 license at Elias, Dietrich and Bumberger (2024) and can be reused accordingly.

References

Barton, K. & Barton, M.K. (2015) Package 'mumin'. *cran,* **1,** 1-79.

Bates, D., Mächler, M., Bolker, B. & Walker, S. (2014) Fitting linear mixed-effects models using lme4. *arXiv* **1406.5823**. https://doi.org/10.18637/jss.v067.i01

Bienert, A., Georgi, L., Kunz, M., von Oheimb, G. & Maas, H.-G. (2021) Automatic extraction and measurement of individual trees from mobile laser scanning point clouds of forests. *Annals of Botany,* **128,** 787-804. https://doi.org/10.1093/aob/mcab087

Bienert, A., Richter, K., Boehme, S. & Maas, H.-G. (2024) Investigating the Potential of Hyper-Temporal Terrestrial Laser Point Clouds for Monitoring Deciduous Tree Growth. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* **48,** 33-40. https://doi.org/10.5194/isprs-archives-XLVIII-2-2024-33-2024

Borer, E.T., Harpole, W.S., Adler, P.B., Lind, E.M., Orrock, J.L., Seabloom, E.W. & Smith, M.D. (2014) Finding generality in Ecology: a model for globally distributed experiments. *Methods in Ecology and Evolution,* **5,** 65-73. https://doi.org/10.1111/2041-210X.12125

Cardinale, B.J., Duffy, J.E., Gonzalez, A., Hooper, D.U., Perrings, C., Venail, P., Narwani, A., Mace, G.M., Tilman, D., Wardle, D.A., Kinzig, A.P., Daily, G.C., Loreau, M., Grace, J.B., Larigauderie, A., Srivastava, D.S. & Naeem, S. (2012) Biodiversity loss and its impact on humanity. *Nature,* **486,** 59-67. https://doi.org/10.1038/nature11148

Chiappini, S., Balestra, M., Giulioni, F., Marcheggiani, E., Malinverni, E.S. & Pierdicca, R. (2024) Comparing the accuracy of 3D urban olive tree models detected by smartphone using LiDAR sensor, photogrammetry and NeRF: a case study of'Ascolana Tenera'in Italy. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* **10,** 61-68. https://doi.org/10.5194/isprs-annals-X-3-2024-61-2024

Cooper, S.D., Roy, D.P., Schaaf, C.B. & Paynter, I. (2017) Examination of the potential of terrestrial laser scanning and structure-from-motion photogrammetry for rapid nondestructive field measurement of grass biomass. *Remote Sensing,* **9,** 531. https://doi.org/10.3390/rs9060531

Dandrifosse, S., Bouvry, A., Leemans, V., Dumont, B. & Mercatoris, B. (2020) Imaging wheat canopy through stereo vision: Overcoming the challenges of the laboratory to field transition for morphological features extraction. *Frontiers in plant science,* **11,** 96. https://doi.org/10.3389/fpls.2020.00096

Demol, M., Verbeeck, H., Gielen, B., Armston, J., Burt, A., Disney, M., Duncanson, L., Hackenberg, J., Kükenbrink, D. & Lau, A. (2022) Estimating forest above-ground biomass with terrestrial laser scanning: Current status and future directions. *Methods in Ecology and Evolution,* **13,** 1628-1639. https://doi.org/10.1111/2041-210X.13906

Elias, M., Dietrich, P. & Bumberger, J. (2024) Advancing Plant Biomass Measurements: Integrating Smartphone-based 3D Scanning Techniques for Enhanced Ecosystem Monitoring [Data set]. *Zenodo*. https://doi.org/10.5281/zenodo.14024991

Enterkine, J., Hojatimalekshah, A., Vermillion, M., Van Der Weide, T., Arispe, S., Price, W., Hulet, A. & Glenn, N. (2023) Voxel Volumes and Biomass: estimating vegetation volume and litter accumulation of exotic annual grasses using automated ultra-high resolution SfM and advanced classification techniques. *Authorea Preprints*. https://doi.org/10.22541/au.169781950.03421718/v1

Fischer, M., Bossdorf, O., Gockel, S., Hänsel, F., Hemp, A., Hessenmöller, D., Korte, G., Nieschulze, J., Pfeiffer, S. & Prati, D. (2010) Implementing large-scale and long-term functional biodiversity research: The Biodiversity Exploratories. *Basic and Applied Ecology,* **11,** 473-485. https://doi.org/10.1016/j.baae.2010.07.009

Habibullah, M.S., Din, B.H., Tan, S.-H. & Zahid, H. (2022) Impact of climate change on biodiversity loss: global evidence. *Environmental Science and Pollution Research,* **29,** 1073-1086. https://doi.org/10.1007/s11356-021-15702-8

Hu, X., Li, Z., Miao, L., Fang, F., Jiang, Z. & Zhang, X. (2023) Measurement Technologies of Light Field Camera: An Overview. *Sensors,* **23,** 6812. https://doi.org/10.3390/s23156812

Keesing, F. & Ostfeld, R.S. (2021) Impacts of biodiversity and biodiversity loss on zoonotic diseases. *Proceedings of the National Academy of Sciences,* **118,** e2023540118. https://doi.org/10.1073/pnas.2023540118

Kobe, M., Elias, M., Merbach, I., Schädler, M., Bumberger, J., Pause, M. & Mollenhauer, H. (2024) Automated Workflow for High-Resolution 4D Vegetation Monitoring Using Stereo Vision. *Remote Sensing,* **16,** 541. https://doi.org/10.3390/rs16030541

Koedel, U., Schuetze, C., Fischer, P., Bussmann, I., Sauer, P.K., Nixdorf, E., Kalbacher, T., Wichert, V., Rechid, D. & Bouwer, L.M. (2022) Challenges in the evaluation of observational data trustworthiness from a data producers viewpoint (FAIR+). *Frontiers in Environmental Science,* **9,** 772666. https://doi.org/10.3389/fenvs.2021.772666

Kolhar, S. & Jagtap, J. (2023) Plant trait estimation and classification studies in plant phenotyping using machine vision–A review. *Information Processing in Agriculture,* **10,** 114-135. https://doi.org/10.1016/j.inpa.2021.02.006

Kröhnert, M., Anderson, R., Bumberger, J., Dietrich, P., Harpole, W.S. & Maas, H.-G. (2018) Watching grass grow-a pilot study on the suitability of photogrammetric techniques for quantifying change in aboveground biomass in grassland experiments. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* **42,** 539-542. https://doi.org/10.5194/isprs-archives-XLII-2-539-2018

Lausch, A., Heurich, M., Magdon, P., Rocchini, D., Schulz, K., Bumberger, J. & King, D.J. (2020) A range of earth observation techniques for assessing plant diversity. *Remote sensing of plant biodiversity***,** 309-348. https://doi.org/10.1007/978-3-030-33157-3

López-Díaz, J., Roca-Fernández, A. & González-Rodríguez, A. (2011) Measuring herbage mass by non-destructive methods: A review. *Journal of Agriculture, Science and Technology,* **1,** 303-314.

Luetzenburg, G., Kroon, A. & Bjørk, A.A. (2021) Evaluation of the Apple iPhone 12 Pro LiDAR for an application in Geosciences. *Scientific Reports,* **11,** 1-9. https://doi.org/10.1038/s41598-021-01763-9

Micheletti, N., Chandler, J.H. & Lane, S.N. (2015) Investigating the geomorphological potential of freely available and accessible structure-from-motion photogrammetry using a smartphone. *Earth Surface Processes and Landforms,* **40,** 473-486. https://doi.org/10.1002/esp.3648

Mollenhauer, H., Kasner, M., Haase, P., Peterseil, J., Wohner, C., Frenzel, M., Mirtl, M., Schima, R., Bumberger, J. & Zacharias, S. (2018) Long-term environmental monitoring infrastructures in Europe: observations, measurements, scales, and socio-ecological representativeness. *Science of the Total Environment,* **624,** 968-978. https://doi.org/10.1016/j.scitotenv.2017.12.095

Ohnemus, T., Zacharias, S., Dirnböck, T., Bäck, J., Brack, W., Forsius, M., Mallast, U., Nikolaidis, N.P., Peterseil, J. & Piscart, C. (2024) The eLTER research infrastructure: Current design and coverage of environmental and socio-ecological gradients. *Environmental and Sustainability Indicators,* **23,** 100456. https://doi.org/10.1016/j.indic.2024.100456

Richter, K. & Maas, H.-G. (2022) Radiometric enhancement of full-waveform airborne laser scanner data for volumetric representation in environmental applications. *ISPRS Journal of Photogrammetry and Remote Sensing,* **183,** 510-524. https://doi.org/10.1016/j.isprsjprs.2021.10.021

Schima, R., Mollenhauer, H., Grenzdörffer, G., Merbach, I., Lausch, A., Dietrich, P. & Bumberger, J. (2016) Imagine all the plants: Evaluation of a light-field camera for on-site crop growth monitoring. *Remote Sensing,* **8,** 823. https://doi.org/10.3390/rs8100823

Siebenkäs, A., Schumacher, J. & Roscher, C. (2016) Resource availability alters biodiversity effects in experimental grass-forb mixtures. *PLoS One,* **11,** e0158110. https://doi.org/10.1371/journal.pone.0158110

Smith, M.D., Wilkins, K.D., Holdrege, M.C., Wilfahrt, P., Collins, S.L., Knapp, A.K., Sala, O.E., Dukes, J.S., Phillips, R.P. & Yahdjian, L. (2024) Extreme drought impacts have been underestimated in grasslands and shrublands globally. *Proceedings of the National Academy of Sciences,* **121,** e2309881120. https://doi.org/10.1073/pnas.2309881120

Tilman, D., Knops, J., Wedin, D., Reich, P., Ritchie, M. & Siemann, E. (1997) The influence of functional diversity and composition on ecosystem processes. *Science,* **277,** 1300-1302. https://doi.org/10.1126/science.277.5330.1300

Tirrell, A.J., Putnam, A.E., Cianchette, M.I. & Gill, J.L. (2023) Using photogrammetry to create virtual permanent plots in rare and threatened plant communities. *Applications in Plant Sciences,* **11,** e11534. https://doi.org/10.1002/aps3.11534

Vinci, A., Todisco, F., Brigante, R., Mannocchi, F. & Radicioni, F. (2017) A smartphone camera for the structure from motion reconstruction for measuring soil surface variations and soil loss due to erosion. *Hydrology Research,* **48,** 673-685. https://doi.org/10.2166/nh.2017.075

von Gönner, J., Herrmann, T.M., Bruckermann, T., Eichinger, M., Hecker, S., Klan, F., Lorke, J., Richter, A., Sturm, U. & Voigt-Heucke, S. (2023) Citizen science's transformative impact on science, citizen empowerment and socio-political processes. *Socio-ecological practice research,* **5,** 11-33. https://doi.org/10.1007/s42532-022-00136-4

Weisser, W.W., Roscher, C., Meyer, S.T., Ebeling, A., Luo, G., Allan, E., Beßler, H., Barnard, R.L., Buchmann, N. & Buscot, F. (2017) Biodiversity effects on ecosystem functioning in a 15-year grassland experiment: Patterns, mechanisms, and open questions. *Basic and Applied Ecology,* **23,** 1-73. https://doi.org/10.1016/j.baae.2017.06.002

Zacharias, S., Loescher, H.W., Bogena, H., Kiese, R., Schrön, M., Attinger, S., Blume, T., Borchardt, D., Borg, E., Bumberger, J., Chwala, C., Dietrich, P., Fersch, B., Frenzel, M., Gaillardet, J., Groh, J., Hajnsek, I., Itzerott, S., Kunkel, R., Kunstmann, H., Kunz, M., Liebner, S., Mirtl, M., Montzka, C., Musolff, A., Pütz, T., Rebmann, C., Rinke, K., Rode, M., Sachs, T., Samaniego, L., Schmid, H.P., Vogel, H.-J., Weber, U., Wollschläger, U. & Vereecken, H. (2024) Fifteen Years of Integrated Terrestrial Environmental Observatories (TERENO) in Germany: Functions, Services, and Lessons Learned. *Earth's Future,* **12,** e2024EF004510. https://doi.org/10.1029/2024EF004510