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Voxel Volumes and Biomass: estimating vegetation volume and litter accumulation of exotic annual grasses using automated ultra-high resolution SfM and advanced classification techniques

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Abstract

Rangelands and semi-arid ecosystems are subject to increasing changes in ecologic makeup from a collection of factors. In much of the northern Great Basin, rangelands invaded by exotic annual grasses such as cheatgrass (Broumus tectorum) and medusahead (Taeniatherum caput-medusae) are experiencing an increasingly short fire cycle which is compounding and persistent. Improving and expanding ground-based field methods for measuring above-ground biomass (AGB) may enable more sample collections across a landscape and over succession regimes, and better harmonize with other remote sensing techniques. Developments and increased adoption of uncrewed aerial vehicles and instrumentation for vegetation monitoring are enabling greater understanding of vegetation in many ecosystems. Research towards understanding the relationship of traditional field measurements with newer aerial platforms in rangeland environments is growing rapidly, and there is increasing interest in exploring the potential use both to quantify AGB and fine fuel load at pasture scales. Our study here uses relatively inexpensive handheld photography with custom sampling frames to collect and automatically reconstruct 3D-models of the vegetation within 0.2 m2 quatrats (n = 288). Next, we examine the relationship between volumetric estimates of vegetation to compare with biomass. We found that volumes calculated with 0.5 cm voxel sizes (0.125 cm3) most closely represented the range of biomass weights. We further develop methods to classify ground points, finding a 2% reduction in predictive ability compared to using the true ground surface. Overall, our reconstruction workflow had an R2 of 0.42, further emphasizing the importance of high-resolution imagery and reconstruction techniques. Ultimately, we conclude that more work is needed of increasing extents (such as from UAS) to better understand and constrain uncertainties in volumetric estimations of biomass in ecosystems with high amounts of invasive annual grasses and fine fuel litter.

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Abstract

Rangelands and semi-arid ecosystems are subject to increasing changes in ecologic makeup from a collection of factors. In much of the northern Great Basin of the western United States, rangelands invaded by exotic annual grasses such as cheatgrass (*Bromus tectorum*) and medusahead (*Taeniatherum caput-medusae*) are experiencing an increasingly short fire cycle, which is compounding and persistent. Improving and expanding ground-based field methods for measuring above-ground biomass (AGB) may enable more sample collections across a landscape and over succession regimes, and better harmonize with other remote sensing techniques. Developments and increased adoption of uncrewed aerial vehicles and instrumentation for vegetation monitoring are enabling greater understanding of vegetation in many ecosystems. Research towards understanding the relationship of traditional field measurements with newer aerial platforms in rangeland environments is growing rapidly, and there is increasing interest in exploring the potential use both to quantify AGB and fine fuel load at pasture and landscape scales. Our study here uses relatively inexpensive handheld photography with custom sampling frames to collect and automatically reconstruct 3D-models of the vegetation within 0.2 m^2quadrats (n = 288). Next, we examine the relationship between volumetric estimates of vegetation to compare with biomass. We found that volumes calculated with 0.5 cm voxel sizes (0.125 cm^3) most closely represented the range of biomass weights. We further develop methods to classify ground points, finding a 2% reduction in predictive ability compared to using the true ground surface. Overall, our reconstruction workflow had an R^2 of 0.42, further emphasizing the importance of high-resolution imagery and reconstruction techniques. Ultimately, we conclude that more work is needed of increasing extents (such as from UAS) to better understand and constrain uncertainties in volumetric estimations of biomass in ecosystems with high amounts of invasive annual grasses and fine fuel litter.

Keywords: rangeland, fine fuels, medusahead, SfM, biomass

Introduction

Semi-arid ecosystems act as carbon sinks and are thought to play a major role in global interannual carbon variations (Ahlström et al. 2015). In addition to soil carbon sequestration, semi-arid ecosystems at regional scales provide important ecosystem services such as wildlife habitat and mesic refugia. Semi-arid ecosystems, such as in the western U.S. are water-limited and pressures from climate change and population growth make these lands vulnerable to degradation. Specifically, the sagebrush-steppe ecosystem is currently under threat from the invasion of exotic annual grasses, such as cheatgrass (*Bromus tectorum* L.) and medusahead (*Taeniatherum caput-medusae* (L.) Nevski), which are decreasing biodiversity (Knapp, 1996), altering the fire cycle (Bradley et al., 2018), and reducing carbon storage (Bradley et al., 2006).

Quantifying vegetation biomass is critical for assessing ecosystem structure, tracking vegetation growth, and quantifying carbon storage (Houghton et al., 2009). Above ground biomass (AGB) in semi-arid ecosystems helps scientists and land managers better understand the contribution of these ecosystems to the global carbon flux, and the impacts of ecosystem shifts towards desertification (Chambers et al., 2014). In particular, AGB is defined as the dried weight of vegetation above the ground including both alive and dead components, is difficult to accurately measure in semi-arid ecosystems because of the heterogeneity and fine-scale structure of vegetation (Fern et al., 2018; Wijesingha et al., 2019). This is especially so for invasive annual grasses such as medusahead and cheatgrass, where previous growth can become a mat of dry litter, decreasing native vegetation growth and further promoting the invasive annual grass species (Evans & Young 1970). As a result, an increase in the continuity of fine fuel loads occurs. This build-up of fine fuels, coupled with senescence early in the growing season promote ignition and increased fire spread. This feedback loop, 'invasive grass-fire cycle' further results in degradation of semi-arid ecosystems (Fernández-Guisuraga et al. 2022).

Management approaches to the invasive grass-fire cycle are varied across techniques and spatial and temporal scales. Approaches such as re-seeding, grazing, and fuel breaks, aim to effect and observe changes in a plot, pasture, or regional scales (100s-1000s km^2). Where the sites may be relatively small in extent (e.g. grazing exclosure scales, or m to km), there is a benefit of reducing the need to destructively harvest samples to observe changes while reducing impact on the vegetation. Monitoring data at high spatial resolutions and with low uncertainty are needed to provide baseline information to both of these scales to be able to extrapolate measurements with greater certainty, and where changes over time and in response to treatments and climate are valuable to observe.

How AGB is Measured in the Field, Destructively and Non-Destructively

Current methods for collecting AGB can be described as a combination of site-specific and extrapolated measurements. An example of site-specific measurements is the destructive harvesting of biomass. Often quantification of biomass at the plot scale is extrapolated to larger scales (Clark et al., 2008). Further, in the field plot-level data collection of plants are destructively harvested, dried, and weighed to obtain a biomass metric, or point frame data is used to relate to biomass. The manual process itself has uncertainty in the collection from human error. Often these plots are small, and the biomass can vary significantly across spatial scales, even within 1 m or less. The act of removing plants itself alters the landscape and impacts future studies of those plots. Advances in remote sensing systems like lidar, unmanned aerial systems (UAS), and structure from motion (SfM) software have led to advances in quantifying biomass in dryland ecosystems (Anderson et al., 2018; Cunliffe et al., 2016). Fine (spatial/structural) resolution remote sensing has potential to help solve the above rangeland vegetation challenges. SfM is photogrammetry, the method of using 2D stereoscopic images and detecting common points, resulting in a 3D reconstruction in the form of a point cloud. SfM provides a similar data product to lidar: a point cloud in which vegetation structure can be interpreted. However since SfM is based on optical passive imagery it does not penetrate the canopy (Salamí et al., 2014). SfM and lidar are similar in their point cloud reconstruction, however because lidar is active, it has an intensity associated with each point. Additionally, lidar can be collected as full-waveform or in discrete returns which can characterize the understory and ground surface (Wallace et al. 2017).

In contrast, SfM is derived from passive remote sensing relying on optical imagery to create point clouds where each point has an associated color value for the spectra of the optical image. This value is rarely radiometrically calibrated. SfM point clouds are not discretized from a waveform but developed based on the overlap of imagery taken. Vegetation parameters such as volume, can be derived from point clouds to develop allometric relationships between vegetation and destructively harvested biomass. SfM offers a low-cost, time efficient, and in some cases, more accurate method compared to terrestrial laser scanning (TLS) for estimating vegetation structure in dryland ecosystems (Cooper et al. 2017, Olsoy et al., 2018; Wallace et al., 2017).

Extremely close-range SfM, defined by the use of hand-held instruments to collect the imagery for the SfM method, has shown success comparable to TLS in deriving parameters such as height and volume from the reconstruction of individual trees (Miller et al., 2015). In grasslands, extremely close-range SfM was shown to outperform TLS and traditional height measurements in developing allometric equations, in part because SfM can capture finer details compared to TLS, dependent upon the experimental setup (Cooper et al., 2017). TLS at plot scale (Anderson et al. 2017) and TLS and hand-held camera photos at 0.5 m x 0.5 m (0.46*0.46, Cooper et al. 2017) had high correlations between SfM and TLS and AGB. SfM has been shown to successfully capture grasses and reconstruct fine features such as leaves and stems (Cooper et al. 2017, Kröhnert et al., 2018). These previous studies demonstrate that SfM shows promise in providing accurate information for allometric equations used to extrapolate biomass of rangeland grass to a landscape-scale.

Field work for capturing extremely close-range SfM imagery requires less training for field crews compared to TLS and UAS data collection and eliminates the need for specialized equipment. Developing an allometric relationship at a plot scale (cm) will inform future SfM studies that utilize UAS imagery (Gillan et al., 2019). Furthermore, close range SfM can be complementary and used as a precursor for extrapolating to scales that are amenable to commonly available UAS (e.g., m to km). However, vegetation and soil classification in such

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a fine resolution dataset remains challenging. Spectral reflectance in the visible spectrum and near-infrared may be able to better separate vegetation and dry biomass litter from one-another, or from the mineral soil or ground surface. Although differences in the soil composition can cause different types of confusion with vegetation and litter, possibly reducing transferability of methods between study sites (Huang et al., 2007), in areas where the ground surface can be largely obscured may benefit from other approaches such as structural analyses from either SfM or active remote sensing technologies may be more successful (Calders et al., 2015).

A common technique for estimation of AGB relies on Digital Terrain Model (DTM) and Digital Surface Model (DSM) computation and the retrieved Canopy Height Model (CHM) and Leaf Area Index (LAI) from them (Ota et al., 2015, Zhang et al., 2018, Xu et al., 2019). The biomass from lidar and UAS-derived point clouds CHM is generally classified into ground and vegetation by setting a height threshold (Cunliffe et al., 2016, Viljanen et al., 2018, Näsi et al., 2018, Navarro et al., 2020). However, the accuracy of CHM mostly exceeds the height of short shrubs and grasses, and thus CHM models are less suitable for aboveground biomass estimation in dryland ecosystems (Zahawi et al., 2015). Schulze-Bruninghoff et al. (2021) suggested a method combining lidar-derived metrics (sum of voxels, canopy height model, and canopy surface structure) and vegetation spectral properties to estimate fresh and dry biomass in a machine learning approach. In addition, by combining ground camera and UAS, Taugourdeau et al. (2022) extracted vegetation metrics from RGB bands and height to estimate aboveground biomass in a random forest model. Therefore, the uncertainty of biomass estimation is limited to the uncertainty in CHM, data resolution, and the type of land treatments (grazed or ungrazed). In this regard, the discrimination between vegetation and bare ground structural properties (smoothness of the surface, randomness of vegetation foliage, and curvature) could improve AGB estimation from high-resolution ground camera and UAS SfM-derived point clouds.

The objectives of this work are to explore the potential for close-range SfM to quantify fine-fuel AGB, with the thought of replacing destructively harvested sampling with the methodology, or to utilize the close-range SfM volumetric estimations to inform potential UAS data collection. To accomplish this, we first developed a method to acquire and process field data from photos to point clouds. Second, we explored how to separate and classify the ground surface through the thick litter layer found in the study area. Third, we examined the relationship between the measurement unit of volumetric calculation and the biomass of the study area's vegetation. Lastly, we discuss some observations on how the SfM point frame might be used, and how this method may inform UAS data seeking to estimate biomass or vegetation volume.

Methods

1. *Study Area*

Our study area is the Three Fingers allotment located in southeastern Oregon (Fig. 1), approximately 80 km west of Boise, Idaho. The Vale District U.S. Bureau of Land Management (BLM) manages the allotment, which has a history of disturbance from grazing, recreation, and fire. The area has experienced significant departure from native vegetation communities, with few remaining native shrubs and an extensive cover of cheatgrass and medusahead, and other annual grasses (>80% in all experimental exclosures).

This study was part of a larger study focused on evaluating the effect of dormant season grazing on fine fuels (Arispe et al. 2022). As part of the project, data were collected across two years and on three different pastures on the Three Fingers allotment—approximately 55,000 hectares. The three pastures within the project included, McIntyre (MCI; 3100 ha), South Camp Kettle (SCK; 2500 ha), and Saddle Butte (SB; 3800 ha). Within each pasture a northern and southern exclosure was randomly placed, for a total of six treatment areas. Each exclosure contained four paddocks 150 m x 150 m in size, for a total of 24 paddocks.

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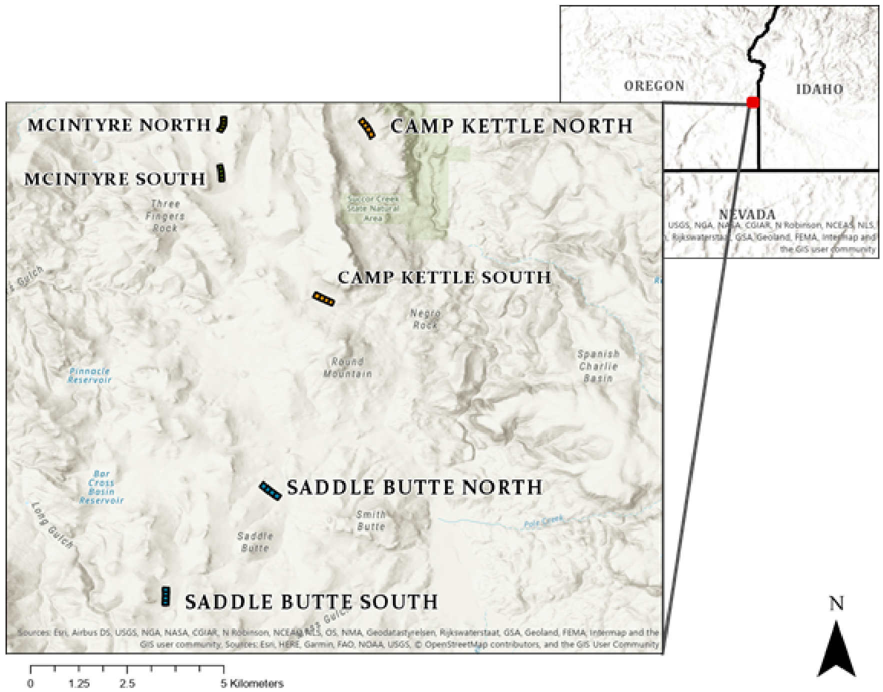

Fig. 1: Study area in southeast Oregon, USA. At each pasture, two sites were established for a total of six treatment areas. At each of the six treatment areas, four paddocks (150 m x 150 m) were established; within each paddock, three transects are established annually. Each transect is sampled in at least three places with destructive harvesting and Structure-from-Motion volumetric estimates.

Field Data and Collection Protocol

Data were collected in June 2020 and June 2021, as supplement to existing protocol (Arispe et al. 2022) for collecting biomass data in each of the 24 experimental paddocks. For each of the 24 paddocks, three transects are established from a randomized central location. Along each transect, three 0.4 m by 0.5 m areas were photographed for Structure-from-Motion reconstruction and then destructively harvested. Vegetation was removed to as near to mineral soil as possible, and separated into annual grasses, perennial grasses, forbs, and litter prior to drying. Plots that contained shrubs were excluded, since shrubs are not destructively harvested for the larger project. Samples were oven-dried for 48 hours at 60° in a commercial drying hood and weighed. Approximately 1/3 of the plots were photographed again immediately after harvesting the vegetation but before disturbing the frames so as to collect the mineral soil surface microtopography.

Structure-from-Motion Protocol and Reconstruction

Two custom quadrat frames were constructed from extruded aluminum, containing custom 3D-printed 0.05 m cubes with coded targets (Fig. 2). These targets are automatically detected in Agisoft Metashape (version 1.6). We used a Sony a6000 with the stock kit lens (16-50 mm F3.5-5.6) to collect approximately 75 photographs per quadrat frame. These were taken approximately 1 m above the plot in a 5 x 5 sampling pattern repeated three times: once at nadir, once at approximately 20-degree tilt away from the photographer, and again tilted towards the photographer. Several additional images were taken at each plot from a greater height, and at several corner-on angles. Care was taken to stand so as to avoid casting a shadow on the plot. One of each of the six sites was collected per day. In total, approximately 216 plots were collected over the six treatment areas in both 2020 and 2021.

Our processing workflow in Agisoft was automated using Python; each plot was processed at high-quality image alignment and medium-quality dense cloud reconstruction. Resulting point clouds had typical densities of 0.5- to 4-million points per square meter with a minimum of 0.001 m spacing between points. After processing and quality assessment, there were 114 plots for 2020 and 174 plots for 2021.

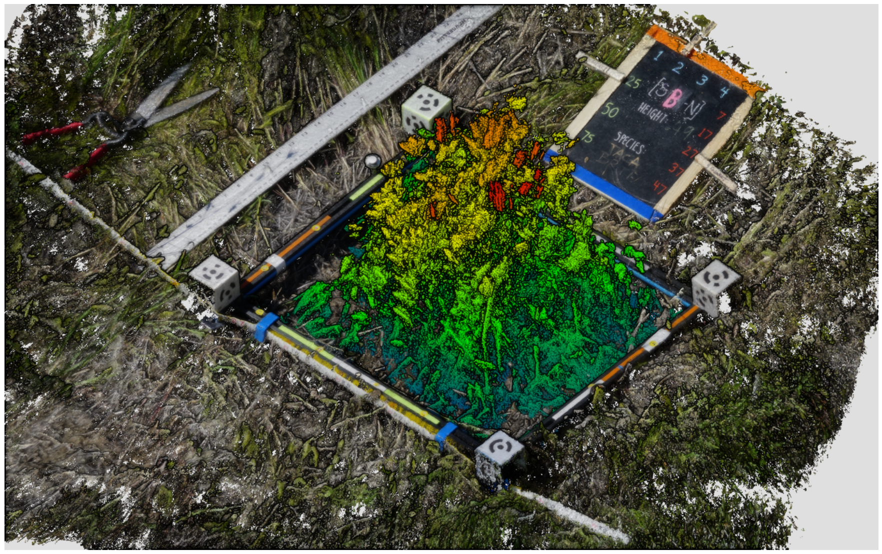

Fig. 2: Point cloud reconstruction of a typical 0.4 m x 0.5 m plot before destructive harvesting, including quadrat frame with coded targets. Vegetation (primarily Taeniatherum caput-medusae) colored by height.

Point Cloud Classification and Volumetric Processing

Following reconstruction, point clouds were imported into Matlab (version R2021a) for classification into ground and vegetation classes and volumetric measurements (Fig. 3). After clipping the point clouds inside the frames, we applied the point cloud denoising algorithm presented by Rusu et al. (2008) to remove the outliers from the point cloud. To classify the point cloud into ground and vegetation classes we applied the simple morphological filter (SMRF) algorithm in Matlab.

The simple morphological filter (SMRF) method (Pingel et al. 2013) classifies the point clouds into vegetation and ground using the elevation and slope threshold. The algorithm tiles the data by a grid resolution, finds the minimum elevation points within each grid and fits a surface to the minimum points. The points that are excluded from the elevation difference between the minimum surface and morphological opened minimum surface by linearly increased window sizes (from 1 to user defined maximum window radius) in an iterative procedure are considered as vegetation and the points that satisfy the elevation threshold are classified as ground (more detail can be found in Pingel et al. 2013).

We used an elevation threshold of 11 cm, slope threshold of 0.1 (as the plots were mostly flat), elevation scale of 0.9 (to detect medium size objects) and max window radius of 10. While this is effective, the ground classified points still contain some vegetation biomass. To separate the remaining vegetation points from the ground class, we applied two gaussian mixture classification algorithms on the curvature of the point clouds using 50 and 200 neighbors (200 neighbors is applied on the ground class from 50 neighbors output). In this method we assume that the ground surface is smoother than the vegetation surface and thus the curvature on the surface is different for those classes. The algorithm extracts curvatures and fits a gaussian distribution, and assumes vegetation and ground curvatures follow two mixed gaussian distributions. After retrieving the vegetation and ground class we merged the vegetation class with the previous vegetation class from the SMRF results.

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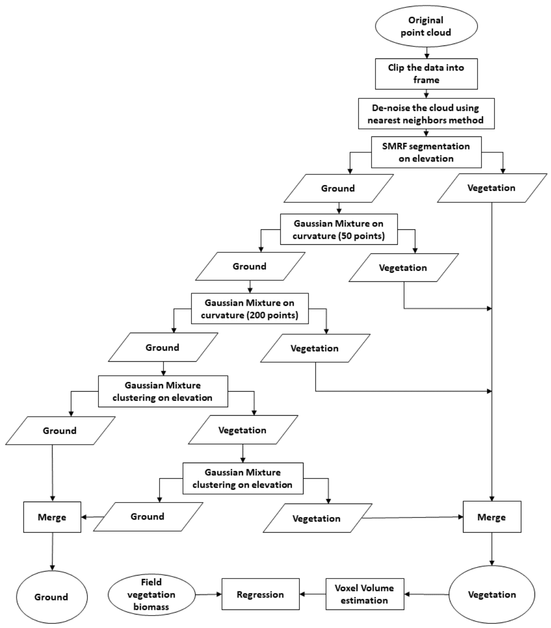

Fig. 3: Point cloud processing workflow.

Evaluating Volumetric Measurement Methods

Once the data were classified into ground and vegetation, we investigated several methods to compare volume with above-ground biomass. We assessed the data based on a per site (n = 6) and as combined sites per year, and by combining years. Our interest in assessing on a per-site basis was to consider possible effects of changing photography conditions (one site photographed per day), or influences of the site location such as general vegetation type. Similar logic was applied to the per year versus both years combined datasets.

We examined how we accounted for voxel volume by using vegetation-classified points as the volumetric measure (vegetation voxel volume), and by using the total plot voxel volume with no classification of vegetation and ground. We performed the latter to test whether litter or other obstructions had a detrimental effect on the ability to detect the ground surface. Ultimately, in this model, litter was considered as part of the biomass volume.

We also computed a vegetation voxel volume above the surface, by fitting a surface to the ground and computing the vegetation volume above the surface. Additionally, we examined the relationships between volumes and vegetation type (e.g. perennial and annual grasses, forbs). Linear models and logarithmic models were both investigated for the relationships between voxel volume and biomass.

Finally, we also assessed the scale at which volumetric data is best reconstructed for sagebrush-steppe vegetation (e.g., fine annual grasses) and to inform the possibility for using volumes reconstructed from UAS imagery. This included voxelizing the point clouds at several resolutions ranging from 2 mm to 100 mm, comparing volumes of all reconstructed points and volumes of vegetation-classified points only.

Results

1. *Volume and Biomass Allometry Modeling and Sensitivity Analysis*

Table 1 depicts the models we tested that had a significant (> 0.30 R^2) relationship between voxel volume and field biomass. We found the best correlation ($R^2 = 0.48$) with a logarithmic regression between 5 mm voxel volumes of vegetation-classified points with above ground biomass for all sites across years (Table 1). We generally found that logarithmic models performed better than linear models when all plots were grouped together across years.

A linear regression of plots (n = 36) from both years from South Camp Kettle (South site) attained an R^2 of 0.62 between classified vegetation points at 5 mm voxel sizes with the biomass of only annual and perennial grasses (i.e. no litter biomass was included). However, generally there was no pattern of linear or logarithmic modeling performing better for any of the comparisons when modeling by site or by year.

Generally, our vegetation voxel volume calculated from classified vegetation points (from Fig. 3, workflow) performed better than using a fitted surface to identify vegetation points and calculate a volume. Using a total plot voxel volume along with only annual and perennial grasses had a relatively high R^2. No relationship with forb biomass was found due to their relative rarity in the study area.

Table 1. The retrieved R^2 by applying a linear and logarithmic regression between biomass and vegetation volume. The reported values are the significant ones according to the f^2 test for the sample size. The minimum threshold for power is 90% here. AG and PG here means annual and perennial grass, respectively. Plot volume is the voxelized volume of the total plot without classification, and vegetation volume is also voxelized volume but after classification per the workflow (Fig. 3).

Comparison (5mm voxel)	Linear regression R^2	Logarithmic regres
Vegetation voxel volume vs vegetation biomass	0.35	0.48
Vegetation voxel volume vs vegetation biomass + litter		0.32
Vegetation voxel volume above reconstructed ground surface with total biomass	0.30	
Vegetation voxel volume and AG+PG	0.33	0.40
Plot voxel volume and AG+PG	0.32	0.39

Voxel Size Comparison

Investigating the effects of volumetric resolution on data distributions was conducted by voxelizing the point clouds in intervals from 2 mm to 100 mm. Distributions of calculated volumes with the differing voxel sizes were all statistically different from one-another (Fig. 4) as determined by a Wilcoxon test (Table 2).

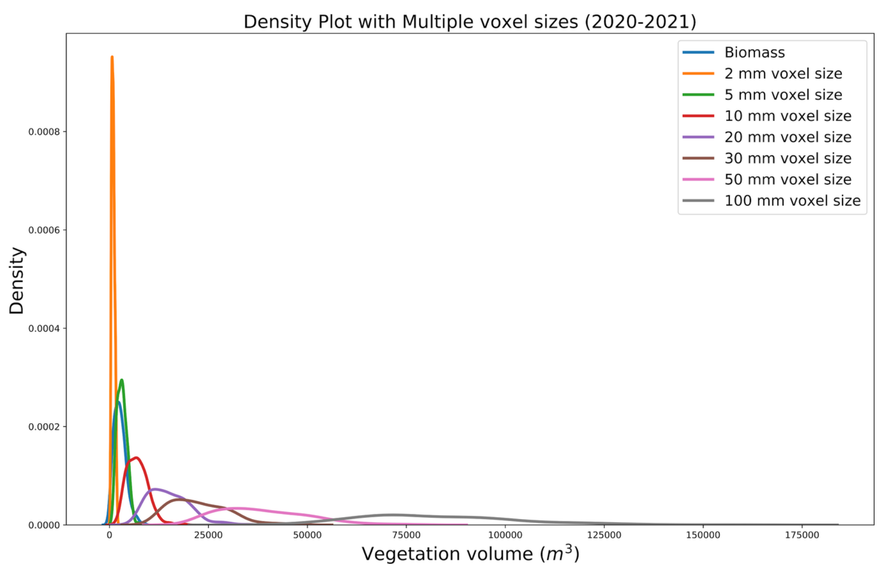

Fig. 4. Biomass and vegetation volume distribution at different voxel sizes for 2020-2021 data.

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Table 2. Wilcoxon test results on plot volume among different voxel sizes. The null hypothesis assumes that the paired volumes are not different. P-values less than 0.05 significance level (5% confidence level) rejects the null hypothesis, meaning that the computed volumes using different voxel sizes are significantly different. As the voxel volumes are not normally distributed, we used the Wilcoxon test.

Voxel size	2 mm	5 mm	10 mm	20 mm	30 mm	50 mm	100 mm
2 mm							
5 mm	< 0.05						
10 mm	< 0.05	< 0.05					
20 mm	< 0.05	< 0.05	< 0.05				
30 mm	< 0.05	< 0.05	< 0.05	< 0.05			
50 mm	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05		
100 mm	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	
Biomass	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05

Reference Surface vs. Reconstructed Surface

Comparing the plots where we collected imagery after destructive harvesting and reconstructed the 'true' reference ground surface using SfM (n = 35) with our reconstructed interpolated ground surface showed a decrease in R^2 from 0.44 to 0.42 at 5 mm voxels (Fig. 5). The mean absolute difference in volumes was 20% of the volume calculated using the reference ground surface.

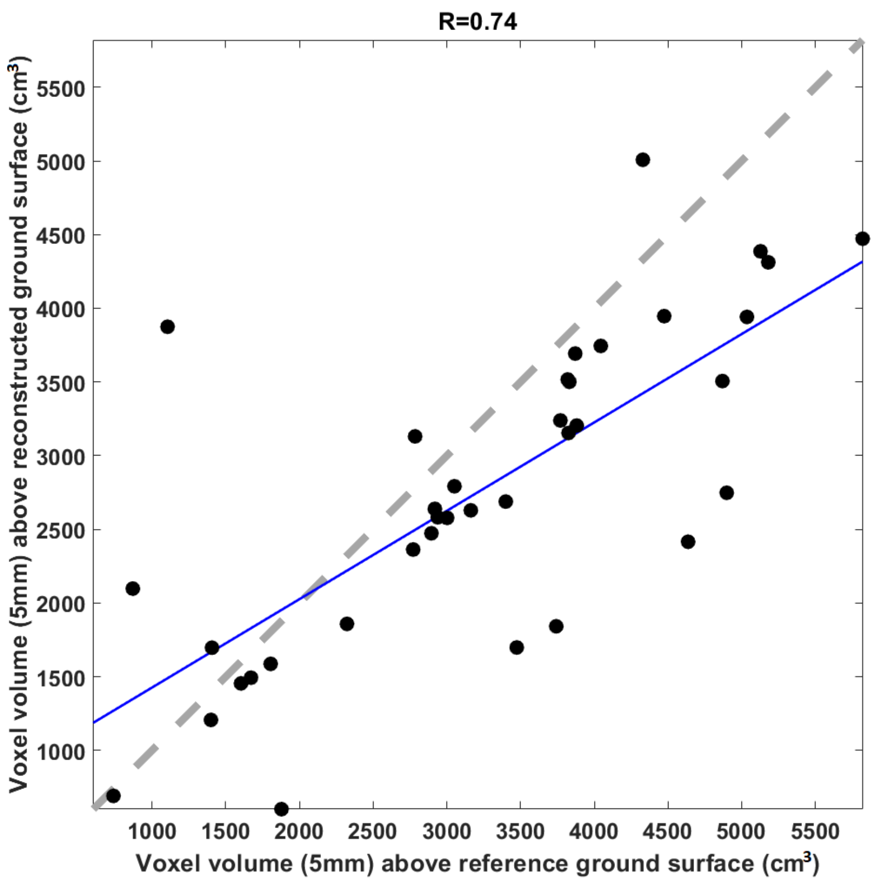

Fig. 5. Calculated vegetation and litter voxel volumes using reference ground surface and reconstructed ground surface.

Discussion

The outcome of this research illuminates some considerations specific to the vegetation of the study area, chiefly the gracile structure of medusahead and the layer of litter that it deposits. Broadly, we found that the largest cause for uncertainty in our estimations resulted from the fine fuel litter layer obscuring the ground surface. However, with some additional processing, we were able to attain some informative results.

Structure-from-Motion Sample Frame and Reconstruction

Reconstructing point clouds from the field photography is a feasible sampling strategy for studies of this scale. However an effort must be taken to automate as much as possible, since it can be labor- and processing-intensive. The addition of coded targets at known, local coordinates greatly reduces the need for manual steps in the process. We observed that reconstruction success of the point clouds was mostly dependent on the photo quality (e.g. not blurry), amount of overlap, and that the targets were not obstructed by even a small amount of vegetation. Environmental conditions also played a role in the success of the point cloud reconstruction; occasionally, lighting conditions created too many shadows or too much variability during the photographing process. Due to the relatively delicate structure of the site vegetation, small gusts of wind can be troublesome and cause a plot to fail reconstruction quality thresholds, or fail to process altogether.

Because the per-year and per-site regressions did not have significant relationships (excepting 2020-2021 South Camp Kettle South, $n = 36$, $R^2 = 0.62$, 5 mm voxel size), we hypothesize that the conditions for all fields were similar and that the reconstructed point clouds were of similar quality and captured the variability of vegetation types equally across the study environment. We observed no significant relationship between vegetation types and volume calculations. The fidelity of the reconstructed point clouds to the vegetation structure was mostly influenced by whether the ground surface was visible, and whether there was a dense layer of litter or stand of vegetation.

Ground and Vegetation Classification and Separability in Point Clouds

Vegetation in the Three Fingers Allotment can often contain a dense layer of dead medusahead from previous growing seasons, or a thick cover of living medusahead, or both. This means that passive remote sensing techniques such as Structure-from-Motion may have difficulty measuring both the internal volume and the ground surface. Such obstructions likely decreased the correlation between calculated volume and measured biomass. Iterative classification of the ground surface points increased the observed relationship between volume and biomass for all combinations of vegetation types and biomass. In addition to occluding the ground surface, the layer of litter also confounded the ability to accurately characterize the ground surface.

However, our comparison between our reconstructed ground surface with the 'true' reference ground surface elucidates two points. First, the decrease in predictive ability between the reference surface and our reconstruction is only 2% (from R^2 of 0.44 to R^2 of 0.42), which assists in constraining uncertainties in volumetric calculations using our ground and vegetation classification or similar process. Second, the range of litter biomass in this regression ranged from 20% to 100% of the total vegetation biomass with evenly distributed errors. This indicates that the disagreement between calculated volumes is independent from the proportion of litter in the total biomass. Thus, it may be possible to adequately quantify uncertainty in volumetric measurements at pasture-scales. It is possible that the observed relationship is related to the compaction of the litter layer over time. However, a larger and more varied sample size at the smaller plot scale would help further understand this relationship.

Additionally, we explored using a convex hull volumetric calculation to compare to the voxel volume calculations. While the convex hull method may better handle the under-sampled volumes internal to a mat of litter or dense vegetation, we found that although the results were similar to the voxel models, the convex hull method generally performed worse across the different classifications and comparison models.

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Voxel Volume Analysis

Because the total volumetric calculations were statistically significant for each voxel size, we ascertain that the volumetric calculations are highly dependent on the resolution of the final point cloud. Volumes from decreasing voxel sizes were increasingly similar to the measured biomass, up to a point: the distribution of voxel volumes at 5 mm more closely matched the biomass distribution than the 2 mm voxel sizes. This may indicate that the scale of obscured volume is exacerbated as decreasing voxel sizes are employed for the vegetation communities; the smaller voxel sizes may be more reflective of the surface of the vegetation. More simply, it may be that the density of such plant communities is beyond the limits of the resolution of the imagery (Wallace et al. 2017).

Considerations for Future UAS-Derived and Non-Destructive Biomass Data

Our study helps inform UAS-derived spatial and structural data in two ways. Primarily, the unique characteristics of the vegetation and ecological communities in this study area (perennial and annual grass-dominated, of varying densities and heights, and with significant layers of litter cover) strongly favor higher-resolution UAS data. While it is not uncommon for UAS sensors to routinely output models at 5 cm pixel sizes, our analysis suggests that additional mission planning and sensor considerations to achieve closer to 1 cm pixel sizes may be important to enable volumetric estimates of biomass in such environments, as found by Cunliffe et al. (2016). Additionally, the complications of our analysis given the common occlusion of the ground surface indicate that volumetric estimations on such a scale (e.g. centimeter to tens of centimeter litter layers, typically shorter than 1 m vegetation heights) are sensitive to the spatial resolution of the remote sensing product and that using an elevation model (e.g. DSM) may be insufficient to reconstruct a ground surface.

Given the uncertainty of identifying ground surface, whether from classified points or a reconstructed surface, our proposed method would benefit from refinement before being considered a replacement for destructive harvesting. Such refinements might include systematic comparisons with other commonly-used biomass sampling techniques for grasslands such as rising plate meter devices. Separating ground from vegetative biomass, or litter from ground and standing biomass may benefit greatly from using multispectral imagery. Active remote sensing techniques such as lidar, whether in conjunction with imaging or alone, may also more reliably return ground points through litter layers and dense vegetation, as well as providing other data such as intensity that may enable greater discernment between ground, litter, and other vegetation.

Other avenues to explore with our proposed method may explore other calculations and measurements from the dense and high-resolution point clouds, such as vegetation height or other allometry (Cunliffe et al. 2022, Schulze-Brüninghoff et al. 2021). This may include relationships between biomass and structure, or as a more direct replacement of other field-measured data such as canopy cover. With other passive sensor types such as multispectral or hyperspectral imaging, or active sensors such as lidar, other metrics such as moisture level or classifications may be possible. Fusion of such data types has shown more success together in grasslands in predicting biomass as well as other properties such as moisture content (Schulze-Brüninghoff et al. 2021).

Conclusion

In this paper we explored using Structure-from-Motion at ultra-fine scales in an environment dominated by exotic annual grasses and associated litter. Understanding the amount of biomass and litter in these rangeland environments is important for managing forage and fuels, and understanding treatments and changes. UAS offer the possibility to scale up traditional field methods to larger areas, yet challenges still remain. This research aims to develop field methods and processes to understand the limits of using Structure-from-Motion in semi-arid ecosystems to estimate biomass. We believe that our research adds to this process by establishing a methodology to further collect and process small plots of biomass into classified point clouds in a largely-automated fashion, so that additional work may be conducted and expanded. Our results indicate that the ability to detect the ground may be the limiting factor in attaining satisfactory volume-to-biomass relationships in similar environments, and reiterating that fine spatial resolutions are needed for fine-scale vegetation.

Author's Contributions

Josh Enterkine: Methodology, Software, Validation, Investigation, Resources, Data Curation, Writing - Review & Editing, Supervision, Visualization. **Ahmad Hojatimalekshah:** Methodology, Software, Validation, Formal Analysis, Data Curation, Writing - review & editing, Visualization. **Monica Vermillion:** Methodology, Software, Investigation, Writing – Original Draft. **Thomas Van Der Weide:** Software. **Sergio A. Arispe:** Conceptualization, Investigation, Supervision, Project administration, Funding acquisition.**William J. Price:** Methodology, Investigation, Resources, Data Curation, Supervision. **April Hulet:** Conceptualization, Methodology, Investigation, Resources, Funding acquisition.**Nancy F Glenn:** Conceptualization, Methodology, Writing – Review & Editing, Supervision, Project administration, Funding acquisition.

Running Title

SfM Volume for Exotic Annual Grass Biomass and Fine Fuels

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Permission to Reproduce Materials from Other Sources

None/not applicable.

Data Availability Statement

Data and code is available for reviewers at https://drive.google.com/drive/folders/1TnYQKFnTyV3aBjx9bWQavYnS7JqHlv2 and will be published via DOI through Boise State University ScholarWorks preceding publication of manuscript.

References

Ahlstrom, A., Raupach, M.R., Schurgers, G., Smith, B., Arneth, A., Jung, M., Reichstein, M., Canadell, J.G., Friedlingstein, P., Jain, A.K., Kato, E., Poulter, B., Sitch, S., Stocker, B.D., Viovy, N., Wang, Y.P., Wiltshire, A., Zaehle, S., Zeng, N., 2015. The dominant role of semi-arid ecosystems in the trend and variability of the land CO2 sink. Science (80-.). 348, 895–899. https://doi.org/10.1126/science.aaa1668

Anderson, K.E., Glenn, N.F., Spaete, L.P. et al. Methodological considerations of terrestrial laser scanning for vegetation monitoring in the sagebrush steppe. Environ Monit Assess 189, 578 (2017). https://doi.org/10.1007/s10661-017-6300-0

Anderson, K.E., Glenn, N.F., Spaete, L.P., Shinneman, D.J., Pilliod, D.S., Arkle, R.S., McIlroy, S.K., Derryberry, D.R., 2018. Estimating vegetation biomass and cover across large plots in shrub and grass dominated drylands using terrestrial lidar and machine learning. Ecol. Indic. 84, 793–802. https://doi.org/10.1016/j.ecolind.2017.09.034

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Arispe, S.A., Johnson, D.D., Wollstein, K.L., Hulet, A., Jensen, K.S., Schultz, B.W., Sprinkle, J.E., McDaniel, M.F., Ryan, T., Mackenzie, M., Cunningham, S., 2022. Strategic Partnerships to Leverage Small Wins for Fine Fuels Management. Rangel. Ecol. Manag. 85, 66–75. https://doi.org/10.1016/j.rama.2022.09.004

Bradley, B.A., Curtis, C.A., Fusco, E.J., Abatzoglou, J.T., Balch, J.K., Dadashi, S., Tuanmu, M.N., 2018. Cheatgrass (Bromus tectorum) distribution in the intermountain Western United States and its relationship to fire frequency, seasonality, and ignitions. Biol. Invasions 20, 1493–1506. https://doi.org/10.1007/s10530-017-1641-8

Bradley, B.A., Houghton, R.A., Mustard, J.F., Hamburg, S.P., 2006. Invasive grass reduces aboveground carbon stocks in shrublands of the Western US. Glob. Chang. Biol. 12, 1815–1822. https://doi.org/10.1111/j.1365-2486.2006.01232.x

Calders, K., Newnham, G., Burt, A., Murphy, S., Raumonen, P., Herold, M., Culvenor, D., Avitabile, V., Disney, M., Armston, J., Kaasalainen, M., 2015. Nondestructive estimates of above-ground biomass using terrestrial laser scanning. Methods Ecol Evol 6, 198–208. https://doi.org/10.1111/2041-210X.12301

Chambers, J.C., Bradley, B.A., Brown, C.S., D'Antonio, C., Germino, M.J., Grace, J.B., Hardegree, S.P., Miller, R.F., Pyke, D.A., 2014. Resilience to stress and disturbance, and resistance to Bromus tectorum L. invasion in cold desert shrublands of western North America. Ecosystems 17, 360–375. https://doi.org/10.1007/s10021-013-9725-5

Clark, Patrick & Hardegree, Stuart & Moffet, Corey & Pierson, Frederick. (2008). Point Sampling to Stratify Biomass Variability in Sagebrush Steppe Vegetation. Rangeland Ecology & Management. 61. 10.2111/07-147.1.

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 Sens. 9. https://doi.org/10.3390/rs9060531

Cunliffe, A.M., Brazier, R.E., Anderson, K., 2016. Ultra-fine grain landscape-scale quantification of dryland vegetation structure with drone-acquired structure-from-motion photogrammetry. Remote Sensing of Environment 183, 129–143. https://doi.org/10.1016/j.rse.2016.05.019

Cunliffe, A.M., Anderson, K., Boschetti, F., Brazier, R.E., Graham, H.A., Myers-Smith, I.H., Astor, T., Boer, M.M., Calvo, L.G., Clark, P.E., Cramer, M.D., Encinas-Lara, M.S., Escarzaga, S.M., Fernandez-Guisuraga, J.M., Fisher, A.G., Gdulova, K., Gillespie, B.M., Griebel, A., Hanan, N.P., Hanggito, M.S., Haselberger, S., Havrilla, C.A., Heilman, P., Ji, W., Karl, J.W., Kirchhoff, M., Kraushaar, S., Lyons, M.B., Marzolff, I., Mauritz, M.E., McIntire, C.D., Metzen, D., Mendez-Barroso, L.A., Power, S.C., Prošek, J., Sanz-Ablanedo, E., Sauer, K.J., Schulze-Brüninghoff, D., Šímová, P., Sitch, S., Smit, J.L., Steele, C.M., Suárez-Seoane, S., Vargas, S.A., Villarreal, M., Visser, F., Wachendorf, M., Wirnsberger, H., Wojcikiewicz, R., 2022. Global application of an unoccupied aerial vehicle photogrammetry protocol for predicting aboveground biomass in non-forest ecosystems. Remote Sens. Ecol. Conserv. 8, 57–71. https://doi.org/10.1002/rse2.228

Evans, R.A. and J.A. Young, Plant Litter and Establishment of Alien Annual Weed Species in Rangeland Communities. Weed Science, 1970. 18(6): p. 697-703.

Fern, R.R., Foxley, E.A., Bruno, A., Morrison, M.L., 2018. Suitability of NDVI and OSAVI as estimators of green biomass and coverage in a semi-arid rangeland. Ecol. Indic. 94, 16–21. https://doi.org/10.1016/j.ecolind.2018.06.029

Fernández-Guisuraga, J.M., Calvo, L., Fernandes, P.M., Hulet, A., Perryman, B., Schultz, B., Jensen, K.S., Enterkine, J., Boyd, C.S., Davies, K.W., Johnson, D.D., Wollstein, K., Price, W.J., Arispe, S.A., 2022. Estimates of fine fuel litter biomass in the northern Great Basin reveal increases during short fire-free intervals associated with invasive annual grasses. Sci. Total Environ. 160634. https://doi.org/https://doi.org/10.1016/j.scitotenv.2022.160634

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Gillan, J.K., McClaran, M.P., Swetnam, T.L., Heilman, P., 2019. Estimating forage utilization with drone-based photogrammetric point clouds. Rangel. Ecol. Manag. 72, 575–585. https://doi.org/10.1016/j.rama.2019.02.009

Houghton, R.A., Hall, F., Goetz, S.J., 2009. Importance of biomass in the global carbon cycle. J. Geophys. Res. Biogeosciences 114, 1–13. https://doi.org/10.1029/2009JG000935

Huang, C., Marsh, S.E., McClaran, M.P., Archer, S.R., 2007. POSTFIRE STAND STRUCTURE IN A SEMIARID SAVANNA: CROSS-SCALE CHALLENGES ESTIMATING BIOMASS. Ecological Applications 17, 1899–1910. https://doi.org/10.1890/06-1968.1

Knapp, P.A., 1996. Cheatgrass (Bromus tectorum L) dominance in the great basin desert. History, persistence, and influences to human activities. Glob. Environ. Chang. 6, 37–52. https://doi.org/10.1016/0959-3780(95)00112-3

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. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. - ISPRS Arch. 42, 539–542. https://doi.org/10.5194/isprs-archives-XLII-2-539-2018

Miller, J., Morgenroth, J., Gomez, C., 2015. 3D modelling of individual trees using a handheld camera: Accuracy of height, diameter and volume estimates. Urban For. Urban Green. 14, 932–940. https://doi.org/10.1016/j.ufug.2015.09.001

Näsi, R., Viljanen, N., Kaivosoja, J., Alhonoja, K., Hakala, T., Markelin, L., Honkavaara, E., 2018. Estimating Biomass and Nitrogen Amount of Barley and Grass Using UAV and Aircraft Based Spectral and Photogrammetric 3D Features. Remote Sensing 10, 1082. https://doi.org/10.3390/rs10071082

Navarro, A., Young, M., Allan, B., Carnell, P., Macreadie, P., Ierodiaconou, D., 2020. The application of Unmanned Aerial Vehicles (UAVs) to estimate above-ground biomass of mangrove ecosystems. Remote Sensing of Environment 242, 111747. https://doi.org/10.1016/j.rse.2020.111747

Olsoy, P.J., Shipley, L.A., Rachlow, J.L., Forbey, J.S., Glenn, N.F., Burgess, M.A., Thornton, D.H., 2018. Unmanned aerial systems measure structural habitat features for wildlife across multiple scales. Methods Ecol. Evol. 9, 594–604. https://doi.org/10.1111/2041-210X.12919

Ota, T., Ogawa, M., Shimizu, K., Kajisa, T., Mizoue, N., Yoshida, S., Takao, G., Hirata, Y., Furuya, N., Sano, T., Sokh, H., Ma, V., Ito, E., Toriyama, J., Monda, Y., Saito, H., Kiyono, Y., Chann, S., Ket, N., 2015. Aboveground Biomass Estimation Using Structure from Motion Approach with Aerial Photographs in a Seasonal Tropical Forest. Forests 6, 3882–3898. https://doi.org/10.3390/f6113882

Pingel, T.J., Clarke, K.C., McBride, W.A., 2013. An improved simple morphological filter for the terrain classification of airborne LIDAR data. ISPRS J. Photogramm. Remote Sens. 77, 21–30. https://doi.org/10.1016/j.isprsjprs.2012.12.002

Rusu, R.B., Blodow, N., Marton, Z.C., Beetz, M., 2008. Aligning point cloud views using persistent feature histograms. 2008 IEEE/RSJ Int. Conf. Intell. Robot. Syst. IROS 3384–3391. https://doi.org/10.1109/IROS.2008.4650967

Salamí, E., Barrado, C., Pastor, E., 2014. UAV flight experiments applied to the remote sensing of vegetated areas. Remote Sens. 6, 11051–11081. https://doi.org/10.3390/rs61111051

Schulze-Brüninghoff, D., Wachendorf, M. and Astor, T. (2021), Remote sensing data fusion as a tool for biomass prediction in extensive grasslands invaded by L. polyphyllus. Remote Sens Ecol Conserv, 7: 198-213. https://doi.org/10.1002/rse2.182

Taugourdeau, S., Diedhiou, A., Fassinou, C., Bossoukpe, M., Diatta, O., N'Goran, A., Auderbert, A., Ndiaye, O., Diouf, A.A., Tagesson, T., Fensholt, R., Faye, E., 2022. Estimating herbaceous aboveground biomass in

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Sahelian rangelands using Structure from Motion data collected on the ground and by UAV. Ecology and Evolution 12. https://doi.org/10.1002/ece3.8867

Viljanen, N., Honkavaara, E., Näsi, R., Hakala, T., Niemeläinen, O., Kaivosoja, J., 2018. A Novel Machine Learning Method for Estimating Biomass of Grass Swards Using a Photogrammetric Canopy Height Model, Images and Vegetation Indices Captured by a Drone. Agriculture 8, 70. https://doi.org/10.3390/agriculture8050070

Wallace, L., Hillman, S., Reinke, K., Hally, B., 2017. Non-destructive estimation of above-ground surface and near-surface biomass using 3D terrestrial remote sensing techniques. Methods Ecol. Evol. 8, 1607–1616. https://doi.org/10.1111/2041-210X.12759

Wijesingha, J., Moeckel, T., Hensgen, F., Wachendorf, M., 2019. Evaluation of 3D point cloud-based models for the prediction of grassland biomass. Int. J. Appl. Earth Obs. Geoinf. 78, 352–359. https://doi.org/10.1016/j.jag.2018.10.006

Xu, K., Su, Y., Liu, J., Hu, T., Jin, S., Ma, Q., Zhai, Q., Wang, R., Zhang, J., Li, Y., Liu, H., Guo, Q., 2020. Estimation of degraded grassland aboveground biomass using machine learning methods from terrestrial laser scanning data. Ecological Indicators 108, 105747. https://doi.org/10.1016/j.ecolind.2019.105747

Zahawi, R.A., Dandois, J.P., Holl, K.D., Nadwodny, D., Reid, J.L., Ellis, E.C., 2015. Using lightweight unmanned aerial vehicles to monitor tropical forest recovery. Biological Conservation 186, 287–295. https://doi.org/10.1016/j.biocon.2015.03.031

Zhang, H., Sun, Y., Chang, L., Qin, Yu, Chen, J., Qin, Yan, Du, J., Yi, S., Wang, Y., 2018. Estimation of Grassland Canopy Height and Aboveground Biomass at the Quadrat Scale Using Unmanned Aerial Vehicle. Remote Sensing 10, 851. https://doi.org/10.3390/rs10060851