2024 IEEE 20th International Conference on Automation
Science and Engineering (CASE)
August 28 - September 1, 2024. Bari, Italy

2024 IEEE 20th International Conference on Automation Science and Engineering (CASE) | 979-8-3503-5851-3/24/$31.00 ©2024 IEEE | DOI: 10.1109/CASE59546.2024.10711468

Non-Destructive Biomass Estimation Based on 3D Reconstruction From A Handheld Camera

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Abstract— **With the recent advancements in sensing technology and machine learning, it has become possible to develop agricultural technologies that can keep pace with the shrinking agriculture workforce and growing population needs. Above-ground biomass (AGB) is a key trait for crop growth monitoring, crop breeding and yield prediction for agricultural scientists as well as for farmers. It is essential to develop an accurate non-destructive method because the destructive measurement of AGB is manual, time-consuming and expensive. In this paper, we propose and validate a new pipeline based on the latest low-cost technologies to accurately acquire 3D point clouds of the crop plots using a consumer camera and an off-the-shelf structure-from-motion reconstruction algorithm. Unlike the previous methods, the proposed non-destructive AGB pipeline does not rely on large amount of training data and high-cost field robots to capture the 3D data. The proposed pipeline for estimating AGB consists of three steps: i) 3D reconstruction of the crop plot, ii) estimating the volume of the crop plot, and iii) estimating the biomass from the volume. The experimental results showed a strong correlation between the plot volume and biomass with the minimum error in the final estimated biomass as compared to the recorded ground truth biomass.**

I. INTRODUCTION

The above-ground biomass (AGB), or simply biomass, of a crop is a critical indicator of the plant health and nutrient levels, especially nitrogen. The traditional method of calculating the AGB is manual, destructive and time-consuming [1]. Thus, various non-destructive techniques have been developed to estimate the AGB for different crops [2], [3], [4]. The accurate, automated and non-destructive measurement of AGB is difficult due to challenges such as occlusion in the crop plants in high-density plots or after flowering and unavailability of large accurate crop biomass datasets [22]. Recently, several techniques for automated non-destructive AGB estimation which utilise computer vision have been proposed, but despite the progress the accuracy of such methods requires further improvements [22], [2], [3].

In this paper, we propose a system for biomass estimation for the small grain cereal plants on a plot scale using a colour consumer camera. Our main contributions are as follows:

- A low-cost pipeline is developed for estimating biomass using volume measurements from 3D point clouds reconstructed from camera images;
- An in-depth analysis of different volume estimation techniques is provided by identifying the critical parameters that strongly impact the estimation of volume and biomass.
- The experimental evaluation of the proposed technique on manually annotated data collected from real plots of wheat and validated on an independent and publicly available dataset.

*This work is partly supported by funding from Innovate UK grant 10044243

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II. RELATED WORK

Remote sensing is one of the many techniques which have been successfully applied to measure the AGB for different crops which include wheat, maize, and rice. The most popular techniques to acquire remote sensing data are satellite platforms [2], man-made aircraft [3], and from ground [4]. The satellite platforms are very useful to acquire remote sensing data over large regions. However, it becomes difficult to acquire satellite imagery over multiple growth stages for small field sizes due to inadequate spatial resolution and frequent cloud cover [5]. Unmanned aerial vehicles (UAV) have become very popular to acquire high spatial resolution remotely sensed data. Multiple types of cameras such as colour cameras, colour-infrared cameras, and hyperspectral cameras can be used with UAVs to acquire the data [7]. However, it is not easy to acquire 3D data using UAVs for reasons such as if a UAV flies close to the crop then the natural pose of the crop gets distorted and if a UAV flies high above then it becomes impossible to acquire the geometric structure of the crop which leads to low-quality data. The ground-based field robots to acquire crop data are more accurate and hence provide satisfactory measurement for crop growth parameters. However, their deployment is costly and difficult to use over large areas [6].

The two most popular approaches used to predict the AGB from remote sensing data are based on the empirical relationship with vegetation indices (VIs) and machine learning models trained directly from sensor data. The first and most commonly used approach to accurately assess the AGB is by establishing the relationship between the vegetation indices and the recorded AGB, however, VIs are influenced by various environmental conditions and can introduce errors and uncertainties into AGB estimation [8], [9], [10]. On the other hand, the machine or deep learning methods can learn from the complicated non-linear data and be able to integrate the multiple factors influencing the AGB to accurately estimate the recorded AGB. Since the last decade, various machine learning models have been used to estimate the AGB which includes multiple linear regression, support vector machine, random forest and multi-layer perceptron. In addition to relying on the traditional machine learning

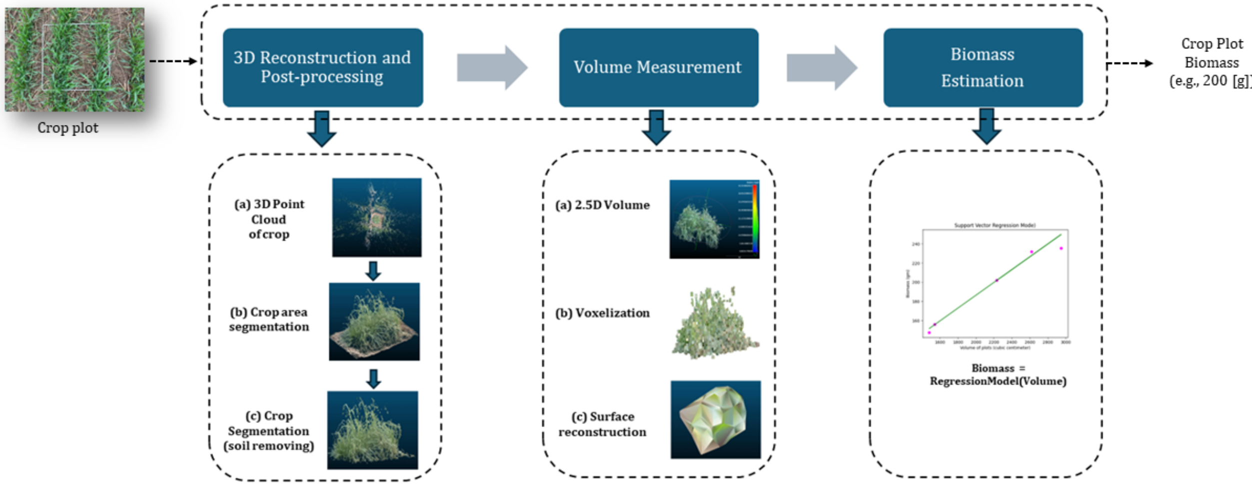


Fig. 1: The proposed pipeline for biomass estimation from 3D point cloud acquired using a consumer camera.

models, deep convolutional neural networks (CNNs) have been also used for AGB estimation [11], [12], [13]. However, AGB estimation usually lacks enough samples to properly train fully-supervised CNNs.

Recently, due to the advancement in technology in terms of acquiring 3D data with the help of light detection and ranging (LiDAR) and fast computing devices to process the high volume data in real time, several techniques have been developed to estimate AGB for crop research. Many of these techniques based on 3D LiDAR data have adopted the canopy height as a proxy to estimate the AGB [14], [15]. However, AGB prediction only based on height is not useful when the variation of height is limited in breeding programs. Moreover, some of the techniques that are based on the canopy height have used stereo reconstruction from the aerial images or ground platforms as an alternative to 3D LiDAR [16]. In contrast to issues with using canopy height, the techniques have been developed to utilize the 3D nature of a point cloud. Voxel-based, and point distribution-based methods are preferred as the density of the point cloud is shown to correlate strongly with the manually measured AGB [17]. In order to process the 3D point clouds, PointNet is one of the first techniques that has achieved tremendous success in directly processing the point cloud. PointNet is based on the MLP to learn the features from the data [18]. PointNet++ [19] which is an extension of PointNet recursively applies PointNet to extract local features from a small neighborhood and further grouping into larger units to produce higher-level features. These deep neural networks are fully supervised and require a large amount of labelled training data to achieve generalization. The scarcity of labelled training data is the biggest hurdle in applying such networks for applications like AGB. Thus, the traditional unsupervised machine learning techniques are still heavily used for AGB estimation.

III. Methodology

The general framework of the proposed pipeline (see Fig. 1) for estimating biomass consists of three primary steps: i) 3D crop plot reconstruction and crop segmentation, ii) volume measurement, and iii) biomass estimation.

A. 3D Crop Plot Reconstruction

The first step of the pipeline involves acquiring a set of images using the consumer camera which is then used for 3D scene reconstruction followed by crop segmentation. This involves the following steps:

1) Place a calibration object of well-defined edges and corners (e.g., Rubik's cube) near the reconstruction plot (e.g., corner) without occluding the plants.
2) Using the consumer camera, capture a set of overlapping 2D colour images of the crop plot and the calibration object from multiple views.
3) Estimate the camera parameters using a standard structure-from-motion (SfM) technique and then reconstruct the 3D crop plot model (i.e., point clouds) using a neural network-based technique. In this paper, COLMAP is used for SfM and NeRF [20] is used for 3D point cloud reconstruction.
4) Calibrate the scale of the 3D reconstructed plot to represent the real-world dimensions with the help of a calibration object.
5) Segment out the 3D points corresponding to the crop from soil and other parts of the environment.

B. Volume Estimation

The plant volume quantifies the above-ground portion of the plant and takes into consideration the important properties of the plant such as height, canopy structure, leaf areas, etc. The three selected techniques for measuring volume from 3D point clouds include 2.5D rasterisation, voxelisation, and mesh surface reconstruction.

1) 2.5D rasterisation: is based on regular 2D grid geometry representing the ground plane with individual cells, each covering area of size δ_{rst}^2, containing the height information. The conversion process from a point cloud to a 2.5D raster involves calculating the cell's height based on the relative distances h_i of all points associated with that cell to the projected ground plane, typically using statistics such as the mean (as in our case), min or max. The raster volume V_{rst} can be then calculated by summing all N individual cell volumes:

$$V_{rst} = \sum_{i=1}^{N} \delta_{rst}^2 h_i. \tag{1}$$

The tuning parameter in this approach is the step size δ_{rst}.

2) Voxelisation: similar to the 2.5D rasterisation, is based on regular grid-based geometry. In this case, the 3D space is discretised into regular cells (i.e. voxels) of a specific size δ_{vox} indicating occupied space. The conversion process from a point cloud to a voxel-based representation simply selects all the voxels containing at least one 3D point. The volume V_{vox} is computed by simply summing up all N individual voxel volumes: $V_{vox} = \delta_{vox}^3 N$. The tuning parameter in this approach is voxel size δ_{vox}.

3) Mesh Surface Reconstruction: is using a polygonal mesh to approximate 3D object boundaries. Popular techniques for mesh-based surface reconstruction, which convert an unorganised point cloud into a mesh, include the Poisson surface reconstruction, ball pivoting and alpha-shapes. For meshes to be useful for volume calculation, there is one condition that needs to be met; the mesh needs to be watertight which implies that the mesh does not contain any hole and has a clearly defined surface. In this work, we have used the alpha-shape technique for surface reconstruction with a tuning parameter α. It is important to note that not all α values generate watertight meshes and therefore it is important to check that condition first.

C. Biomass Estimation

The final step of the proposed pipeline is to use the calculated volume for biomass estimation. For this purpose, we employ the Support Vector Regression (SVR) technique which maps the independent variable *volume* onto the dependent variable *biomass*. The regression process, in this case, estimates de facto the density of the crop.

D. Ground Truth Measurements

The proposed pipeline for biomass estimation relies on precise volume measurements of a crop plot. For experimental evaluation of the presented pipeline, we collected manual reference measurements of the fresh/dry biomass and volume by destructive means from a set of plots which include the following steps:

1) Cutting the crop at the ground level from the experimental plot of the defined size.
2) Weighing the fresh biomass using a laboratory scale.
3) Chopping the crop into smaller, uniform parts for easier handling in the measuring step.
4) Measuring crop volume by placing the plant matter into a water-filled container using the water displacement principle. The container should be of known size and the original water level marked. The crop volume is equal to the amount of displaced water volume indicated by the new water level mark.
5) Finally, drying the crop and measuring the dry biomass using a laboratory scale.

IV. Experiments

To evaluate the proposed system (see Fig. 1), we have collected a dataset consisting of 3D scans of 5 crop plots (winter rye at mid-growth stage, $0.25\ \text{m}^2$ each) grown under a polytunnel at the research farm at the Riseholme campus of the University of Lincoln in November 2023 (Riseholme dataset), followed by manual volume and biomass measurements.

The scanning for 3D reconstruction was undertaken with an iPad Pro 2022 with an ultra-wide camera (10MP, *f*/2.4 aperture and 125° field of view) according to the procedure discussed in Sec. III-A. For 3D reconstruction, we have used a Neural Radiance Field- based (NeRF) technique [20] employed by the Luma AI application[1]. To segment out the crop parts of the point cloud from the background, we have relied on manual segmentation undertaken in the Cloud Compare software. The quality and detail of the reconstructed 3D point cloud are shown in Fig. 2(a).

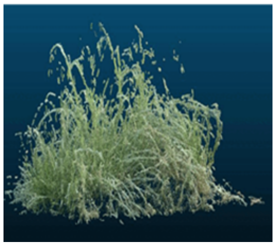
The manual measurements of volume and biomass for all 5 plots were undertaken by following the procedure described in Sec. III-D. For biomass measurements, we have used the Mettler Toledo Standard ME Precision Lab Balance with a precision of 0.01 g. The drying process for dry biomass measurements took 48 h at 65° until a constant dry weight was reached. The water container for volume measurements was a plastic, transparent box of dimensions $10.5 \times 20.0 \times 26.5$ cm.

TABLE I: Ground truth measurements for volume and fresh/dry biomass.

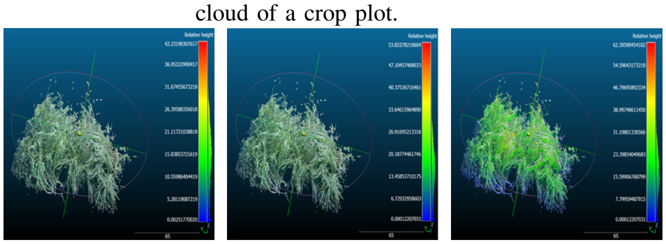
Plot No.	Volume [cm^3]	Fresh Biomass [g]	Dry Biomass [g]
1	2232	932.02	202.05
2	2620	1094.06	231.84
3	2948	1231.09	235.42
4	1542	644.01	155.84
5	1480	618.04	147.48
r		0.999	0.987

Table I presents the manual measurements of volume and fresh/dry biomass obtained from all 5 plots. In addition to weight measurements, we also provide Pearson's correlation coefficient r between the volume and fresh/dry biomass measurements. The high values of r in both cases indicate a very close relationship between the volume and mass measurements indicating that the volume is a good proxy

[1] https://lumalabs.ai/

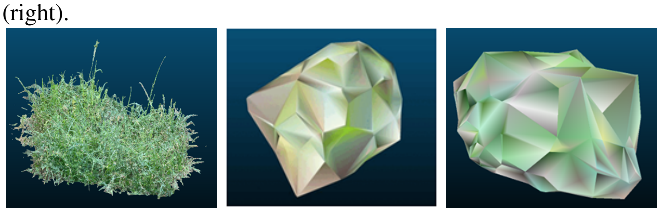


(a) An example 3D point cloud of a crop plot.



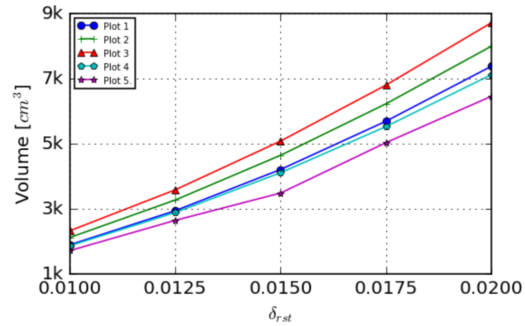
(b) 2.5D rasterisation: $\delta_{rst} = 1.0$ (left), $\delta_{rst} = 0.5$ (center), $\delta_{rst} = 0.1$ (right).

(c) Voxelisation: $\delta_{vox} = 1.0$ (left), $\delta_{vox} = 0.5$ (center), $\delta_{vox} = 0.1$ (right).

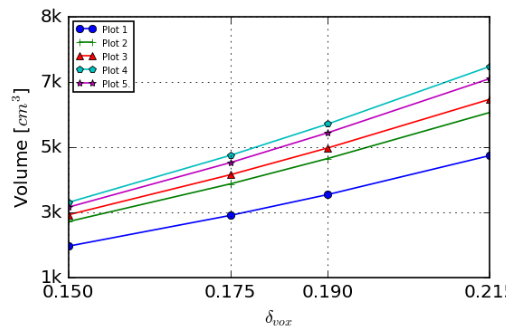


(d) Mesh surface reconstruction: $\alpha = 1.0$ (left, non-watertight), $\alpha = 20$ (centre, watertight) and $\alpha = 30$ (right, watertight).

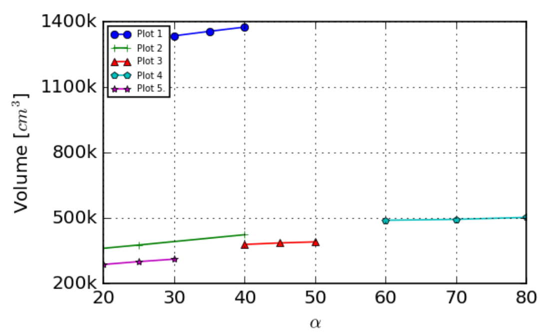
Fig. 2: Visual comparison of the selected volume estimation methods under change of critical parameters on an example point cloud of a crop plot.



(a) 2.5D rasterisation



(b) voxelisation



(c) alpha-shape

Fig. 3: The impact of δ_{rst}, δ_{vox}, and α parameters on estimating volume using 2.5D rasterisation, voxelisation, and alpha-shape methods for the Riseholme dataset.

for the biomass measurements. A slightly lower coefficient for the dry biomass might indicate that the material density of fresh crop varies slightly between the individual plots.

A. Volume Estimation

We have applied the three selected volume estimation techniques to our dataset for comparative studies. Fig. 2 illustrates the output of 2.5D rasterisation (b), voxelisation (c) and alpha-shape (d) techniques on an example point cloud (a). The quality of the output and level of detail depend heavily on the choice of critical parameters for each method. The influence of each parameter on the estimated volume values can be further seen in Fig. 3 indicating high sensitivity of volume estimation to the choice of parameters. The estimated values for 2.5D rasterisation are characterised by lower spread and correct ordering of volume values for each plot. The voxelisation technique is likely affected by occlusions and results in estimates inconsistent with the ground truth, e.g., plot 1. The alpha-shape technique is unable to generate watertight meshes for smaller values of the α parameter resulting in very crude volume approximations and estimates 2 orders of magnitude higher than GT and large variations between the individual plots. In addition, the change in values of α has a rather small impact on the resulting volume values.

Table II shows the volume estimated using all three techniques for the optimal choice of critical parameters. The values for each method were experimentally determined and then applied to all the plots. The final parameter values include $\delta_{rst} = 0.0104$ and $\delta_{vox} = 0.1352$. For the alpha-shape method, it was impossible to select a single optimal

TABLE II: Comparison of different volume estimation techniques for each plot together with the overall RMSE.

Plot No.	GT Volume [cm^3]	2.5D raster [cm^3]	voxels [cm^3]	alpha-shape [cm^3]
1	2232	2052	1484	322,717
2	2620	2292	2108	360,930
3	2948	2517	2273	359,989
4	1542	2018	2560	413,947
5	1480	1854	2441	276,785
r		0.936	-0.386	0.161
RMSE		372.07	804.63	347691.15

value, due to watertight constraints and therefore we present the values for the lowest α value which meets that condition. Pearson's correlation coefficient r between the estimated and manually measured volume for all three techniques indicates that the best method is 2.5D rasterisation which together with the lowest RMSE value of 372.07 cm^3 makes that method the most accurate and suitable for further experiments. Both the voxel-based representation and alpha-shape techniques indicate large discrepancies and inconsistent ordering of individual plot values with ground truth rendering those methods unsuitable for the proposed application.

B. Biomass Estimation

TABLE III: The biomass estimation results for the selected SVR kernels on the Riseholme dataset.

	Linear		RBF		Polynomial	
	Fresh	Dry	Fresh	Dry	Fresh	Dry
r	0.936	0.936	0.941	0.936	0.94	0.936
RMSE	161.70	24.74	152.38	23.71	180.60	24.14

We use 2.5D rasterisation representation to estimate the fresh and dry biomass values using Support Vector Regression (SVR). The proposed regressor estimates the material density linking volume and mass quantities. We compare three different kernels, which are the key parameters for the method, including linear, RBF and polynomial (see Table III). The RBF kernel provides the lowest RMSE for both fresh (152.38 g) and dry (23.71 g) biomass, followed by the linear and polynomial kernels. The value of r is very high and approximately similar for all kernels for both fresh and dry biomass with a preference for the RBF kernels. Due to the small size of the dataset, however, the parameter tuning and estimation results were undertaken on the same dataset.

To further validate the biomass estimation method, we have performed experiments on the publicly available small grain cereals biomass prediction (SGCBP) dataset[21]. The dataset consists of 3D point clouds of wheat plots and corresponding dry biomass. For our experiments, we randomly selected 40 samples (20 early stage and 20 flowering stage) and divided those into a train and test set consisting of 16 and 24 samples, respectively. We have calculated the volume using density and biomass, the ground truth biomass for each plot is provided in the dataset and we have calculated the

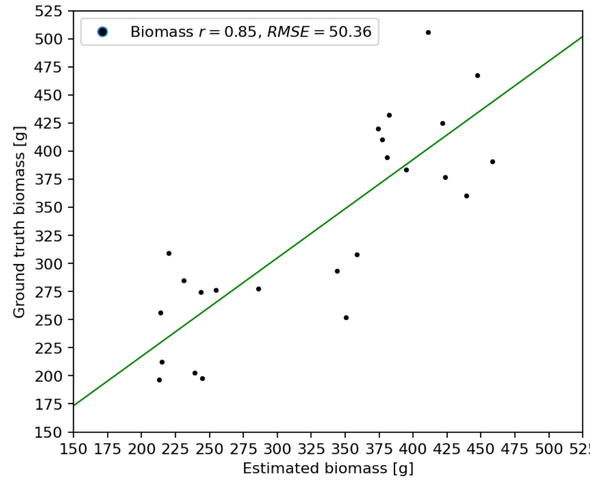


Fig. 4: The estimated and ground truth biomass for the 24 samples selected from the SGCBP dataset [21].

density using the Riseholme dataset which is 0.4175 g/ml. We performed the volume estimation using 2.5D rasterisation and the tuning parameter 'step size' is chosen similar to the previous experiment using only the training set. Next, the SVR model using the RBF kernel is trained using the training set to estimate the biomass from the volume. After training, the volume and biomass are estimated over the unknown test set of 24 plots. The r and RMSE between the estimated volume and ground truth volume is 0.86 and 101.71 while the r and RMSE between the estimated and ground truth biomass is 0.85 and 44.24 for the training set. Similarly, the r and RMSE between the estimated volume and ground truth volume are 0.84 and 148.23 while the r and RMSE between the estimated and ground truth biomass is 0.85 and 50.36 for the testing set. The distribution of estimated biomass and ground truth biomass is shown in Fig. 4. Table IV shows the comparison between the proposed (ours) and state-of-the-art PointNet and PointNet++ for estimating the biomass. The proposed method first estimates the volume and then biomass while PointNet and PointNet++ directly estimate the biomass from the given 3D point clouds. The PointNet and PointNet++ are trained over 204 samples belonging to the SGCBP dataset and tested using 102 samples. The root mean square error (rmse) obtained by PointNet is 189.80 and 188.85 while the rmse obtained by the method proposed in the paper (ours) is 50.36. The reason behind the low rmse for the proposed method is that the proposed method is tested only using 24 samples instead of 102 samples.

TABLE IV: The comparison between the proposed (ours) and state-of-the-art PointNet and PointNet++ for biomass estimation on the SGCBP dataset.

	Ours	PointNet	PointNet++
RMSE	50.36	189.80	188.85

V. Conclusions and Future Work

In this paper, we developed a pipeline to acquire high-quality 3D point cloud data of crop plots using a low-cost hand-held device and estimated the biomass from the reconstructed 3D crop plot model. The following conclusions are made after conducting a series of experiments. The developed 3D crop plot reconstruction procedure provides a very high-quality 3D model of the crop plot which is highly useful for plant phenotyping. The crop volume and biomass have a strong relationship ($r \geq 0.98$). Thus, we used the volume to estimate the biomass. We evaluated three volume estimation techniques which are 2.5D rasterisation, voxelisation and alpha shape. We experimentally found that 2.5D rasterisation estimation is highly accurate and has a strong relationship with ground truth volume ($r \geq 0.93$). We have estimated the crop biomass from the volume using different SVR kernels. The non-linear RBF kernel provides the lowest error for the Riseholme dataset which is 23.71 for dry biomass and 152.38 for fresh biomass. Similarly, for the second dataset, the r and RMSE between the estimated and ground truth biomass is 0.85 and 50.36.

The proposed pipeline is limited in its scope due to the following reasons. The pipeline is not fully automatic and the steps such as crop plot area segmentation and calibration of 3D reconstructed model to real dimensions are performed manually. Further, the biomass estimation is validated at a single growth stage of the crop not at multiple growth stages. In future work, we will make the system fully automated and evaluate the ability of the proposed pipeline to estimate the biomass at different growth stages of the wheat by acquiring more data at different growth stages.

References

[1] JD Pask, Julian Pietragalla, DM Mullan, and MP Reynolds.Physiological breeding II: a field guide to wheat phenotyping. Cimmyt, 2012.

[2] Onisimo Mutanga, Elhadi Adam, Moses Azong Cho, "High density biomass estimation for wetland vegetation using WorldView-2 imagery and random forest regression algorithm." International Journal of Applied Earth Observation and Geoinformation, 18, (2012): 399-406.

[3] Greaves, H.E., Vierling, L.A., Eitel, J.U., Boelman, N.T., Magney, T.S., Prager, C.M. and Griffin, K.L., "High-resolution mapping of aboveground shrub biomass in Arctic tundra using airborne lidar and imagery." Remote sensing of environment 184 (2016): 361-373.

[4] Jin, X., Kumar, L., Li, Z., Xu, X., Yang, G. and Wang, J., "Estimation of winter wheat biomass and yield by combining the aquacrop model and field hyperspectral data." Remote Sensing 8.12 (2016): 972.

[5] Li, W., Niu, Z., Chen, H., Li, D., Wu, M. and Zhao, W., "Remote estimation of canopy height and aboveground biomass of maize using high-resolution stereo images from a low-cost unmanned aerial vehicle system." Ecological indicators 67 (2016): 637-648.

[6] Zheng HengBiao, Z.H., Cheng Tao, C.T., Li Dong, L.D., Zhou Xiang, Z.X., Yao Xia, Y.X., Tian YongChao, T.Y., Cao WeiXing, C.W. and Zhu Yan, Z.Y., "Evaluation of RGB, color-infrared and multispectral images acquired from unmanned aerial systems for the estimation of nitrogen accumulation in rice." Remote Sensing 10.6 (2018): 824.

[7] Schut, A.G., Traore, P.C.S., Blaes, X. and de By, R.A., "Assessing yield and fertilizer response in heterogeneous smallholder fields with UAVs and satellites." Field Crops Research 221 (2018): 98-107.

[8] Zheng, H., Cheng, T., Zhou, M., Li, D., Yao, X., Tian, Y., Cao, W. and Zhu, Y., "Improved estimation of rice aboveground biomass combining textural and spectral analysis of UAV imagery." Precision Agriculture 20 (2019): 611-629.

[9] Zhang, L., Verma, B., Stockwell, D. and Chowdhury, S., "Density Weighted Connectivity of Grass Pixels in image frames for biomass estimation." Expert Systems with Applications 101 (2018): 213-227.

[10] Breunig, F.M., Galvão, L.S., Dalagnol, R., Dauve, C.E., Parraga, A., Santi, A.L., Della Flora, D.P. and Chen, S., "Delineation of management zones in agricultural fields using cover–crop biomass estimates from PlanetScope data." International Journal of Applied Earth Observation and Geoinformation 85 (2020): 102004.

[11] Yue, J., Feng, H., Jin, X., Yuan, H., Li, Z., Zhou, C., Yang, G. and Tian, Q., "A comparison of crop parameters estimation using images from UAV-mounted snapshot hyperspectral sensor and high-definition digital camera." Remote Sensing 10.7 (2018): 1138.

[12] Wang, Y., Zhang, K., Tang, C., Cao, Q., Tian, Y., Zhu, Y., Cao, W. and Liu, X., "Estimation of rice growth parameters based on linear mixed-effect model using multispectral images from fixed-wing unmanned aerial vehicles." Remote sensing 11.11 (2019): 1371.

[13] Yue, J., Feng, H., Yang, G. and Li, Z., "A comparison of regression techniques for estimation of above-ground winter wheat biomass using near-surface spectroscopy." Remote Sensing 10.1 (2018): 66.

[14] Tilly, N., Hoffmeister, D., Cao, Q., Huang, S., Lenz-Wiedemann, V., Miao, Y. and Bareth, G., "Multitemporal crop surface models: accurate plant height measurement and biomass estimation with terrestrial laser scanning in paddy rice." Journal of Applied Remote Sensing 8.1 (2014): 083671-083671.

[15] Loudermilk, E.L., Hiers, J.K., O'Brien, J.J., Mitchell, R.J., Singhania, A., Fernandez, J.C., Cropper, W.P. and Slatton, K.C., "Ground-based LIDAR: a novel approach to quantify fine-scale fuelbed characteristics." International Journal of Wildland Fire 18.6 (2009): 676-685.

[16] Aasen, H., Burkart, A., Bolten, A. and Bareth, G., "Generating 3D hyperspectral information with lightweight UAV snapshot cameras for vegetation monitoring: From camera calibration to quality assurance." ISPRS Journal of Photogrammetry and Remote Sensing 108 (2015): 245-259.

[17] Jimenez-Berni, J.A., Deery, D.M., Rozas-Larraondo, P., Condon, A.T.G., Rebetzke, G.J., James, R.A., Bovill, W.D., Furbank, R.T. and Sirault, X.R., "High throughput determination of plant height, ground cover, and above-ground biomass in wheat with LiDAR." Frontiers in plant science 9 (2018): 237.

[18] Qi, C.R., Su, H., Mo, K. and Guibas, L.J., "Pointnet: Deep learning on point sets for 3D classification and segmentation." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

[19] Qi, C.R., Yi, L., Su, H. and Guibas, L.J., "Pointnet++: Deep hierarchical feature learning on point sets in a metric space." Advances in neural information processing systems 30 (2017).

[20] Mildenhall, B., Srinivasan, P.P., Tancik, M., Barron, J.T., Ramamoorthi, R. and Ng, R., "Nerf: Representing scenes as neural radiance fields for view synthesis." Communications of the ACM 65.1 (2021): 99-106.

[21] Estavillo, Gonzalo; Anthony, Condon; Pan, Liyuan; Bull, Geoff; Coe, Robert (2021): Biomass and LiDAR data from wheat and triticale plots grown at Yanco (NSW) in 2019 to improve prediction of digital biomass. v1. CSIRO. Data Collection.

[22] Pan, L., Liu, L., Condon, A.G., Estavillo, G.M., Coe, R.A., Bull, G., Stone, E.A., Petersson, L. and Rolland, V., "Biomass prediction with 3D point clouds from LiDAR." In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pp. 1330-1340. 2022.