WHEEL-BASED LIDAR DATA FOR PLANT HEIGHT AND CANOPY COVER EVALUATION TO AID BIOMASS PREDICTION

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ABSTRACT

Biomass estimation is fundamental for a variety of plant ecological studies. Direct measurement of aboveground biomass by clipping and sorting is destructive, time-consuming and laborious, thus reducing the ability of extensive sampling. Various plant traits, such as plant height, canopy cover, and leaf and plant structure contribute towards its biomass. In this study, we focus on exploiting wheel-based LiDAR data over an agricultural field to perform growth monitoring and canopy cover estimation, which would play a crucial role in the future to develop a non-invasive technique for biomass prediction.

Index Terms— Biomass, plant traits, plant height, canopy cover, LiDAR data

1. INTRODUCTION

According to [1], plant height is among the most important biomass yield components. Several authors have suggested that there is a considerable relationship between canopy cover and biomass [2]-[4]. In this regard, 3D geospatial data plays an increasingly important role in precision agriculture, e.g., for modeling in-field variations of grain crop features in order to ensure an accurate biomass prediction. In this paper, we address the prediction of two specifically important plant traits – plant height and canopy cover – derived from wheel-based LiDAR data in order to be incorporated into a biomass prediction model along with information from UAV-based RGB and hyperspectral sensors.

Over the past few years, several remote sensing techniques and prediction models have been developed to estimate biomass. In [5], the authors developed a UAV-based high-throughput phenotyping system for sorghum plant height and assessed its response to nitrogen availability. The system consisted of either an RGB or a NIR-GB camera mounted on the UAV. The authors assessed the correlation between the plant height measured by the UAV remote sensing and the manually measured plant height. The performance of UAV remote sensing was observed to be similar to that of traditional measurements in genomic prediction modeling. [6] provided an extensive review of various machine learning approaches used to estimate vegetation biomass from remote sensing data. [7] suggested a non-destructive method for above-ground biomass prediction by utilizing terrestrial laser scanning data to predict the volume of trees and combine them with the density information, thus leading to accurate biomass predictions.

In this study, we mainly focus on wheel-based LiDAR data acquired using a high clearance tractor driven over an agricultural field. The ability of LiDAR scans to penetrate through dense canopies enables us to derive the plant structure, plant height, and canopy cover for individual agricultural plots. These attributes play a major role in accurate biomass estimation. LiDAR data can be used to generate Crop Surface Models (CSMs) in order to study the variations in crop height and canopy cover. In this research, we first aim to create rasterized CSMs by assigning the 90^{th} percentile height, 60^{th} percentile height, and 30^{th} percentile height for each grid cell. In case of LiDAR data, the CSMs generated using maximum height would be subject to high noise and so, without loss of accuracy, we can instead use the 90^{th} percentile height to represent the actual crop height. The variations between the 30^{th}, 60^{th}, and 90^{th} percentile heights would represent the ability of the system to penetrate the plant structure. The obtained CSMs would then be combined with a Digital Terrain Model (DTM) to obtain the canopy cover for each plot in an agricultural field.

In this paper, we discuss the approach used for generating Crop Surface Models (CSMs) with varying height percentiles and then, combining these with a DTM to obtain the canopy cover for individual plots within an agricultural field. Finally, we provide some preliminary results obtained for plots located at the Agronomy Center for Research and Education (ACRE), Purdue University and provide some discussions and conclusions drawn from the obtained results.

2. MOBILE MAPPING SYSTEM

In this research, a PhenoRover-based mobile mapping system, as shown in Figure 1, is used to collect LiDAR data for 3D point cloud reconstruction. The mobile mapping system onboard the PhenoRover consists of two Velodyne HDL-32E laser scanners, which are directly georeferenced by an Applanix POSLV-125 unit. For the POSLV-125, the post-processing accuracy in position can be 2-5 cm and the achieved accuracy

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Fig. 1. PhenoRover-based Mobile Mapping System

for the roll/pitch and heading can be 0.025˚ and 0.06˚, respectively. The Velodyne HDL-32E consists of 32 radially-oriented laser rangefinders that are aligned from +10.67˚ to -30.67˚. In total, the vertical Field of View (FOV) is 41.34˚. It can rotate the whole unit to achieve a 360˚ horizontal FOV. The reliable return range is approximately from 1 m to 70 m and the point capture rate is around 700,000 points per second. In order to derive direct georeferencing data, the POSLV-125 supplies sequentially precise time pulses, known as pulse-per-second (PPS) signals, which gives the ability to generate a time-tagged point cloud. Furthermore, the POSLV-125 provides a navigation message, also known as GPRMC message (including information regarding position, rotation, and GPS time), which is recorded over a dedicated RS-232 serial port and received by the LiDAR units via the interface box in the form of serial data. The block diagram of the PhenoRover-based MMS, indicating triggering signals, feedback signals, and communication wires/ports between sensors and power connections is shown in Figure 2.

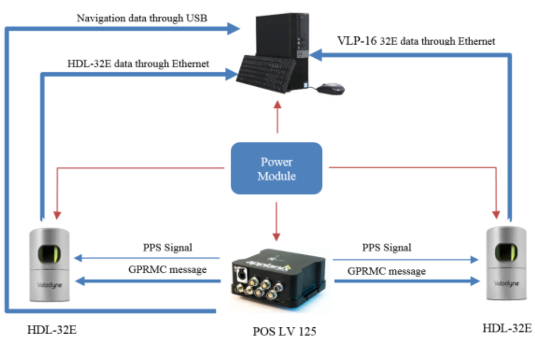


Fig. 2. Integration Scheme for the PhenoRover-based Mobile Mapping System

3. CANOPY COVER ESTIMATION

3.1. Crop Surface Model Generation

CSMs are vital for monitoring plant growth in an agricultural field. Plant growth is always defined as the spatio-temporal difference in height, so in this study, we would focus on generating CSMs for various plots of a field for different days. A CSM is usually a rasterized map depicting the maximum height over each grid cell. In this project, we are interested in determining the canopy cover for a plot using LiDAR data. Since LiDAR data can often be noisy, there would usually be outliers in the LiDAR-based 3D point cloud, thus resulting in an inaccurate CSM. Also, we are interested in conducting a spatio-temporal analysis of the CSMs, which would be skewed by the presence of noise in the point cloud. Hence, we propose a methodology to estimate more accurate estimates of multi-temporal canopy cover by generating a 90^{th} percentile height map, which can be defined as a rasterized map which depicts the height for which 90% of the points within a grid have a height less than the assigned height value for the grid cell. Using this criteria for CSM generation would alleviate the effect of noisy LiDAR points on the CSM. Also, [8] found that the 90^{th} percentile CSMs are independent of LiDAR point density. This allows the mitigation of the effects of variation in point density for datasets captured on different days due to varying driving speeds, crop growth, and so on.

Since we are interested in using the canopy cover estimates for aboveground biomass prediction of crops, we should consider the variation of the plant structure across its entirety rather than just the topmost points captured for the crops. One should note that LiDAR data is capable of canopy penetration, unlike RGB-image or hyperspectral image-based data. Hence, we also propose a height map generation with the 30^{th} and 60^{th} percentile heights, which can be further used to obtain canopy cover estimates for the entire plant for better biomass estimation of plants.

The following steps summarize the algorithm adopted for CSM generation:

• First, the bounding boxes denoting the XY-coordinates of two diagonally opposite corners of a plot in the mapping frame are acquired. The plot map is semi-automatically derived from RGB orthophotos using image processing techniques that identify the plant rows. Then, different rows within a given plot are manually adjusted, aggregated, and labeled.

• The region of interest (or, the portion of interest in the agricultural field) is divided into grid cells of user-defined dimensions.

• For each grid cell that lies within the bounding box of any of the plots, all the LiDAR points captured within the grid are sorted by height (Z-values).

• Then, the 30^{th}, 60^{th}, and 90^{th} percentile height values are assigned to the respective grid by identifying the height value for the $0.3n^{th}$, $0.6n^{th}$, and $0.9n^{th}$ points within the grid (where 'n' denotes the total number of points captured within the grid cell).

• Finally, a nearest neighbor interpolation is applied to all the grids within the plots to account for the grids where no points have been captured.

3.2. Estimation of Canopy Cover

In this section, we discuss the estimation of canopy cover using the point density maps and the height maps (30^{th}, 60^{th}, and 90^{th} percentile). In this research, canopy cover is defined as the ratio of above-ground points (or, crop points) to the total number of LiDAR points. The following steps summarize the approach proposed for canopy cover estimation for each plot within an agricultural field:

• First, the Digital Terrain Model (DTM) is obtained for the region of interest, which contains the bare earth height for the area. The DTM is derived using LiDAR data acquired before any plant growth over the field of interest. This is used to obtain the average bare earth height for each plot (as it can be assumed to be constant within a plot, considering that the size of each plot is small enough to ignore any variation in the bare earth height). Note that the same DTM can be used for canopy cover estimation of all the datasets as these are all georeferenced.

• Now, within each grid of a plot, the points with a height value more than 10 cm above the bare earth height for the respective plot is considered to be point belonging to a crop (denoted as crop points) and the rest of the points are considered to be ground points.

• Then, the ratio of the number of crop points to the total points captured within a grid is computed and again, a nearest neighbor interpolation is applied.
• Finally, these values are averaged for all the grids within a plot to obtain the canopy cover estimate for the plot.

4. EXPERIMENTAL RESULTS

4.1. Height Maps or Crop Surface Models

The height maps were generated for three different days (6th, 19th and 26th July, 2017) for Plots – 4101 to 4172 located in Field 41 at ACRE, Purdue University. Note that the different plots signify different genotypes of the same crop. Hence, the plant height and canopy cover evaluation is done for individual plots to enable biomass prediction for each plot to assess the comparative productivity of the various genotypes. The point density for the LiDAR point cloud is approximately 100,000 pts/m^2.

Figure 3(a) shows the DTM for the area of interest and Figures 3(b-d) show the RGB-based orthophotos of the plots for three days closest to the dates of LiDAR data analysis in order to be used as reference for further results.

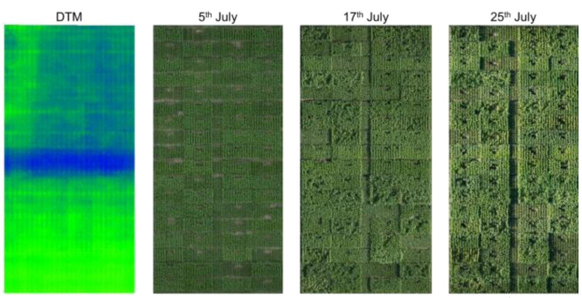


Fig. 3 Plots – 4101 to 4172: (a) DTM, (b) RGB-orthophoto for 5th July, 2017, (c) RGB-orthophoto for 17th July, 2017, and (d) RGB-orthophoto for 25th July, 2017

30th, 60th, and 90th Percentile Height Maps: The height maps generated for 30th, 60th, and 90th percentile heights are shown for one of the three days (Figure 4 for 6th July, 2017). All these maps are colored using the same scale for allowing an easy comparison between them. Figure 4 shows an increase in the 30th, 60th, and 90th percentile heights as is observed for the other two days as well. The point density maps along with the PhenoRover trajectory for the three days are shown in Figure 5. These height maps can be used for an efficient plant growth monitoring for each plot. Figure 6 shows a side projection of 90th percentile heights for each plot (colored by the day). In this figure, we can see a consistent increase in the crop heights over the days. From Figure 6, we can identify the plots where the plant growth in uniform over the entire plot and the ones where the plant growth is not uniform. In this research, we further aim to analyze the plant growth variation across the plots for the identification of the genotypes which induce significant plant growth rate.

Canopy Cover Estimation: The methodology described in Section III (B) is used to derive canopy cover estimates using a grid size of 4 cm x 4 cm. Figure 7 shows the canopy cover maps obtained for the three days.

From Figure 7, we can see that the canopy cover map is colored as binary, i.e., each grid is either blue or red. This can be attributed to the fact that the grid size is too small to be able to contain points both from crop and ground. Hence, within a single grid, all the points would either be ground points or all crop points. However, this scenario might change on increasing the grid size. One should note that there are some plots, where there are grids with no color assigned to them (white). This can be seen to be in accordance with the point density map and these white grids can be safely assumed to be ground points that could not be captured owing to the trajectory of the vehicle due to which the laser beams could not pass through the intermediate crops to scan the ground points because of the viewing angle. This is also visible in the blue striping visible between the rows, which is more pronounced in the regions lying just below the PhenoRover trajectory than the plots located sideways from the trajectory.

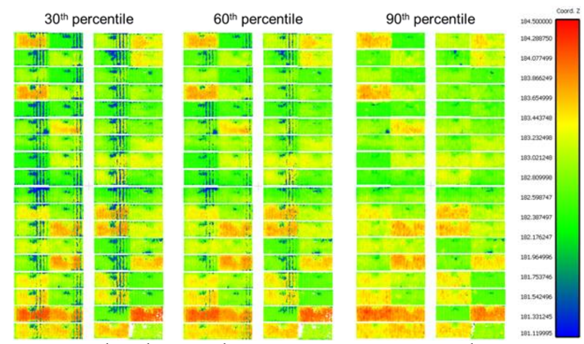


Fig. 4 30th, 60th, and 90th percentile height maps for 6th July, 2017

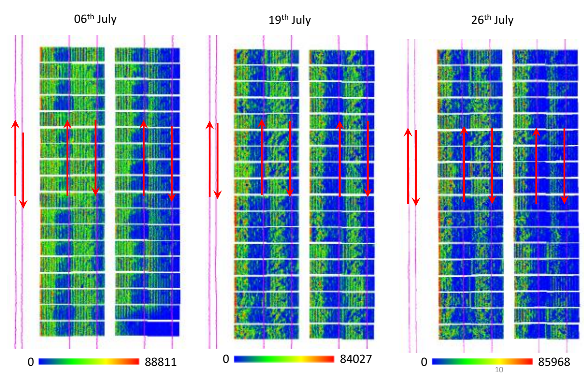


Fig. 5. Point density maps for 6th, 19th, and 26th July, 2017

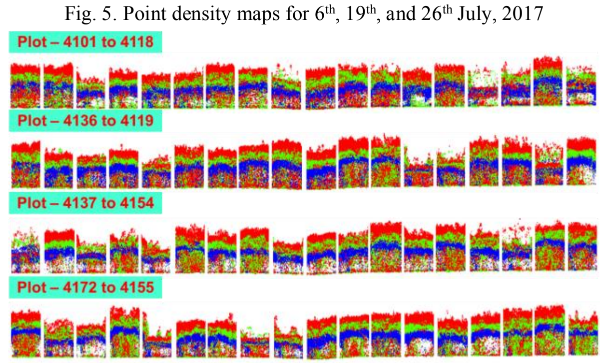


Fig. 6. Plant Growth Monitoring: Side view of 90th percentile heights colored by day – Blue (6th July, 2017), Green (19th July, 2017), and Red (26th July, 2017)

Now, the canopy cover values obtained for all the grids within a plot are averaged to obtain the canopy cover estimate for the plot. These values obtained for all the plots over the three days are plotted and shown in Figure 8(a) along with the corresponding values obtained from RGB-orthophotos plotted in Figure 8(b). The RGB-orthophoto-based canopy cover estimate is obtained by first, performing a leaf segmentation over the region of interest using the method proposed by [9] and then, finding the ratio of the number of pixels segmented as leaf to the total number of pixels within each plot. Figure 8(c) shows the average canopy cover over all the plots together as obtained from LiDAR data and RGB data.

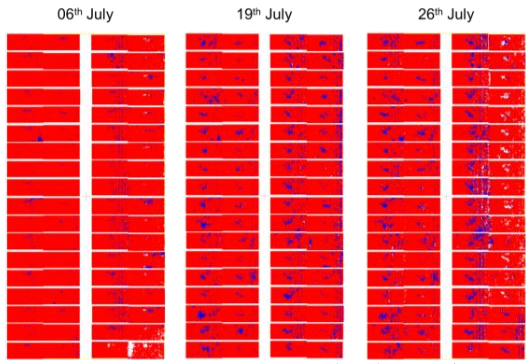
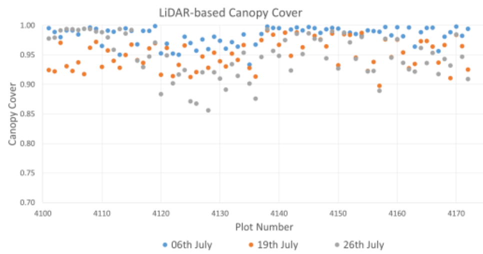
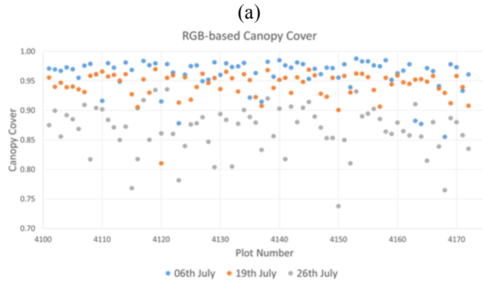


Fig. 7. Rasterized Canopy Cover Maps for 6th, 19th, and 26th July, 2017 – Colored by canopy cover with blue denoting 0% and red denoting 100%



(a)



(b)

	06th July	19th July	26th July
LiDAR-based Avg. CC	0.9830	0.9511	0.9480
RGB-based Avg. CC	0.9606	0.9428	0.8672

(c)

Fig. 8. Canopy Cover Estimates for all the plots: (a) LiDAR-based canopy cover estimates, (b) RGB-orthophoto-based canopy cover estimates, and (c) Average canopy cover over all the plots from LiDAR and RGB data

In Figure 8(a), we can see a decrease in the canopy cover over the days and this is counter-intuitive. This trend can be explained by the destructive sampling that occurred between each of these days, thus resulting in more ground being exposed to LiDAR (as clearly visible in the RGB-orthophotos shown in Figure 3) which contributes to the decrease in canopy cover. Moreover, this fact is bolstered by the presence of the same trend in RGB-based canopy cover estimates as well. Apart from this, we can see that the estimates of canopy cover obtained from LiDAR data is consistently more than that obtained from RGB-orthophotos. This is attributed to the fact that RGB data takes into consideration only the topmost visible layer of the plants for canopy cover estimation. However, since LiDAR data can penetrate through the canopy, the points captured over the entire plant structure are taken into consideration during the respective canopy cover estimation. Hence, it is valid for the LiDAR-based canopy cover estimates to be higher than RGB-orthophoto-based estimates. Since the focus of canopy cover estimation is to include it with other plant traits for biomass prediction, LiDAR-based canopy cover estimation is preferred over RGB-orthophoto-based estimates as the aboveground biomass is a function of the entire plant (captured in LiDAR) except just the plant crown (captured in RGB-imagery).

5. RECOMMENDATIONS FOR FUTURE WORK

In the future, we aim to study the sensitivity of estimated canopy cover to the grid cell size. Also, we plan to do a comparative analysis of the canopy cover estimates obtained using wheel-based LiDAR data with ones obtained using UAV-based LiDAR data and RGB imagery to prove the validity of the proposed approach. This work will also be extended to devise a more robust approach in order to estimate canopy cover while taking into account the areas where destructive sampling is done in order to remove the resultant bias. Finally, the obtained plant height and canopy cover estimates should be integrated with other plant traits captured using aerial RGB and hyperspectral imagery results in order to estimate biomass for each plot.

7. REFERENCES

[1] Yuan, J. S., Tiller, K. H., Al-Ahmad, H., Stewart, N. R., & Stewart, C. N. (2008). Plants to power: bioenergy to fuel the future. *Trends in plant science*, *13*(8), 421-429.

[2] Jonasson, S. (1988). Evaluation of the point intercept method for the estimation of plant biomass. *Oikos*, 101-106.

[3] Chiarucci, A. J. B. W., Wilson, J. B., Anderson, B. J., & Dominicis, V. (1999). Cover versus biomass as an estimate of species abundance: does it make a difference to the conclusions?. *Journal of Vegetation Science*, *10*(1), 35-42.

[4] Röttgermann, M., Steinlein, T., Beyschlag, W., & Dietz, H. (2000). Linear relationships between aboveground biomass and plant cover in low open herbaceous vegetation. *Journal of Vegetation Science*, *11*(1), 145-148.

[5] Watanabe, K., Guo, W., Arai, K., Takanashi, H., Kajiya-Kanegae, H., Kobayashi, M., Iwata, H. (2017). High-Throughput Phenotyping of Sorghum Plant Height Using an Unmanned Aerial Vehicle and Its Application to Genomic Prediction Modeling. Frontiers in Plant Science, 8, 421. http://doi.org/10.3389/fpls.2017.00421.

[6] Ali, I., Greifeneder, F., Stamenkovic, J., Neumann, M., & Notarnicola, C. (2015). Review of machine learning approaches for biomass and soil moisture retrievals from remote sensing data. Remote Sensing, 7(12), 16398-16421.

[7] Hackenberg, J., Wassenberg, M., Spiecker, H., & Sun, D. (2015). Non destructive method for biomass prediction combining TLS derived tree volume and wood density. Forests, 6(4), 1274-1300.

[8] Hämmerle, M., & Höfle, B. (2014). Effects of Reduced Terrestrial LiDAR Point Density on High-Resolution Grain Crop Surface Models in Precision Agriculture. Sensors (Basel, Switzerland), 14(12), 24212–24230. http://doi.org/10.3390/s141224212.

[9] Ribera, J., He, F., Chen, Y., Habib, A. F., & Delp, E. J. Estimating Phenotypic Traits From UAV Based RGB Imagery.