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UTILIZING UAS-LIDAR FOR HIGH THROUGHPUT PHENOTYPING OF ENERGY CANE

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ABSTRACT

Uncrewed Aerial Systems (UAS) equipped with digital cameras and sensors is an effective remote sensing tool for High Throughput Phenotyping (HTP) in precision agriculture. While studies have established relations to estimate crop height and biomass from UAS data, there has been limited work that examines the relationship between field measured biomass to UAS-Light Detection and Ranging (lidar) estimated biomass for the energy cane crop. This study explored the utility of UAS-lidar for phenotyping energy cane crops. The study collected lidar and ground truth data from an energy cane experimental plot in Weslaco, Texas-USA. Random Forest (RF) regression analysis showed high correlation between modelled crop height from lidar and field measured crop height ($r^2 = 0.94,\ rmse = 0.12\,m,\ me = -0.002,\ mae = 0.009, n = 400$). Also a RF model between field measured biomass and modelled crop height, point cloud density, intensity, and number of returns generated from the lidar showed high performance ($r^2 = 0.85, rmse = 92.00\ g/m^2,\ mae = 76.11,\ me = 0.50, n = 300$). These results buttress the capability of UAS-lidar for high throughput phenotyping as has been reported in other studies.

***Index Terms*—** UAS-lidar, Biomass, Crop Height Model, Energy cane, RECON-A

1.0 INTRODUCTION

Remotely sensed data from Uncrewed Aerial Systems (UAS) has been integral in High Throughput Phenotyping (HTP) of crops [1]. Researchers and farmers usually develop a relation between variables obtained from a UAS-based sensor and compare it to field measured values [2]. The best fit model or equation arising from such comparison is then typically applied to the UAS data to estimate phenotypic characteristics of crops over a whole area, especially where ground data could not cover [3]. While studies have used Light Detection and Ranging (lidar) sensors onboard UAS (UAS-lidar) to derive empirical, semi-analytic, or machine learning models to phenotype different crops [4], no study for which the authors are aware, has examined the empirical relationship between UAS-lidar extracted structural features with vegetation variables of the energy cane crop. Thus, the aim of this study is to estimate height and biomass of energy cane cultivars using UAS-lidar data. Specifically, (1) The study wishes to use UAS-lidar derived variables to estimate crop height of energy cane; 2) The study wishes to establish an empirical relation between UAS-lidar generated variables and field measured biomass of energy cane cultivars.

2.0 MATERIALS

2.1 Study area

The area considered for this study is the Texas A&M AgriLife Research and Extension Center site in Weslaco, Texas (Figure 1). The terrain of the area is relatively flat with a gentle slope. The climate is humid subtropical with hot temperatures during the summer. Precipitation amount is low within the months of November to April, making the area ideal for assessing drought resistance of perennial crops.

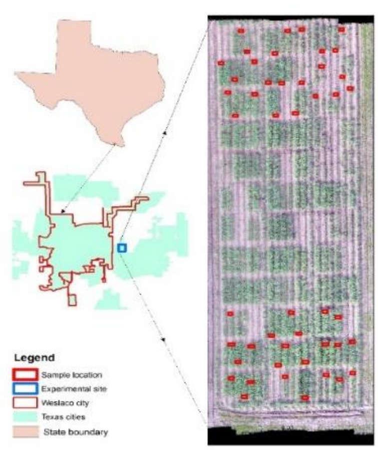

Figure 1 A map of the Weslaco energy cane field showing a UAS RGB orthomosaic and field sampled locations.

2.2 Field preparation

The selected site (experimental field) extends by 155 m in length and 47 m in width. We created a total of total of 108, 1 m by 10 m beds, on which 7 energy cane cultivars were planted. The energy cane beds were interspersed with sorghum and switchgrass beds. Nine (9) Ground Control Points (GCPs) were placed on the outer plots and their coordinates established using a multi-band RTK GNSS receiver Emlid Reach RS2. The study performed an initial UAS flight equipped with a Red-Green-Blue (RGB) digital camera to produce orthomosaic of the study area via Structure-from-Motion/Multi-View-Stereo (SfM/MVS) photogrammetry. The orthomosaic was used for visualization as shown in Figure 1.

2.3 UAS-lidar

The study collected UAS-lidar data using the Phoenix RECON-A integrated system onboard a Freefly Astro UAS rotary platform (Figure 2). The RECON-A is an all-in-one payload for use on small UAS that integrates a GNSS/inertial navigation system (INS) plus lidar sensor payload (Phoenix Lidar Systems, 2021). The system is also integrated with a high-resolution camera that helps in yielding maximum RGB colorization of the point cloud (Phoenix Lidar Systems, 2021). The RECON-A navigation system supports the following constellations: GPS, GLONASS, BEIDOU, GALILEO. Characteristics of the Livox Avia Lidar sensor integrated with the RECON-A are shown in Table 1.

Figure 2 A typical setup before a flight showing the RECON-A payload and the Astro UAS platform.

3.0 METHODOLOGY

Four instances of data collection with the UAS-lidar were performed between 12/02/2023 and 05/16/4024. The missions planning were performed in Auterion Mission Control (AMC). In all the flights, the UAS was flown at a height of 22 m above ground level at a speed of 4 m/s. For each data collection, calibration of the lidar sensor was performed using recommended guidelines. For this RECON-A sensor, calibration goes through three steps namely, Statistic Alignment, Kinematic Alignment and Navigation System Stabilization (NSS). Static alignment was performed both before and after a scan, for a period of 5 – 10 minutes. During these times both the IMU (Inertial Movement Unit) and vehicle remain completely static, and the lidar is not activated. In performing the kinematic alignments, the vehicle travels in a straight line for a period of at least 10 seconds, exceeding velocity of 5 m/s (18 km/h) at the beginning and end of the data collection. In performing the NSS, the vehicle is made to conduct at least two sets of figure-eight patterns, either manually or using waypoint mode, before and after the scan of the main area of interest.

Table 1 Characteristics of the lidar system used for energy cane phenotyping. Information was extracted from product documentation https://www.phoenixlidar.com/lidarmill/. *H means horizontal, V means vertical

Attribute	Value
Lidar scanner	Livox Avia
Laser properties	905 nm
Distance random error	1σ @ 20 m < 2 cm (80% Reflective)
Maximum range	190 m
Range accuracy	±2 cm
Scan rate	240,000 points/s (first or strongest return)
	480,000 points/s (dual return)
	720,000 points/s (triple return)
Field of view (H x V)	Non-repetitive scanning pattern: 70.4° × 77.2°
	Repetitive line scanning: 70.4° × 4.5°
Beam divergence	0.03° x 0.28°

3.1 UAS-lidar data processing and extraction

Once a mission is completed, the data is transferred into Phoenix LidarMill, a cloud-based platform designed to post-process lidar data. This platform provides a step-by-step processing workflow that results in generating lidar products (for Lidar Mill workflow and more explanation readers are encouraged to visit the Phoenix Lidar Mill website and documentations https://www.phoenixlidar.com/lidarmill/). For this study, the cloud-based processing generated colorized 3D point cloud with average point density > 16,000 pulses/metre^2 for each mission. The online processing workflow also produced Digital Surface Model (DSM), Digital Terrain Model (DTM), and Canopy Height Model (CHM), which were all set to 0.05 m resolution. After this, point cloud density, intensity, and number of returns of the point cloud data were extracted and exported as raster files using the Quantum Geospatial Information System (QGIS) open-source software version 3.32.

3.2 Field (manual) data collection

The study collected field data of crop height and biomass to provide field samples for comparison with the UAS data. Field sampling were conducted just after the UAS flights, targeting crop plots that have been pre-marked as part of stratified sampling approach. Height measurements were performed by using metric scale rule to measure the heights of five (5) plants within a 1 m x 1 m area on each targeted plot. An average of the 5 heights was calculated to represent the height of the plants within the sampled location. After recording the height measurements, plants within the enclosure were cut to the base for oven drying and dry biomass measurement. A total of 400 samples were collected for the four sampling campaigns. These samples comprised all the different energy cane cultivars in the experiment.

3.3 Random Forest modelling

The study used the QGIS to create 1 m x 1 m boundary polygons corresponding to the ground sampled locations. Using these polygons, zonal statistics was performed on the CHM, point cloud density, intensity, and number of returns. A Random Forest (RF) regression analysis was first performed between the field height and the CHM produced from all the missions. This step was followed by regression analysis between the field measured biomass and the mean values of the CHM, point cloud density, intensity, and number of returns using RF. For both crop height and biomass modeling, the two RF hyperparameters, *mtry* and *ntree* were tuned using the grid search method. The data were split into 70:30 for training and testing samples respectively.

4. RESULTS

4.1 Crop height estimation from UAS-lidar

The results indicated that, after 8 months of planting, heights of all the energy cane cultivars ranged between 1.90 to 2.70 m, with differences in height resulting from differences in genotypes. The regression analysis showed a strong positive correlation ($r^2 = 0.94,\ rmse = 0.12\,m,\ me = -0.002,\ mae = 0.009, n = 400$) between the field measured crop height and the UAS-lidar CHM (Figure 3). This result shows the capacity of UAS-lidar to phenotype the energy cane crop.

4.2 Energy cane biomass estimation from UAS-lidar

The regression (Figure 4) between field measured biomass and UAS-lidar generated CHM, point cloud density, intensity, and number of returns showed a strong positive correlation ($r^2 = 0.845, rmse = 91.981\ g/m^2,\ mae = 72.846,\ me = 0.505, n = 300$). Among the four lidar variables used, CHM was the most important variable in the prediction. This was followed by lidar intensity, density, and the number of returns. The results of this modelling show the capacity of UAS-lidar for phenotyping energy cane crop. The study used the developed model to predict the biomass of the cultivars on the 12/02/2023 lidar data for the whole field (Figure 4). Average biomass of the seven energy cane cultivars was then computed from the produced map.

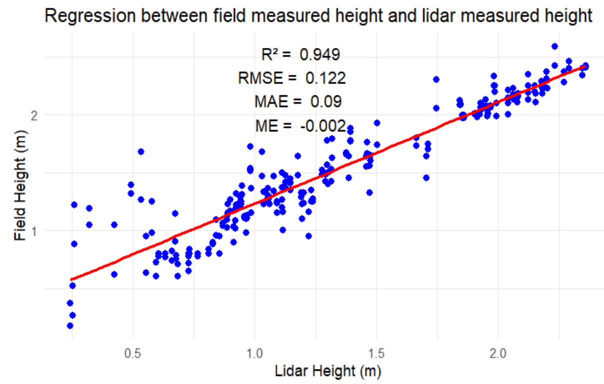

Figure 3 Random Forest regression plot between measured crop height and crop height modelled from UAS lidar.

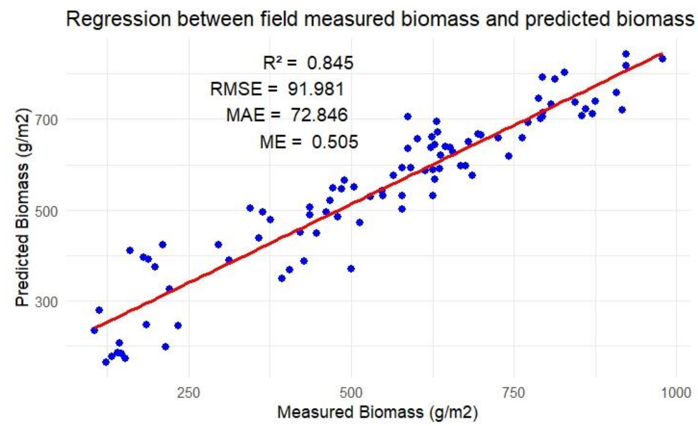

Figure 4 Relationship between lidar derived biomass and field measured biomass.

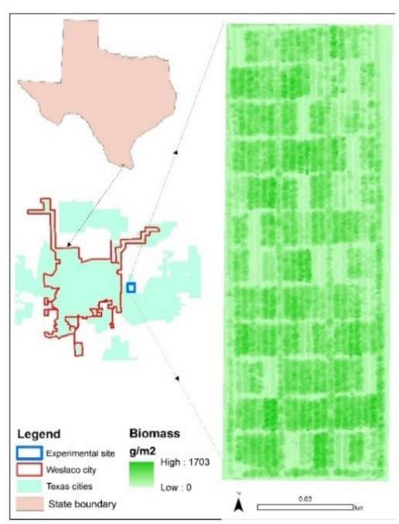

Figure 5 Estimated biomass map of plant cultivars on the Weslaco energy cane experimental field after 72 days of planting.

Table 2 Average biomass of the energy cane cultivars estimated from the UAS-lidar after 72 days of planting.

Energy cane cultivar	Estimated biomass (g/m^2) as at 12/02/2023
TH16-13	671.69
TH16-24	544.82
TH16-16	737.10
TH16-18	552.76
TH16-22	917.79
Ho02-113	504.92
TCP10-4928	499.19

5.0 DISCUSSION

This study used a UAS-lidar system to capture data over an experimental energy cane field in Weslaco-Texas. The study then derived a CHM from the UAS-lidar data to measure crop height and compare with ground truth data. RF regression showed a performance $r^2 = 0.94$, $rmse = 0.12\ m$, between the modelled values and field measured values, providing a good indication of the utility of UAS-lidar modelled CHM for estimating crop height of energy cane. The result also confirms the high performance of UAS-lidar for phenotyping crops as has been indicated in earlier studies such as [4,5,6] and offers good promise of utilizing UAS-lidar for HTP of energy cane.

The study also performed similar regression analysis between UAS-lidar crop height, point cloud density, intensity, and number of returns and field measured biomass of energy cane. The RF model explained 84% of the variability between the field and lidar datasets with a rmse of 108 g/m^2. The high performance of UAS-lidar shown in this study buttresses the finding of earlier studies that used UAS-lidar to estimate crop biomass [7,8]. The RF model was used to predict the biomass of the cultivars after 72 days of planting (Table 2).

6.0 Conclusion

The study demonstrates the efficacy of UAS-lidar technology in accurately estimating crop height and biomass of energy cane in an experimental field. Utilizing CHM, point cloud density, intensity, and number of returns derived from UAS-lidar, strong positive correlations were observed between field-measured crop height and biomass and modeled values, indicating precise phenotyping capabilities. These findings underscore the potential of UAS-lidar for high-throughput phenotyping in agricultural research, offering valuable insights for crop management and breeding programs.

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7. REFERENCES

[1] M. Bhandari *et al.*, "Assessing winter wheat foliage disease severity using aerial imagery acquired from small Unmanned Aerial Vehicle (UAV)," *Comput Electron Agric*, vol. 176, Sep. 2020, doi: 10.1016/j.compag.2020.105665.

[2] J. Jung, M. Maeda, A. Chang, M. Bhandari, A. Ashapure, and J. Landivar-Bowles, "The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems," *Current Opinion in Biotechnology*, vol. 70. Elsevier Ltd, pp. 15–22, Aug. 01, 2021. doi: 10.1016/j.copbio.2020.09.003.

[3] A. Montagnoli *et al.*, "Estimating Forest aboveground biomass by low density lidar data in mixed broadleaved forests in the Italian pre-alps," *For Ecosyst*, vol. 2, no. 1, Dec. 2015, doi: 10.1186/s40663-015-0035-6.

[4] Yue, J., Feng, H., Li, Z., Zhou, C., & Xu, K. (2021). Mapping winter-wheat biomass and grain yield based on a crop model and UAV remote sensing. International Journal of Remote Sensing, 42(5), 1577-1601.

[5] Dhami, H., Yu, K., Xu, T., Zhu, Q., Dhakal, K., Friel, J., Li, S. and Tokekar, P., 2020, October. Crop height and plot estimation for phenotyping from unmanned aerial vehicles using 3D LiDAR. In 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (pp. 2643-2649). IEEE.

[6] Hütt, C., Bolten, A., Hüging, H., & Bareth, G. (2023). UAV lidar metrics for monitoring crop height, biomass and nitrogen uptake: A case study on a winter wheat field trial. PFG–Journal of Photogrammetry, Remote Sensing and Geoinformation Science, 91(2), 65-76. Luo, S., Liu, W.,

[7] Zhang, Y., Wang, C., Xi, X., Nie, S., Ma, D., Lin, Y., & Zhou, G. (2021). Maize and soybean heights estimation from unmanned aerial vehicle (UAV) LiDAR data. Computers and Electronics in Agriculture, 182, 106005.

[8] Shendryk, Y., Sofonia, J., Garrard, R., Rist, Y., Skocaj, D., & Thorburn, P. (2020). Fine-scale prediction of biomass and leaf nitrogen content in sugarcane using UAV LiDAR and multispectral imaging. International Journal of Applied Earth Observation and Geoinformation, 92, 102177.