Unmanned Aerial Vehicle (UAV) Imaging and Machine Learning Application for Plant Phenotyping

Department of Agricultural and Biological Engineering, University of Florida

Fitsum Teshome| Ph.D. Student, Haimanote Bayabil| Assistant Professor

INTRODUCTION

Background of the study

- Remote sensing imageries can improve efficiency and effectiveness of monitoring and controlling agricultural operations (Huang et al., 2018).
- Coarse spatial and temporal resolutions of satellite images are always a challenge for agriculture applications (Veysi et al., 2017).
- Autonomous flight capability (Klemas, 2015), spatial and temporal resolution flexibility (Doughty and Cavanaugh, 2019), and cost-effectiveness (Singh and Frazier, 2018) have given UAV more popularity (Jang et al., 2020).
- UAV images could efficiently replace the traditional crop scouting and phenotyping, which is often laborious, time-consuming, and subjective process (Zhang et al., 2022).
- The ML algorithms could improve and fasten the process of detecting the relationships between plant phenotypic parameters (Linaza et al., 2021).

OBJECTIVES

- To evaluate the applicability of UAV-based imaging and machine learning algorithms to estimate sweet corn (Zea mays var. saccharata) plant height, yield, and biomass.

METHODS

Research site

- This experiment was conducted at Tropical Research Education Center.
- Sweet corn was grown on 16 plots (9 m x 5.5 m) from 24 Nov 2020 to 19 Feb 2021.

Estimating plant height using UAV imageries

- Plant height and biomass were collected bi-weekly.
- At the end of the experiment, grain yield.
- High-resolution multispectral imageries were collected daily using a RedEdge-MX sensor (Fig 1).
- DSM and DTM are generated using Pix4DMapper.
- The pixel level difference between two models has given CSM (Fig. 2).

Figure 1. DJI Matrices 210 v2 UAV an sensors

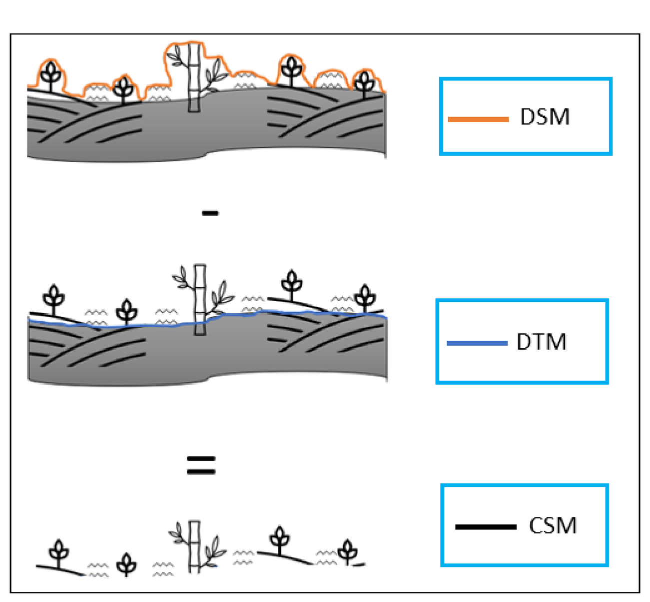

Figure 2. Schematic of DSM, DTM, and CSM

Estimating plant biomass and yield using UAVH

- Field-based measurements were regressed against UAV-estimated plant heights utilizing simple linear regressions.
- About 60% of the data were used to develop a regression model with the remaining 40% of the data held back for validation.

Estimating plant phenotypes using machine learning models

- We derived eight vegetation indices (VIs) from UAV imagery.
- The indices with UAVH were used to evaluate the performance ML models (SVM, kNN, RF, LM, and GLMNET).
- VIs was used to evaluate performance of ML models for sweet corn height estimation.

RESULTS

Estimating plant height from UAV imagery

- The CSM model was able to estimate sweet corn height with relatively high r2 and RMSE values for specific dates ranging between 0.63-0.80 and 1-12 cm, respectively.
- The result of combined data from all measurement dates showed a strong agreement between measured plant height and UAVHs with the RMSE and r2 of 6.6 cm and 0.99, respectively (Fig. 3).

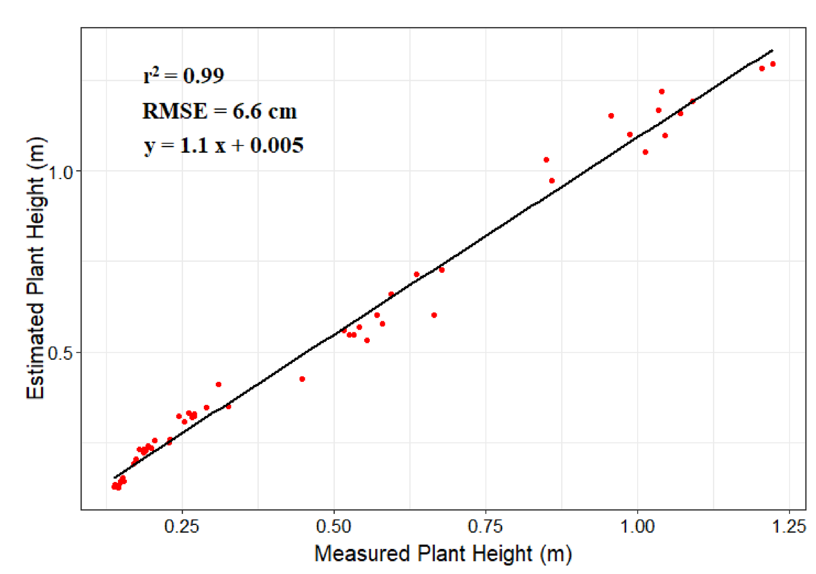

Figure 3. Scatter plot between measured plant heights and estimated plant heights

Estimating sweet corn biomass and yield from UAV images

- A positive linear relationship between the measured total fresh biomass and UAVH was found with adjusted r2 and RSE of 0.88 and 230 g·m-2, respectively.
- The adjusted r2 and RSE of 0.90 and 51.5 g·m-2 were found between measured fresh leaf biomass and UAVH.
- Comparable results were observed for fresh stem biomass and total dry biomass, where the adjusted r2 and RSE were 0.87 and 185.9 g·m-2 and 0.78 and 87.87 g·m-2, respectively.
- A positive correlation between the measured yield and UAVH was found with adjusted r2 and RSE of 0.63 and 77.49 g·m-2, respectively.

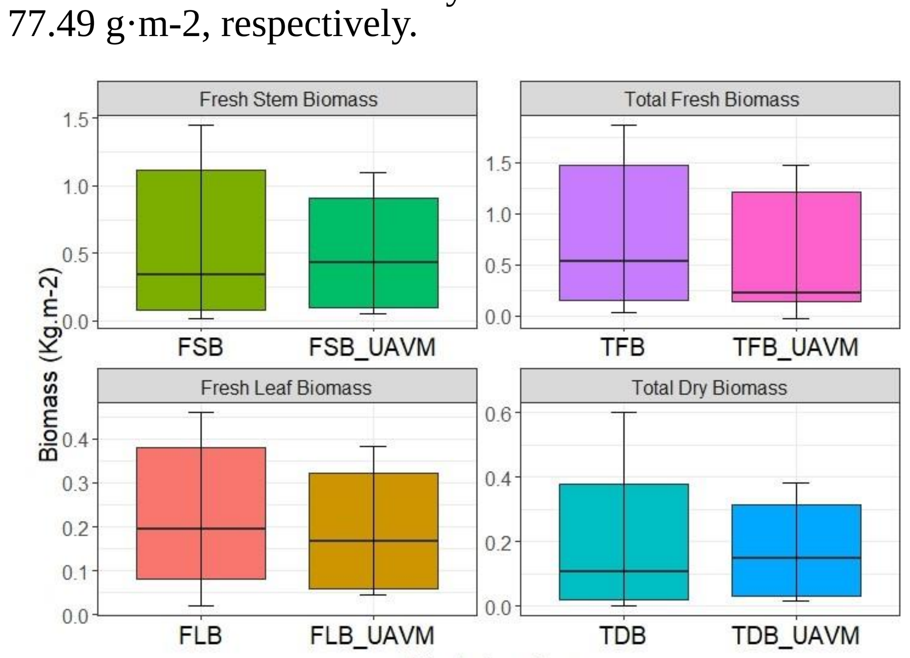

Figure 4. Box plots for estimated biomass against measured respective biomass

Vegetation Indices (VIs)

- The correlation results between measured plant height with the VIs were mixed.
- A good correlation was observed between plant height and NIRRENDVI, RENDVI, and NGRDI indices.

Plant height estimation using ML models

- The GLMNET and LM models performed well in estimating plant height. The GLMNET model had an estimation accuracy r2 of 0.81 and RMSE of 2.2 cm.
- While the LM model estimated plant height with an r2 of 0.79 and RMSE of 2.2 cm.

Biomass estimation using ML models

- The kNN, SVM, and RF were able to accurately estimate the total fresh biomass of sweet corn. The testing r2 results of the kNN, SVM and RF were 0.86, 0.85, and 0.78, respectively.
- The r2 revealed that they were able to provide an accurate estimate of the total dry biomass with r2 of 0.76, 0.84, and 0.85, respectively.
- The kNN model was able to estimate the fresh leaf biomass with an accuracy of 0.92 (r2) and 70 g·m-2 (RMSE).
- The SVM model estimated the fresh leaf biomass with an accuracy of 0.92 r2 and 60 g·m-2 RMSE.
- While the RF model estimated the fresh leaf biomass with 0.87 r2 and 60 g·m-2 RMSE.
- Overall, the SVM and kNN models performed well in estimating the plant biomass. However, the former performed better than the latter.

CONCLUSIONS

- Monitoring plant phenotypes is critical to take timely corrective actions to address problems before crop growth is affected, and yield loss is incurred.
- Field sampling and data collection are often very costly and time-consuming.
- Findings from this study demonstrated that UAV-based multispectral imaging and machine learning algorithms can be effectively used to estimate sweet corn height, biomass, and yield with reasonable accuracy
- The result could be used to make informed decisions at plot and field levels.

REFERENCES

- Huang, Y., Reddy, K.N., Fletcher, R.S., Pennington, D., 2018. UAV Low-Altitude Remote Sensing for Precision Weed Management. Weed Technology 32, 2–6. https://doi.org/10.1017/wet.2017.89
- Veysi, S., Naseri, A.A., Hamzeh, S., Bartholomeus, H., 2017. A satellite based crop water stress index for irrigation scheduling in sugarcane fields. Agricultural Water Management 189, 70–86.
- Zhang, Y., Li, M., Li, G., Li, J., Zheng, L., Zhang, M., Wang, M., 2022. Multi-phenotypic parameters extraction and biomass estimation for lettuce based on point clouds. Measurement 204, 112094. https://doi.org/10.1016/j.measurement.2022.112094
- Linaza, M.T., Posada, J., Bund, J., Eisert, P., Quartulli, M., Döllner, J., Pagani, A., G. Olaizola, I., Barriguinha, A., Moysiadis, T., Lucat, L., 2021. Data-Driven Artificial Intelligence Applications for Sustainable Precision Agriculture. Agronomy 11, 1227. https://doi.org/10.3390/agronomy11061227

ACKNOWLEDGMENTS

- Funding for this research was provided by the National Institute of Food and Agriculture, U.S. Department of Agriculture, under award number 2020-67021-31965, and the Hatch Project No. FLA-TRC-005751. Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the authors and do not necessarily reflect the view of the U.S. Department of Agriculture.

Contact: fteshome@ufl.edu 786-491-5076