Final Goal – First Draft before 6/15

Materials:

* Paper draft
* Code
* Figures
* Tables
* Demo Videos
* Dataset and description
* Slides

|  |  |  |  |
| --- | --- | --- | --- |
| Date | FL time | LiDAR | MSI |
| 0728 | 1204 |  |  |
| 0731 | 1057 |  |  |
| 0806 | 1055 |  |  |
| 0810 | 1049 |  |  |
| 0814 | 1148 |  |  |
| 0821 | 1044 |  |  |
| 0824 | 1132 |  |  |
| 0826 | 1129 |  |  |

## CloudCompare steps:

1. make polygons for cropping. (python, CloudCompare, Excel)
   1. manually find the corners of the polygons from data 202008241132.
   2. save the corners as polygons in file ‘G:\My Drive\code\plantCount\polgonCorners.xlsx’.
2. load the point cloud (e.g., E:\2020snapbeans\20200728\lidar\1204\lidar\_spat\_cropped\_rn1\_remDup005\_SOR\_10\_1\_Tshft\_N\_trim\_small\_angle20.csv), with fixed Translation: (-334248.00; -4748090.00; -178.69) (CloudCompare)
3. load DEM (E:\2020snapbeans\20200701\lidar\1150\lidar\_N\_trim\_small\_angle20\_dem.csv)with the same translation in step-2; (CloudCompare)
4. calculate the difference between and , export the C2C\_distance as Z-coordinate and get a point cloud with z-coordinates normalized . (CloudCompare)
5. filter out the points of the markers, with ; (CloudCompare)
6. load the polygons in step-1 with the same translation in step-2 (CloudCompare)
7. crop the point cloud using the polygons and get point clouds , and then combine them to as one point cloud (CloudCompare)
8. rotate the point clouds with the following matrix (CloudCompare)

|  |
| --- |
| 0.993331968784 -0.115289263427 0.000000000000 0  0.115289263427 0.993331968784 0.000000000000 0  0.000000000000 0.000000000000 1.000000000000 0.000000000000  0.000000000000 0.000000000000 0.000000000000 1.000000000000 |

1. save the point clouds as one point cloud , and then feed the point cloud to python scripts to do the row segmentations (Python)
2. After row segmentation, the point clouds were then fed into the combineSeg2Plot.py file to get the combined file. In this process, the calculated representative for each row were averaged among the 4 rows in each plot and then saved in .txt file and .xlsx file.

## MSI data processing:

1. make a stack of multiple layers and export it a ENVI .dat file, and then modify the bands’ info in the header file, finally utilize a pre-drawn ROI to save the spatial subset. (ENVI)
2. calculate the VIs and stack them together to make a multi-band VI image . (ENVI-spectral indices, 38 indices were available, therefore 38 bands.)
3. do SAM segmentation on the cropped five-band image and get the segmentation mask . (ENVI)
4. attach the the cropped five-band image , VI image , and segmentation mask to make a multi-band image with a mask . (Cropped, Vegetation indices and Mask; ENVI)
5. rotate the image (python) (I tried QGIS, but it could not export the result in proper format).
6. segment the image of the whole field into rows by geometric boundaries. (Python)
7. calculate the VI representative for each row and each VI. (Python)
8. combine the row-level VI representative to plot-level. (Python)

Make multivariate regression between the features from each flight and the ground truth data. By comparing the results from each date, we could select the best date for yield prediction.

Build LSTM model between features from multiple previous days and the ground truth data to do prediction.

1. we need to determine which dates to be used as inputs;
2. we need to determine the architecture of the model.

## Sensor Fusion

In autonomous driving, three approaches to combine sensory data from various sensing modalities:

* high-level fusion (HLF)
  + each sensor carries out object detection or a tracking algorithm independently and subsequently performs fusion
* low-level fusion (LLF)
  + data from each sensor are integrated (or fused) at t**he lowest level of abstraction (raw data)**
  + E.g. Sankey et al. (2017) did data fusion of LiDAR and hyperspectral image to do forest vegetation classification. The fusion performs better (88% overall accuracy) than either data type alone, particularly for species with similar spectral signatures, but different canopy sizes. [1]
  + In Sankey et al. (2018), the fusion of LiDAR and hyperspectral image approach provides 84–89% overall accuracy (kappa values of 0.80–0.86) in target species classification at the canopy scale, leveraging a wide range of target spectral responses in the hyperspectral data and a high point density (50 points/m2) in the lidar data. [2]
  + Joel et al. (2021) demonstrate UAV hyperspectral and LiDAR fusion in detecting the spatial patterning of shrubs, grasses, and soils got high accuracy in classification.[3]
* mid-level fusion (MLF)
  + **feature-level fusion**, It fuses multi-target features extracted from the corresponding sensor data (raw measurements), such as color information from images or location features of radar and LiDAR, and subsequently perform recognition and classification on the fused multisensor features.
  + E.g., Jose et al. (2016) fused LiDAR and multispectral image by back-projecting the LiDAR points onto the multispectral image. A multivariate data set of both LiDAR and multispectral metrics was related with a multivariate data set of stand structural variables measured in a Scots pine forest through canonical correlation analysis (CCA) [4]. (Similar to what I did in the LAI paper).
  + Ranjani and Sorin used the fusion of lidar with multispectral data for regression models for quantify salt marsh above-ground biomass.[5]
  + Almeida et al. (2021) used UAV-LiDAR-HSI system to evaluate the above ground biomass, they derived LiDAR metrics and HSI VIs separately and then evaluated the predictive power of AGB from lidar and HSI variables using simple and multiple ordinary least square regressions. The assessment of model accuracy was performed by a leave-one-out cross-validation (LOOCV) procedure.
  + Shendrk et al. (2020) used UAV-derived LiDAR and multispectral imagery were used to predict sugarcane biomass. They used PCA on LiDAR- and MSI-derived metrics respectively and jointly, since the number of observations was 56, while the # of predictors from Lidar was 48 and from MSI was 70. LiDAR and multispectral imagery performed similarly in predicting biomass (). [6]

## Reference

[1] T. Sankey, J. Donager, J. McVay, and J. B. Sankey, “UAV lidar and hyperspectral fusion for forest monitoring in the southwestern USA,” *Remote Sens. Environ.*, vol. 195, pp. 30–43, 2017, doi: 10.1016/j.rse.2017.04.007.

[2] T. T. Sankey, J. McVay, T. L. Swetnam, M. P. McClaran, P. Heilman, and M. Nichols, “UAV hyperspectral and lidar data and their fusion for arid and semi-arid land vegetation monitoring,” *Remote Sens. Ecol. Conserv.*, vol. 4, no. 1, pp. 20–33, 2018, doi: 10.1002/rse2.44.

[3] J. B. Sankey *et al.*, “Quantifying plant-soil-nutrient dynamics in rangelands: Fusion of UAV hyperspectral-LiDAR, UAV multispectral-photogrammetry, and ground-based LiDAR-digital photography in a shrub-encroached desert grassland,” *Remote Sens. Environ.*, vol. 253, 2021, doi: 10.1016/j.rse.2020.112223.

[4] J. A. Manzanera *et al.*, “Fusion of airborne LiDAR and multispectral sensors reveals synergic capabilities in forest structure characterization,” *GIScience Remote Sens.*, vol. 53, no. 6, pp. 723–738, 2016, doi: 10.1080/15481603.2016.1231605.

[5] R. W. Kulawardhana, S. C. Popescu, and R. A. Feagin, “Fusion of lidar and multispectral data to quantify salt marsh carbon stocks,” *Remote Sens. Environ.*, vol. 154, pp. 345–357, 2014, doi: 10.1016/j.rse.2013.10.036.

[6] Y. Shendryk, J. Sofonia, R. Garrard, Y. Rist, D. Skocaj, and P. Thorburn, “Fine-scale prediction of biomass and leaf nitrogen content in sugarcane using UAV LiDAR and multispectral imaging,” *Int. J. Appl. Earth Obs. Geoinf.*, vol. 92, 2020, doi: 10.1016/j.jag.2020.102177.