

# Predicting Table Beet Root Yield via UAS-based Hyperspectral Imagery



*Mohammad S Saif, Robert Chancia, Sarah Pethybridge, Sean P. Murphy, Amirhossein Hassanzadeh and Jan van Aardt*

# Objectives

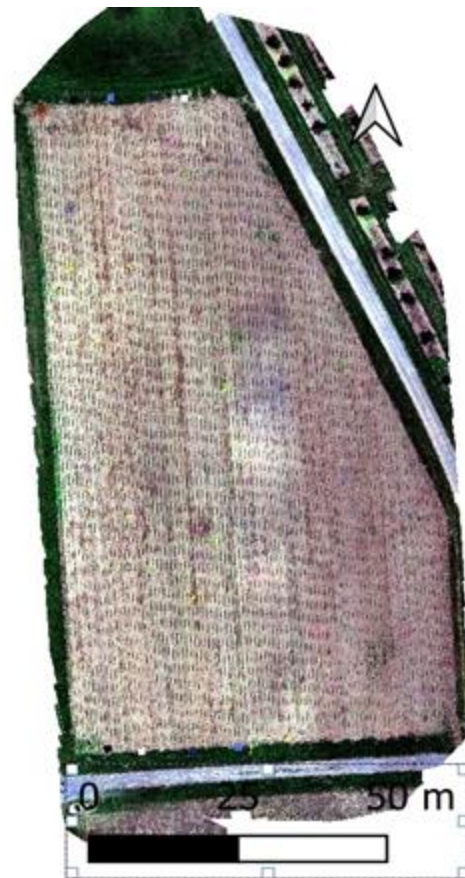
**We proposed to develop UAS-based techniques to forecast *beet root weight*. This includes:**

- **Identifying the spectral regions that are predictive of beet root weight.**
- **Evaluating the predictability at five different growth stages.**
- **Assessing the extension of results to affordable, operational silicon-based detectors. Note: We used hyperspectral imagery to determine the optimal wavelengths in the Si-range (400-900 nm).**

# Data collection process



Headwall Nano  
Hyperspec  
400-1000 nm: Visible and  
Near Infrared (VNIR)  
272 bands; 2-3 nm spectral  
resolution

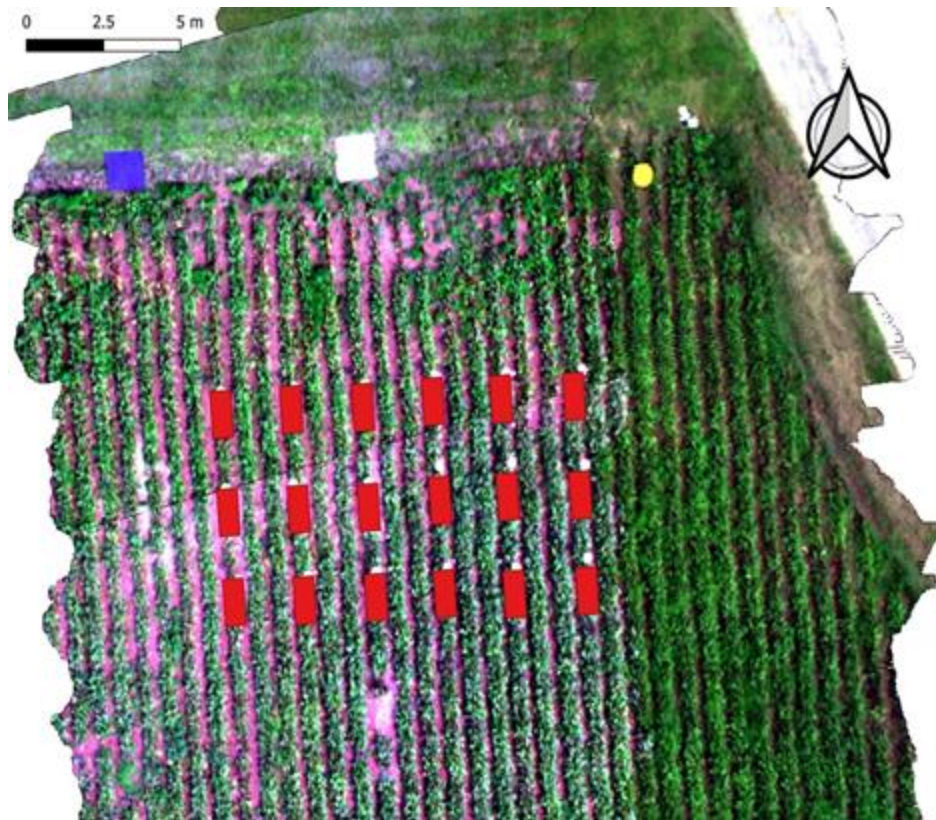


# UAS data collection: 2021 flight milestones

| Date     | Milestone     | Growth Stages                                  |
|----------|---------------|--|
| May 20   | Beets planted | Germination                                    |
| June 16  | 1st Flight    | Leaf Development (Crop Emergence)              |
| July 7   | 2nd Flight    | Leaf Development (more than 9 leaves unfolded) |
| July 15  | 3rd Flight    | Rosette growth                                 |
| July 20  | 4th Flight    | Rosette growth                                 |
| August 2 | 5th Flight    | Harvest-ready                                  |
| August 5 | Harvest       | Harvest-ready                                  |

# Plot extraction

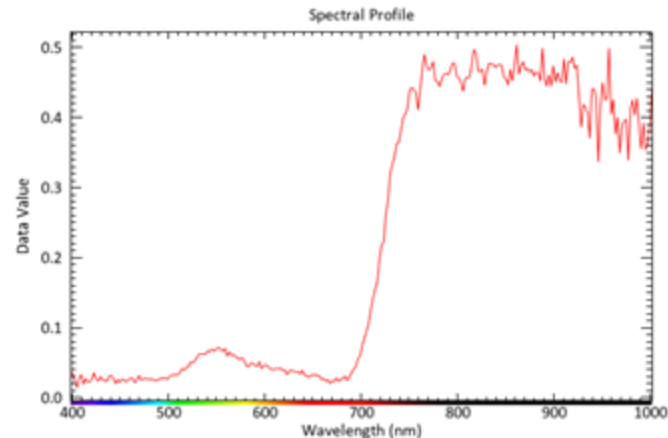
- Convert from radiance to reflectance (via ELM)
- Perform denoising
- 18 plots in our study
- Width of box = 0.67 m (roughly the distance between two adjacent rows)
- Height of box = 1.46 m (roughly the size of the plot)





# Challenges related to hyperspectral data

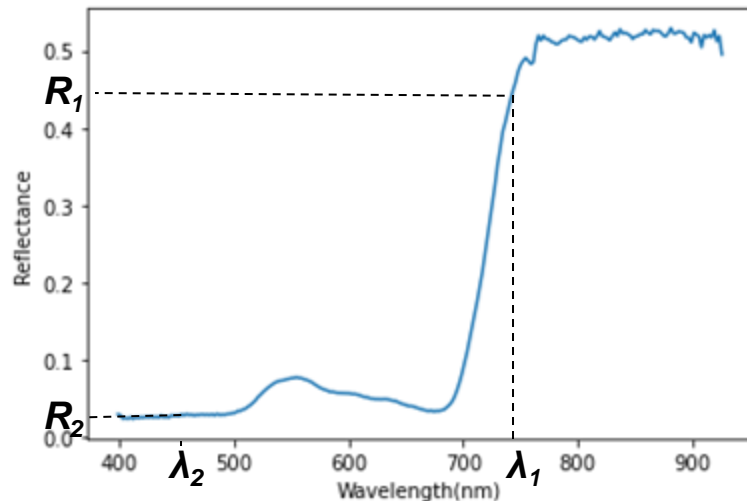
- We have ~272 spectral bands
- Hyperspectral data suffer from the curse of dimensionality
- Identify the useful features:
  - Find all possible pairs of normalised difference indices from mean vegetation spectra of the plot (reflectance features).
  - Find the GLCM mean of a plot (texture features).
  - Find all possible pairs of normalised differences for the GLCM mean



# Predictor variable extraction

- **Extract normalized difference indices at various wavelength pairs**
  - We calculate for both reflectance and texture features
  - For reflectance: Normalized difference reflectance indices (NDRI)
  - For texture: Normalised texture reflectance indices (NDTI)
- **Fit a linear relationship between this feature and the value to predict (e.g., root weight)**

$$\text{Normalized Difference Indices} = \frac{R_1 - R_2}{R_1 + R_2}$$



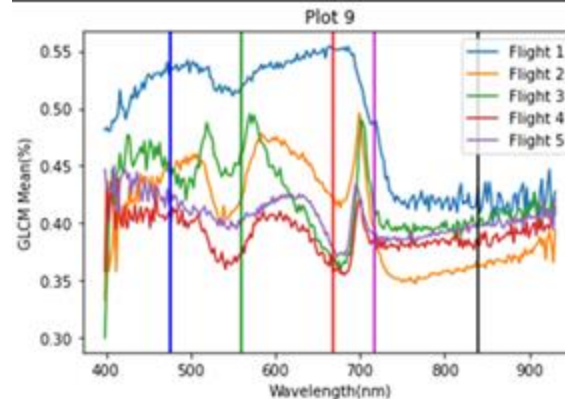
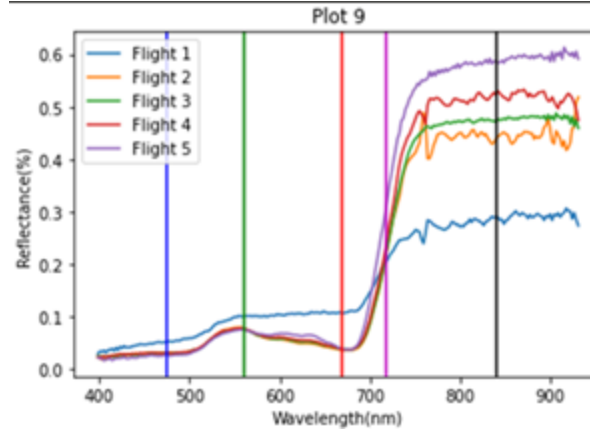
# Feature extraction



Reflectance features



Texture features  
(GLCM)



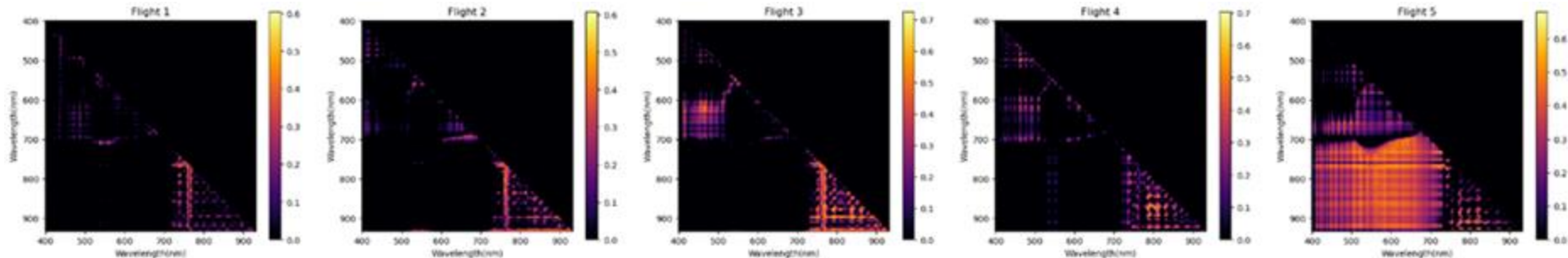
Extract a spectrum of mean reflectance features and mean texture features from each plot



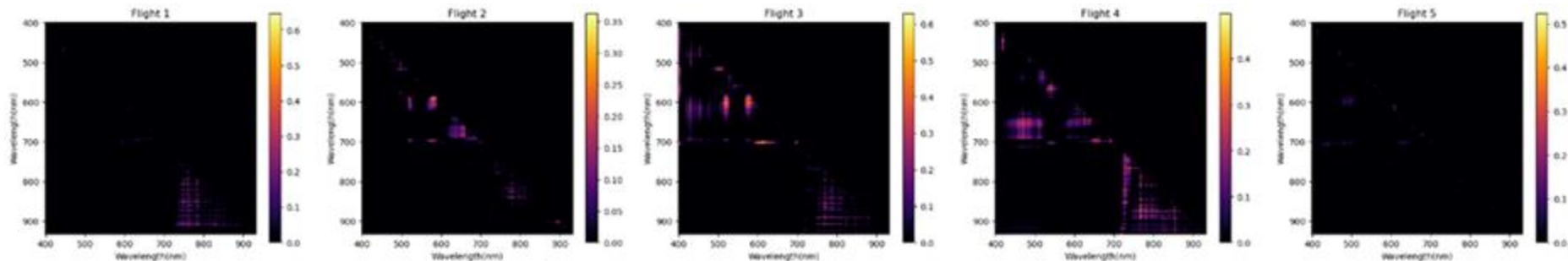
# Plot of coefficient of determination at various wavelength pairs during each flights



NDRI



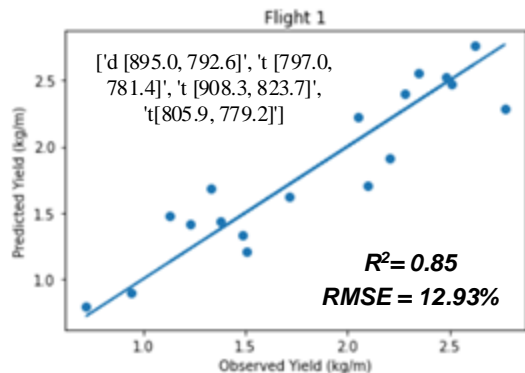
NDTI



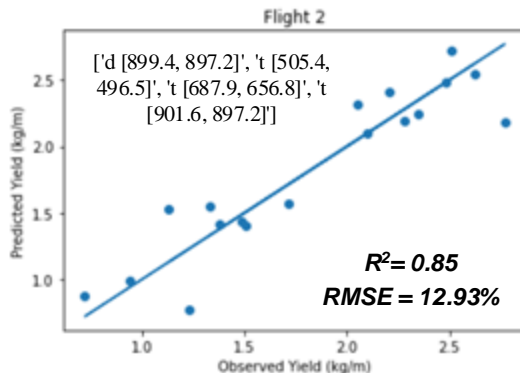
# Feature selection for better-performing model

- **Select top 10 ( $R^2$ ) from each indices**
- **Run modified stepwise regression**
  - Stepwise regression only accounts for a particular set of features at fixed permutations
  - Here all the top performing feature combinations are reported
  - We randomly select the order of feature
  - First forward select, then perform backward elimination after each selection (to ensure model with a low number of features)
  - Filter out the models containing low VIF (variance inflation factor)

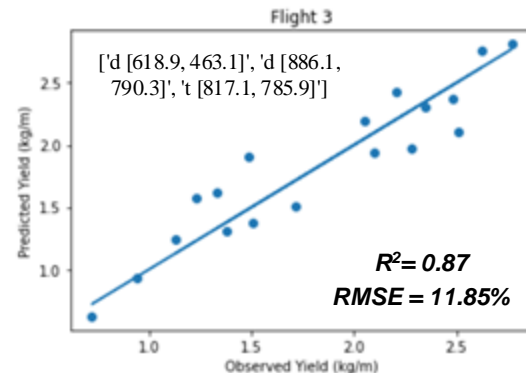
# Performance of the best performing models



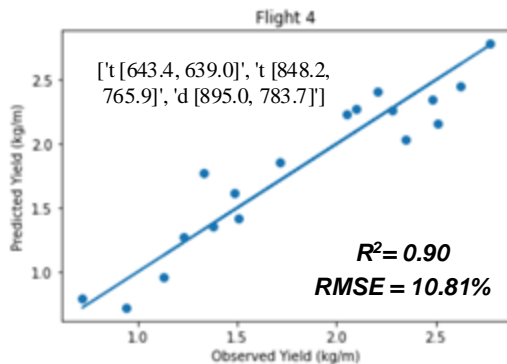
(a)



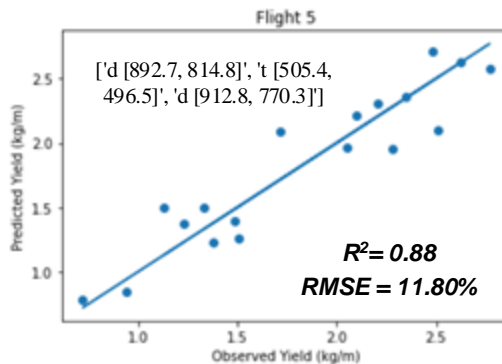
(b)



(c)

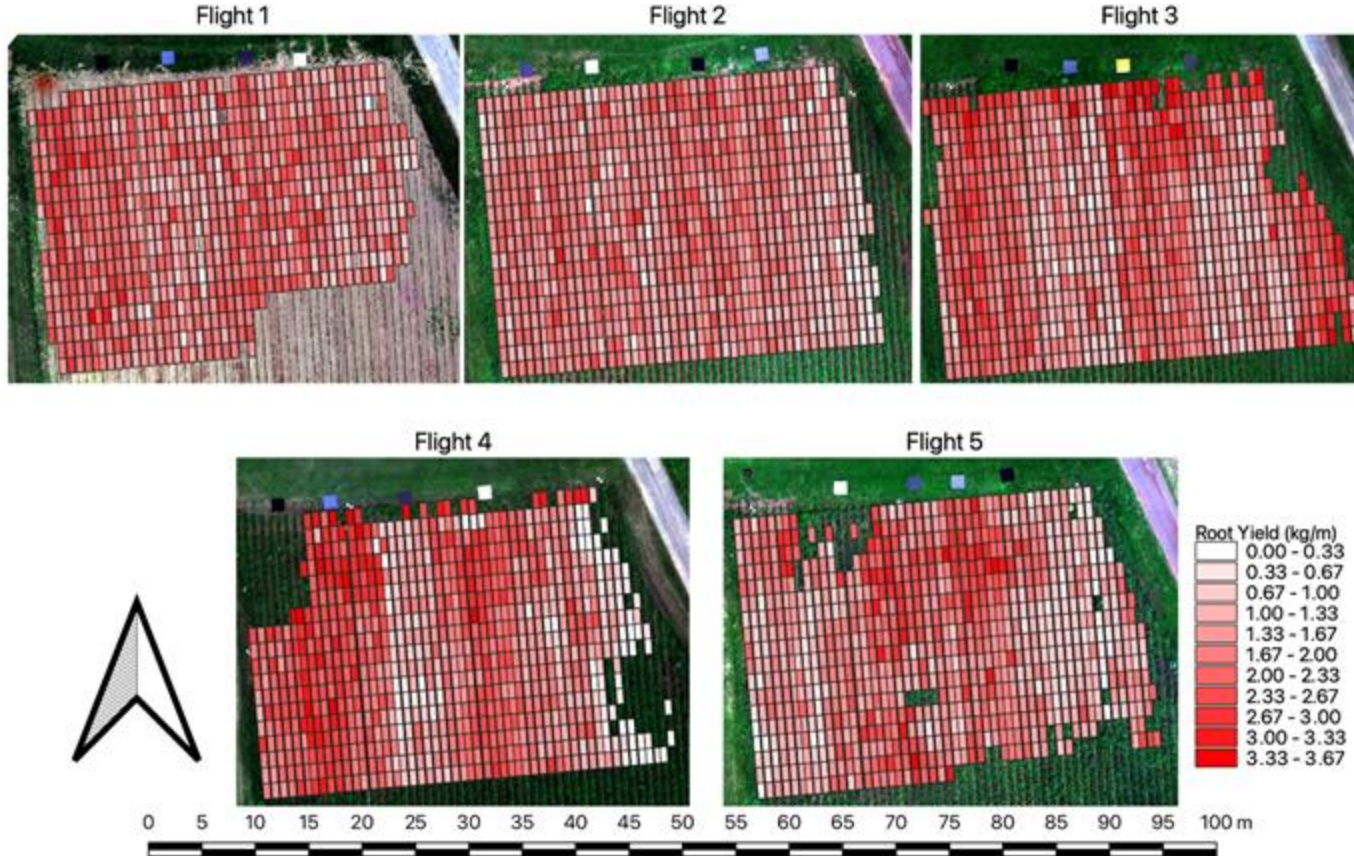


(d)



(e)

# Extrapolating yield results to the field scale



# Conclusion and future work

- **Feature pairs around the NIR region are most responsive to root yield**
- **The spectral region of most responsive predictive regions changes with time**
- **The “rosette” growth stage (flights 3 & 4) are the most suitable time to collect data**
- **Further verification of the features are required with data sets collected across growing seasons**

# Questions?

For more details: **Forecasting Table Beet Root Yield Using Spectral and Textural Features from Hyperspectral UAS Imagery**, *Remote Sensing* 2023, 15

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