RIT

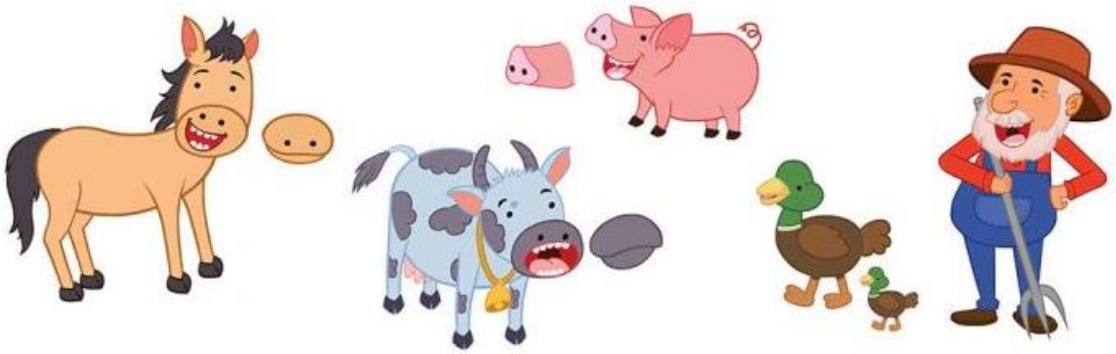
Advancing the Utility of Unmanned Aerial Systems (UAS)-Based Imaging Techniques in Broadacre Agriculture: A Multimodal Case Study on Table Beets

Mohammad Saif

Advisor: Dr. Jan van Aardt

Chester F. Carlson CENTER for IMAGING SCIENCE

Old Macdonald had a farm ……….



Sponsored by:

……. And on that farm he grows beets.

- In 2024, approximately 9,700 acres of table beets were harvested in US, generating an estimated value of $86 million *(USDA-NASS)*.
- Table beets are growing in demand due to known health benefits *(Sokolova et al., 2024)*.
- Driving the need for more efficient farming practices.

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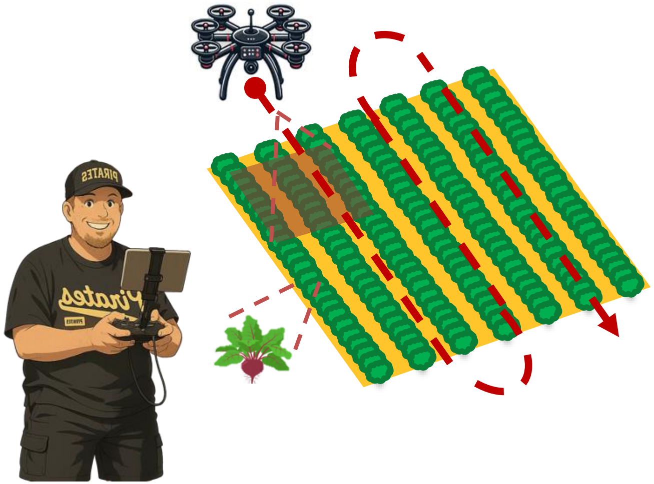
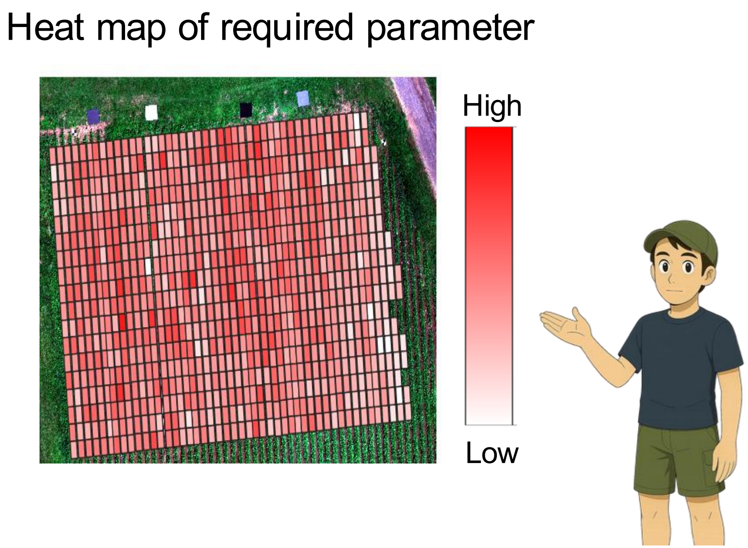
- USDA-NASS:United States Department of Agriculture National Agriculture Statistics Service. 2016. Available online: https://quickstats.nass.usda.gov/results/27FA1853-448A-39A7-9CF4-E457154D6482
- Sokolova, Diana V., et al. "Characterization of Betalain Content and Antioxidant Activity Variation Dynamics in Table Beets (Beta vulgaris L.) with Differently Colored Roots." *Agronomy* 14.5 (2024): 999.

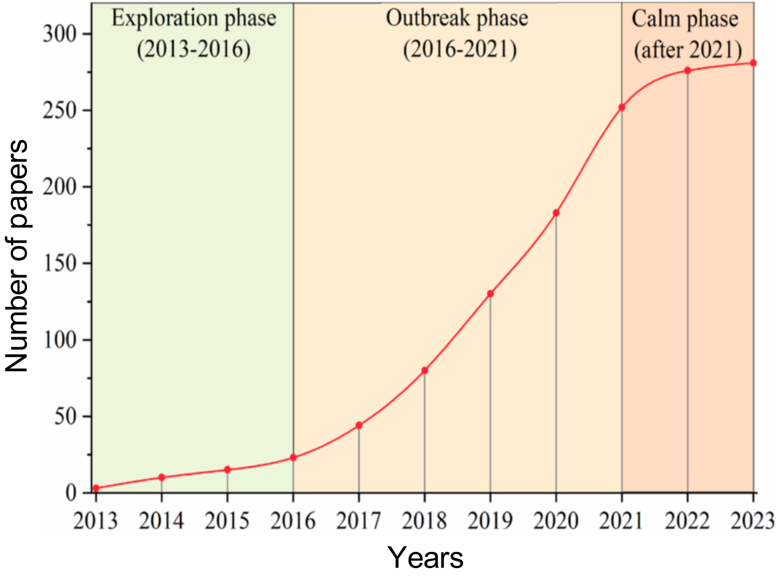
Old Macdonald buys a drone ……..



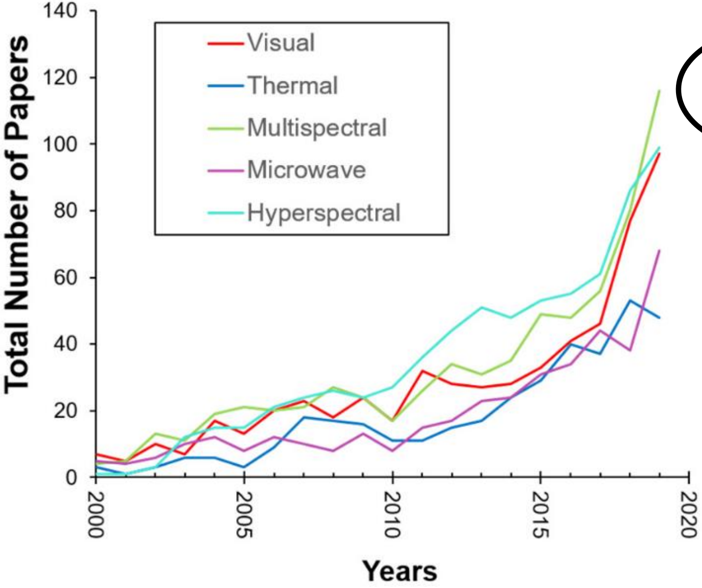


- UAS enables non-invasive, high-throughput data collection.
- Provides spatially explicit insights for precision agriculture.
- Supports decisions like logistic planning and targeted intervention.

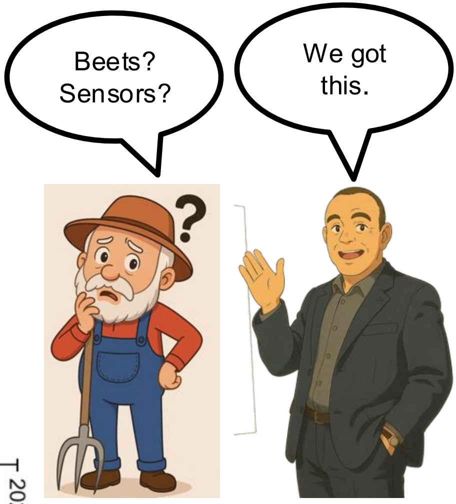
UAS Research



* *Wang, Jingzhe, et al. "UAS-based remote sensing for agricultural Monitoring: Current status and perspectives." Computers and Electronics in Agriculture 227 (2024): 109501.*



* *Khanal, Sami, et al. "Remote sensing in agriculture—accomplishments, limitations, and opportunities." Remote sensing 12.22 (2020): 3783.*



- Limited research focused on **table beets** and comparative evaluation of **sensor** modalities for agricultural monitoring

Objectives

- Assess the feasibility of using narrowband spectroscopy for table beet yield prediction.
- Develop and compare robust harvest yield prediction models using UAS data across multiple sensor configurations.
- Evaluate *Cercospora* leaf spot (CLS) disease severity and compare the performance of multispectral and hyperspectral sensors.

Outline

- Data collection
- Spectral band selection for yield prediction
- Robust yield prediction model
- CLS disease severity estimation
- Conclusions and key takeaways

Data collection

Unmanned Aerial Systems (UAS)

Headwall Nano Hyperspec

400-1000 nm: Visible and Near Infrared (VNIR)
272 bands; 2-3 nm spectral resolution
640 Spatial band pushbroom sensor

Velodyne Airborne LiDAR

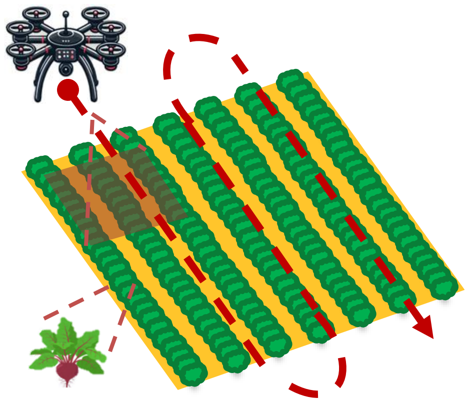
16 channels spanning 30° vertical FOV
Weight: 830 g

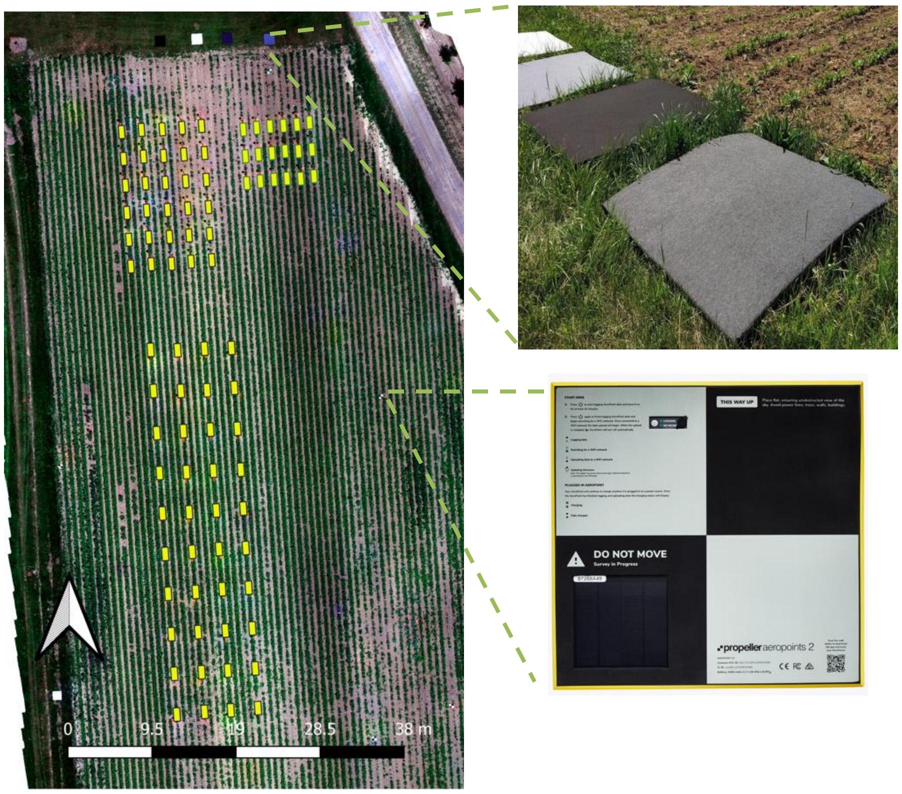
MicaSense Rededge-M

Blue, green, red, red-edge, and near infrared bands

UAS Flight and Image Acquisition

- UAS flown in lawnmower pattern to ensure complete field coverage.
- Geometric and radiometric corrections applied to generate ortho-mosaic imagery.





Field data collection

- Conducted several flights over Cornell Agritech field in Geneva, NY, during 2021 and 2022 seasons.
- Dimensions of the plots are 5ft x 1 ft.
- Table beetroot weight measured at harvest only.
- CLS disease severity assessed by plant pathologists.

Field view of the beet plots under study

Ortho-mosaic of the entire beet plot. The yellow rectangles are the plots under study.

Outline

Data Collection

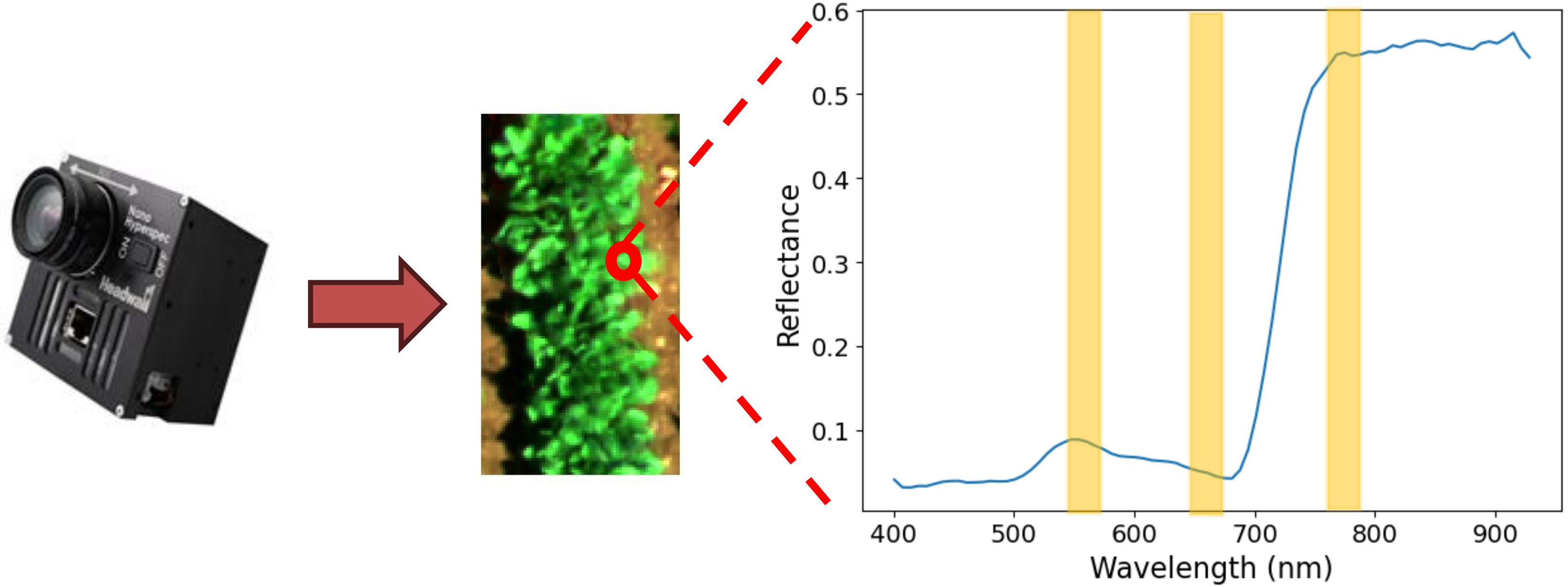
Spectral band selection

Robust Yield Model

CLS DS estimation

Conclusions

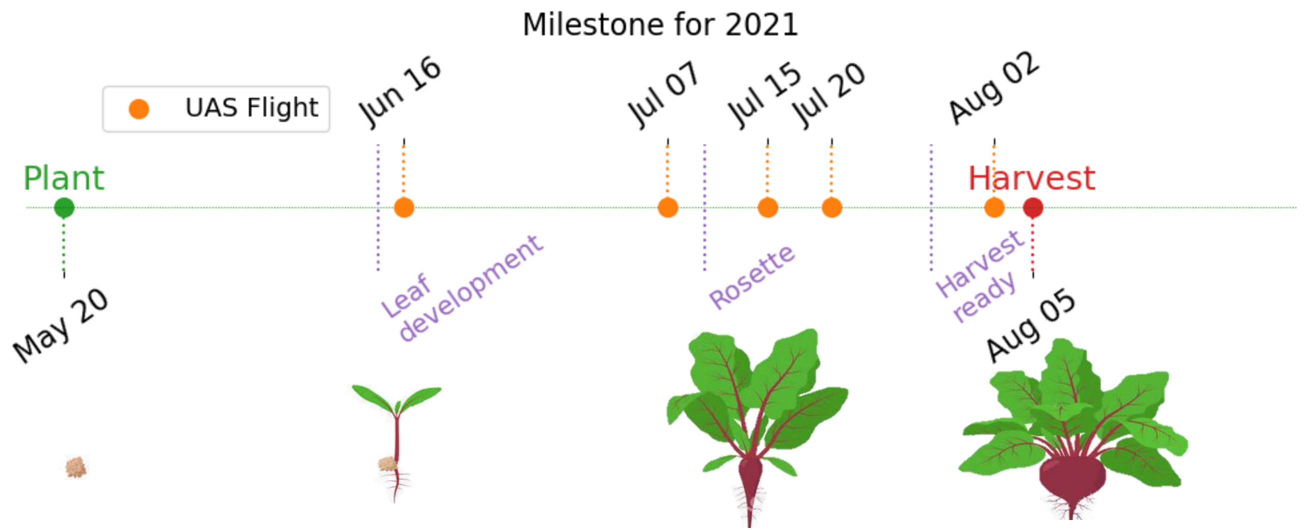
Research question



Which specific narrow spectral bands are most predictive of harvest root yield in table beets?

Timeline

- Flights conducted at different times during a growing season.
- Estimate the end of season root yield (weight of beet root).

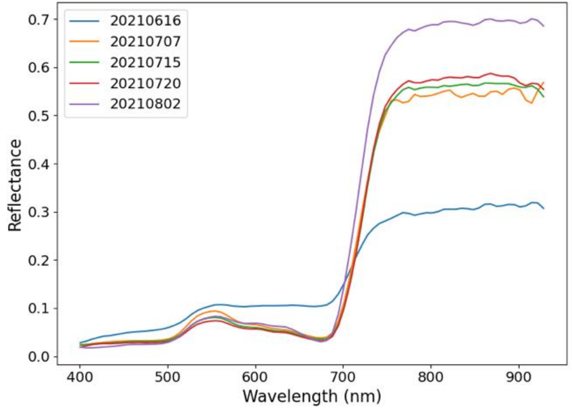


Beet cartoons from:https://depositphotos.com

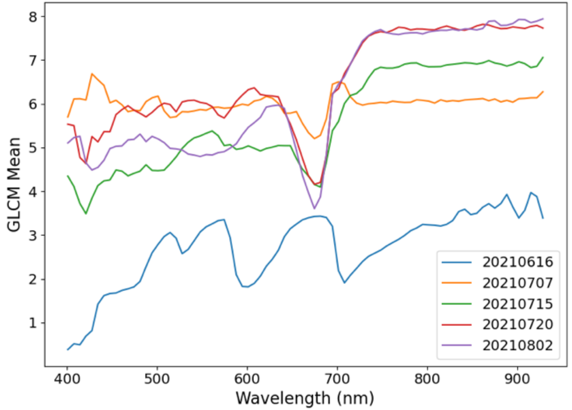
Feature extraction

- Extracted mean reflectance features across spectral bands.
- Computed mean texture metrics based on gray-level co-occurrence matrices *(Haralick et al., 1973).*
- Mean texture reflects average co-occurring pixel intensity, indicating spatial brightness trends in a band.

Mean Reflectance



Mean Texture

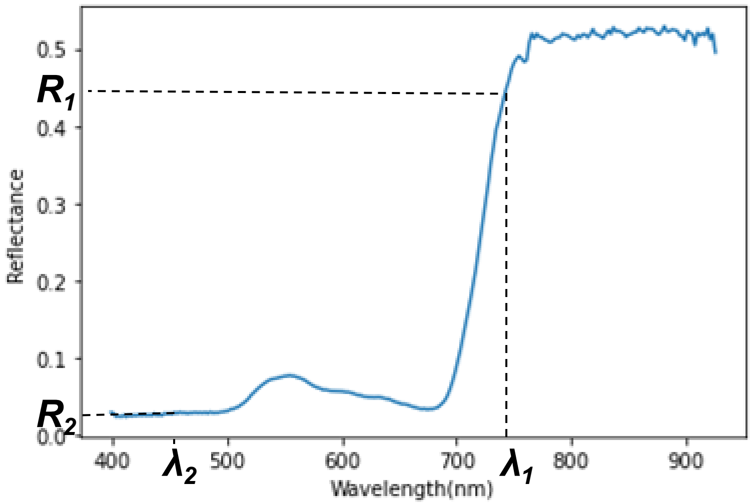


* Haralick, Robert M., Karthikeyan Shanmugam, and Its' Hak Dinstein. "Textural features for image classification." IEEE Transactions on systems, man, and cybernetics 6 (2007): 610-621.

Predictor variable extraction

- Computed normalized difference indices across all wavelength pairs
- Applied to both spectral reflectance and texture-based features
- Defined as NDRI for reflectance and NDTI for texture metrics

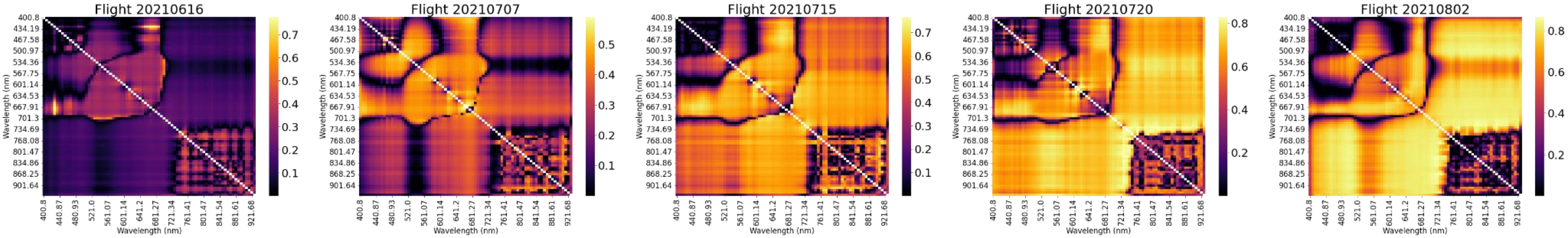
$$\textit{Normalized Difference Indices} = \frac{R_1 - R_2}{R_1 + R_2}$$



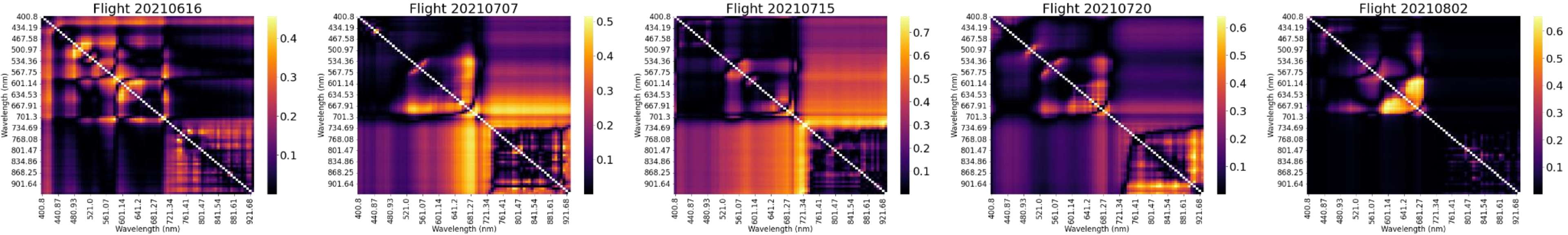
Evaluating predictive power of wavelength combinations

Computed R^2 values for each wavelength pair using linear models

NDRI

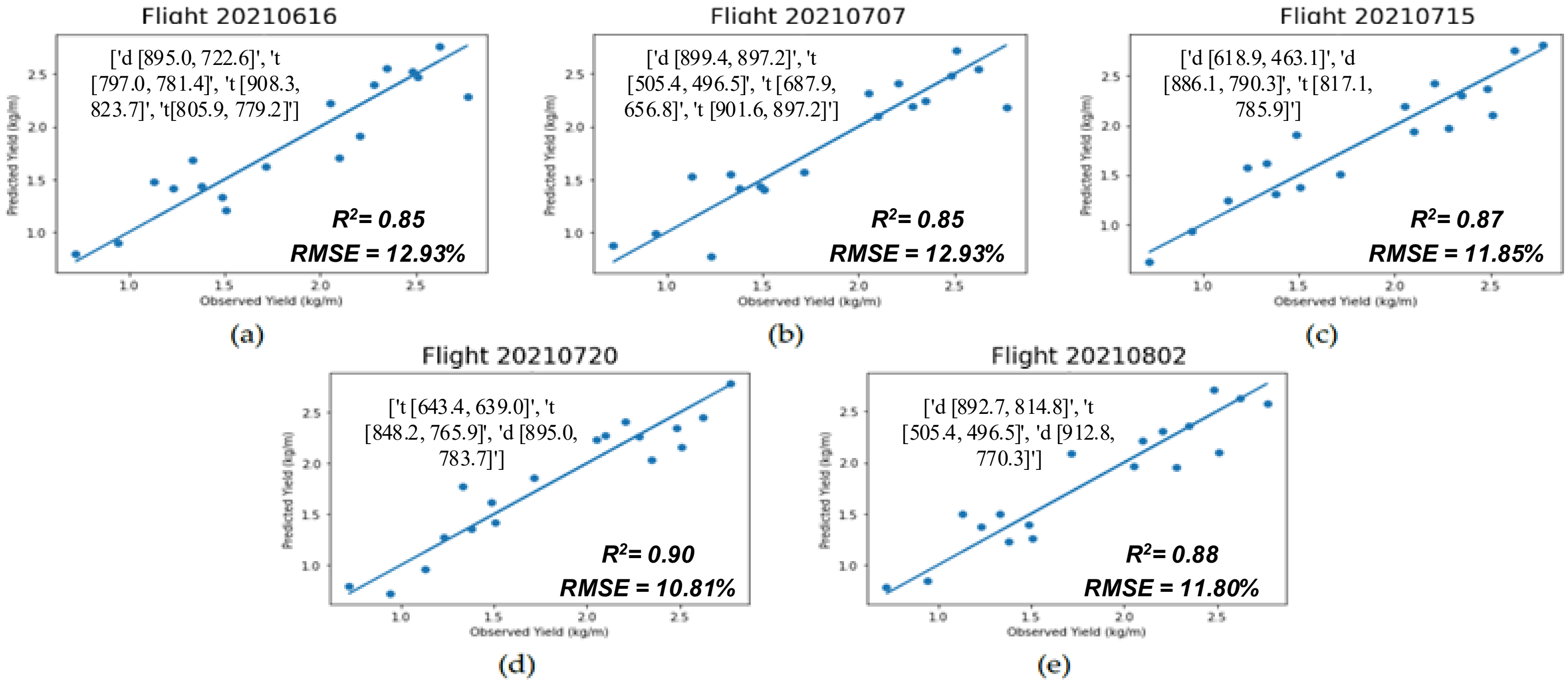


NDTI



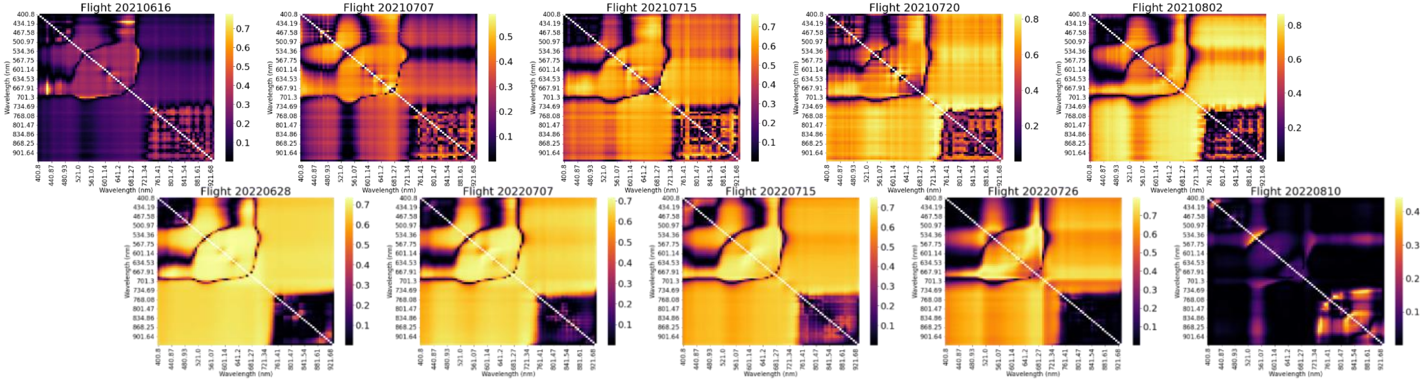
Model performance across flights

Applied stepwise multivariate linear regression using top 10 NDRI and NDTI predictors to model harvest root yield.

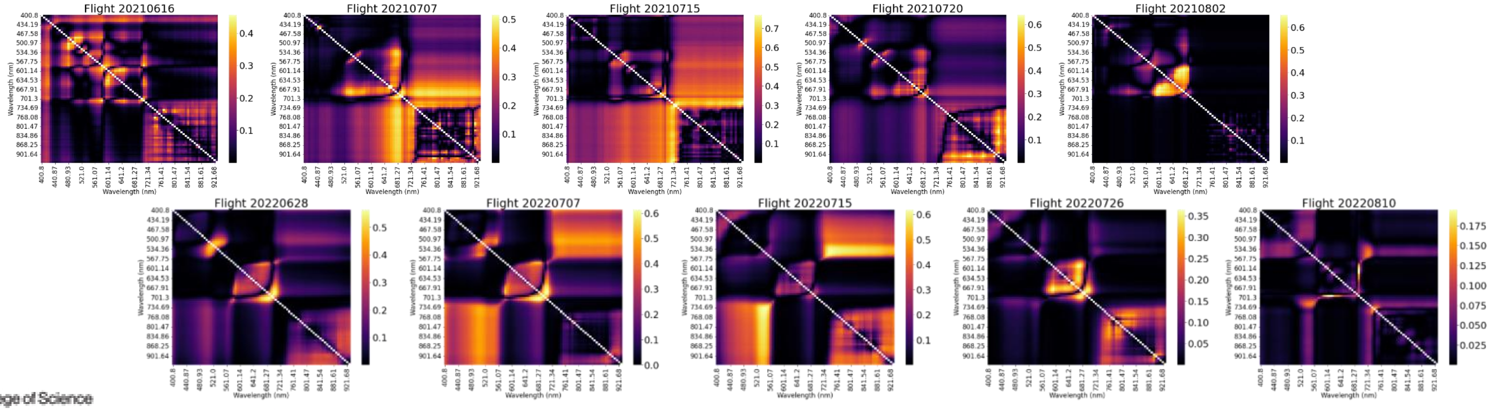


Transferring to new seasons

NDRI



NDTI



Conclusion

- Identified key wavelength features associated with different growth stages.
- However, these indices show limited transferability within and across seasons.
- NDRI features demonstrate consistent patterns across narrowband wavelengths and growth stages, whereas NDTI features exhibit poor cross-stage and cross-season generalization.

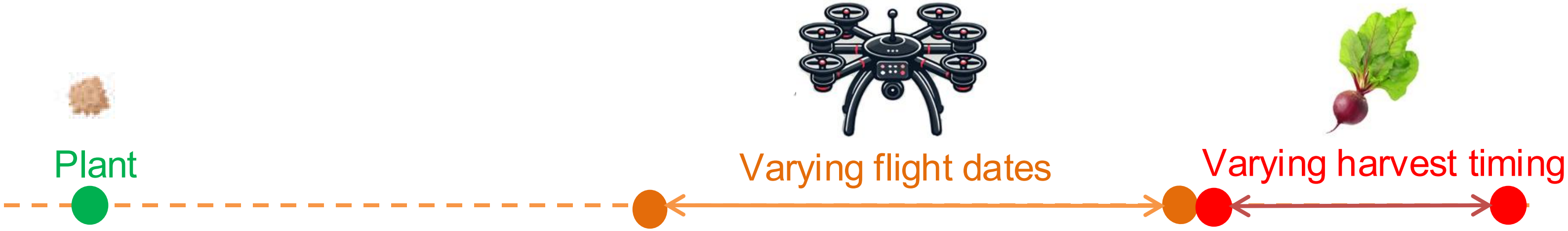
Outline

- Data Collection
- Spectral band selection
- Robust Yield Model
- CLS DS estimation
- Conclusions

Research gap for practical yield modeling

- Lack of **robust models**: Most existing yield models are tailored to specific growth stages or seasons, limiting their real-world usability. A unified, flexible model is essential for operational deployment.

- Unclear **sensor guidance**: There is limited comparative analysis on sensor performance, making it difficult to determine the optimal sensor for yield prediction.



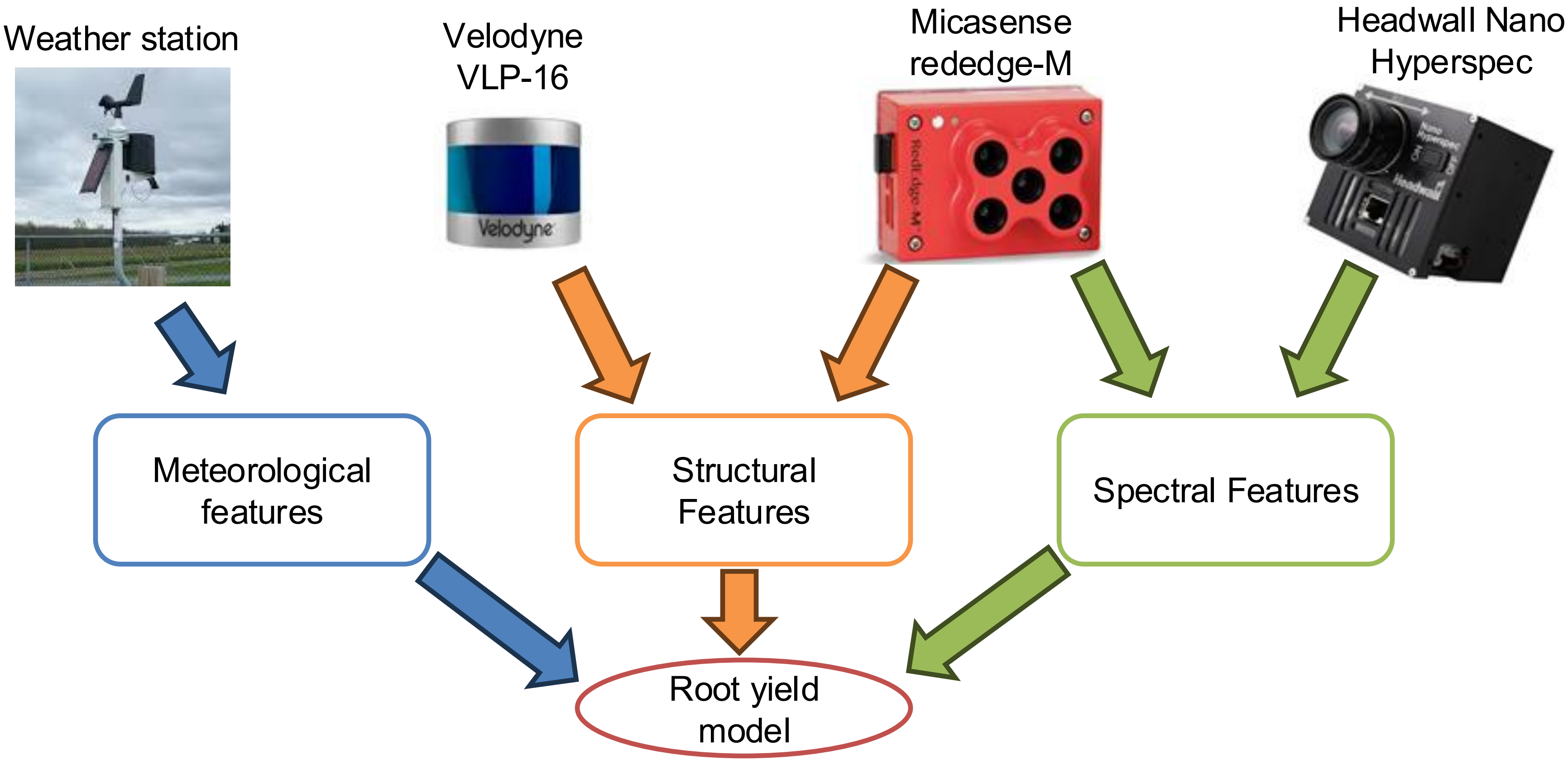
Objective

- Develop a robust yield prediction model for table beets using UAS-derived multispectral, hyperspectral, and LiDAR data.

- Evaluate model performance across multiple growth stages and growing seasons to ensure generalizability.

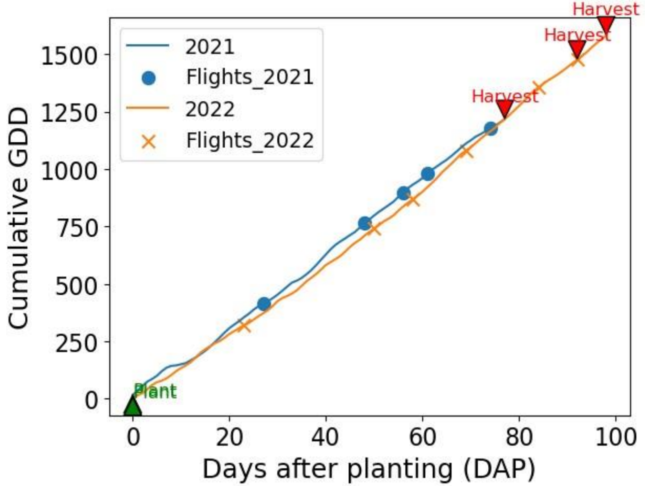
- Compare and contrast the predictive capabilities of different sensor modalities.

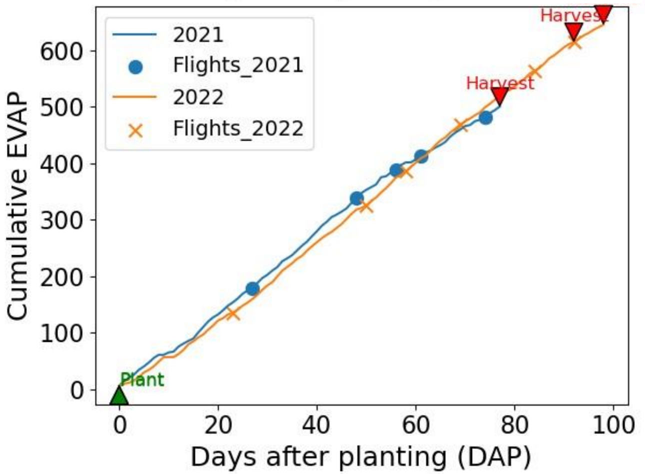
Features for root yield modeling



Meteorological features

- Growing degree days (GDD) is widely used strategy to track growth stages in crops (Maimaitijiang et al., 2020).
  - $$GDD = \frac{T_{max}+T_{min}}{2} - T_{base}$$
- Evapotranspiration has been shown to be directly proportional to yield (Cheng et al., 2022).
  - Accumulated pan evaporation data was used as model feature.

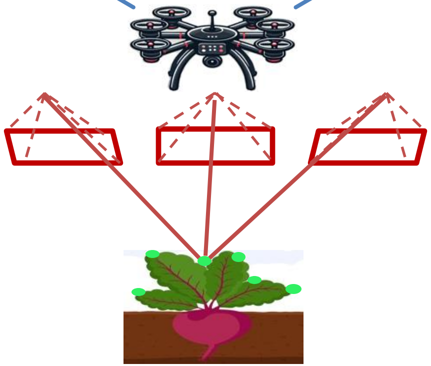




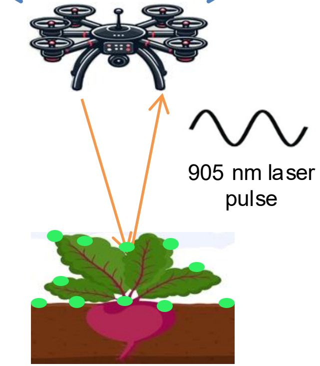
- Maimaitijiang, Maitiniyazi, et al. "Soybean yield prediction from UAV using multimodal data fusion and deep learning." Remote sensing of environment 237 (2020): 111599.
- Cheng, Minghan, et al. "Combining multi-indicators with machine-learning algorithms for maize yield early prediction at the county-level in China." Agricultural and Forest Meteorology 323 (2022): 109057.

Structural features

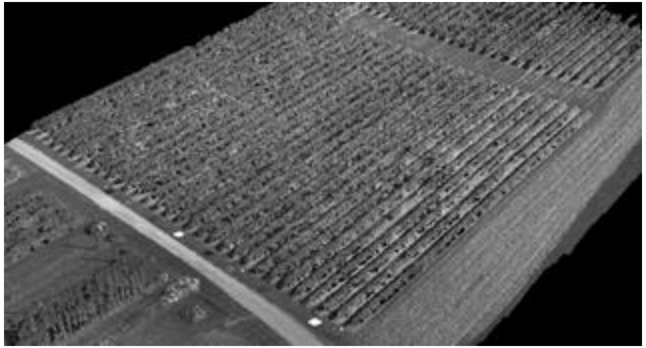
MSI



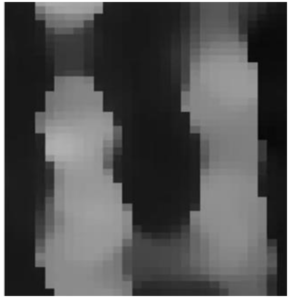
LiDAR



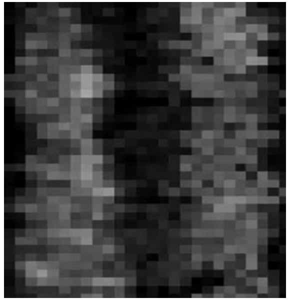
Point clouds



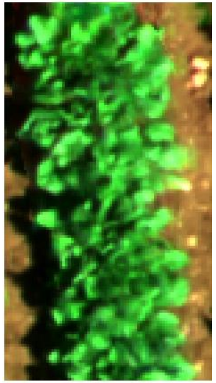
Canopy height model (CHM)



Add height to estimate **canopy volume**



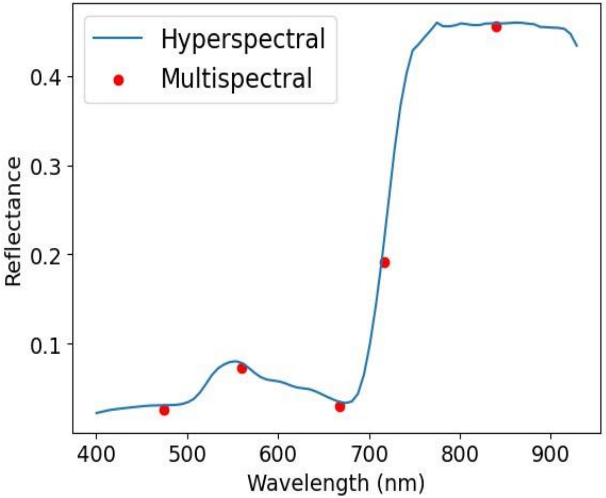
Spectral features



Vegetation extraction

RDVI + Otsu thresholding

Mean



MSI

TCARI, GNDVI, and Green

Mutual information (MI) above 75th percentile with root yield while having inter feature below 0.8

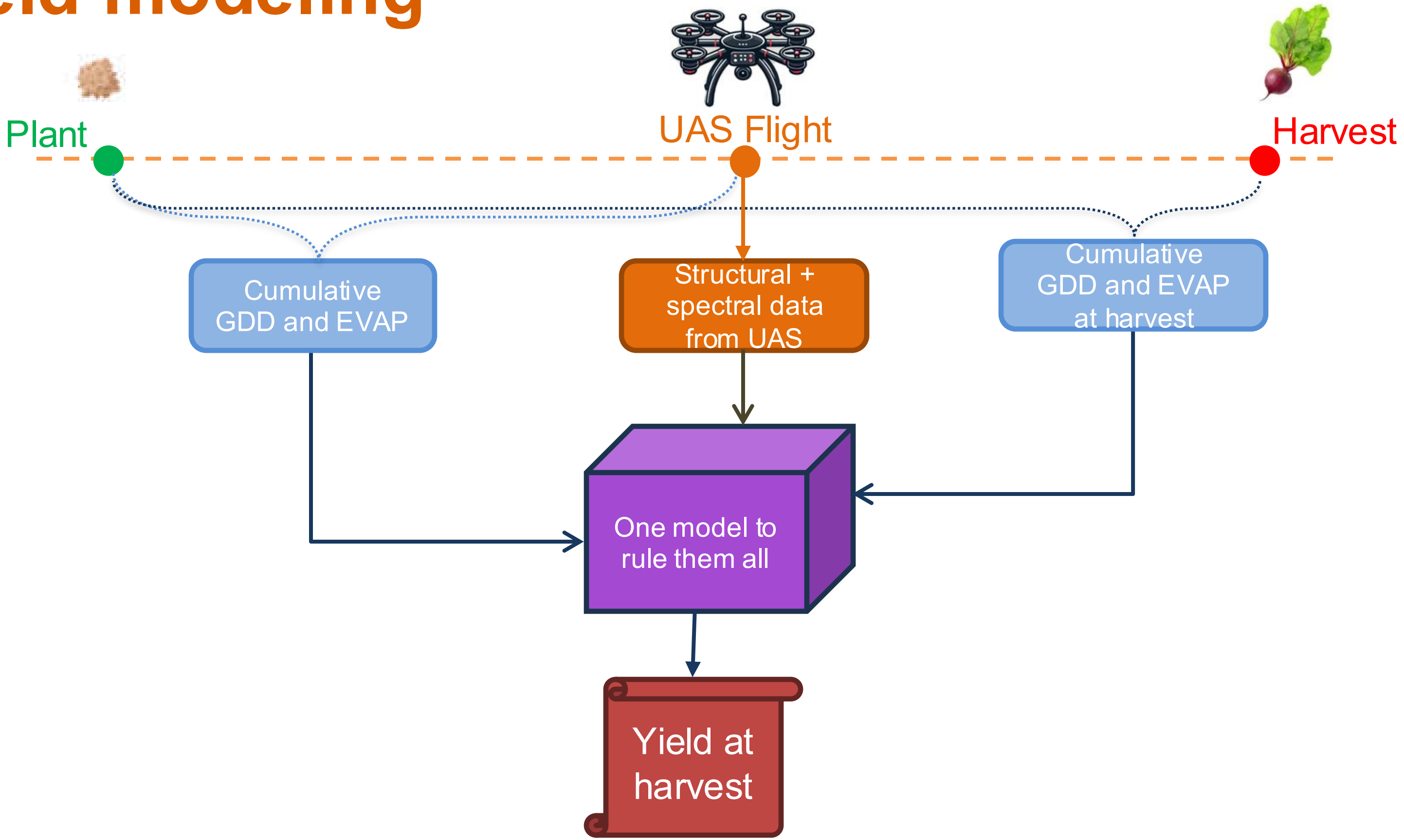
HSI

First 3 principal component bands

Explains 99% variance

Name	Formula
Green normalized difference vegetation index (GNDVI)	$\frac{R_{800} - R_{570}}{R_{800} + R_{570}}$
Transformed chlorophyll absorption ratio index (TCARI)	$3 \times [(R_{700} - R_{670}) - 0.2 \times (R_{700} - R_{550})(R_{700}/R_{670})]$
Mean green reflectance	R_{550}

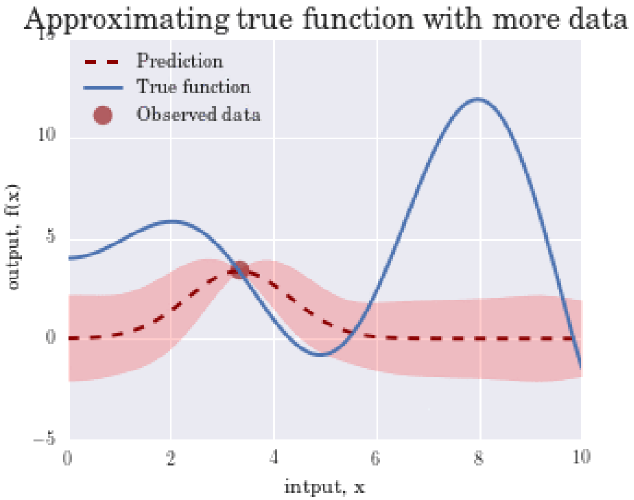
Yield modeling



Gaussian Process Regression

- Non-parametric Bayesian regression model
  - Assumes data follows a joint multivariate Gaussian distribution
  - Begins with a prior over functions and updates to a posterior using observed data

- Why use GPR?
  - Provides predictive uncertainty for each estimate
  - Data-efficient: leverages covariance structure for generalization



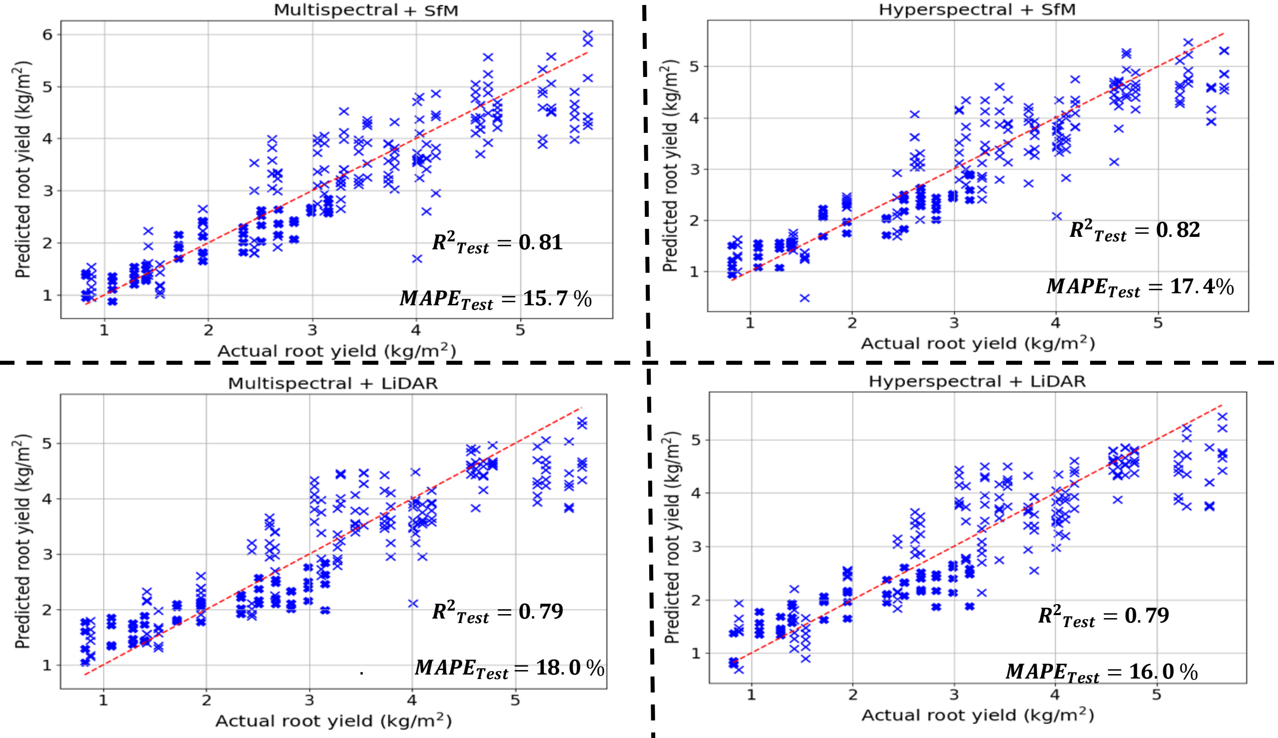
Source: https://gist.github.com/ilanman/312d0489763b9c19164a

Model Performances across sensors

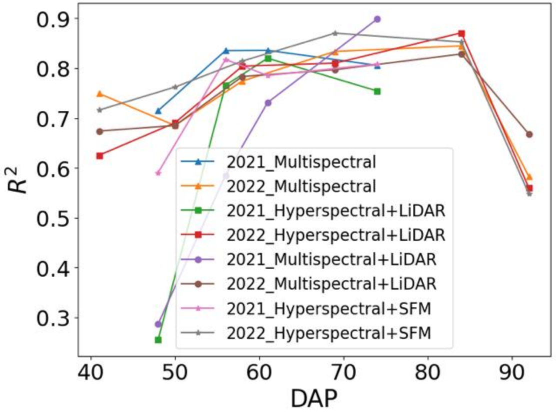
Spectral Features from

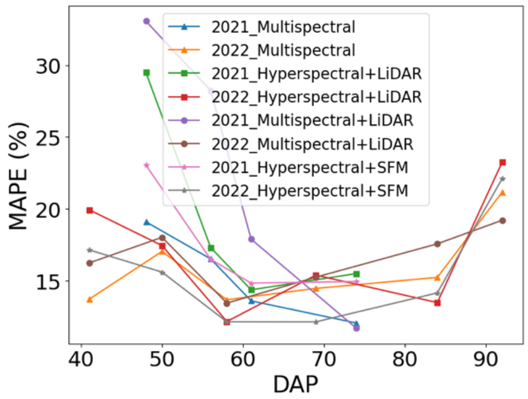
	Multispectral	Hyperspectral

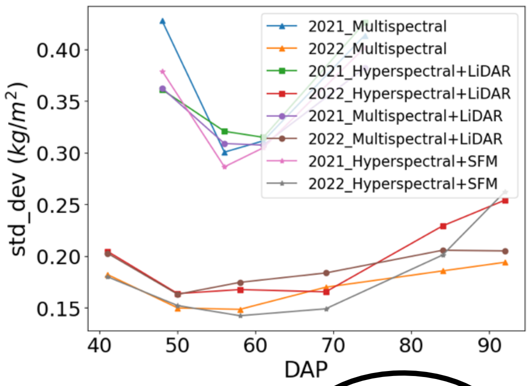
Structural Features from: Multispectral SfM; LiDAR



Performance across flight timing





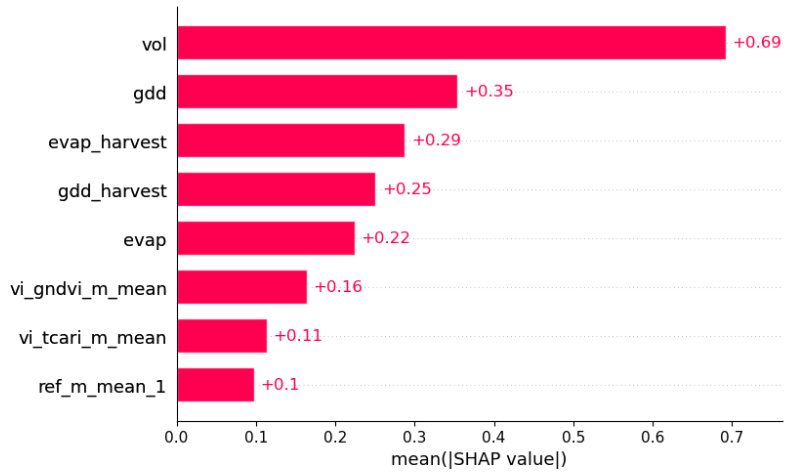


- Consistent model performance across multiple flight dates.
- Highest accuracy observed during the late Rosette and early harvest stage (55–75 DAP).
- Lower performance in early 2021 linked to LiDAR's limited accuracy in estimating canopy volume.

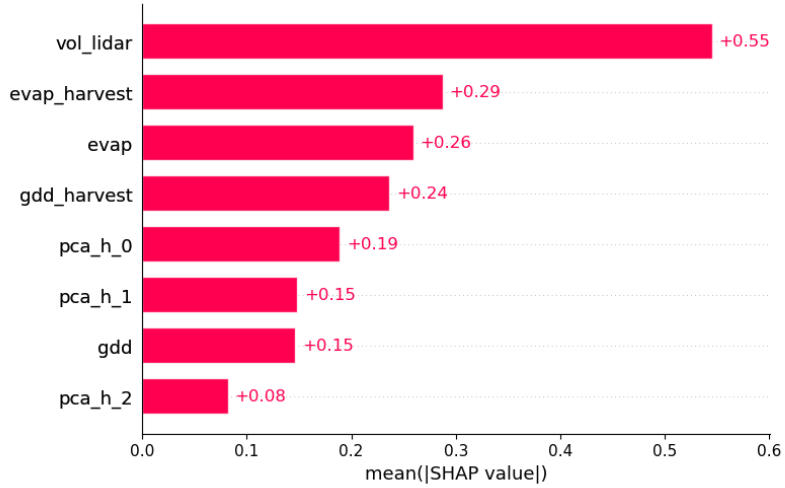
Feature contributions

- SHAP analysis calculates the marginal contribution of each feature in the model.
- Canopy volume is the most influential predictor in both models

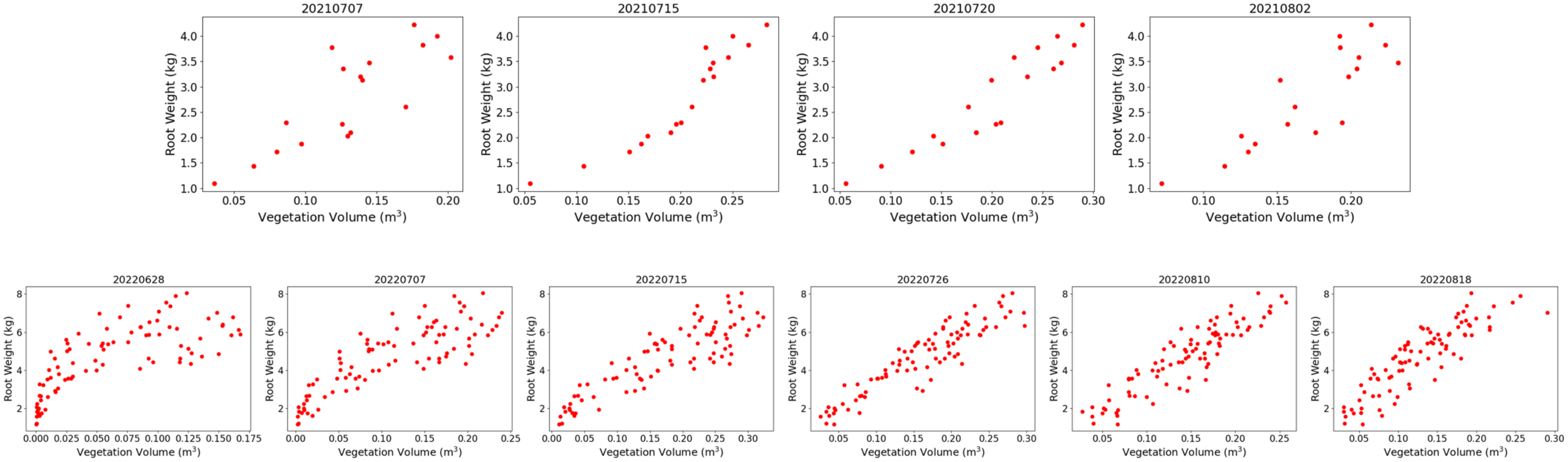
Multispectral



Hyperspectral + LiDAR



Relationship between canopy volume and root weight



Conclusion

- Harvest root yield of table beets was successfully estimated across two seasons using UAS data.
  - Multispectral model achieved an overall $R^2 = 0.81$, MAPE = 15.7%
  - Hyperspectral + LiDAR model achieved $R^2 = 0.79$, MAPE = 17.4%

- Model performance was consistent across time, with peak accuracy observed during the late Rosette to early harvest ready growth stage.

- Canopy volume and meteorological variables were the most influential predictors of yield.

Outline

- Data Collection
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CLS Disease severity estimation

- *Cercospora* leaf spot (CLS) is a foliar fugal disease prevalent in beet plants.
- Defoliation from CLS hampers mechanical harvesting and reduces yield.
- Disease severity—defined as the proportion of leaf area affected—is typically assessed through manual field surveys.

Reddish brown spots of 2-5 mm

Necrosis

Defoliation

Research Gap

- Most existing studies use high spatial resolution (~1 mm GSD), which often leads to underestimation of CLS severity due to missed sub-canopy symptoms (Barreto et al., 2023; Görlich et al., 2021; Rangarajan et al., 2022; Yamati et al., 2022).

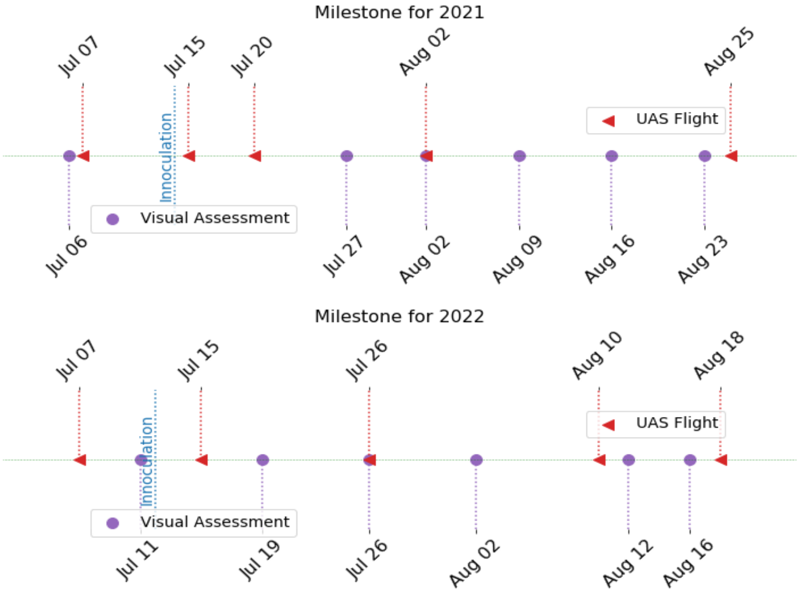
- Limited exploration of hyperspectral imaging systems for disease severity assessment in beet crops.

Objective

- Assess *Cercospora* leaf spot (CLS) severity in table beets using UAS-based multispectral and hyperspectral imagery at operational (1–3 cm) spatial resolution.
- Compare and contrast the performance of multispectral and hyperspectral systems for disease severity estimation.
- Identify key features driving CLS prediction across sensor types.

Timeline for Data Collection

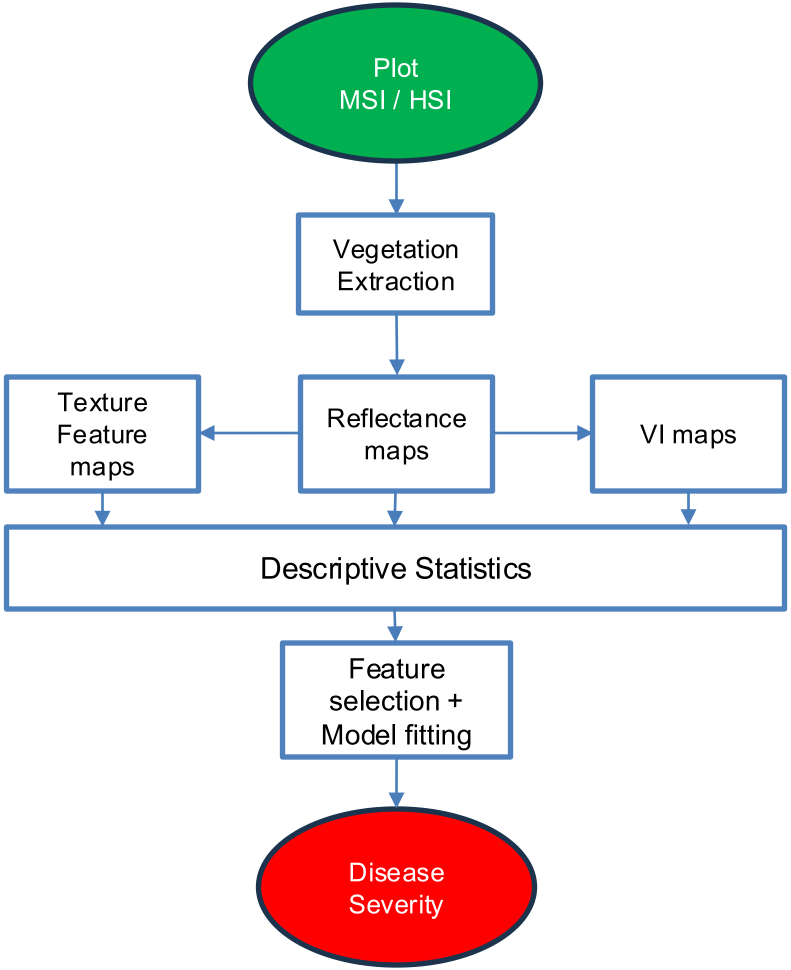
- Five flight campaigns were performed each season, resulting a total of 10 flights across two seasons.
- For 2021 and 2022 there were 40 plots each year.



Processing Flow Chart

- Texture represents the spatial tonal variation for each band. It is derived from the Gray Level Co-occurance matrix (*Haralick et al., 1973*).

- Six descriptive statistics are extracted from each map for each band.
  - Mean
  - Coefficient of variation
  - First quartile
  - Third quartile
  - Skewness
  - Kurtosis



Texture Features

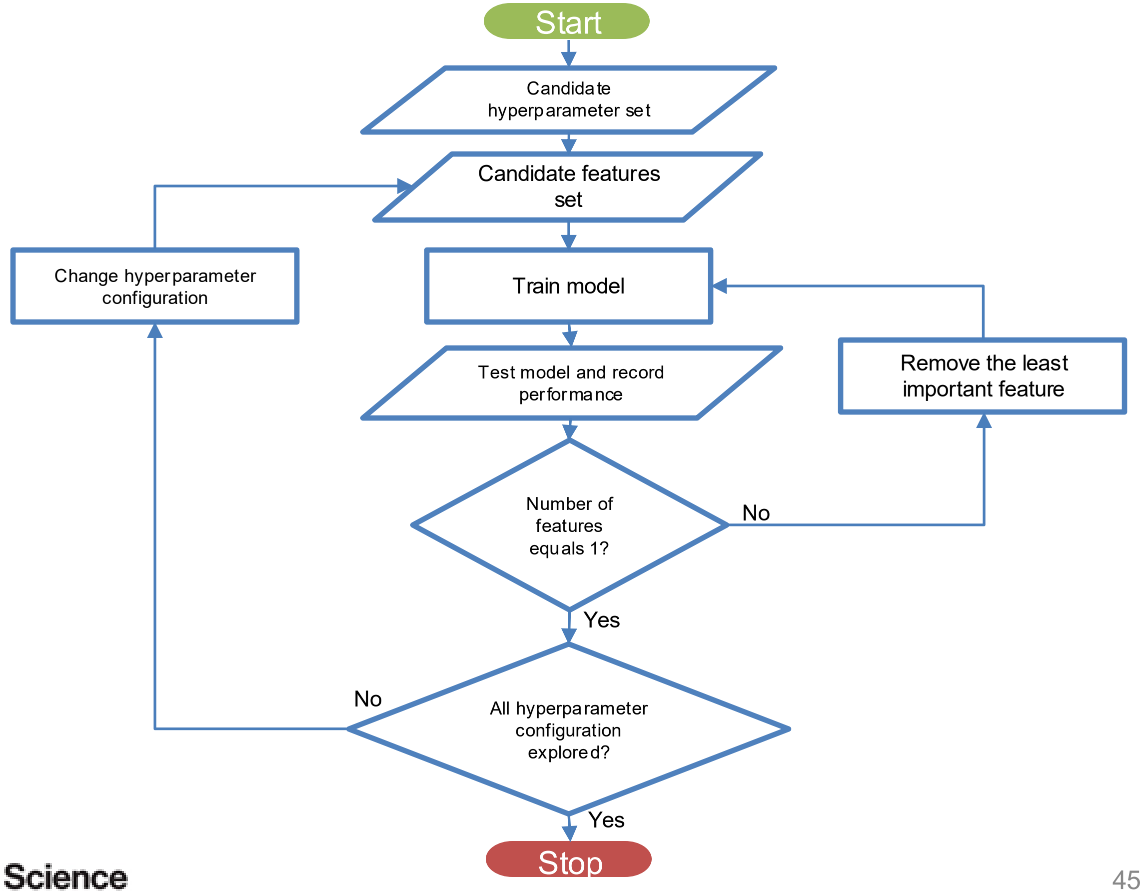
- Spatial variation of pixels could provide information about the frequency of CLS presence in a plot.
- Extract each texture feature using descriptive statistics of GLCM.
- A single four band image generates 4x8 = 32 feature maps.

No.	Texture Features	Formula
1	Mean (mean)	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} i * P(i,j)$
2	Variance (var)	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} (i - ME)^2 * P(i,j)$
3	Contrast (cont)	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} (i - j)^2 * P(i,j)$
4	Dissimilarity (dis)	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \lvert i - j\rvert * P(i,j)$
5	Homogenity (homo)	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} i * \frac{P(i,j)}{1 + (i - j)^2}$
6	Entropy (ent)	$-\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P(i,j) * \ln P(i,j)$
7	Angular Second Moment (asm)	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P(i,j)^2$
8	Correlation	$\frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} ijP(i,j) - \mu_x\mu_y}{\sigma_x\sigma_y}$ Where μ_x, μ_y, $\sigma_x$and $\sigma_y$are the means and standard deviations of p_x and p_y $p_x(i) = \sum_{j=1}^{N_g} P(i,j)$ and $p_y(j) = \sum_{i=1}^{N_g} P(i,j)$

Hyperparameter Tuning and Feature Selection

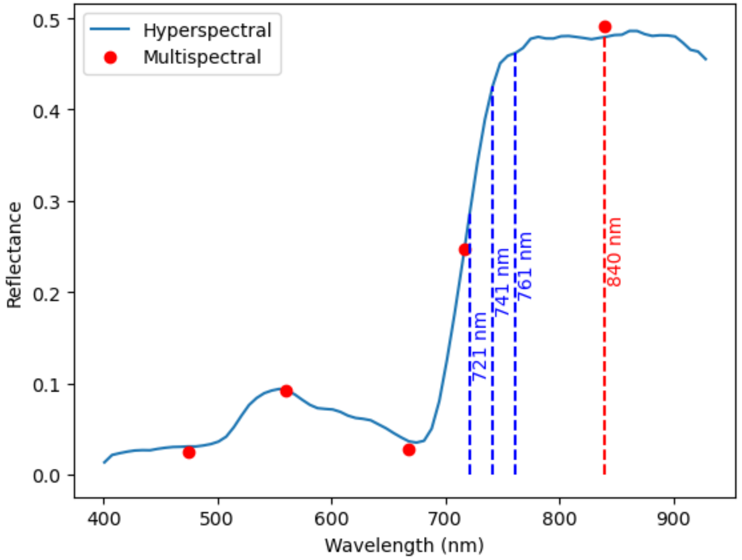
- Test different types of machine learning models at different feature combination.

- Goal here was to find the **best fit model,** while having the **least number of features.**



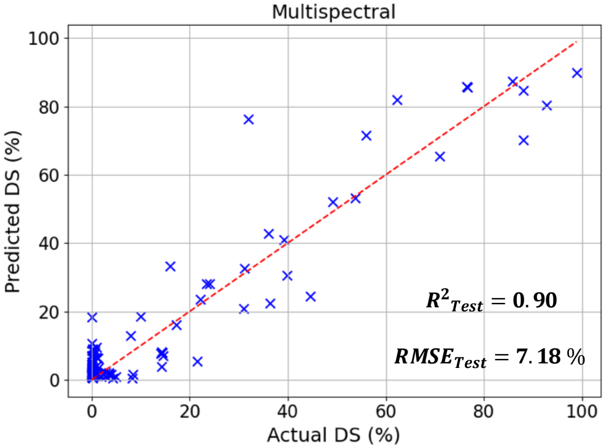
Features for CLS estimation modeling

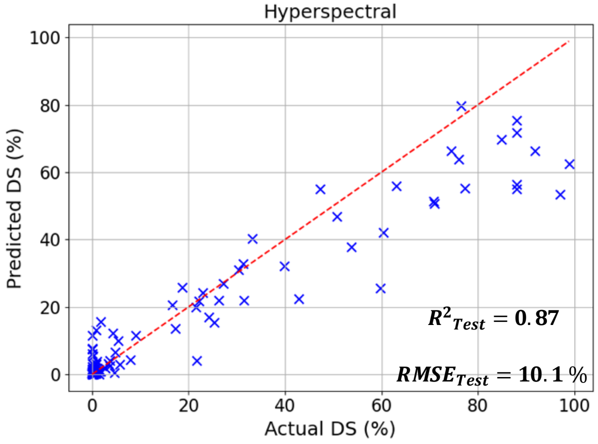
- Multispectral Imagery
  - RDVI skewness
  - NIR texture homogeneity (coefficient of variation)
- Hyperspectral Imagery
  - MCARI2 skewness
  - 721 nm texture homogeneity (coefficient of variation)
  - 741 nm texture homogeneity (kurtosis)
  - 761 nm texture dissimilarity (skewness)



Model performance

- **Random forest regressor** model tested on 30% of the data.
- HSI estimations tended to underestimate at high values.
- MSI performed better than HSI.

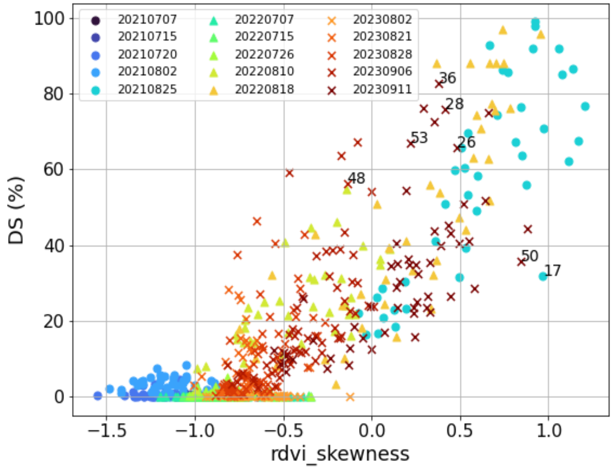


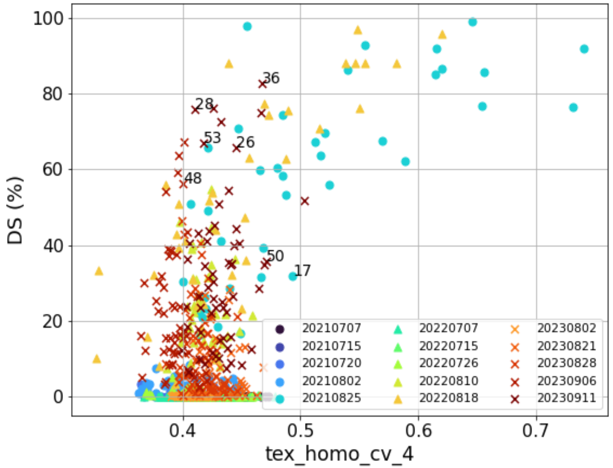


Feature Analysis

DIRS

- RDVI skewness was the primary driving factor for model.
- Texture features, particularly homogeneity variation were the delineating factor for high DS.





Conclusions

- UAS-based multispectral and hyperspectral imagery accurately estimated CLS severity, with
  - multispectral achieving $R^2 = 0.90$, RMSE = 7.18%, and
  - hyperspectral achieving R^2=0.87, RMSE = 10.1%

- RDVI skewness emerged as the primary driving feature for disease prediction, particularly effective for identifying low severity cases.

- Texture features provided added value in delineating plots with high disease severity, highlighting the benefit of integrating spatial metrics.

Outline

- Data Collection
- Spectral band selection
- Robust Yield Model
- CLS DS estimation
- Conclusions

Conclusions

- Developed an end-to-end methodology for non-invasive crop monitoring of table beets using UAS.
- Built models that perform well with limited data and minimal input features, reducing risk of overfitting and enhancing interpretability.
- Compared sensor configurations for both root yield estimation and disease severity, finding that simple multispectral systems offer competitive performance across use cases.

Future Work

- Field collection perspective
  - Acquire more diverse data across growth conditions, season, and varieties.

- Imaging perspective
  - Evaluate performance impacts of varying spatial resolutions.
  - Assess optimal image overlap needed to capture accurate structural information from UAS imagery.

- Modeling perspective
  - Apply unsupervised learning to leverage unlabeled datasets.
  - Investigate multi-task transfer learning to improve generalizability.

Broader Impact

- The modeling framework developed is transferable to other crops, supporting broader applications in precision agriculture.
- Sensor performance comparisons provide guidance to practitioners on selecting the most effective sensor for their use case.
- All code and datasets have been made publicly available to support future research and reproducibility.

Contributions

- Journals

1. **Saif, M.S**., Chancia, P., Murphy, S.P., Pethybridge, S. and van Aardt, J., "Advancing harvest table beet root yield estimation via unmanned aerial systems (UAS) multi-modal sensing" *(Under review)*.

2. **Saif, M.S**., Chancia, R., Sharma, P., Murphy, S.P., Pethybridge, S. and van Aardt, J., "Estimation of *Cercospora* Leaf Spot Disease Severity in Table Beets from UAS Multispectral Images." *(Under review, second round in Computer and Electronics in Agriculture)*.

3. **Saif, M.S**., Chancia, R., Pethybridge, S., Murphy, S.P., Hassanzadeh, A. and van Aardt, J., "Forecasting Table Beet Root Yield Using Spectral and Textural Features from Hyperspectral UAS Imagery." *Remote Sensing*, *15*(3), p.794, Jan 2023.

- Conference talks

1. **Saif, M.S.**, Chancia, P., Murphy, S.P., Pethybridge, S. and van Aardt, J., "Exploring UAS imaging modalities for precision agriculture: predicting table beet root yield and disease severity estimation using multispectral, hyperspectral, and LiDAR." *SPIE Defense + Commercial Sensing 2025*, Apr 2025.

2. **Saif, M.S.**, Chancia, P., Murphy, S.P., Pethybridge, S. and van Aardt, J., "Assessing Multiseason Table Beet Root Yield from Unmanned Aerial Systems." *AGU24*, Dec 2024.

3. **Saif, M.S**., Chancia, R., Sharma, P., Murphy, S.P., Pethybridge, S. and van Aardt, J., "Agricultural Disease Management: Estimation of *Cercospora* Leaf Spot Severity in Table Beets using UAS." *Stratus conference 2024*, May 2024.

4. **Saif, M.S**., Chancia, R., Pethybridge, S., Murphy, S.P., Hassanzadeh, A. and van Aardt, J., 2023, May. "Predicting Table Beet Root Yield via UAS-based Hyperspectral Imagery." *Stratus conference 2023,* May 2023.

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We're the world, We're the Beets ……..

Questions?

- *Illustrations generated using Sora*

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