

# Agricultural Disease Management: Estimation of *Cercospora* Leaf Spot Severity in Table Beets using UAS



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

# Background

- *Cercospora* leaf spot (CLS) is a foliar fungal disease common in beet plants.
- CLS causes reddish brown spots of size 2-5 mm on foliage.
- Spots spread and grow, eventually leading to defoliation.
- Early onset leading to significant yield losses.
- Associated defoliation poses a challenge for mechanical harvesters.



# Disease Severity

- Disease severity (DS) is a metric that is used to quantify CLS in table beets, i.e., the percentage of leaf area covered by the lesions.
- Several leaves are sampled and visually scored to assess an entire plot.
- The same observer must score DS each season to ensure consistency.





# Objective

Assess *Cercospora* leaf spot (CLS) disease severity in table beets using unmanned aerial systems (UAS).



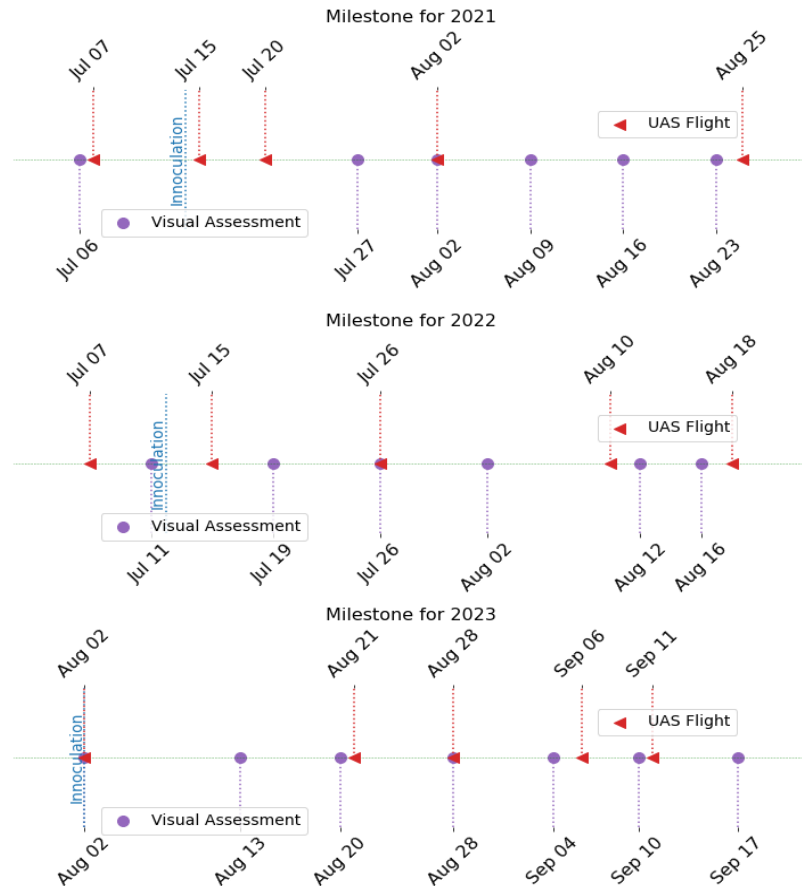
# Data Collection

- **Study area:** Geneva, New York, USA, at Cornell AgriTech.
- **2021 & 2022 flights:** DJI Matrice-600 with a MicaSense RedEdge-M camera capturing five-band multispectral images (475, 560, 668, 717, & 840 nm).
- **2023 Flight:** DJI Mavic 3M was used to capture four-band multispectral images (560, 650, 730, & 860 nm)
- **Dimension of plot:** 10ft x 2, each plot demarcated by flags



# Timeline for Data Collection

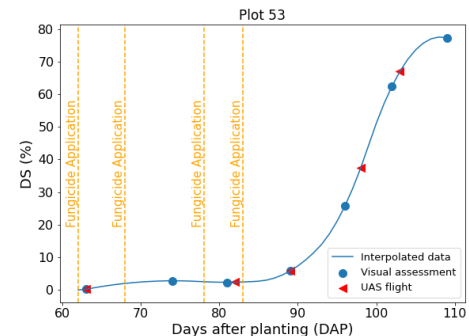
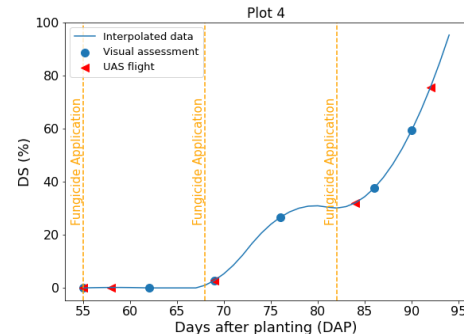
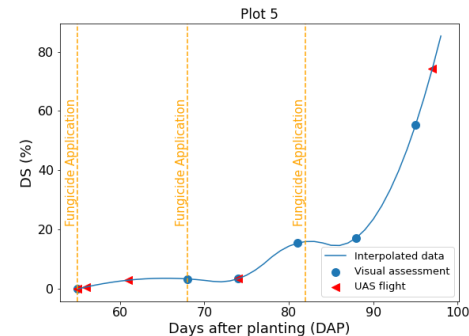
- Five flight campaigns were performed each season, resulting a total of 15 flights across three seasons.
- For 2021 and 2022 there were 40 plots each year.
- For 2023 there were 56 plots.
- Total data points =  $40 \times 5 + 40 \times 5 + 56 \times 5 = 680$



# Note: Data Alignment



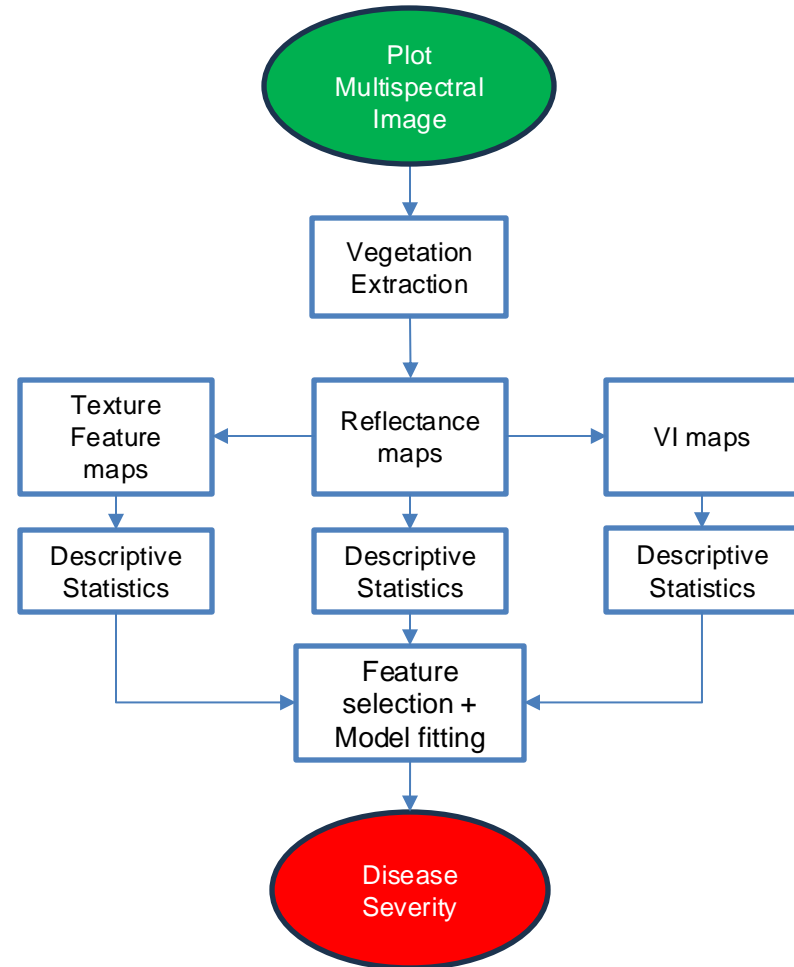
- Visual disease assessment did not always align with flight date.
- We thus used a 2nd order linear interpolation to approximate the disease severity on the day of the flight.



# Processing Flow Chart



- $MSAVI2 > 0.25$  is used to extract beet vegetation canopy.
- Reflectance maps consists of 4 bands (green, red, red-edge, NIR).
- 6 descriptive statistics are extracted from each maps for each bands.





# Vegetation Indices

- VI a placeholder for vegetation health
- VIs chosen based on past studies

Abbreviation	Name	Formula	Ref
RDVI	Renormalized Difference Vegetation Index	$\frac{R_{NIR} - R_{Red}}{\sqrt{R_{NIR} + R_{Red}}}$	Steddom et al., (2005)
NGRDVI	Normalized Green-Red difference vegetation index	$\frac{R_{Green} - R_{Red}}{R_{Green} + R_{Red}}$	Jay et al., (2020)
HI	Health Index	$\frac{R_{534} - R_{698}}{R_{534} + R_{698}} - 0.5R_{704}$	Mahlein et al. (2013)
CLSI	Cercospora Leaf Spot Index	$\frac{R_{698} - R_{570}}{R_{698} + R_{570}} - R_{734}$	
MCARI2	MCARI (variant with reduced soil contamination)	$\frac{1.5[2.5(R_{800} - R_{670}) - 1.3(R_{800} - R_{550})]}{\sqrt{(2R_{800} + 1)^2 - (6R_{800} - 5\sqrt{R_{670}}) - 0.5}}$	Barreto et al. (2023)
MSAVI2	Modified Soil-adjusted Vegetation Index (variant)	$\frac{2R_{NIR} + 1 - \sqrt{(2R_{NIR} + 1)^2 - 8(R_{NIR} - R_{Red})}}{2}$	
GVI	Green Vegetation Index	$-0.283R_{Green} - 0.660R_{Red} + 0.577R_{RedEdge} + 0.388R_{NIR}$	
MCARIOSAVI	Modified chlorophyll absorption ratio/ Optimized soil adjusted vegetation indices	$\frac{[(R_{700} - R_{670}) - 0.2(R_{700} - R_{550})](R_{840} + R_{670} + 0.16)}{1.16(R_{840} - R_{670})(R_{700}/R_{670})}$	

# Texture Features



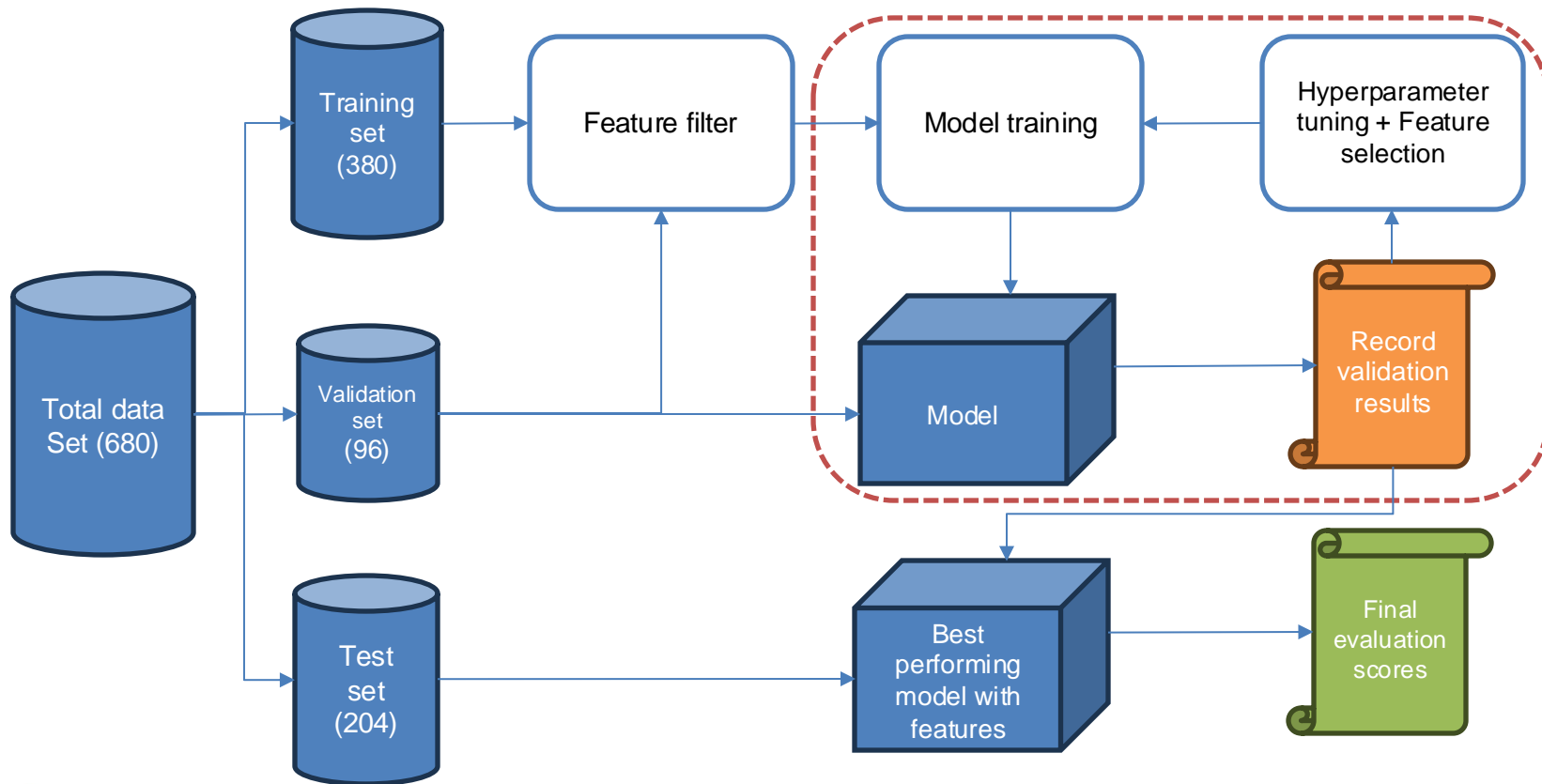
- Proxy for a pixel-spatial relationship.
- Spatial variation of pixels could provide information about the frequency of CLS presence in a plot.
- Find gray level co-occurrence Matrix (GLCM) (Haralick et al., 1973).
- Extract each texture feature using descriptive statistics of GLCM.
- A single four band image generates  $4 \times 8 = 32$  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)	$\sum_{i=1}^{N_g} \sum_{j=1}^{N_g}  i - j  * P(i, j)$
5	Homogeneity (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	$\frac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} ij P(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y}$ <p>Where <math>\mu_x</math>, <math>\mu_y</math>, <math>\sigma_x</math> and <math>\sigma_y</math> are the means and standard deviations of <math>p_x</math> and <math>p_y</math></p> <p><math>p_x(i) = \sum_{j=1}^{N_g} P(i, j)</math> and <math>p_y(j) = \sum_{i=1}^{N_g} P(i, j)</math></p>

# Feature Extraction

- Calculate **mean**, **coefficient of variation**, **first quartile**, **third quartile**, **skewness** and **kurtosis** from each feature maps.
- Total number of features:
  - $8 \text{ VIs} \times 6 \text{ statistics} + 4 \text{ bands} \times 6 \text{ statistics} + 4 \text{ bands} \times 8 \text{ texture features} \times 6 \text{ statistics} = \mathbf{264}$

# Model Development



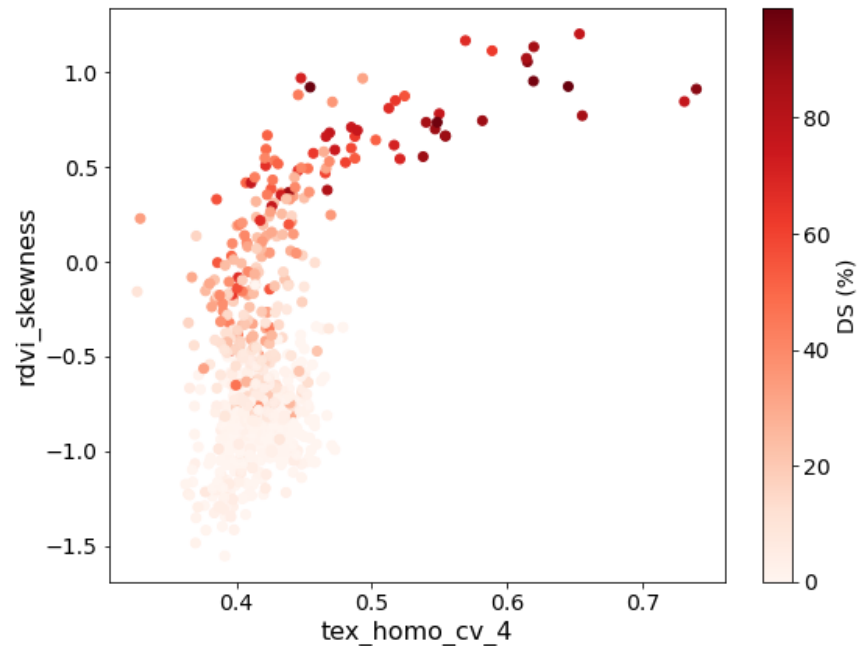
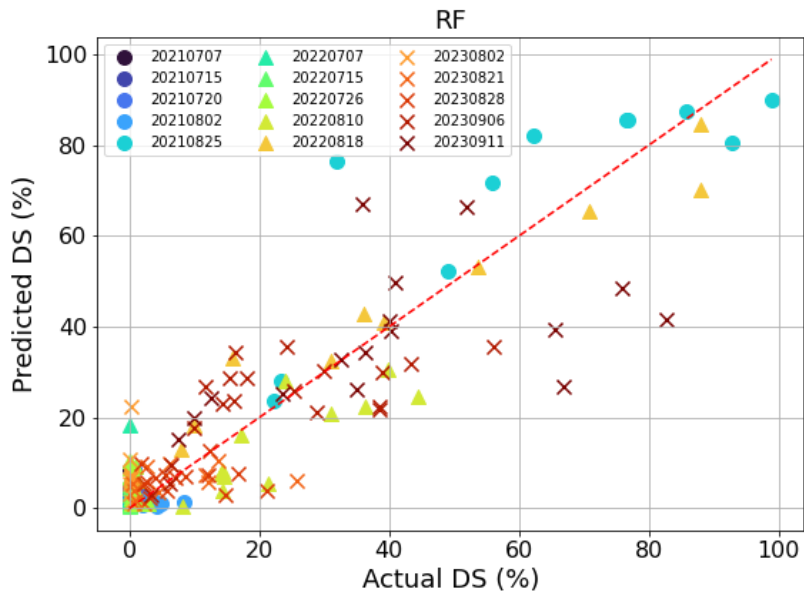


# Best-performing Results

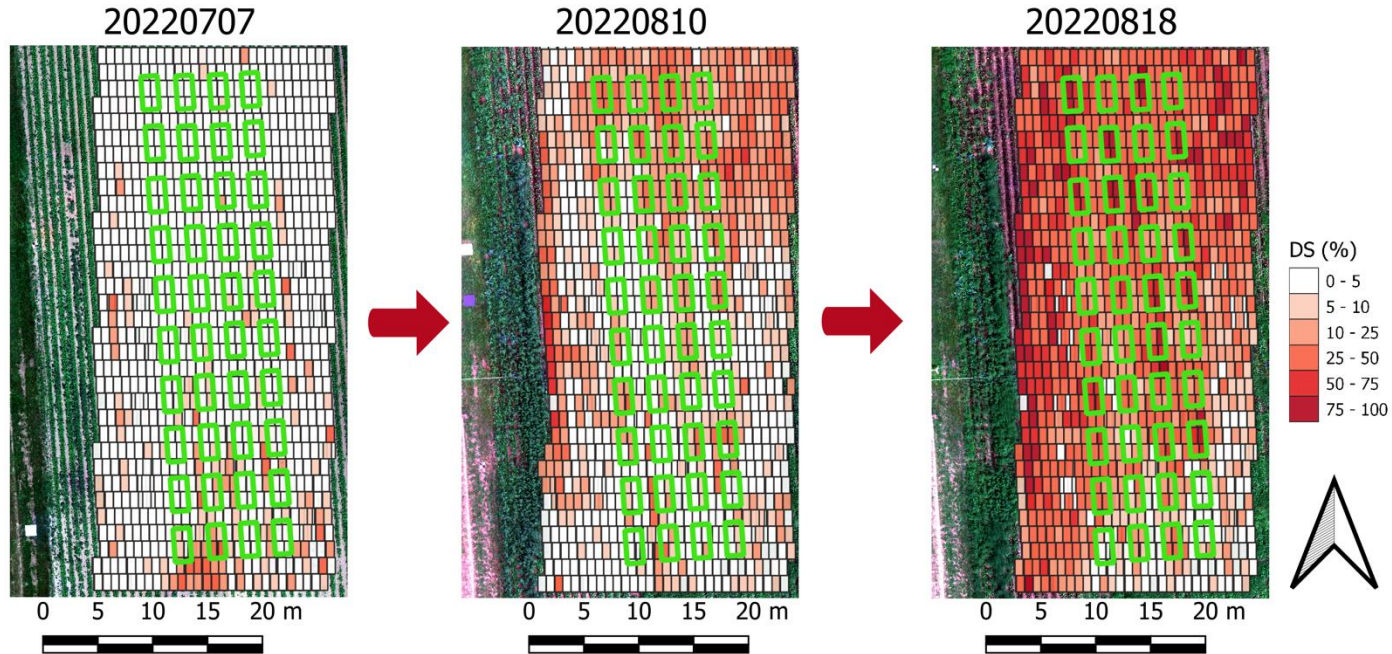
Random forest model exhibited the best result with the least number of features.

Models	Hyperparameters	No. of features	Features used	$R^2_{train}$ /	$R^2_{val}$ /	$R^2_{test}$ /
				RMSE <sub>train</sub> (%)	RMSE <sub>val</sub> (%)	RMSE <sub>test</sub> (%)
RF	n_estimators: 100, max_depth: 8, min_samples_split: 3, min_samples_leaf: 2	2	rdvi_skewness, tex_homo_cv_4	0.89 /	0.87 /	<b>0.82 /</b>
				6.92	8.09	<b>9.31</b>
XGB	n_estimators: 50, learning_rate: 0.1, max_depth: 3	7	rdvi_skewness, ref_q3_3, tex_cont_cv_2, tex_cont_q3_4, tex_homo_cv_4, tex_homo_kurtosis_4, tex_mean_q3_1	0.93 /	0.89 /	0.81 /
				5.82	7.61	9.65
SVR	kernel: rbf, C: 1, epsilon: 0.001	8	gvi_kurtosis, ref_skewness_3, ref_skewness_4, tex_cont_q1_4, tex_homo_cv_3, tex_homo_skewness_4, tex_mean_cv_4, tex_var_kurtosis_4	0.88 /	0.81 /	0.78 /
				7.50	9.90	10.27
PLSR	n_components: 5	5	gvi_kurtosis, ref_skewness_3, ref_skewness_4, tex_homo_cv_3, tex_mean_mean_4	0.76 /	0.83 /	0.79 /
				10.33	9.36	10.17

# Model Performance and Feature Analysis



# CLS Maps: Examples of Field-level CLS



# Conclusions

- Our work demonstrates the feasibility of utilizing multiple UAS systems for estimating CLS disease severity.
- We achieved comparable accuracy to contemporary literature at a relatively low resolution ( $\sim 1$  cm).
- RDVI skewness (red and NIR band) and texture homogeneity coefficient of variation of NIR band are important indices for determining CLS.



# Questions?



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