Metropolitan Water Reclamation District of Greater Chicago

Welcome to the May Edition of the 2024 M&R Seminar Series

NOTES FOR SEMINAR ATTENDEES

- Remote attendees' audio lines have been muted to minimize background noise. For attendees in the auditorium, please silence your phones.
- A question and answer session will follow the presentation.
- For remote attendees, please use the "**Chat**" feature to ask a question via text to "**Host.**" For attendees in the auditorium, please raise your hand and wait for the microphone to ask a verbal question.
- The presentation slides will be posted on the MWRD website after the seminar.
- This seminar has been approved by the ISPE for one PDH and approved by the IEPA for one TCH. Certificates will only be issued to participants who attend the entire presentation.

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Dr. Yi Wang is an associate professor in precision agriculture in the department of plant and agroecosystem sciences, University of Wisconsin-Madison. Dr. Wang received a Bachelor of Science in Biological Science from Nanjing Agricultural University , Jiangsu, China, and a Ph.D. in Plant Genetics, from the University of Wisconsin-Madison. Dr. Wang's research focuses on using AI-driven techniques including machine learning, drone-based hyperspectral spectroscopy, and robotics to increase crop yield and improve agricultural sustainability.

Using Hyperspectral Remote Sensing on Farmland for Reducing Environmental Impacts

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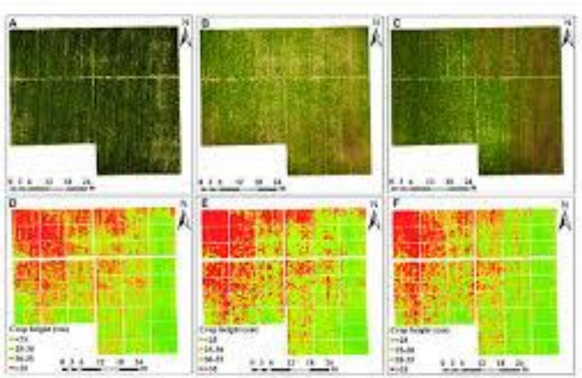
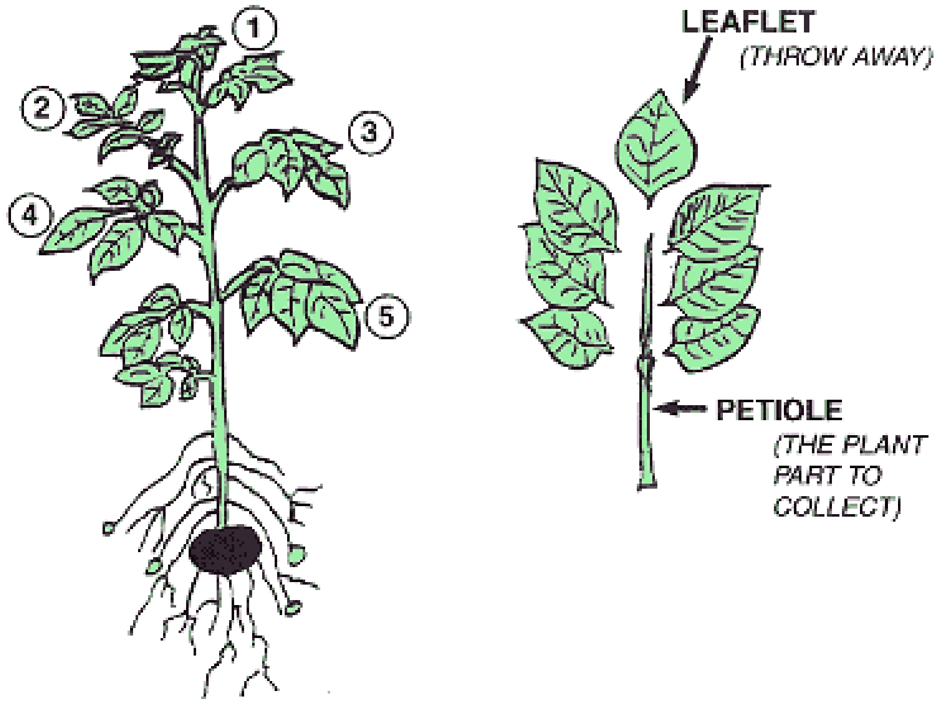
Department of Plant and Agroecosystem Sciences

University of Wisconsin – Madison

Background



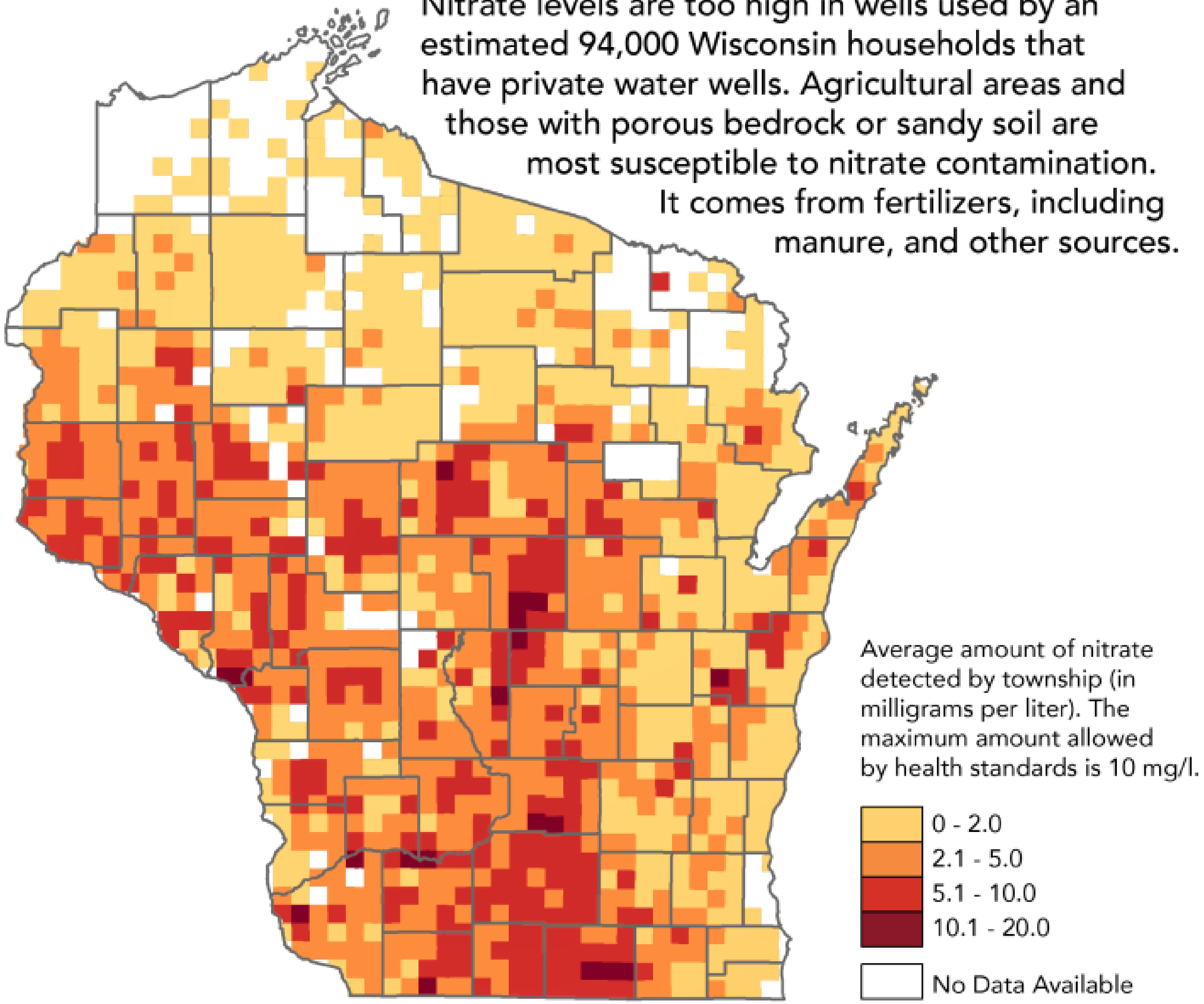
- Agricultural sustainability requires efficient use of resources (water, fertilizer, pesticide) to reduce impact on the environment
- Traditional methods to monitor plant growth is destructive, labor-intensive, time-consuming, and cannot cover spatio-temporal variability
- Using AI-driven techniques could build robust models that predict crop growth and yield using sensor-based data, which will provide precise information about resource application, and avoid excessive use that results in environmental degradation



Stage of growth (days after emergence)	Dry weight basis (% NO_3–N) Norkotah Norland Atlantic Kennebec	Shepody R. Burbank Snowden	Onaway Superior
30	2.5–2.8	2.0–2.3	2.3–2.5
40	2.3–2.5	1.7–2.2	2.0–2.3
50	1.8–2.3	1.2–1.6	1.5–1.9
60	1.3–1.9	0.8–1.1	0.9–1.2
70	0.8–1.1	0.5–0.8	0.4–0.6

Nitrate in drinking water around Wisconsin

Nitrate levels are too high in wells used by an estimated 94,000 Wisconsin households that have private water wells. Agricultural areas and those with porous bedrock or sandy soil are most susceptible to nitrate contamination. It comes from fertilizers, including manure, and other sources.

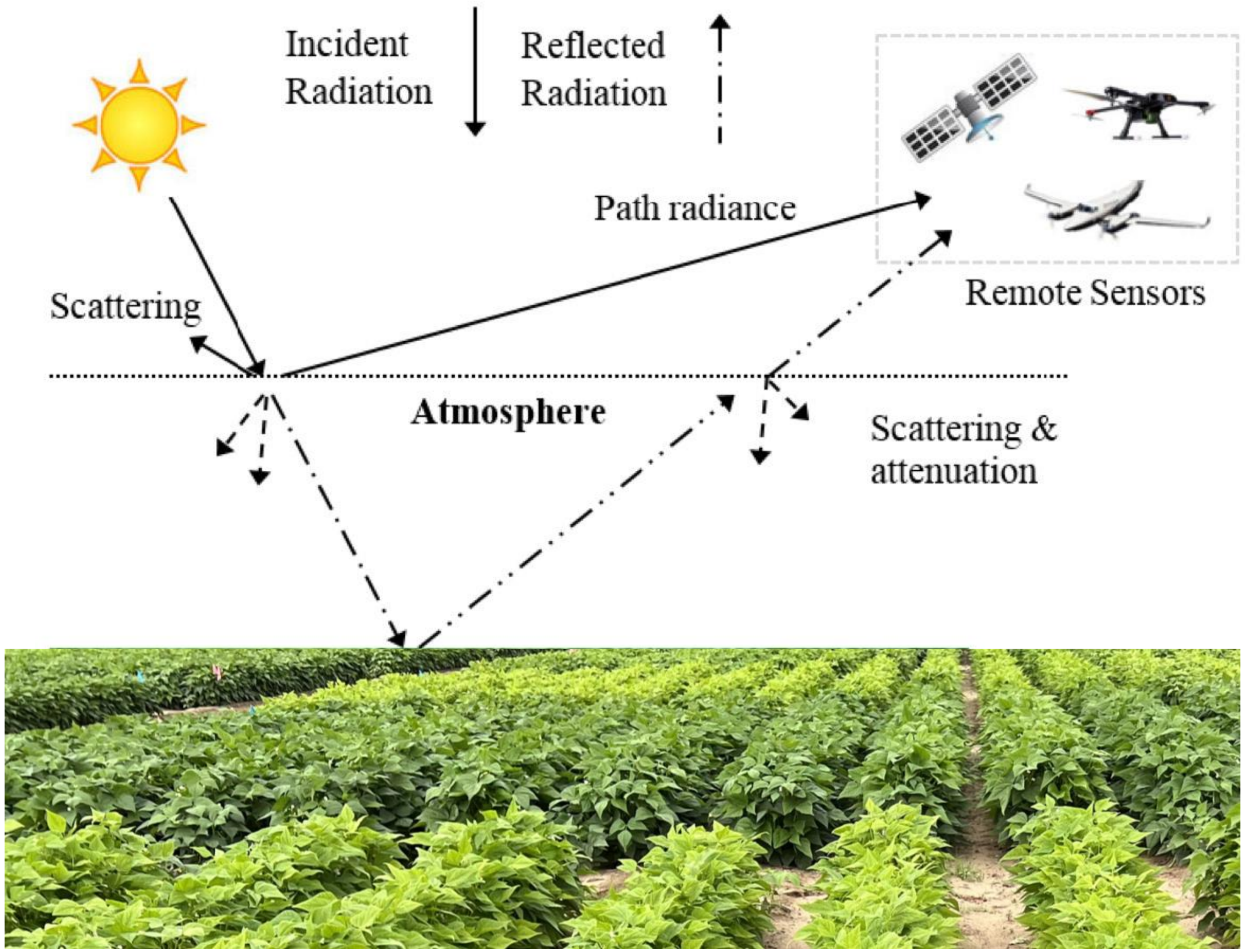


CREDIT: Katie Kowalsky/Wisconsin Center for Investigative Journalism

SOURCE: Well Water Quality Viewer, University of Wisconsin-Stevens Point's Center for Watershed Science and Education. Private Drinking Water Quality in Rural Wisconsin, Journal of Environmental Health, 2013.

Use Hyperspectral Imaging to Predict Potato Aboveground and Underground Traits

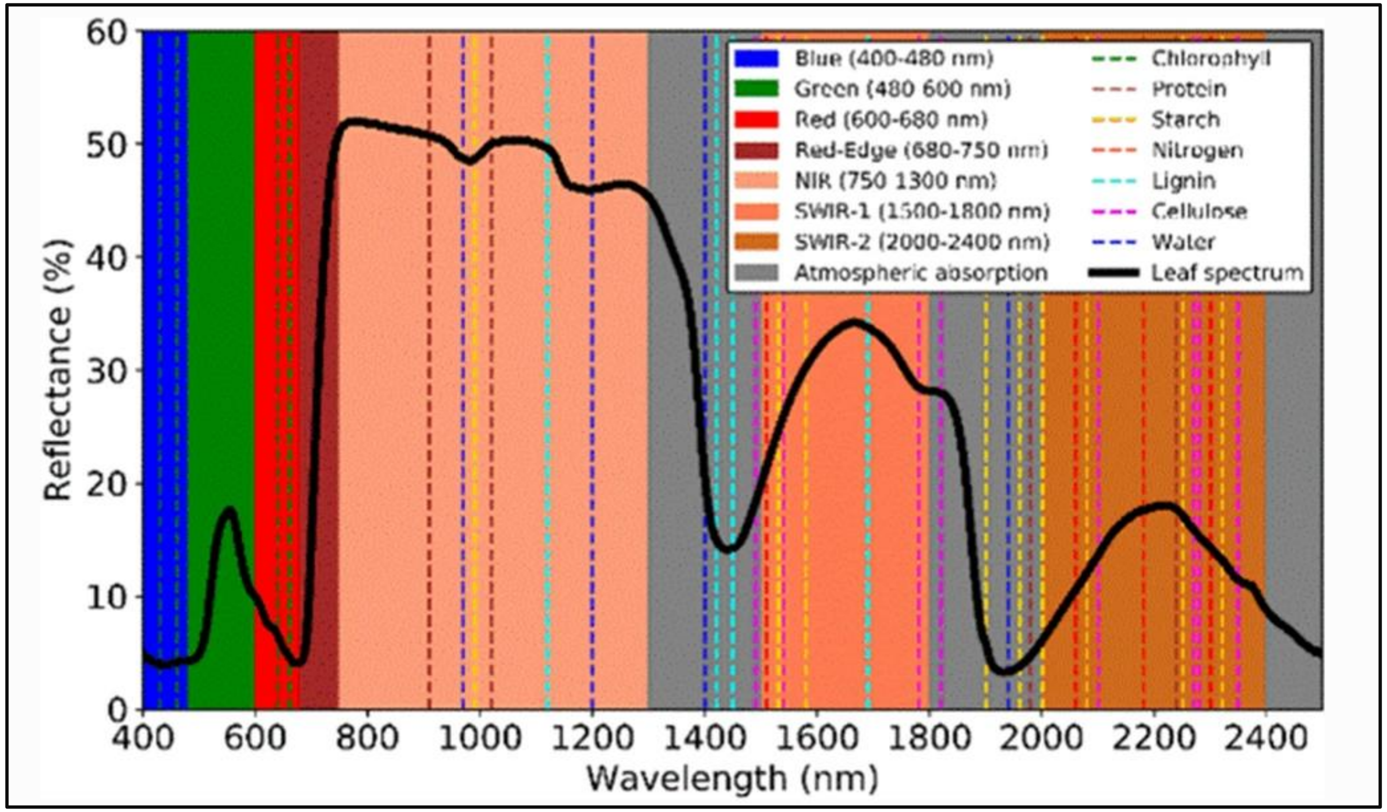
Plants have Unique Spectral Signatures



Atmospheric effect on radiation measured by remote sensors

Spectral signature and plant traits

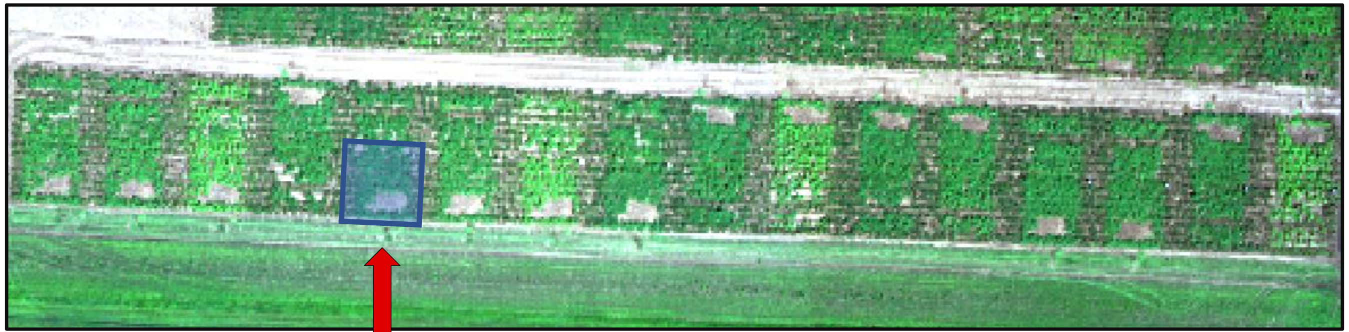
- Spectral – biological relationship
- Visible-to-near infrared (VNIR)
  - Chlorophyll activity and canopy density
- Short wave infrared (SWIR)
  - Water content
  - Biomass



Curran (1989)

Experimental Design

- Two growing seasons 2020, 2021
- Russet Burbank (RB) and Soraya (S)
- Four nitrogen rates + four blocks
  - Varied amount + timing
- Sampling occurred weekly from late June to August
  - Petiole, whole leaf, vine, and tuber N
  - LAI, specific gravity, yield
- Harvested in Mid-September
  - Yield, N removal, specific gravity

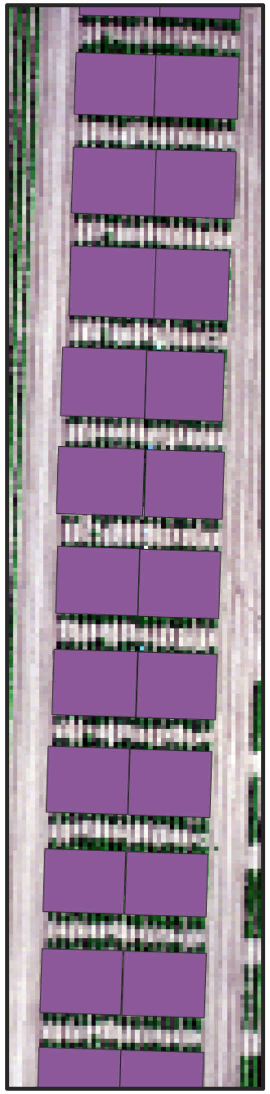


Russet Burbank, Rate 3, Block 3, 2020

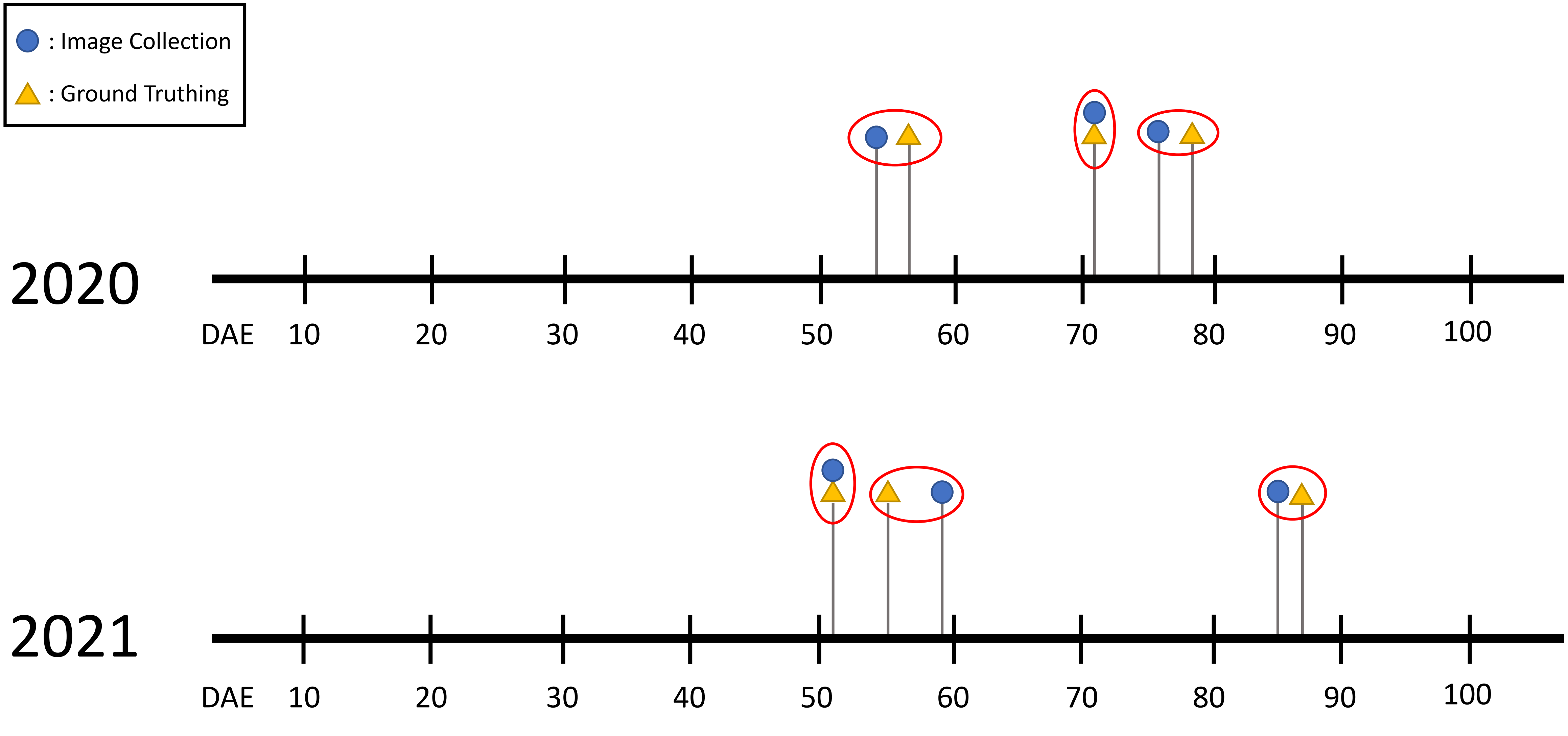
Soraya, Rate 1, Block 2, 2021

Experimental Design – Imaging & Modeling

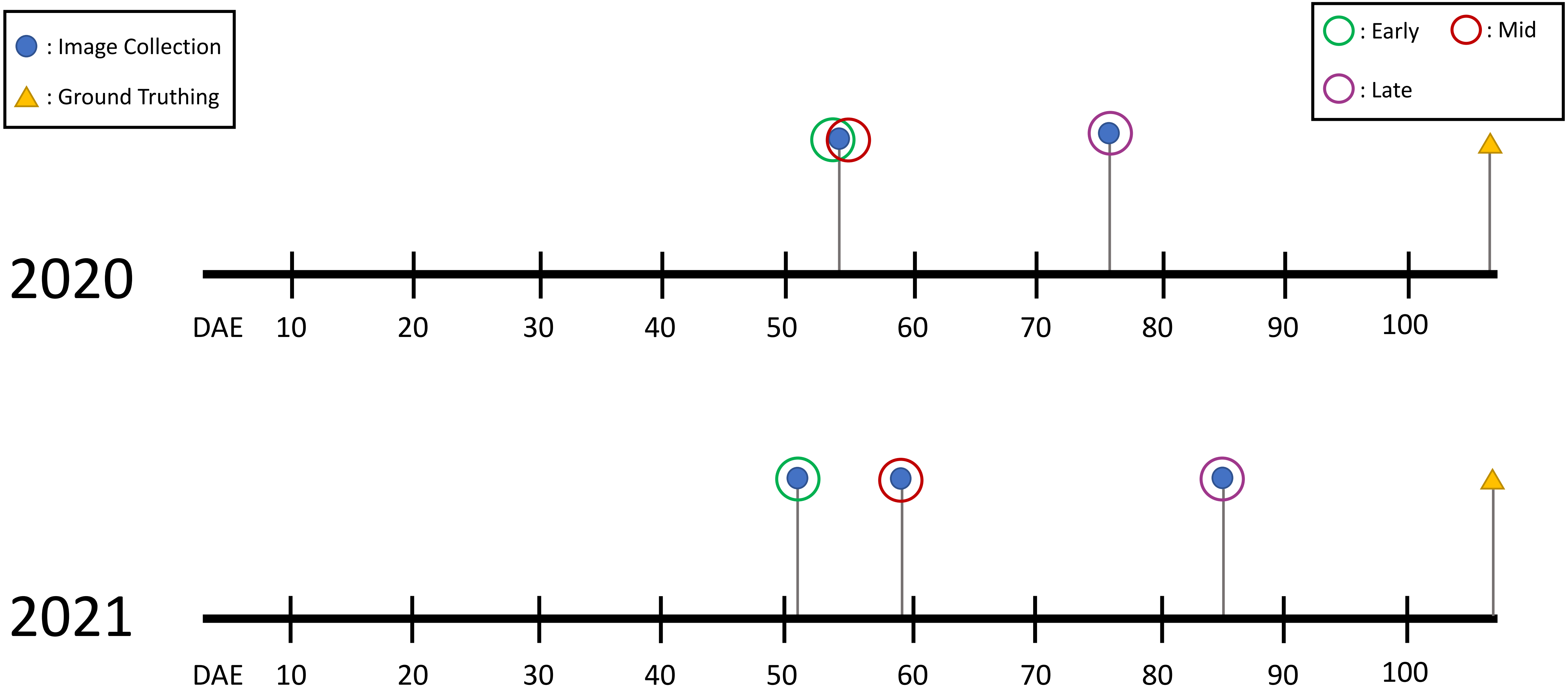
1. Image Collection
2. Image Correction Process
3. Extraction of HS Data from Pixels
4. Pixels are Averaged by Plot
5. Compare Ground Truthing Data with HS Data
6. PLSR Modeling
7. Evaluate Models (R^2, RMSE)



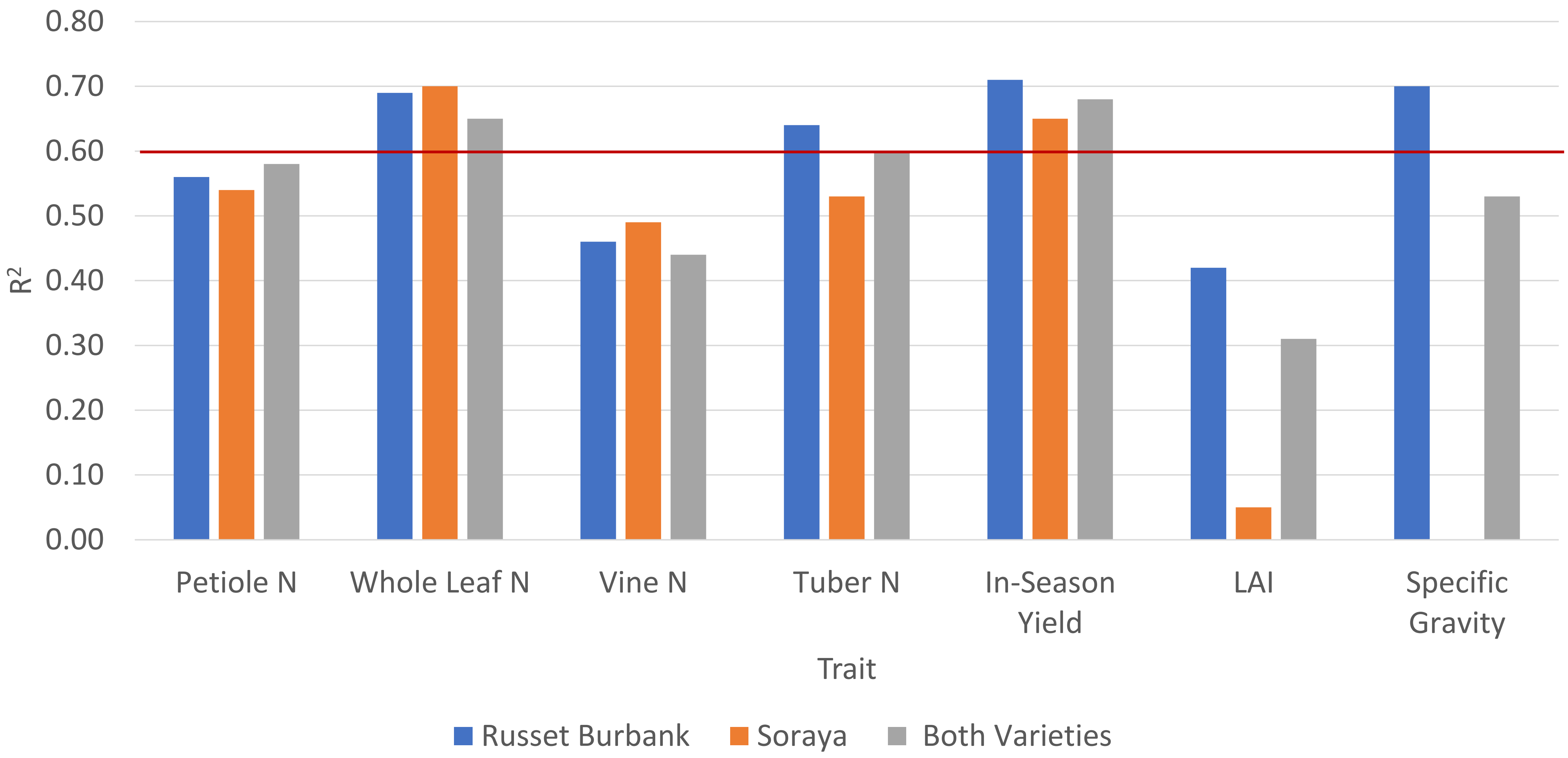
Imagery and Ground Truthing Timeline
In-Season Predictions



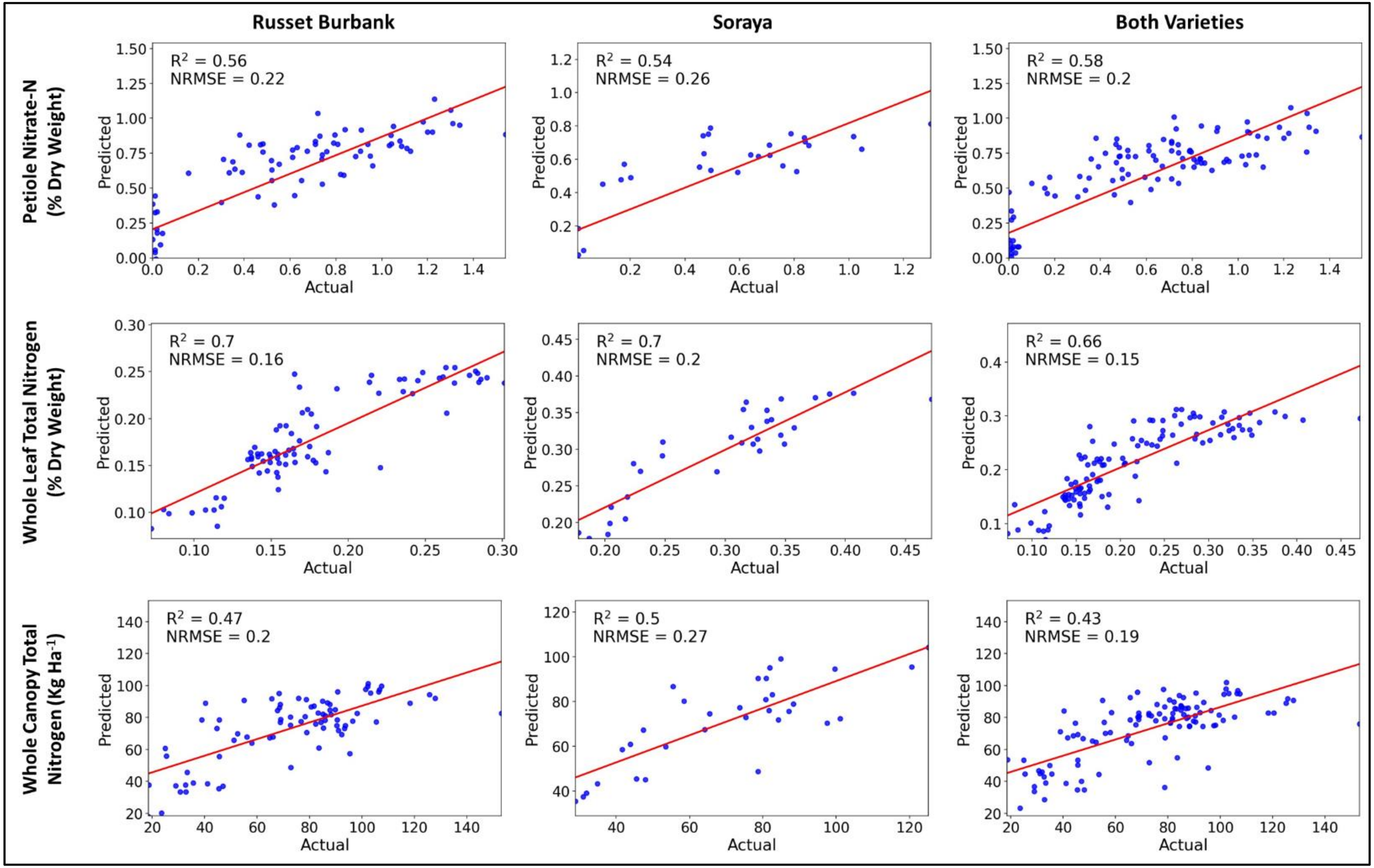
Imagery and Ground Truthing Timeline
At-Harvest Predictions



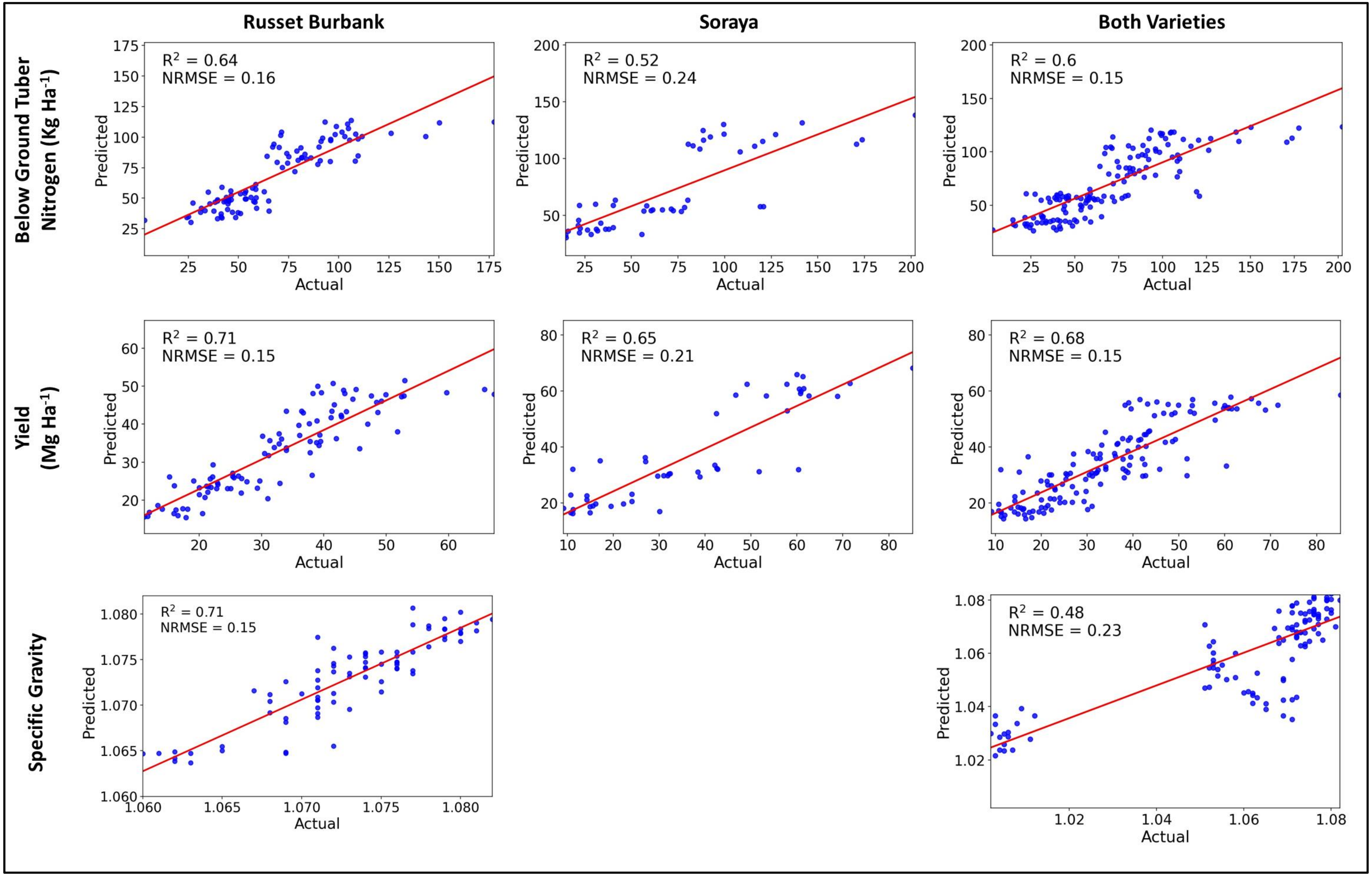
In-Season Trait Predictions (Full Spectrum)



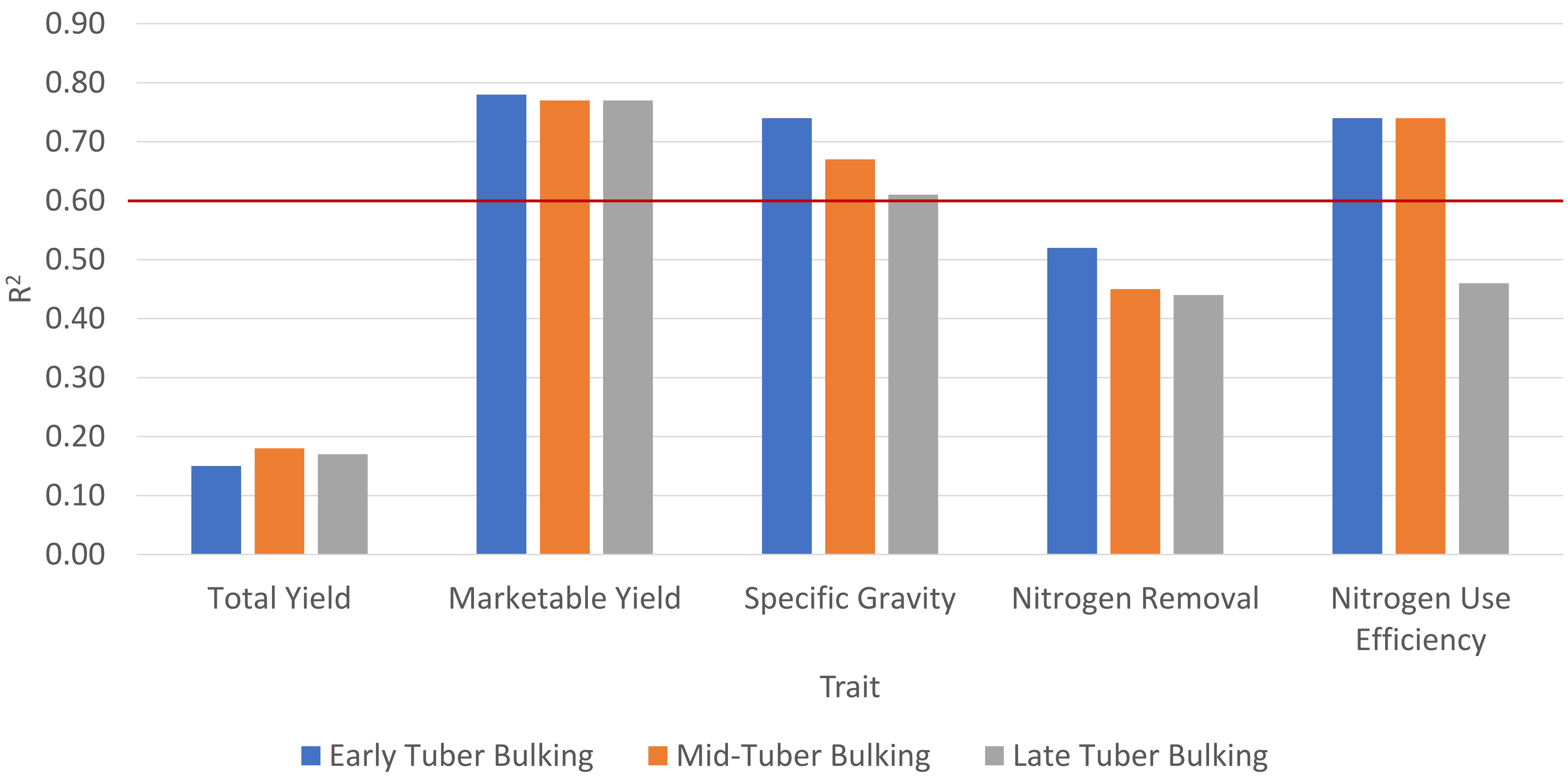
In-Season Trait Predictions (AGB)



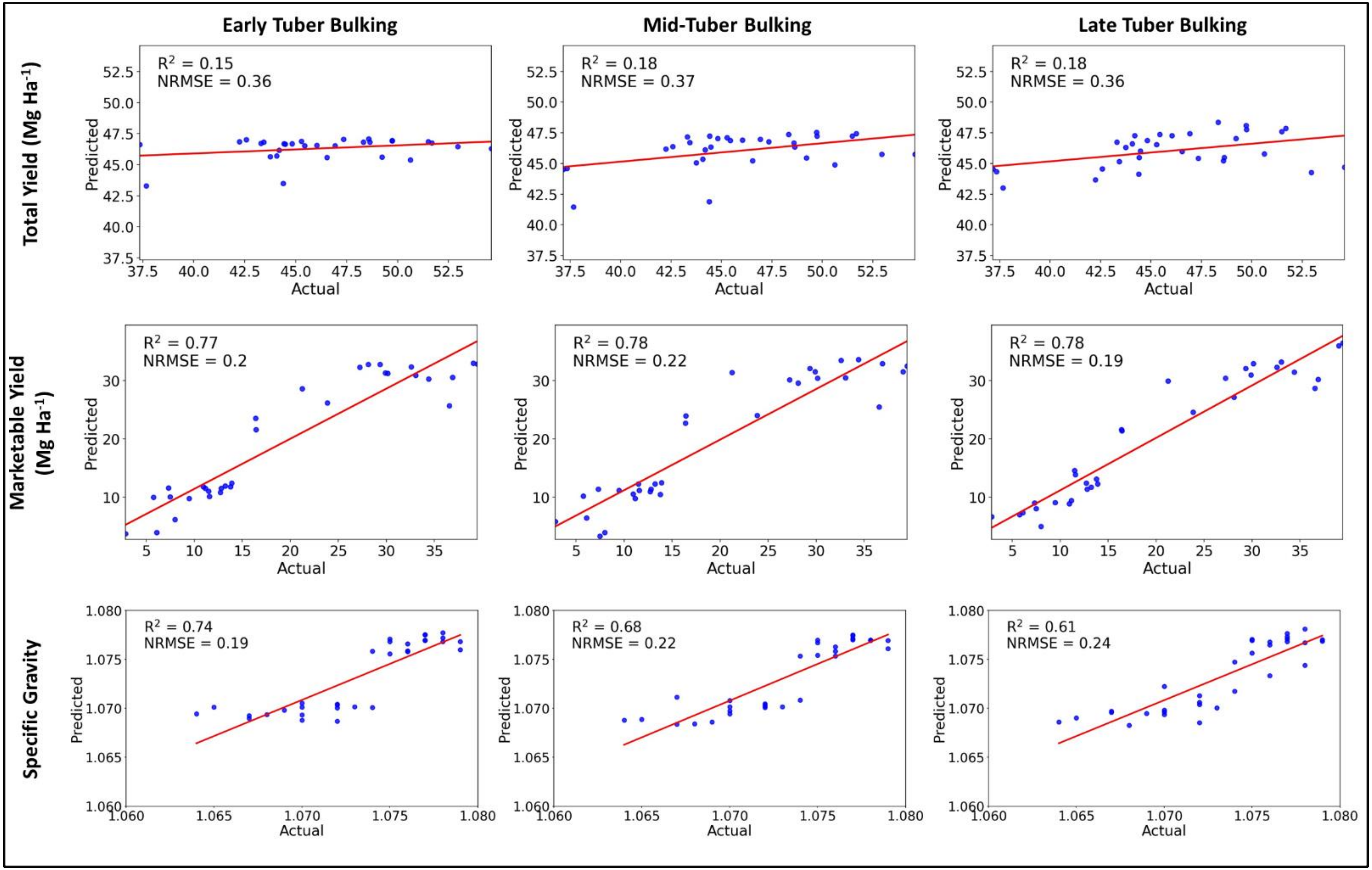
In-Season Trait Predictions (BGB)



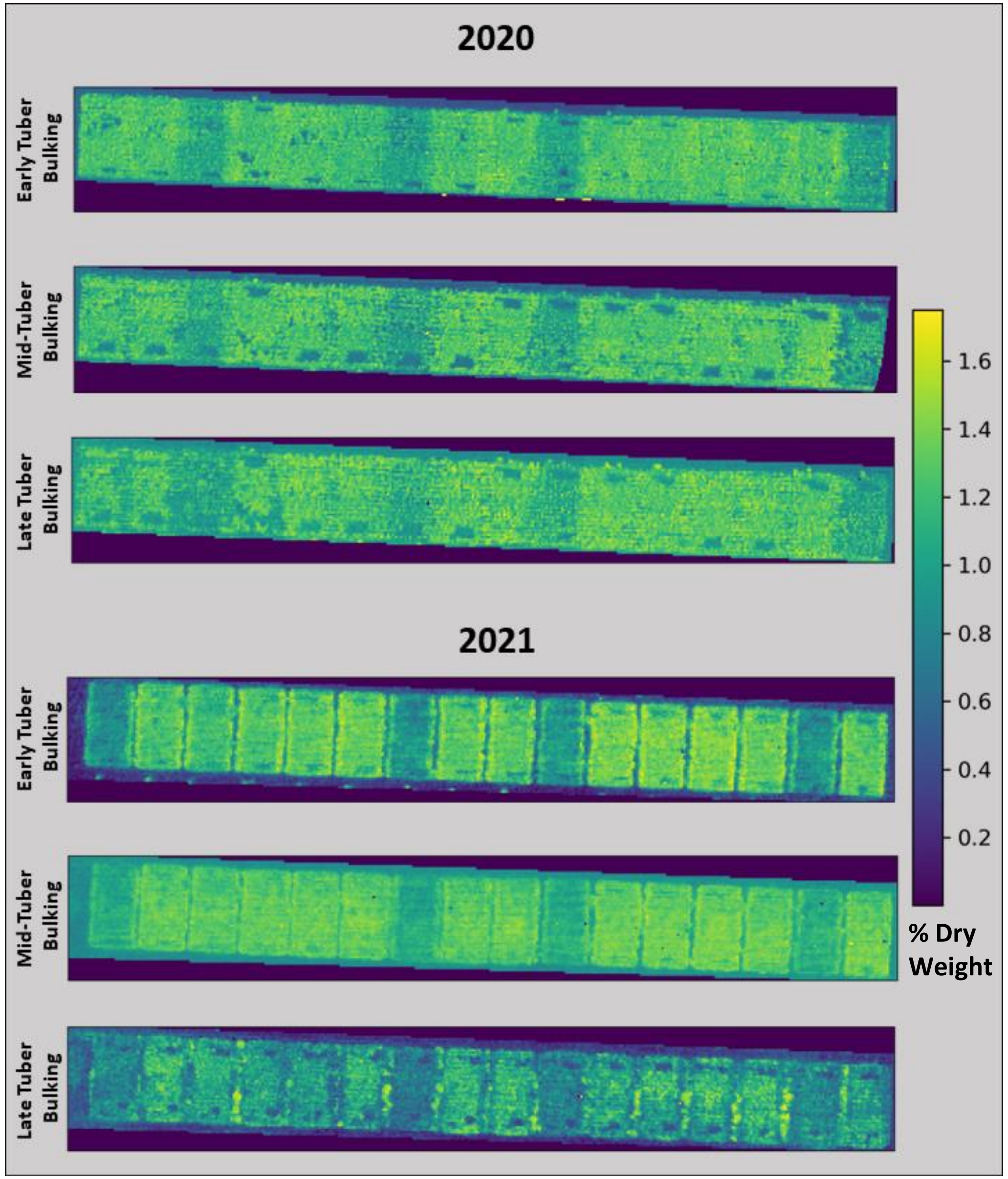
At-Harvest Trait Predictions



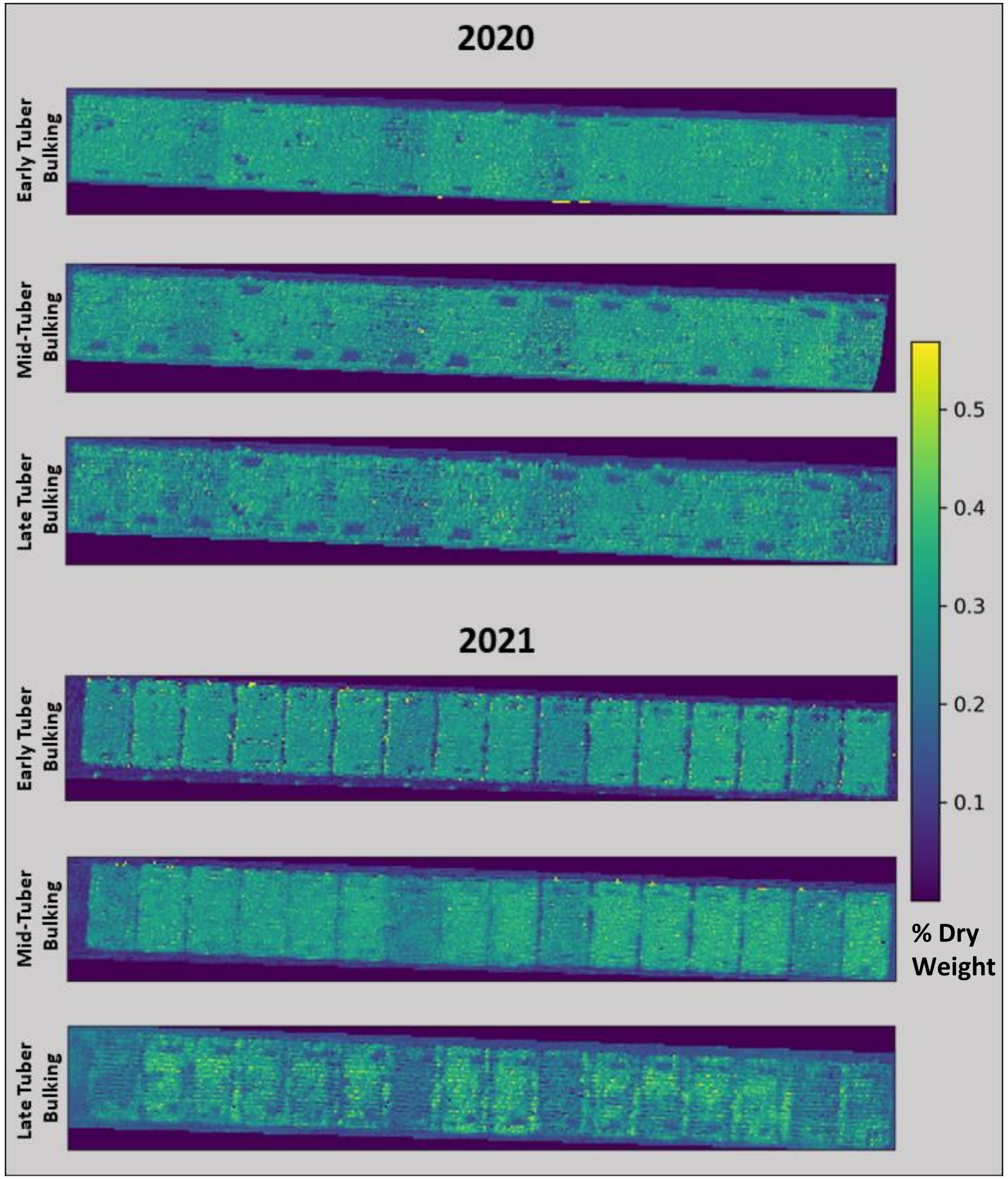
At-Harvest Trait Predictions



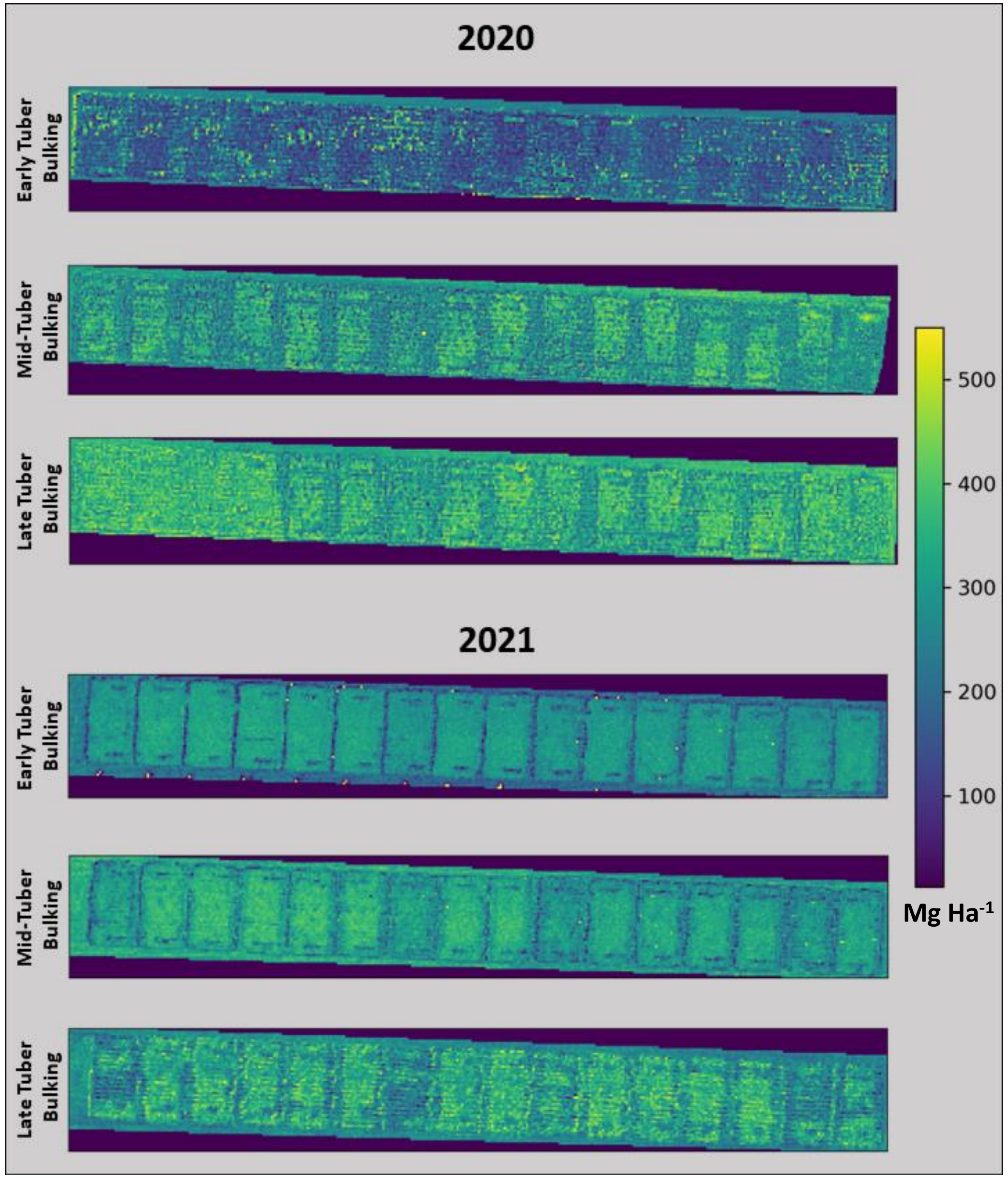
Predicted Petiole Nitrate-N Map



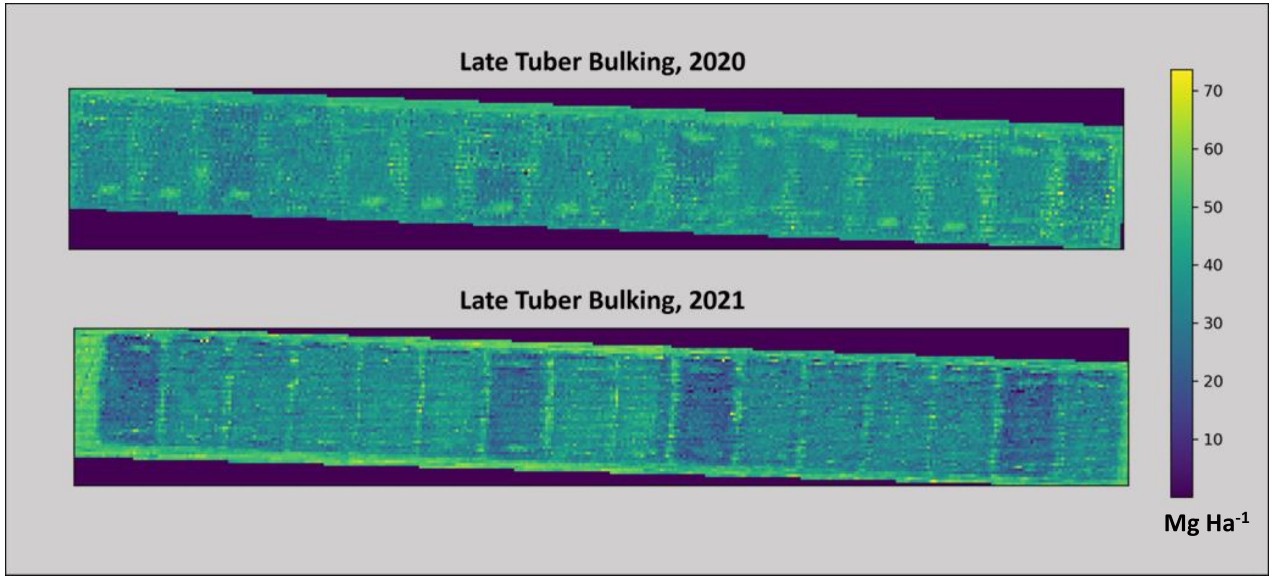
Whole Leaf N



Predicted In-Season Yield



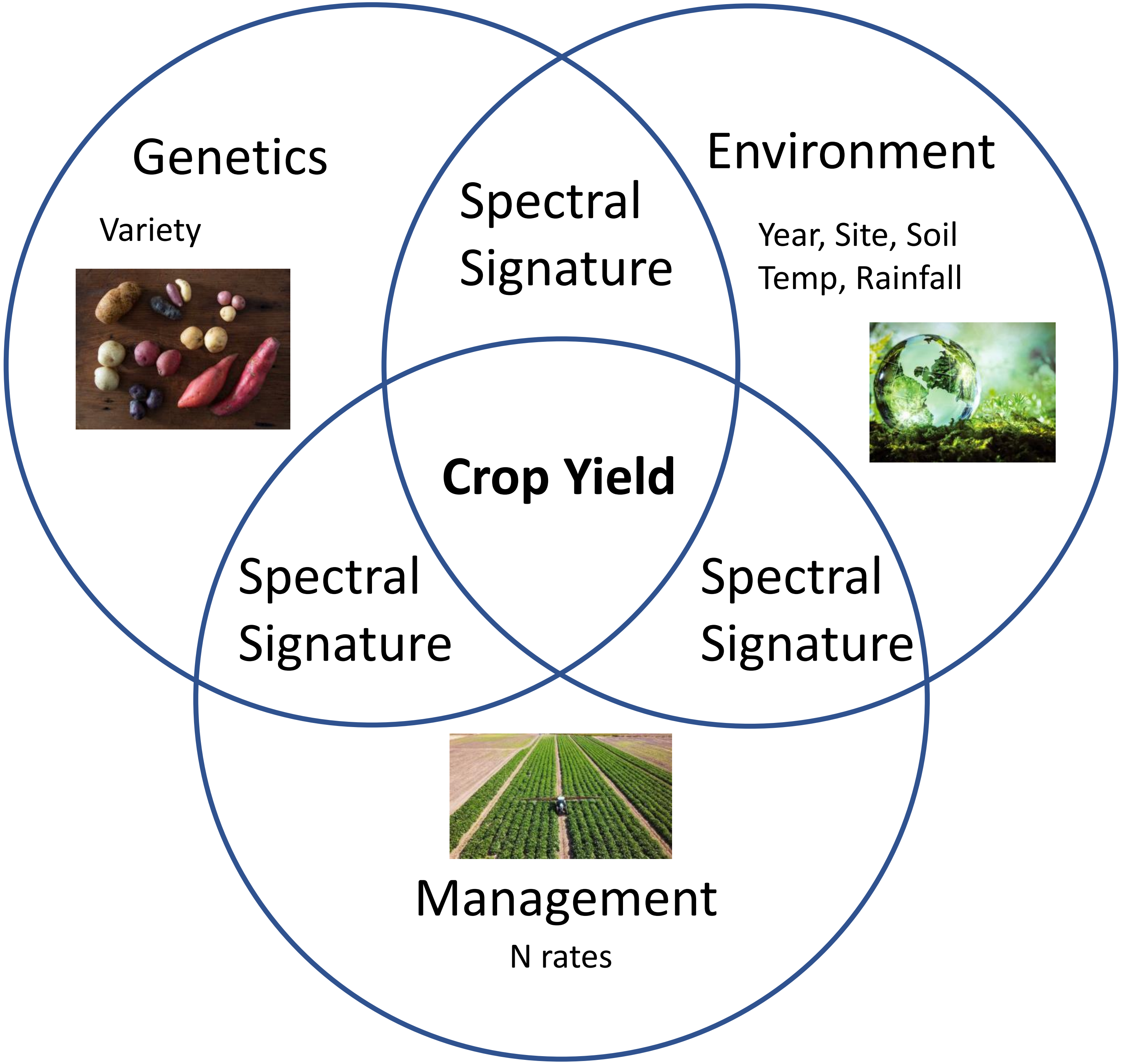
Predicted At-Harvest Marketable Yield



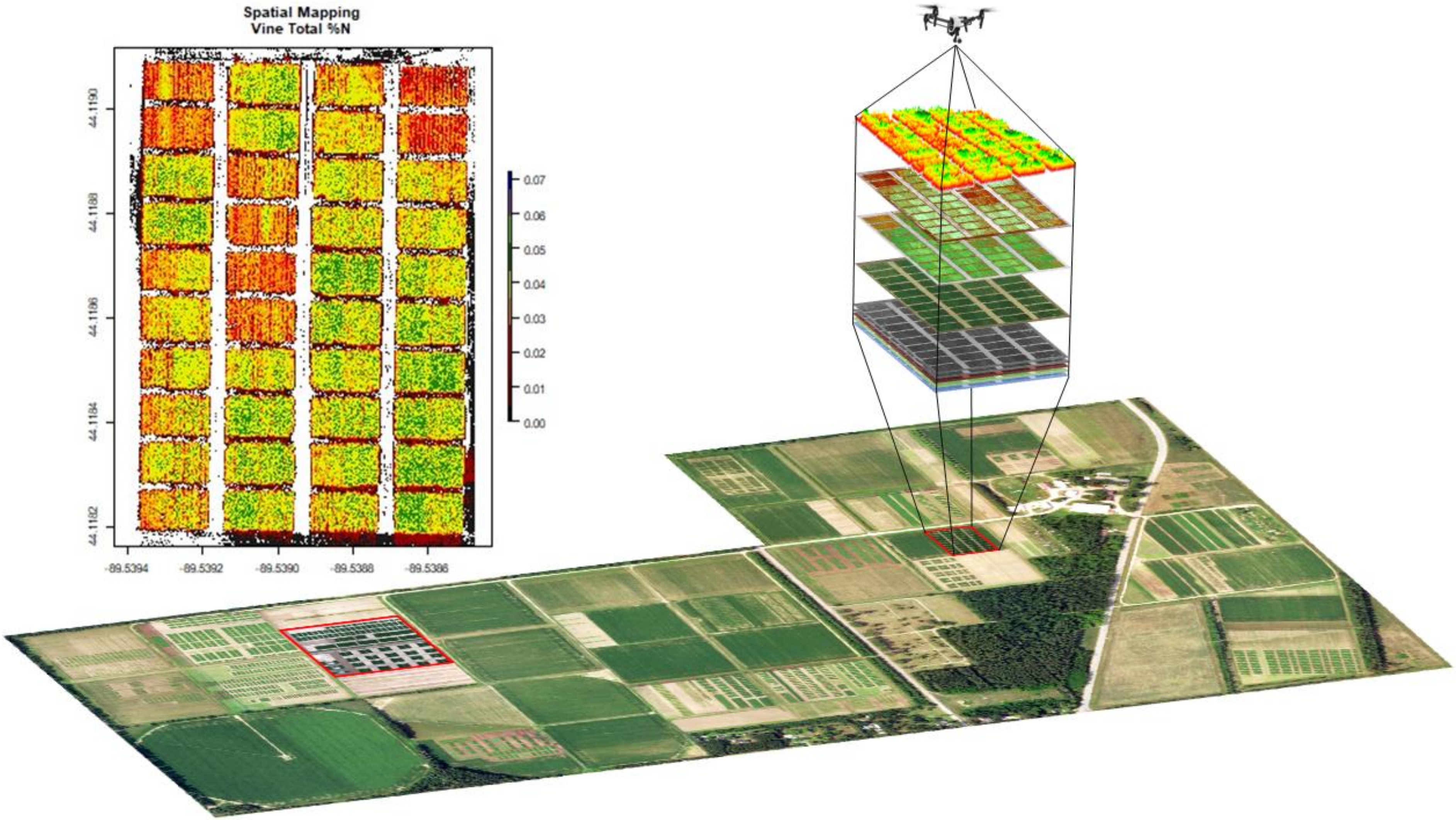
Conclusions

- **Multi-year and multi-growth stage PLSR models provided moderate to accurate predictions of both aboveground and underground potato traits using hyperspectral imagery**
  - In-season N status and yield
  - At-harvest yield and quality

Using a multi-year dataset to test different ML inputs for predicting potato response to nitrogen


Genetics
Variety
Spectral
Signature
Environment
Year, Site, Soil
Temp, Rainfall
Crop Yield
Spectral
Signature
Spectral
Signature
Management
N rates

Study design: 5 N rates, 4 varieties, 4 replications, 2018 – 2020



RGB Orthomosaic

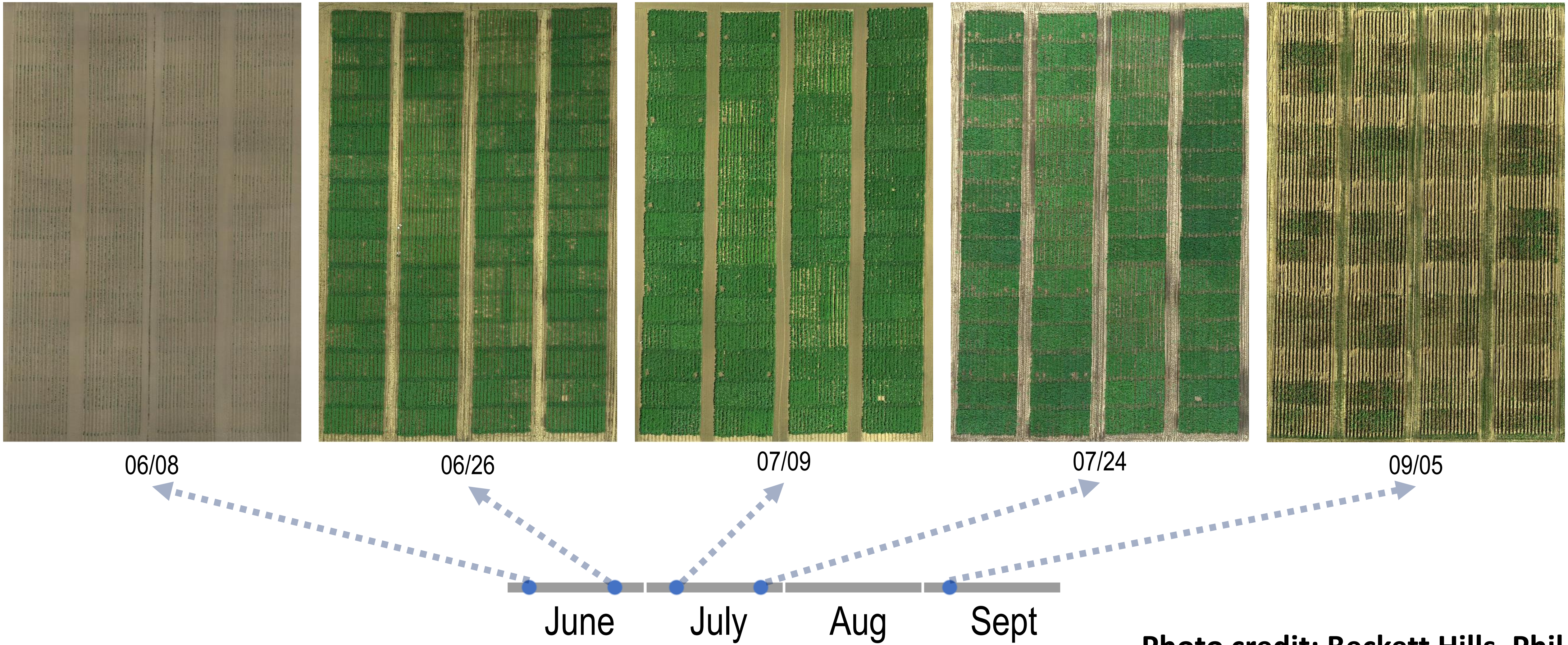


Photo credit: Beckett Hills, Phil Townsend

$$\text{NDVI} = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}}$$

NDVI values range from -1 to 1

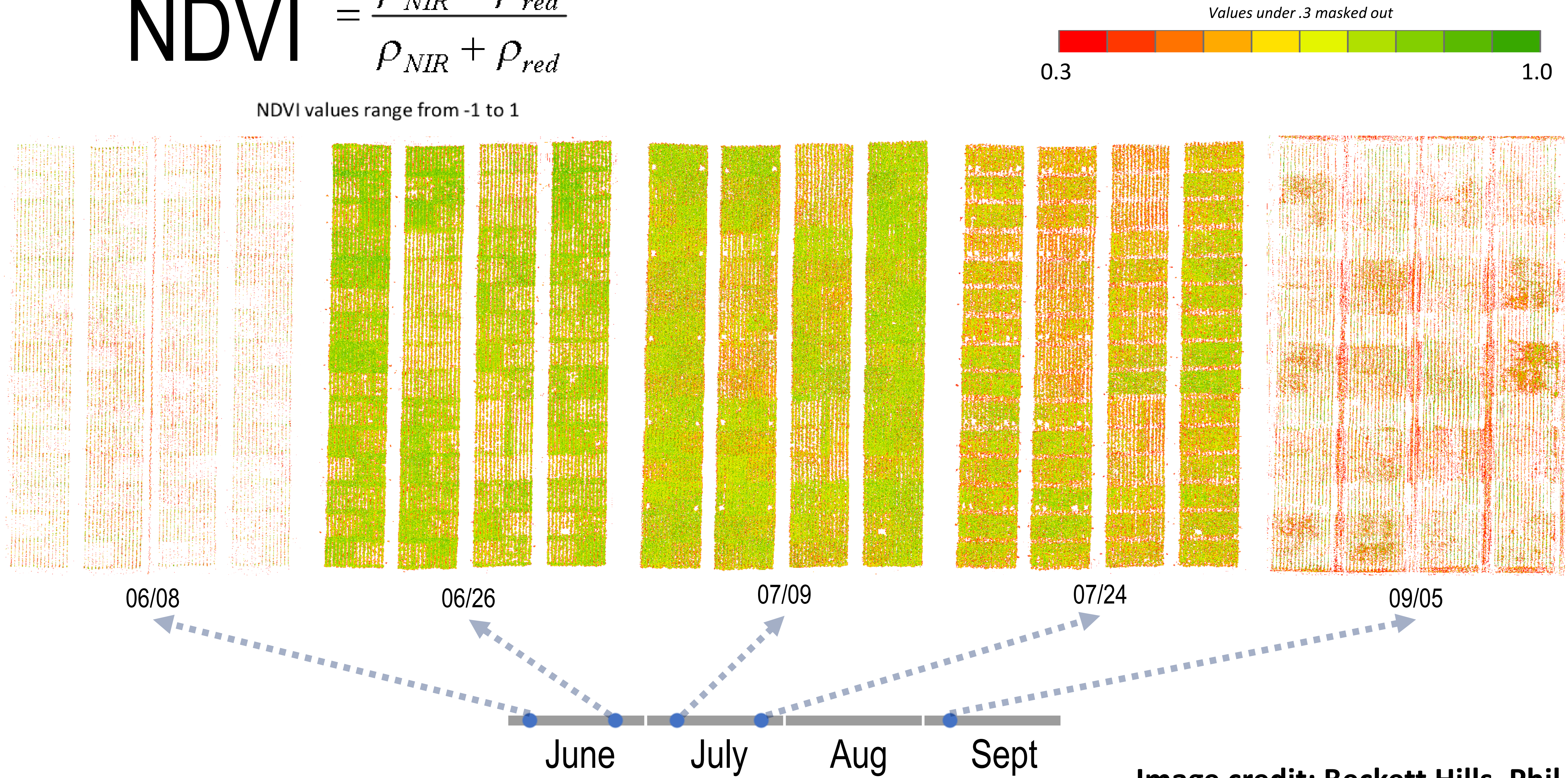
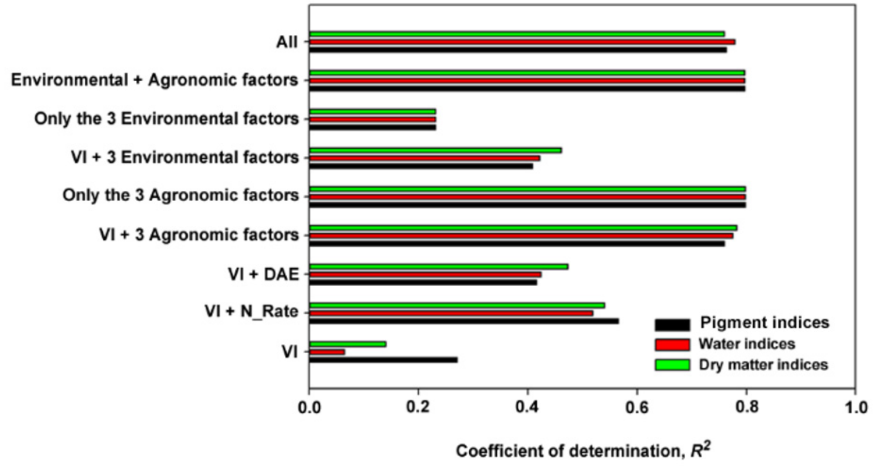


Image credit: Beckett Hills, Phil Townsend

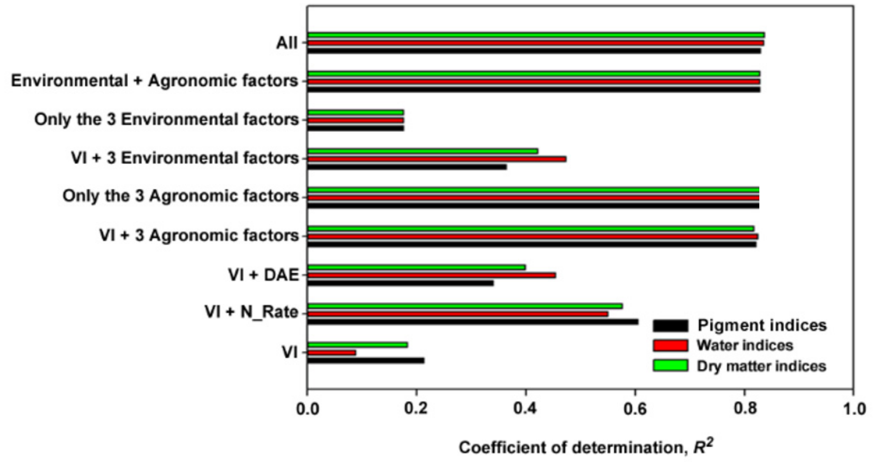
Vegetation indices and machine learning models

- Vegetation indices (VIs) are mathematical combinations of reflectance at two to five spectral bands
- VIs are designed to highlight particular biophysical or biochemical properties of vegetation
- Six different machine learning models were used including random forest (RF), support vector machine (SVM), k-nearest neighbor (kNN), etc.

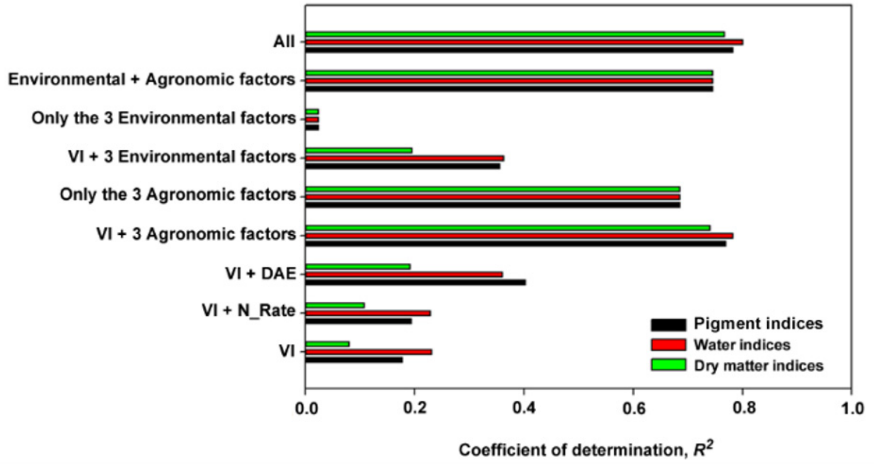
Petiole nitrate-N



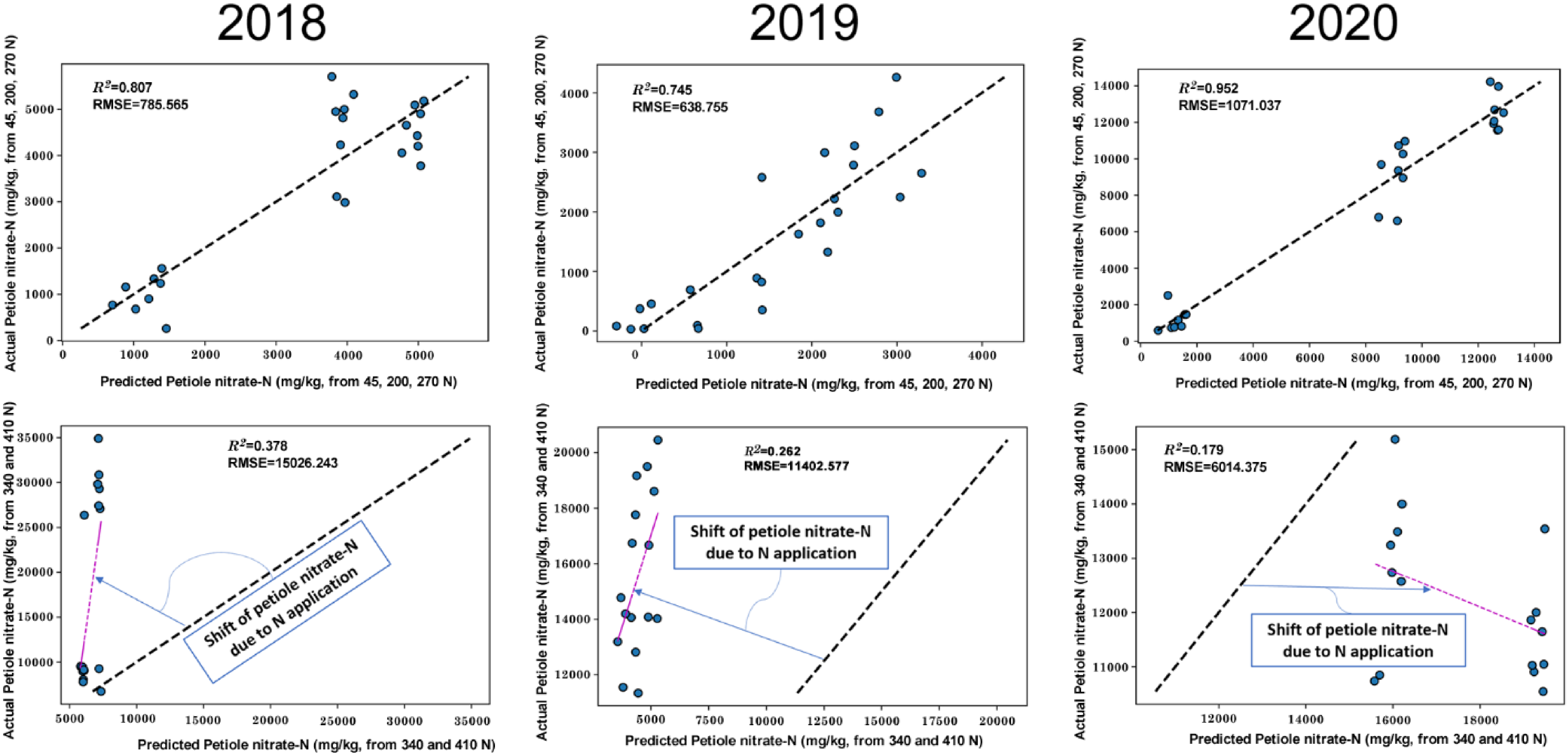
Whole leaf total N

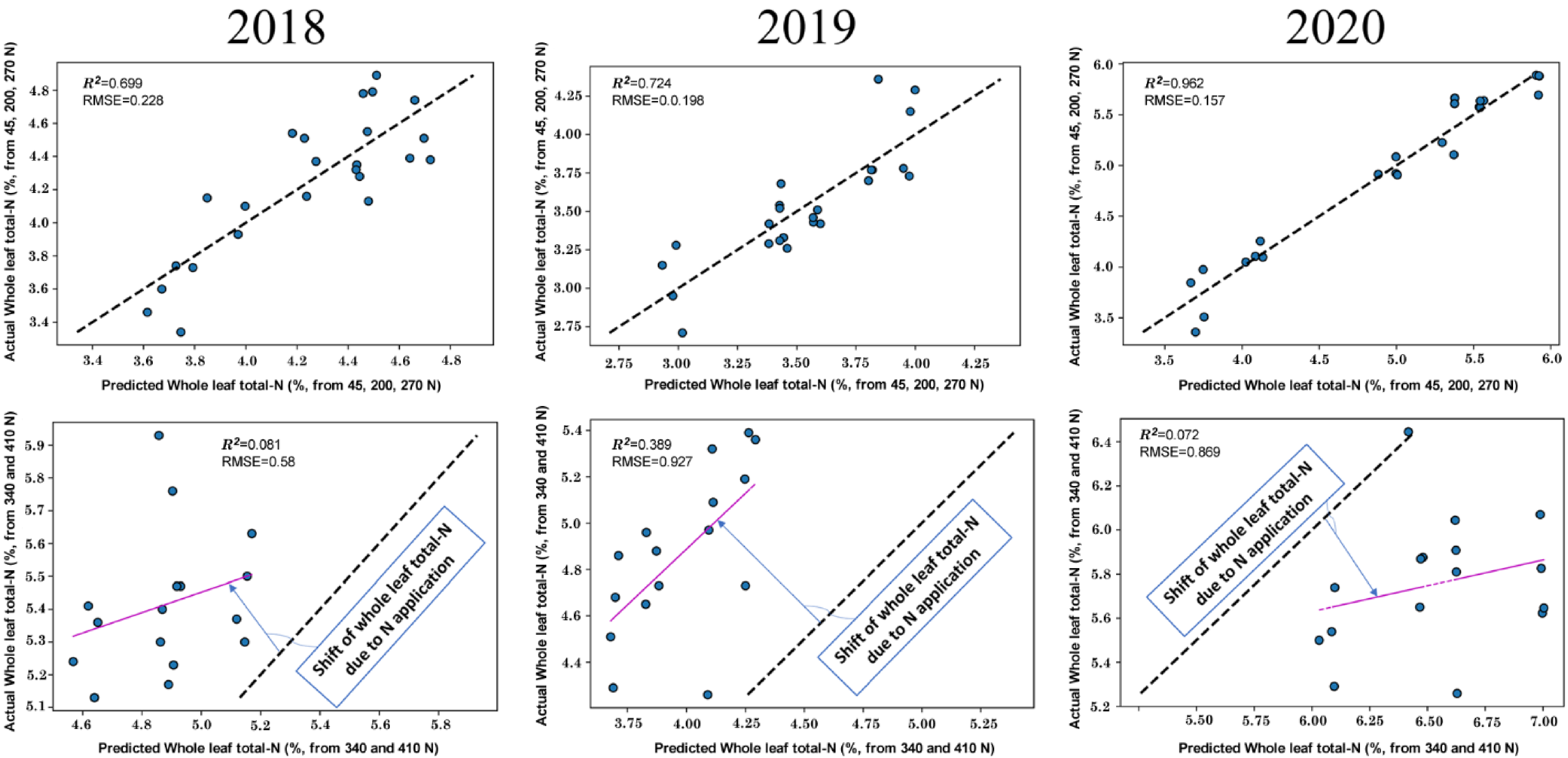


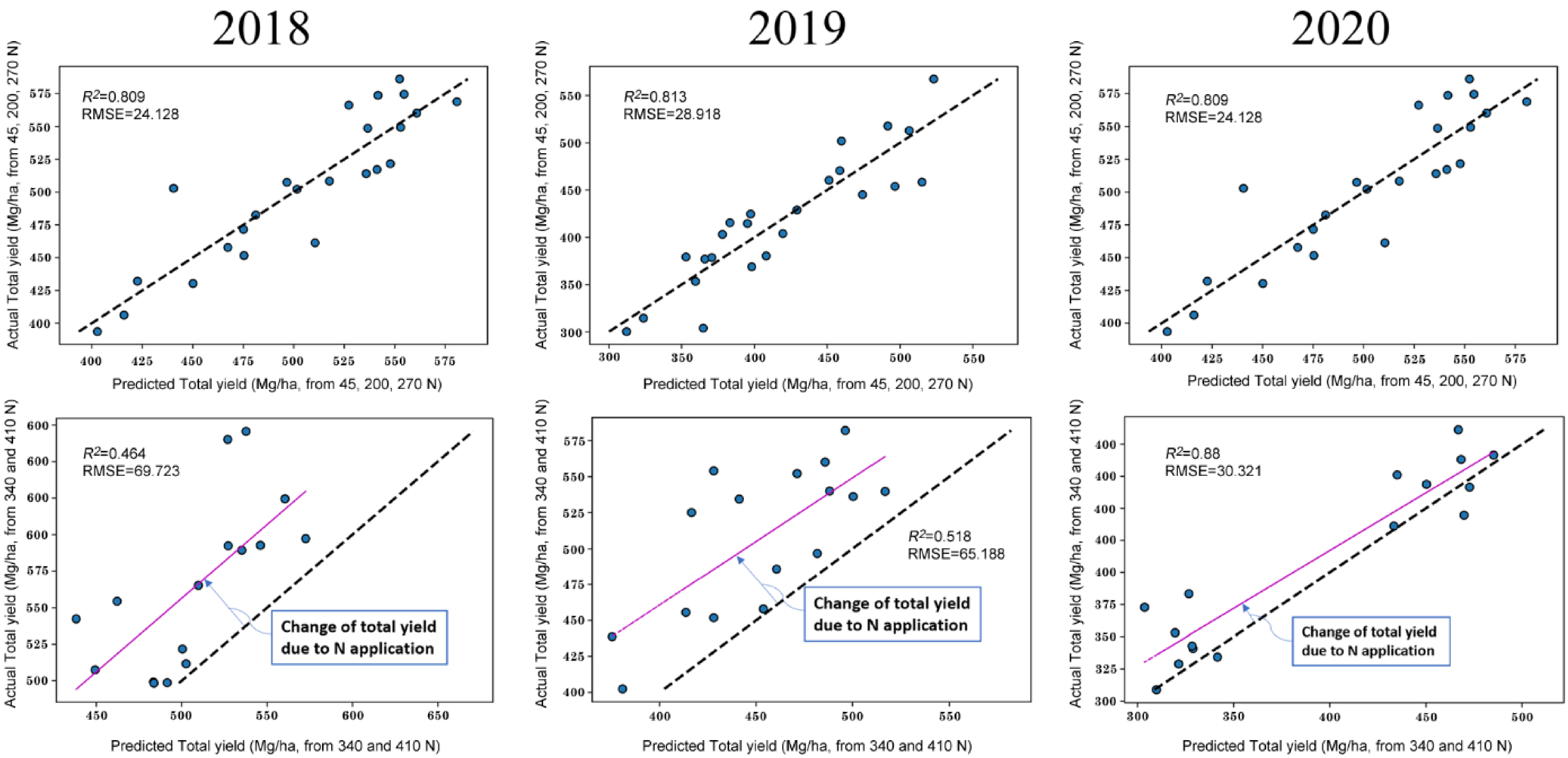
Final yield



Plant Traits	Year/ Year Combination	Best Model	R^2
Petiole nitrate-N	**2018**	kNN	0.381
	2019	XGB	0.744
	2020	XGB	0.563
	2018 & 2019	RF	0.829
	2018, 2019 & 2020	Linear	0.476
Whole leaf total N	**2018**	RF	0.782
	2019	SVM	0.796
	2020	XGB	0.601
	2018 & 2019	RF	0.877
	2018, 2019 & 2020	Linear	0.487
Final yield	**2018**	RF	0.589
	2019	XGB	0.570
	2020	RF	0.654
	2018 & 2019	Linear	0.546
	2018, 2019 & 2020	RF	0.661


2018
2019
2020
R^2=0.807
RMSE=785.565
R^2=0.745
RMSE=638.755
R^2=0.952
RMSE=1071.037
Actual Petiole nitrate-N (mg/kg, from 45, 200, 270 N)
Predicted Petiole nitrate-N (mg/kg, from 45, 200, 270 N)
R^2=0.378
RMSE=15026.243
R^2=0.262
RMSE=11402.577
R^2=0.179
RMSE=6014.375
Shift of petiole nitrate-N due to N application
Actual Petiole nitrate-N (mg/kg, from 340 and 410 N)
Predicted Petiole nitrate-N (mg/kg, from 340 and 410 N)


2018
2019
2020
R^2=0.699
RMSE=0.228
R^2=0.724
RMSE=0.0.198
R^2=0.962
RMSE=0.157
Actual Whole leaf total-N (%, from 45, 200, 270 N)
Predicted Whole leaf total-N (%, from 45, 200, 270 N)
R^2=0.081
RMSE=0.58
R^2=0.389
RMSE=0.927
R^2=0.072
RMSE=0.869
Actual Whole leaf total-N (%, from 340 and 410 N)
Predicted Whole leaf total-N (%, from 340 and 410 N)
Shift of whole leaf total-N due to N application



2018
2019
2020
R2=0.809
RMSE=24.128
R2=0.813
RMSE=28.918
R2=0.809
RMSE=24.128
Actual Total yield (Mg/ha, from 45, 200, 270 N)
Predicted Total yield (Mg/ha, from 45, 200, 270 N)
R2=0.464
RMSE=69.723
R2=0.518
RMSE=65.188
R2=0.88
RMSE=30.321
Change of total yield due to N application
Actual Total yield (Mg/ha, from 340 and 410 N)
Predicted Total yield (Mg/ha, from 340 and 410 N)

Conclusion

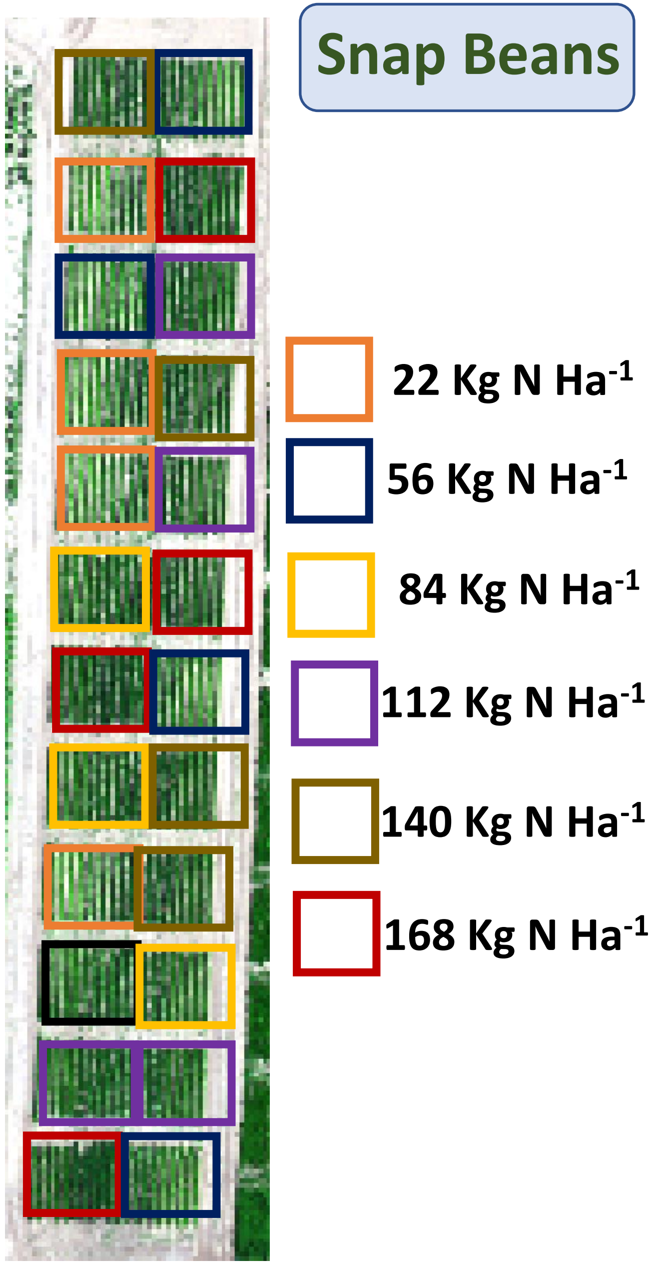
- Model need GEM and spectral data to generate good prediction results
- Best performing machine learning models depend on the year
- Yield gain in response to N fertilization could be predicted across the three years, but response of in-season crop N status to supplemental N application showed high year-to-year variations

Using hyperspectral imaging and ML for predicting responses of snap beans and kidney beans to nitrogen

Field Design

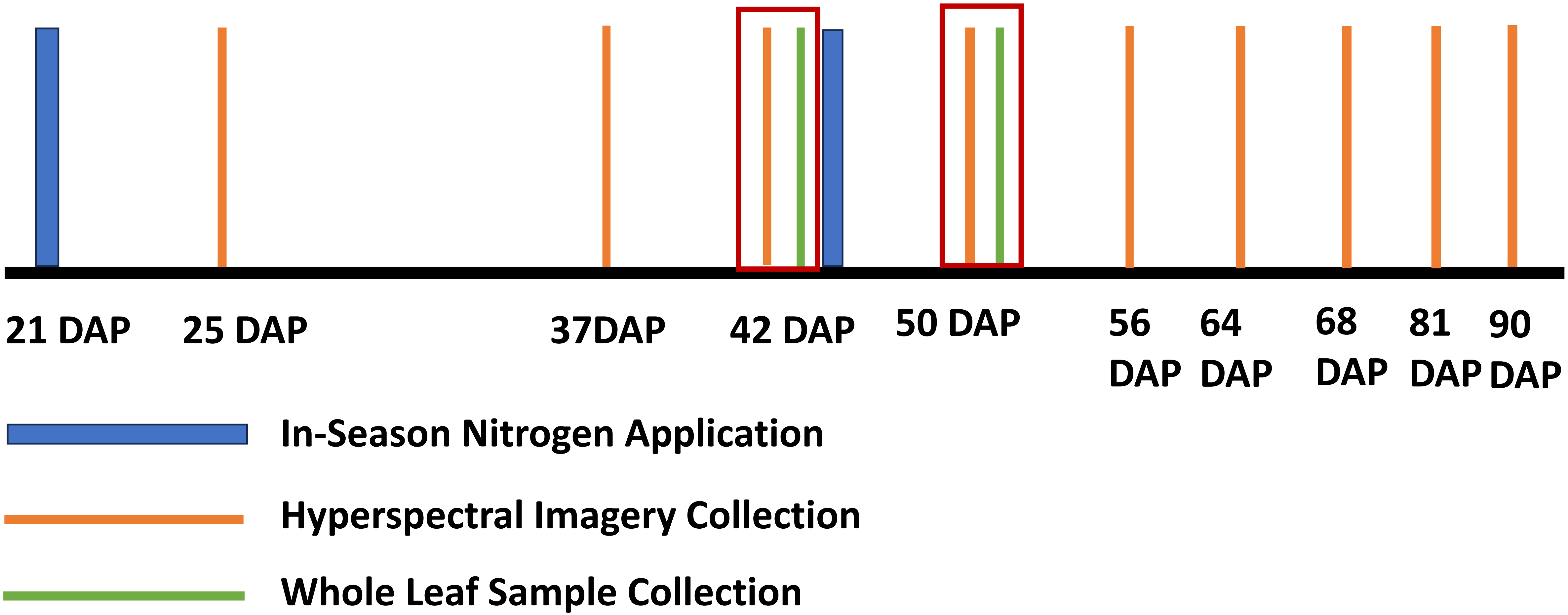
- Planting: June 02nd, 2022
- Final harvest was conducted on August 09th 2022
- Cultivars: DM 88 and Huntington
- Nitrogen fertilizer rates included:

	Planting	V2-V3 growth stage	V7-V8 growth stage
		Kg N ha^{-1}	
22	22	0	0
56	22	17	17
84	22	31	31
112	22	45	45
140	22	59	59
168	22	73	73



RGB image

Timeline


21 DAP
25 DAP
37DAP
42 DAP
50 DAP
56 DAP
64 DAP
68 DAP
81 DAP
90 DAP
In-Season Nitrogen Application
Hyperspectral Imagery Collection
Whole Leaf Sample Collection

Methodology

Hyperspectral imagery: HySpex

Specifications	VNIR-1800	SWIR-384
Spectral range (nm)	400–1000	953–2518
FWHM (nm)	3.26	5.45
Number of bands	186	288
Spatial pixels	1800	384
FOV across track (deg)	34	32
IFOV across/along track (mrad)	0.32/0.64	1.46/1.46

Image processing: Sensor boresighting, radiometric calibration, smile-effect correction, geometric correction, atmospheric correction, (BRDF) correction, spectral smoothing and data extraction, vector normalization

QGIS to draw polygons to extract reflectance at plot level

Spectral information

Top twenty wavelengths that correlate with crop yield and nitrogen status

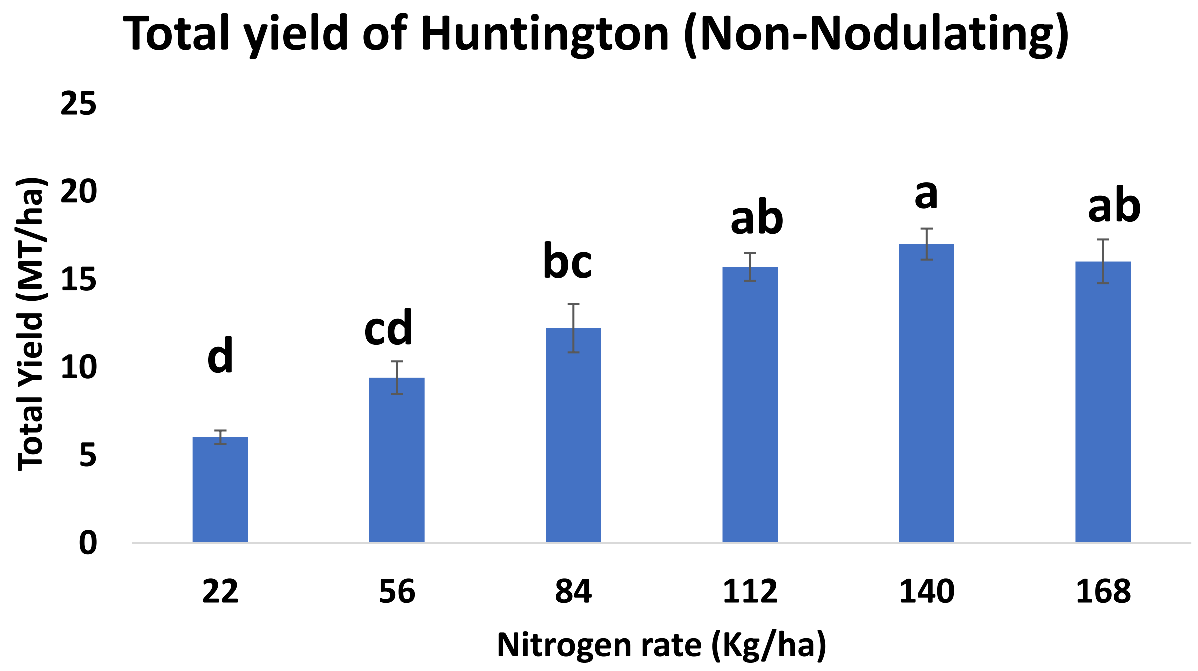
+

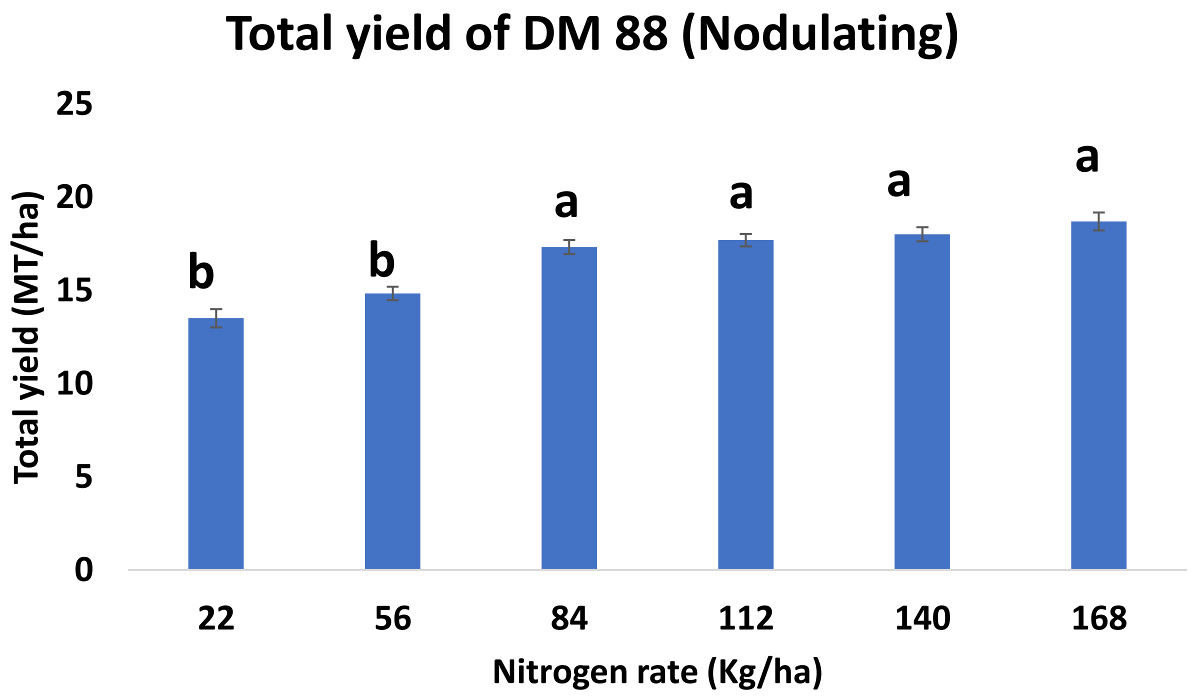
Genetic (Cultivar), **Environmental** (Soil Temperature, Precipitation) and **Management** (N rate) factors

Machine learning models: Random Forest

Crop Yield Increased at Higher N Treatments

Snap Beans





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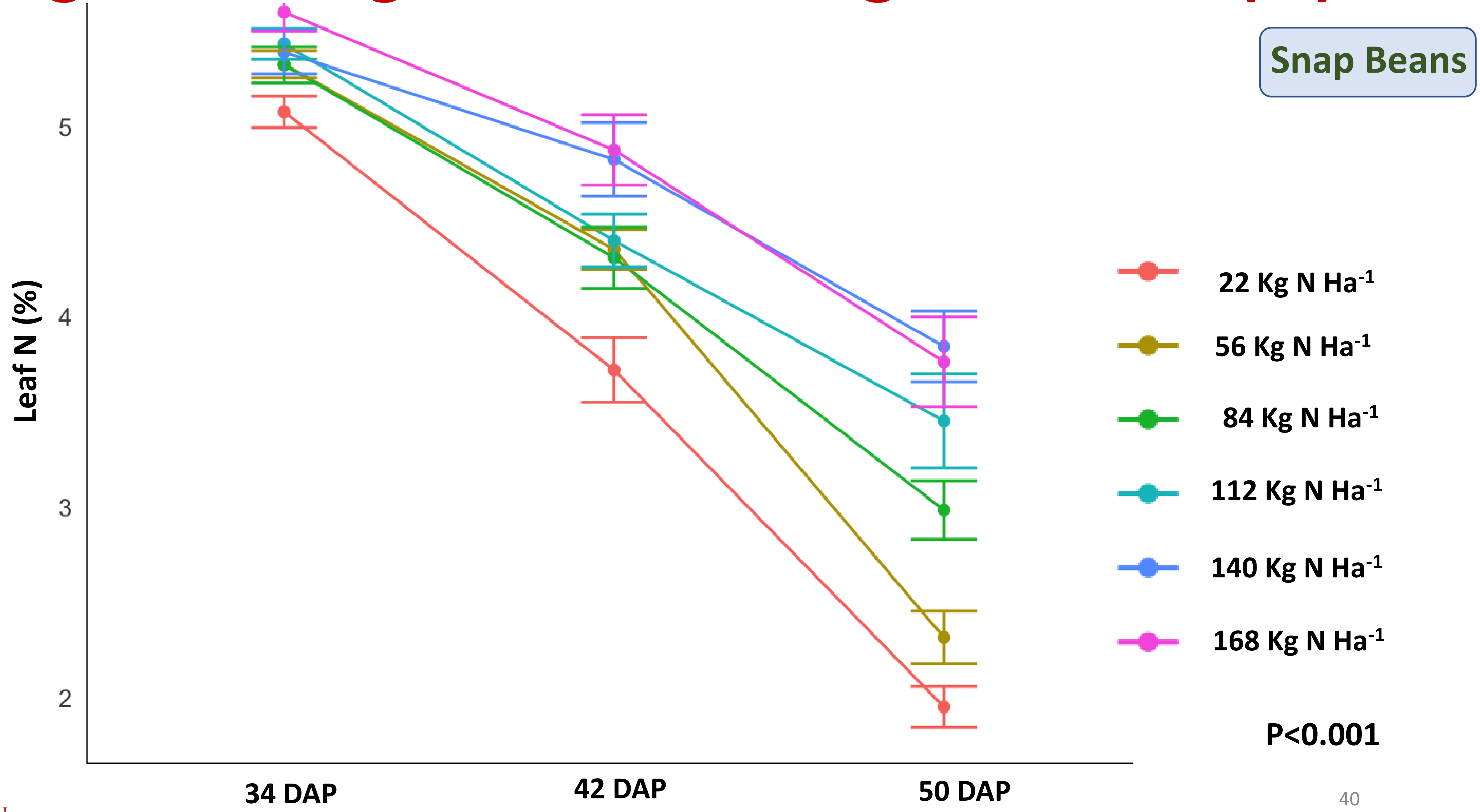
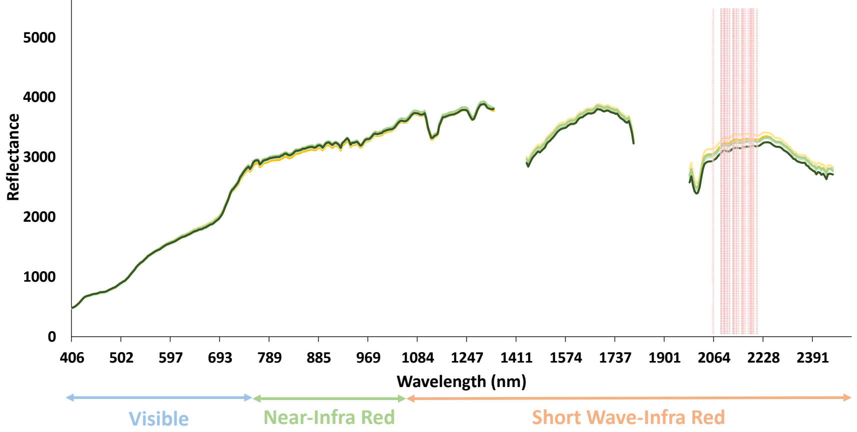
Higher Nitrogen Rate had Higher Leaf N (%)



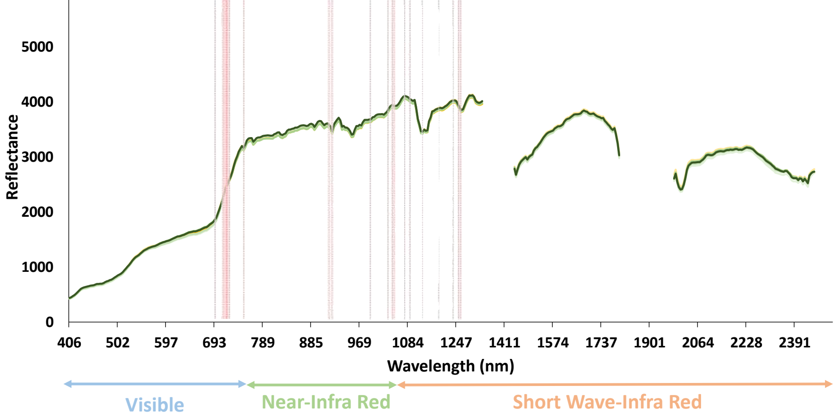
Spectral Signature Varies Across Different N Treatments

Snap Beans

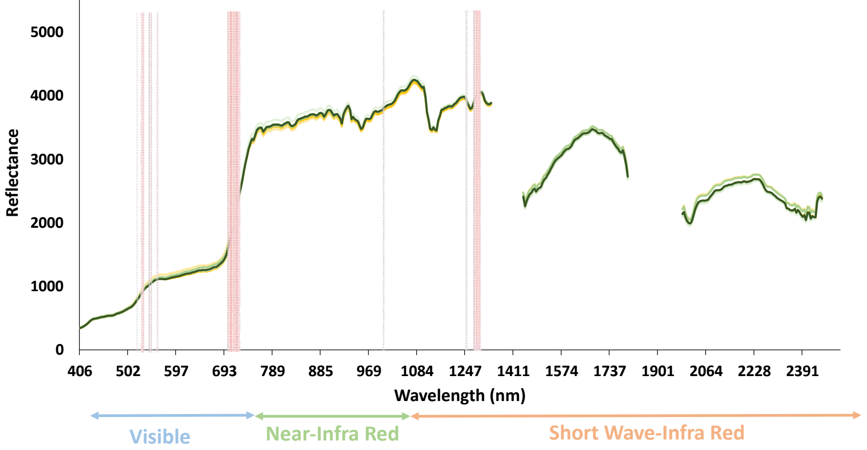
25 DAP (V4-V5 Growth Stage)



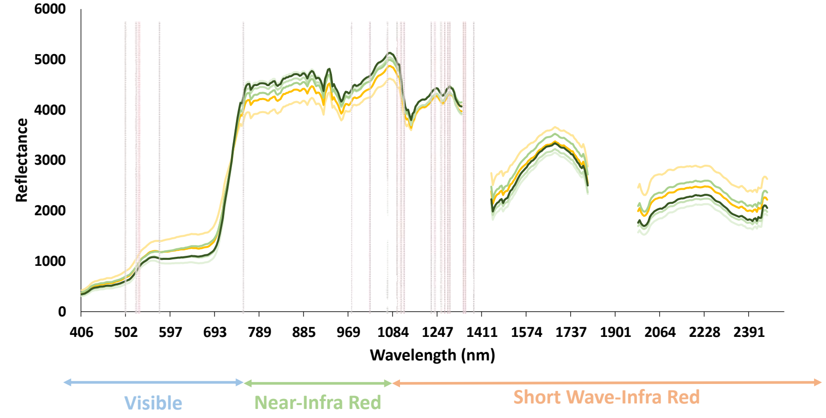
37 DAP (V6 Growth Stage)



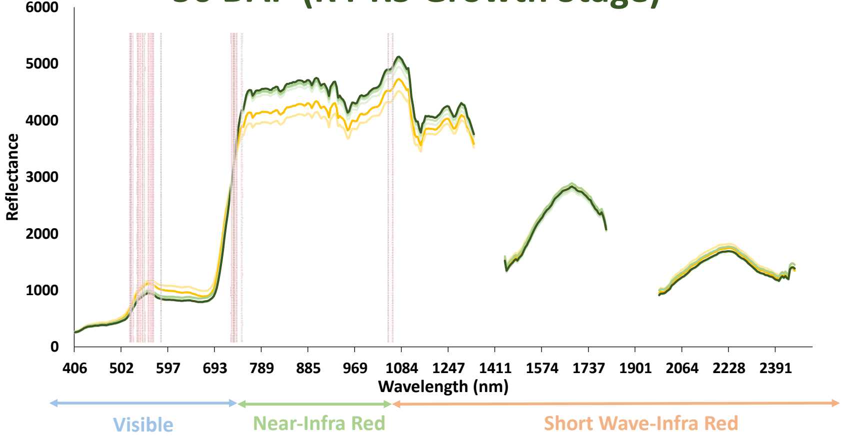
42 DAP (R1 Growth Stage)



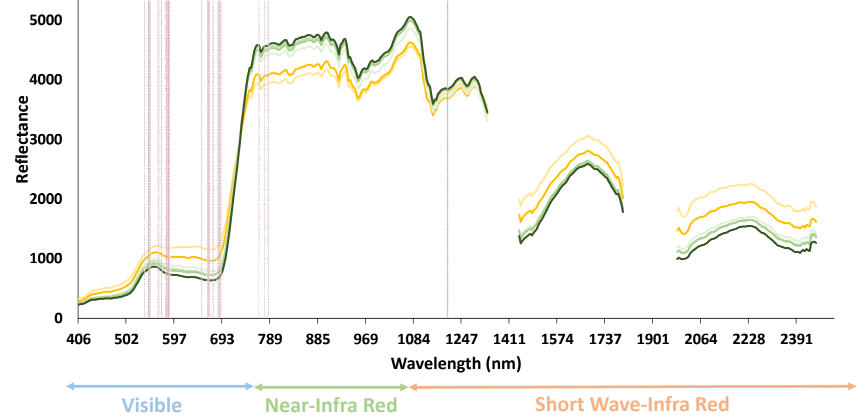
50 DAP (R2-R3 Growth Stage)



56 DAP (R4-R5 Growth Stage)



64 DAP (R6 Growth Stage)



22 Kg N Ha^{-1} | 56 Kg N Ha^{-1} | 84 Kg N Ha^{-1} | 112 Kg N Ha^{-1} | 140 Kg N Ha^{-1} | 168 Kg N Ha^{-1}

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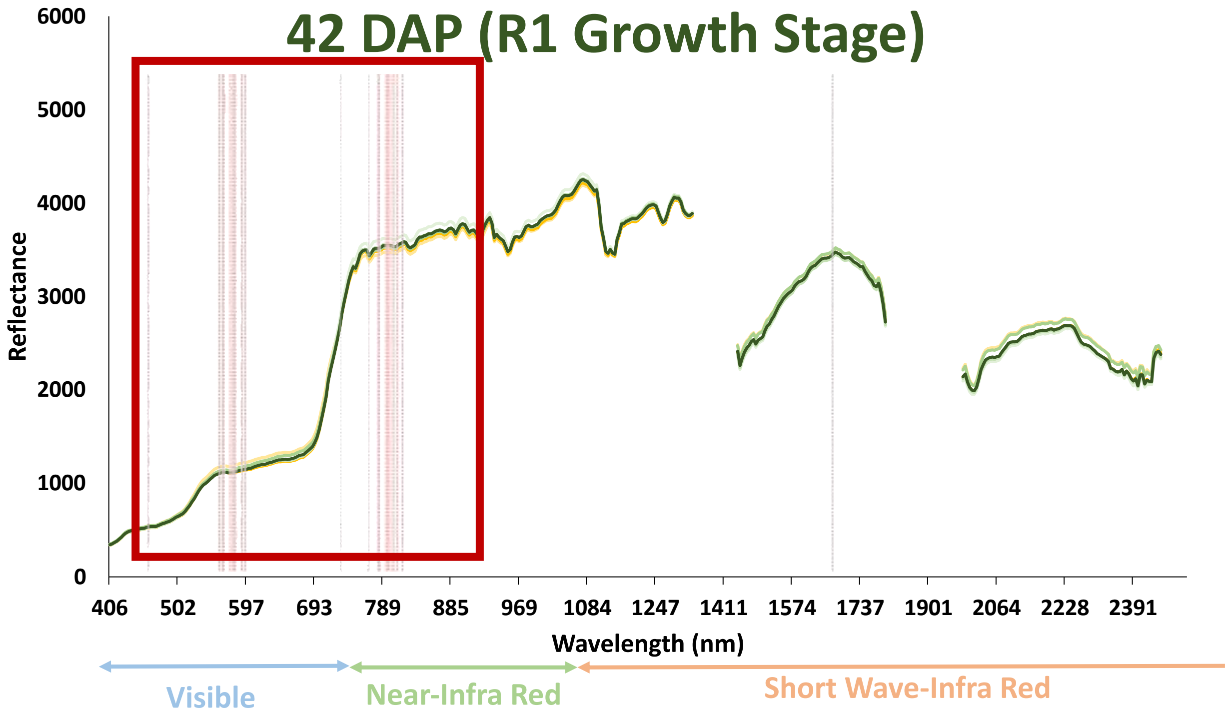
Hyperspectral Imagery Along With G E M Factors Best Predict Snap Bean Yield (R^2)

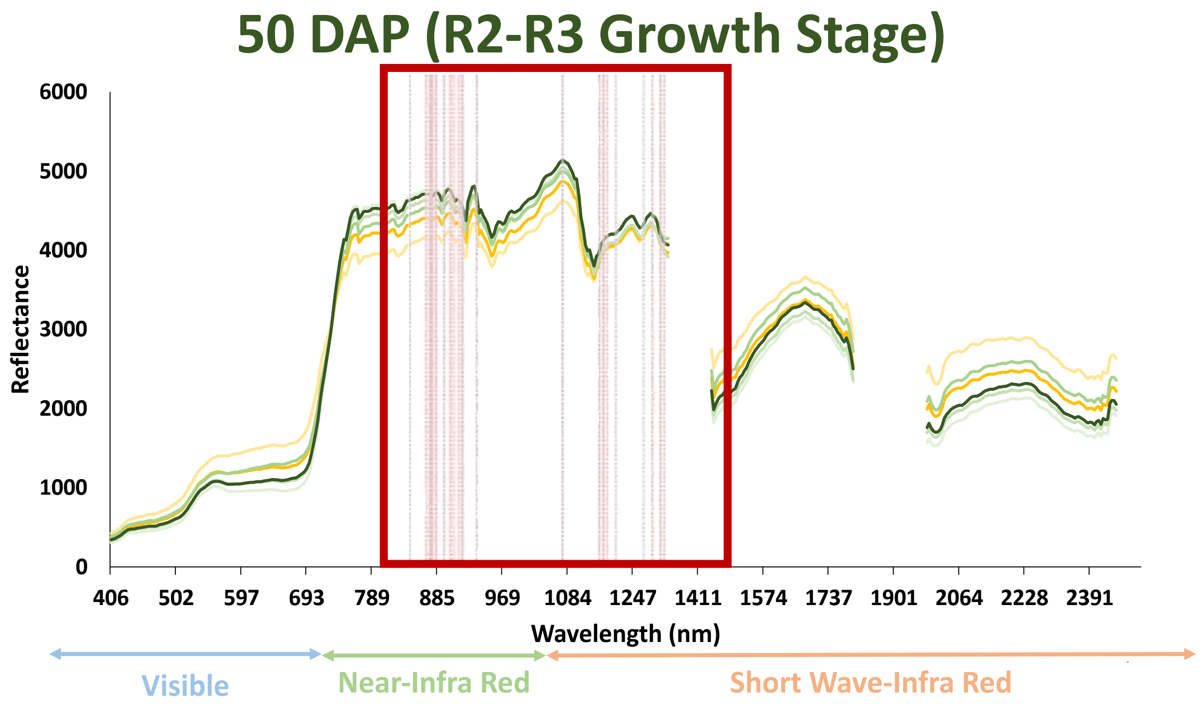
Snap Beans

Growth Stage	V4-V5	V6	R1	R2-R3	R4-R5	R6
DAP	25	37	42	50	56	64
20 Best Wavelengths + G + E + M	0.763	0.805	0.657	0.696	0.748	0.748
20 Best Wavelengths + G	0.479	0.228	0.271	0.671	0.723	0.733
20 Best Wavelengths + E	0.176	0.195	0.267	0.589	0.647	0.611
20 Best Wavelengths + M	0.418	0.720	0.495	0.602	0.658	0.640
20 Best Wavelengths	0.189	0.226	0.267	0.593	0.652	0.602

Different Wavelengths Correlate With Leaf Nitrogen Content (%) at Different Growth Stages

Snap Beans





22 Kg N Ha^{-1} | 56 Kg N Ha^{-1} | 84 Kg N Ha^{-1} | 112 Kg N Ha^{-1} | 140 Kg N Ha^{-1} | 168 Kg N Ha^{-1}

43

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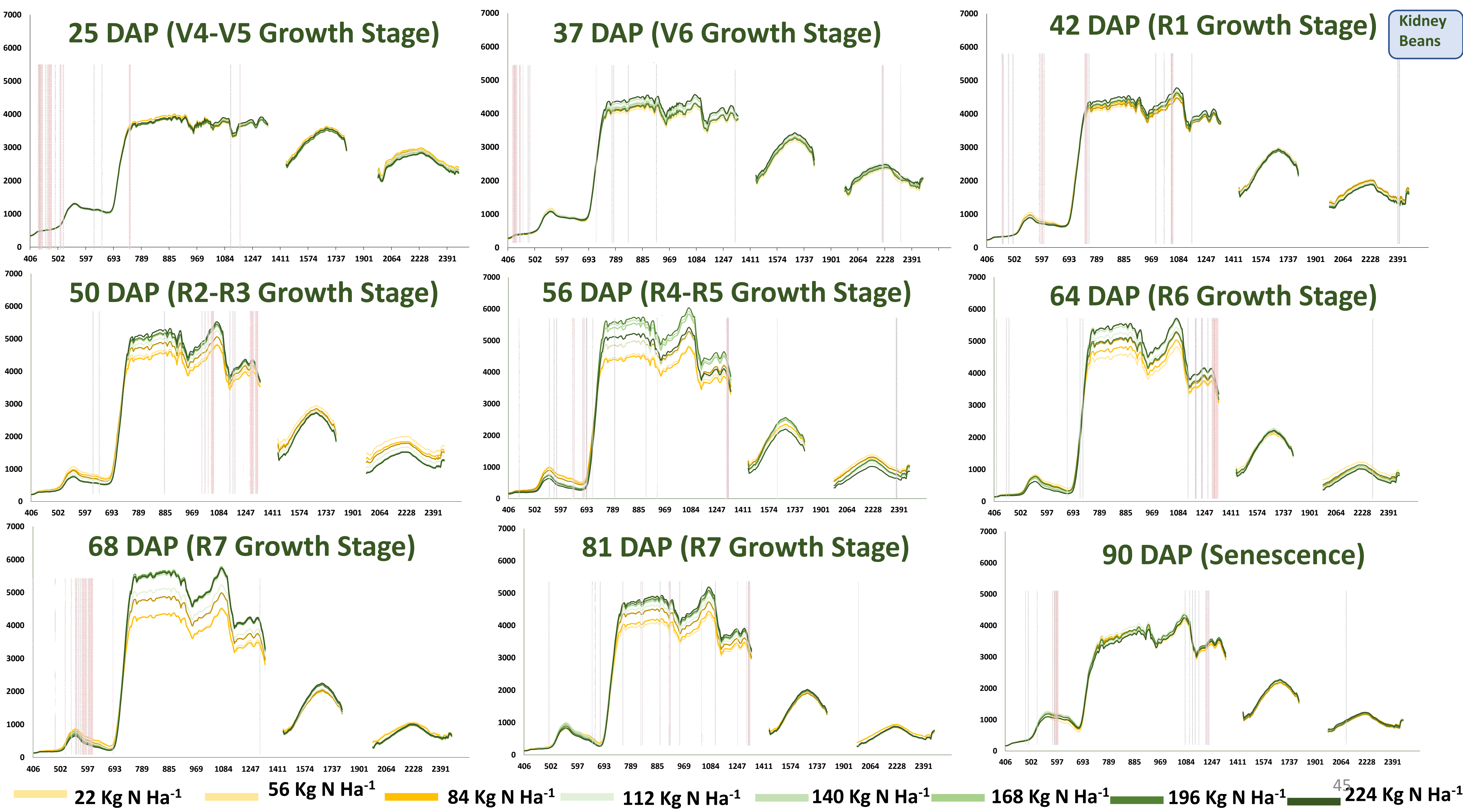
Prediction of In-Season Leaf N (%) (R^2)

Snap Beans

Growth Stage	R1	R2-R3
DAP	42	50
20 Best Wavelengths + G + E + M	0.712	0.676
20 Best Wavelengths + G	0.637	0.697
20 Best Wavelengths + E	0.665	0.633
20 Best Wavelengths + M	0.701	0.609
20 Best Wavelengths	0.669	0.636



Kidney Beans
25 DAP (V4-V5 Growth Stage)
37 DAP (V6 Growth Stage)
42 DAP (R1 Growth Stage)
50 DAP (R2-R3 Growth Stage)
56 DAP (R4-R5 Growth Stage)
64 DAP (R6 Growth Stage)
68 DAP (R7 Growth Stage)
81 DAP (R7 Growth Stage)
90 DAP (Senescence)
0 1000 2000 3000 4000 5000 6000 7000
406 502 597 693 789 885 969 1084 1247 1411 1574 1737 1901 2064 2228 2391
22 Kg N Ha-1
56 Kg N Ha-1
84 Kg N Ha-1
112 Kg N Ha-1
140 Kg N Ha-1
168 Kg N Ha-1
196 Kg N Ha-1
224 Kg N Ha-1

Hyperspectral Imagery Along With G E M Factors Best Predict Kidney Bean Yield (R^2)

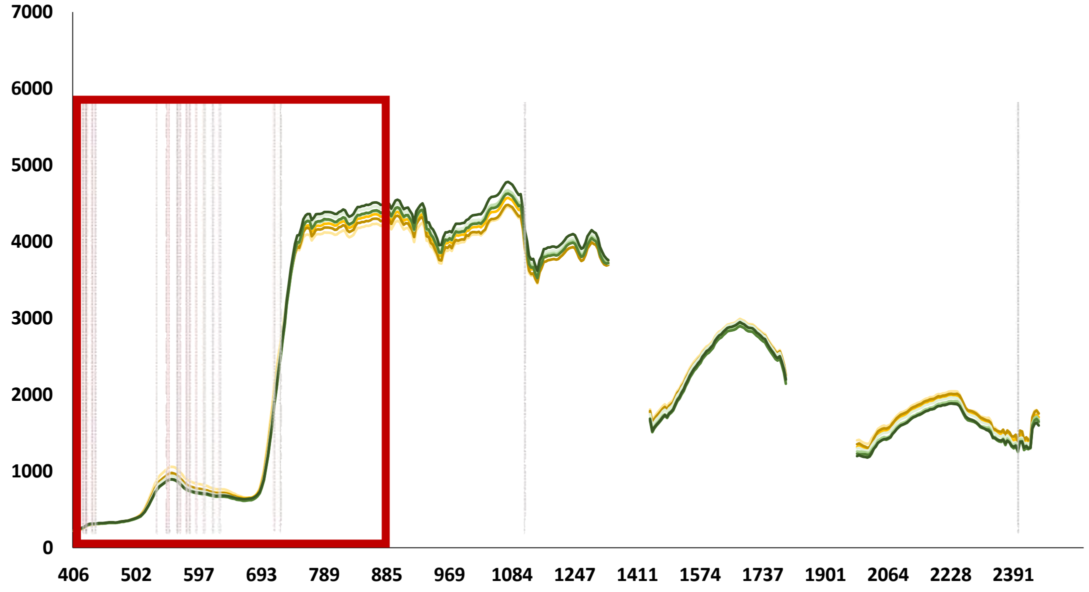
Kidney Beans

Growth Stage	V4-V5	V6	R1	R2-R3	R4-R5	R6	R7	R8	Senescence
DAP	25	37	42	50	56	64	68	81	90
20 Best Wavelengths + G + E + M	0.328	0.203	0.506	0.305	0.308	0.158	0.390	0.313	0.278
20 Best Wavelengths + G	0.118	0.199	0.412	0.210	0.333	0.057	0.371	0.303	0.245
20 Best Wavelengths + E	0.149	0.150	0.330	0.283	0.292	0.111	0.366	0.136	0.193
20 Best Wavelengths + M	0.295	0.171	0.397	0.282	0.266	0.089	0.384	0.193	0.213
20 Best Wavelengths	0.099	0.110	0.329	0.282	0.291	0.018	0.365	0.137	0.193

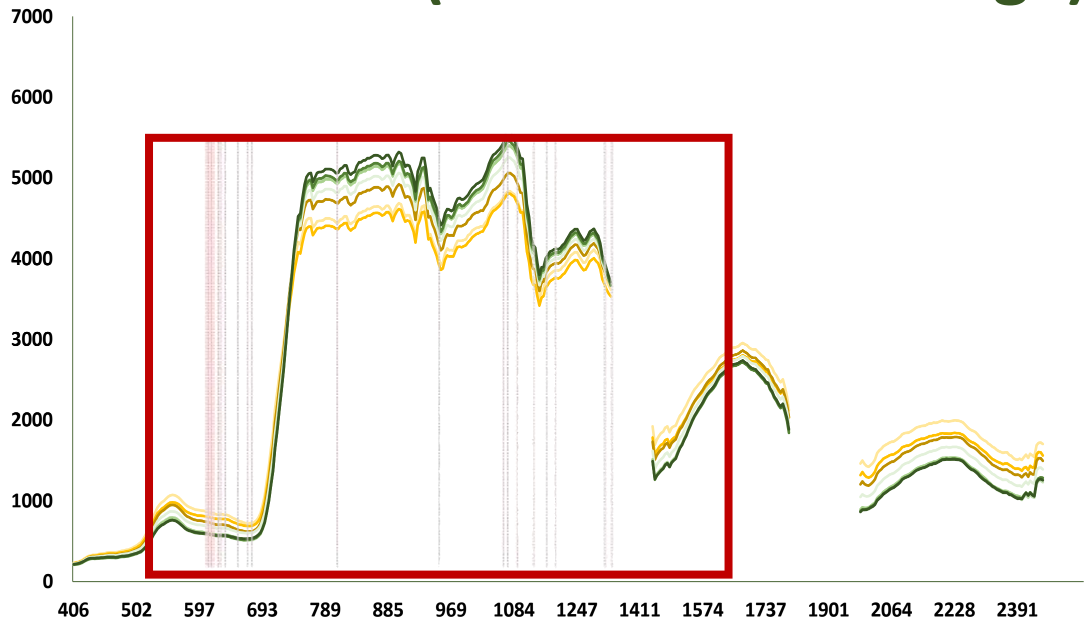
Different Wavelengths Correlate With Leaf Nitrogen Content (%) at Different Growth Stages

Kidney Beans

42 DAP (R1 Growth Stage)



50 DAP (R2-R3 Growth Stage)



22 Kg N Ha-1 56 Kg N Ha-1 84 Kg N Ha-1 112 Kg N Ha-1 140 Kg N Ha-1 168 Kg N Ha-1 196 Kg N Ha-1 224 Kg N Ha-1

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Prediction of In-Season Leaf N (%) (R^2)

Kidney Beans

Growth Stage	R1	R2-R3
DAP	42	50
20 Best Wavelengths + G + E + M	0.578	0.513
20 Best Wavelengths + G	0.564	0.514
20 Best Wavelengths + E	0.568	0.514
20 Best Wavelengths + M	0.580	0.511
20 Best Wavelengths	0.570	0.512

Discussion & Conclusion

- Higher N resulted in:
  - Higher bean yield, but the response is variety-dependent
  - Higher total N% in leaves
  - Different spectral signatures in plant canopies

- Machine learning algorithm can simulate snap bean and kidney bean response to different N fertilization treatments, but need both GEM and plant spectral signatures for better prediction results

- Snap beans and kidney beans showed difference in response to N and their spectral signatures


YELLOWSTONE


MONCLER


LAWN ENFORCEMENT OFFICER
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USDA NIFA

United States Department of Agriculture
National Institute of Food and Agriculture

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