EUROPEAN UNION

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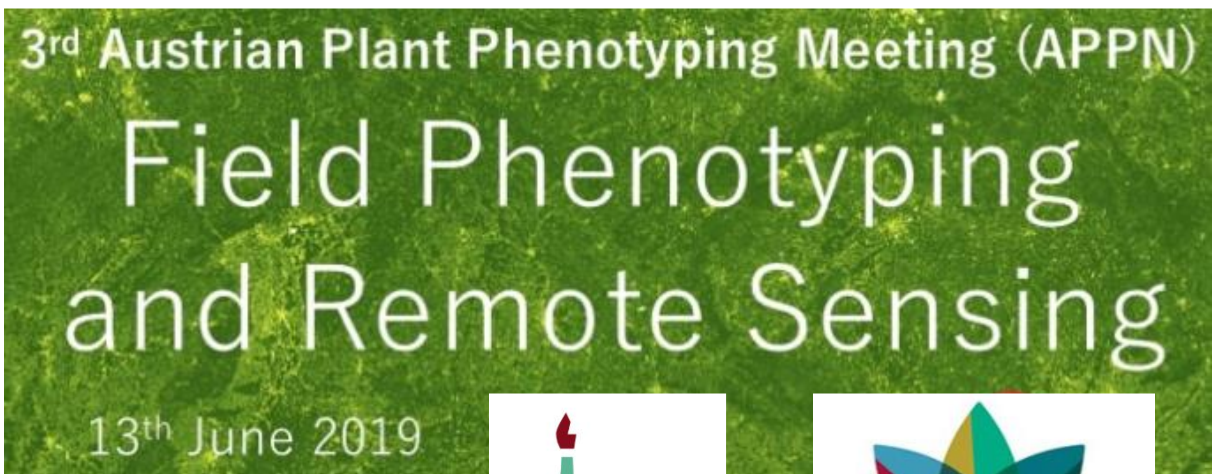
Interreg
EUROPEAN UNION
Austria-Czech Republic
European Regional Development Fund

Field crops phenotyping – disease and yield by spectral sensing



המעבדה לחישת צמחים
The Plant Sensing Lab
مختبر استشعار النبات

THE HEBREW UNIVERSITY OF JERUSALEM

The Robert H Smith
Faculty of Agriculture, Food and Environment

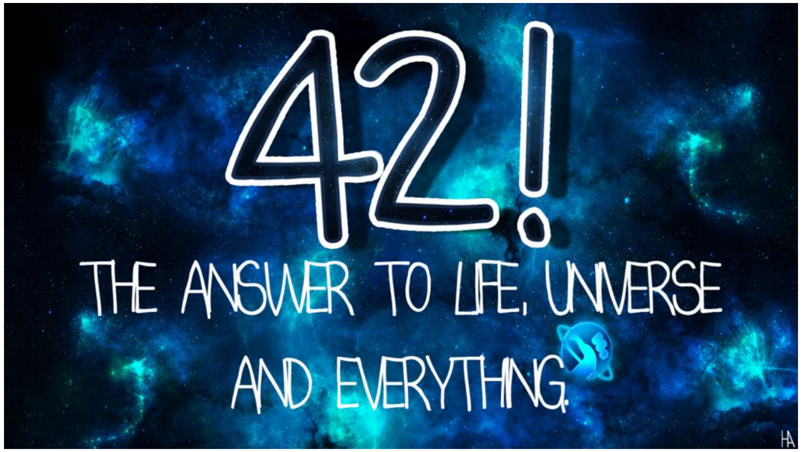
Ittai Herrmann

The essence

Trait assessment is part of a structure:

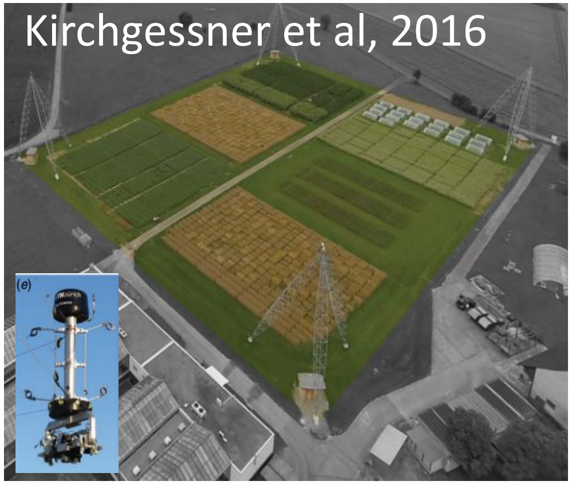
1. Data collection
2. Data analyses
3. Conclusions – for Breeding
4. For Precision Agriculture:
   - ✓ Spatial Decision Support Systems
   - ✓ Variable rate application

Hyperspectral sensing is an efficient research tool but it might not be the answer to life, universe and everything…..
Data fusion



The Hitchhiker's Guide to the Galaxy / Douglas Adams

High throughput phenotyping



http://www.publish.csiro.au/fp/pdf/FP16165

http://www.lemnatec.com/science/phenotyping/

https://www.youtube.com/watch?v=DNQPhQ0CpI0

https://www.youtube.com/watch?v=T0cPc4MCEOQ

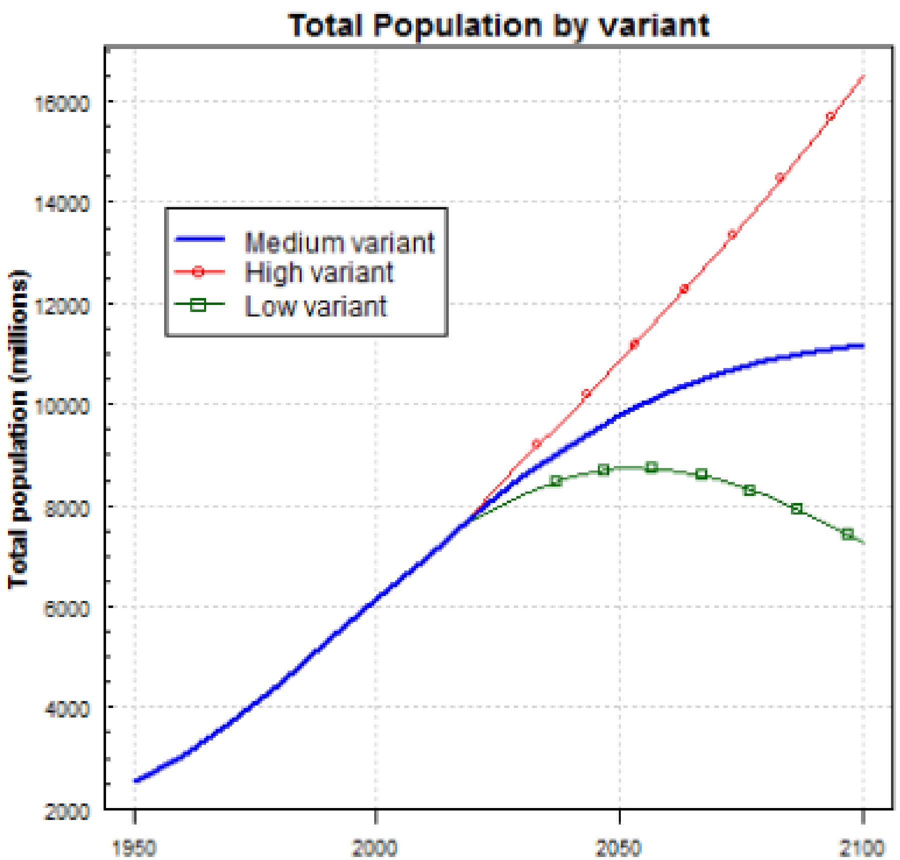
https://nph.onlinelibrary.wiley.com/doi/epdf/10.1111/nph.15817

Outline

- **Motivation & background**
- **Spectral signature of vegetation**
- **SDS and yield detection on ground**
- **Yield detection from air**

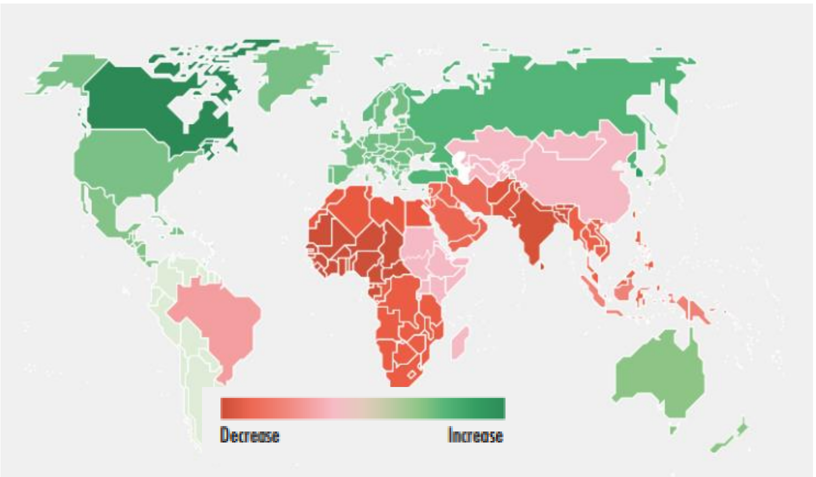
Motivation

Increase in human population together with climatic variability are a danger to global food security.



https://sites.google.com/site/ihst1110group5/home/threats-to-future-food-security

Changes in agricultural production by the year 2050.
Food and Agriculture Organization of the United Nations

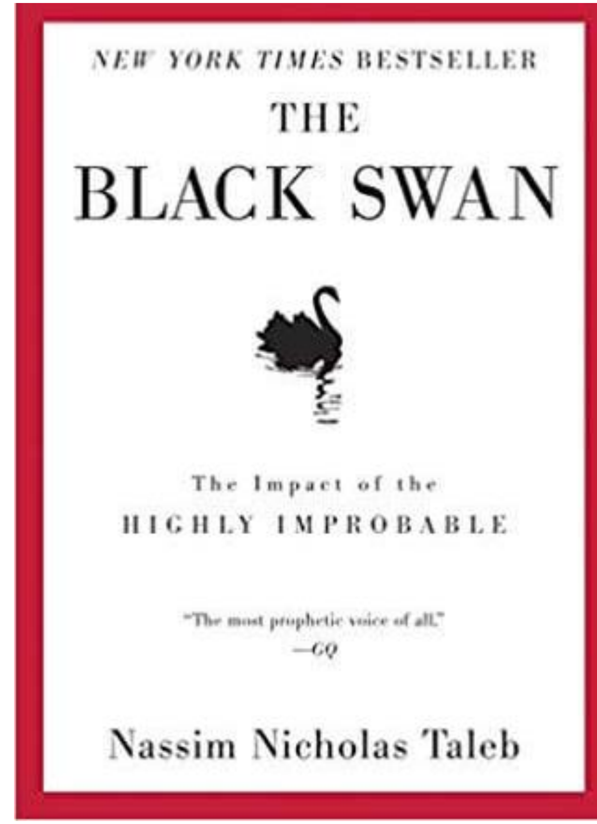


https://www.cnbc.com/2018/09/17/un-report-shows-climate-change-effect-on-farming.html

Black Swan

1000 white swans => no black swans.

- Unpredictable outlier.
- Extreme impact.
- Retrospective – rationalizing an explanation.



Personal Computers & Internet for Agriculture

https://www.kidsdiscover.com/shop/issues/medicine-for-kids/

Penicillin 1928

Dust Bowl 30's

https://www.smithsonianmag.com/science-nature/are-we-headed-for-another-dust-bowl-129556121/

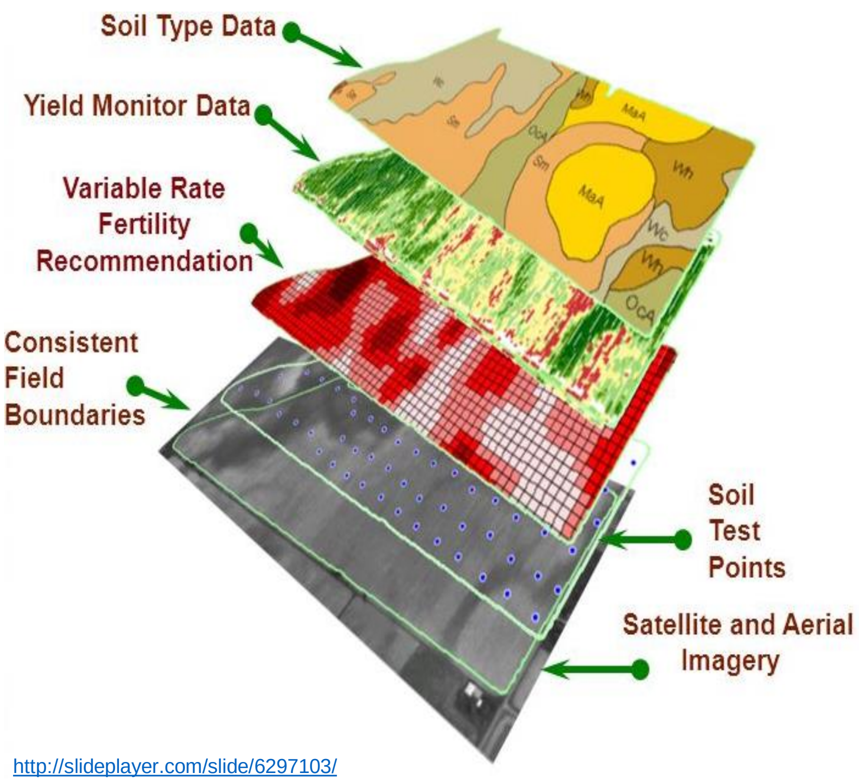
Agronomical practices and breeding are increasing yield.

Precision agriculture allows improved efficiency in food production and reduces environmental impact.

Rapid and precise phenotypic assessment accelerates the development of new and improved cultivars.

http://www.polaris-emp.eu/index.php?action=fiche_thematique&id=297&lang=en

https://i.pinimg.com/originals/73/95/ab/7395ab324eea187f3839dc06a499f95d.jpg



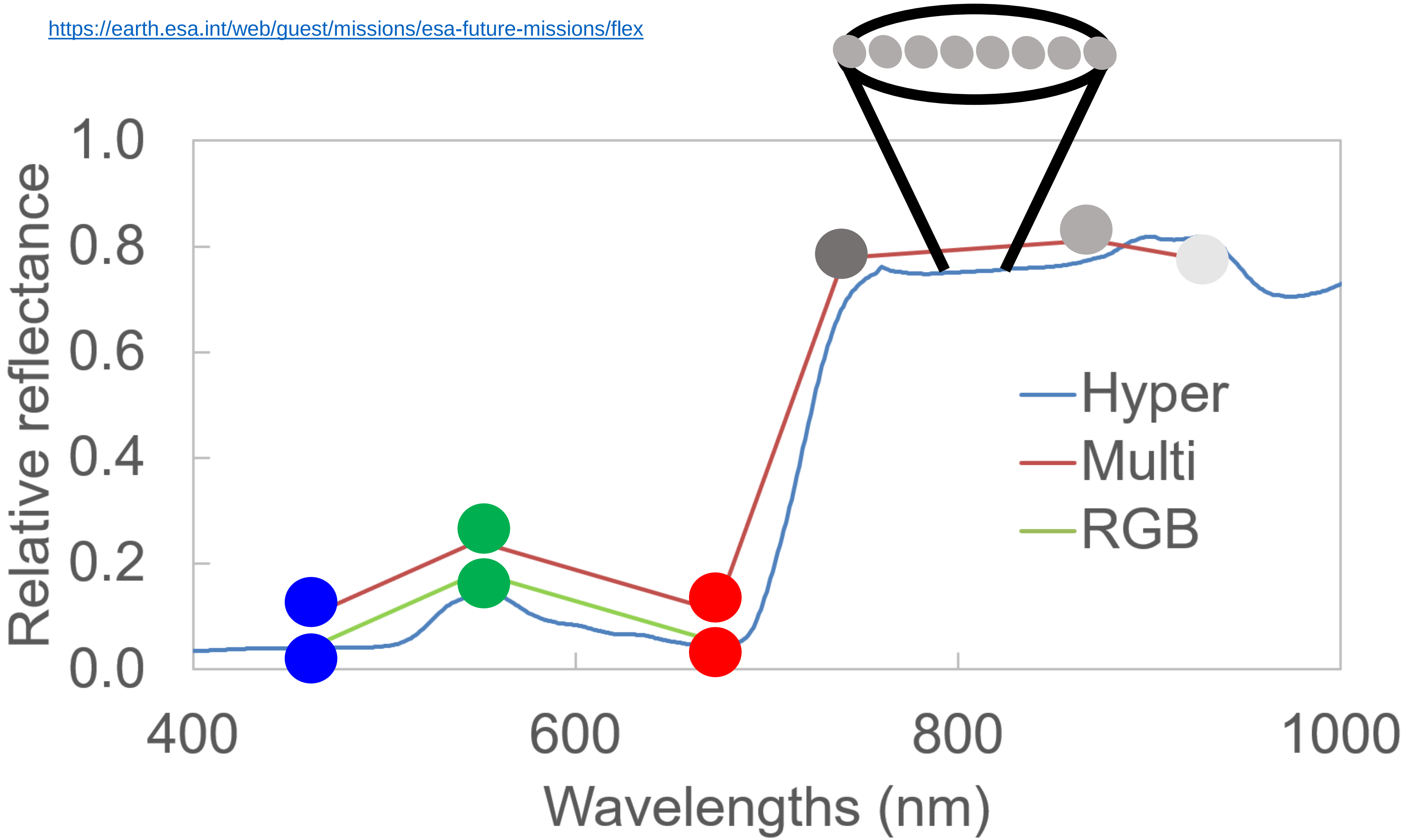
http://slideplayer.com/slide/6297103/

Kefauver et al. (2017) Frontiers in plant science

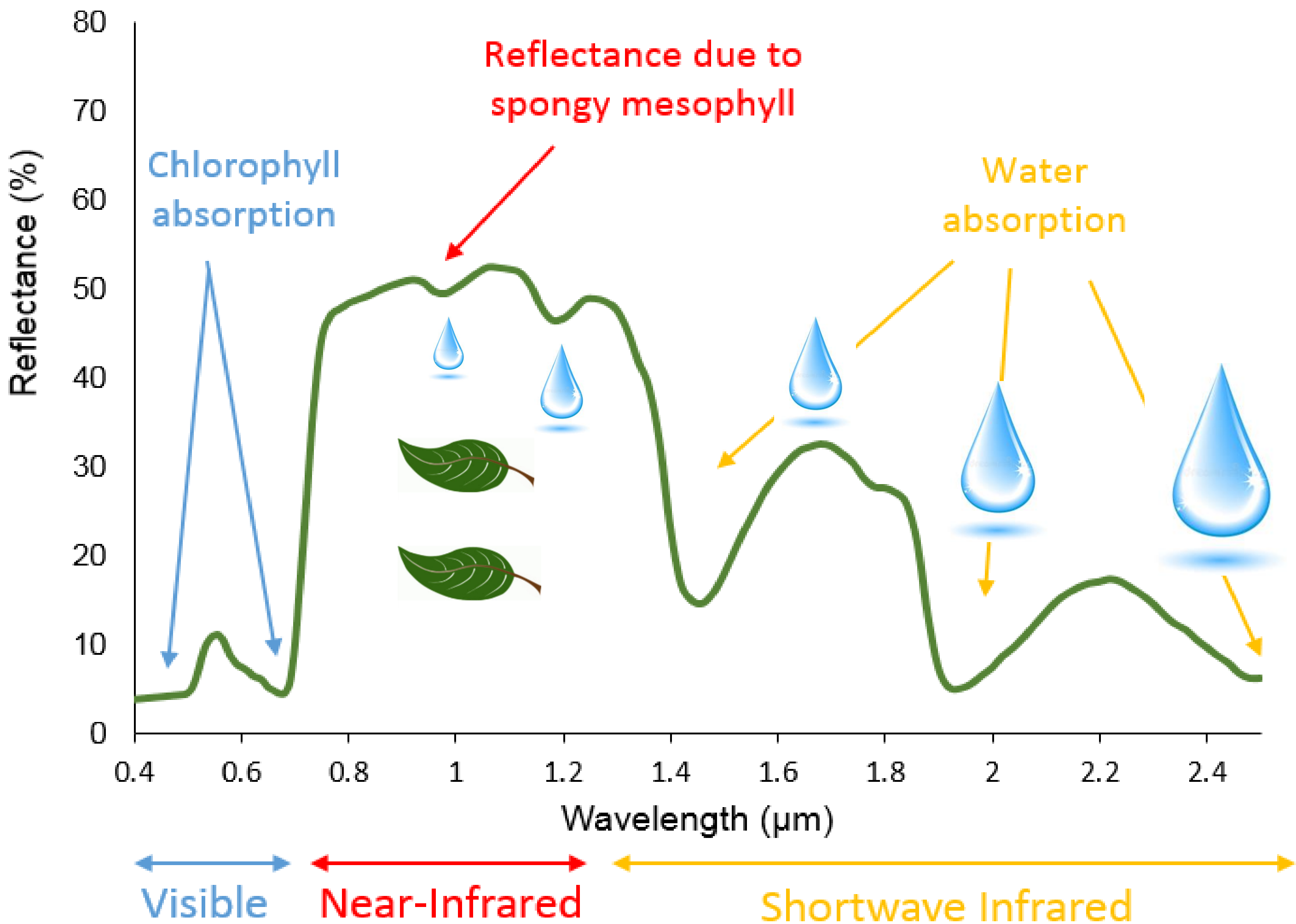
Spectral resolution

The Earth Explorer - Fluorescence Explorer (FLEX) mission (2022) will map vegetation fluorescence to quantify photosynthetic activity.

https://earth.esa.int/web/guest/missions/esa-future-missions/flex



Spectral signature of vegetation



Chemical and physical properties of the vegetation are affecting light interaction, the hyperspectral data is the pool of all traits (Jetz et al. 2016; Townsend et al. 2016).

http://gsp.humboldt.edu/OLM/Courses/GSP_216_Online/lesson2-1/vegetation.html

To answer a research question resolutions are to be chosen

- Spatial: 1mm (and less) – 30m (and more).
- Spectral: 1band and more.
- Temporal: continuous – whenever.

https://www.nasa.gov/sites/default/files/thumbnails/image/ed12-0345-09.jpg

"You can't always get what you want" (Jagger et al., late 60s)

….but…

"It's getting better all the time" (Lennon et al., late 60s)

How early can the effect of sudden death syndrome on soybean plants be detected?

- Spectral – hyperspectral.
- Spatial – canopy and leaf.
- Temporal – weekly.

Sudden death syndrome (SDS) of soybeans

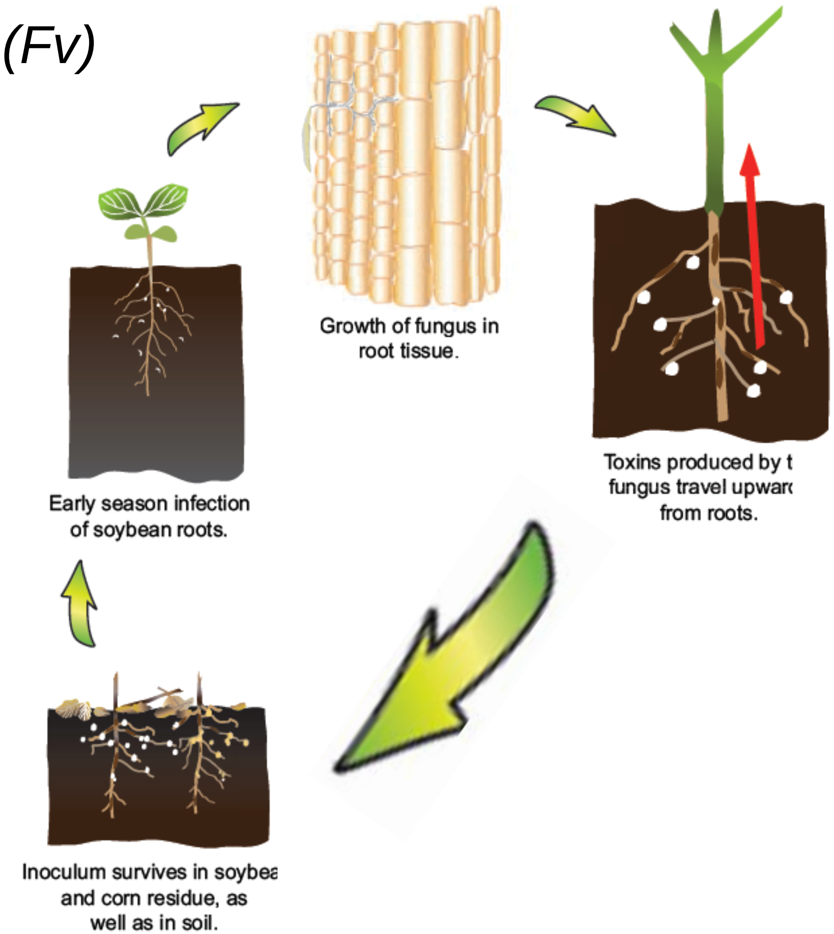
The pathogen is - *Fusarium virguliforme (Fv)*

There is no treatment after seed infection.

Early detection of the disease can allow early gene detection as a tool for resistance detection and developing resistant varieties.

Preventive management can include: late planting date, resistant varieties, crop rotation and seed treatments.

Yield can be affected despite low levels of visible canopy symptoms.

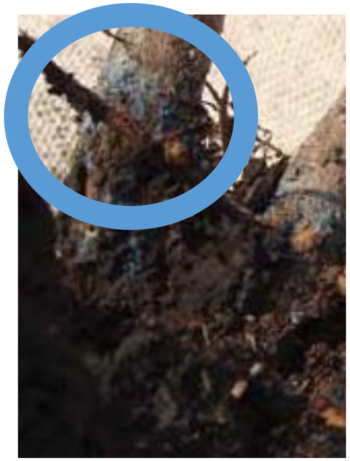


http://cropprotectionnetwork.org/soybean/sds/

Sudden death syndrome (SDS) of soybeans

SDS identification:

- Blue fungus on the roots – often not visible in dry soil.
- Cut the root open (right – infected; left – healthy), similar to other root infections.
- Check the canopy – can be infected with little or no visible canopy symptoms.
- Laboratory analysis – quantitative real-time polymerase chain reaction (qPCR).



http://www.coolbean.info/library/documents/Corn_Soy_Expo_14.pdf

http://www.apsnet.org/edcenter/intropp/lessons/fungi/ascomycetes/pages/suddendeath.aspx

Piccolo

Flame 350 – 1020 nm ; 1 nm resolution.
NIRQuest 900 – 1700 nm ; 1 nm resolution.

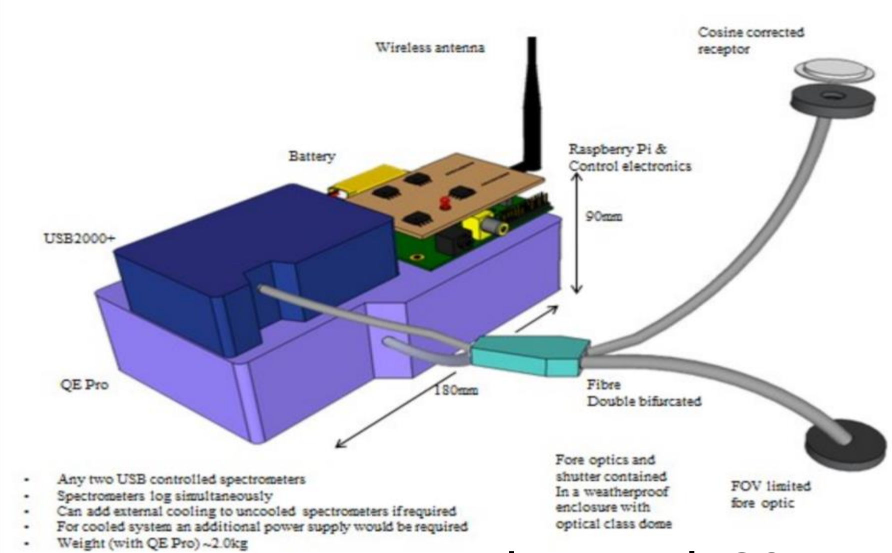
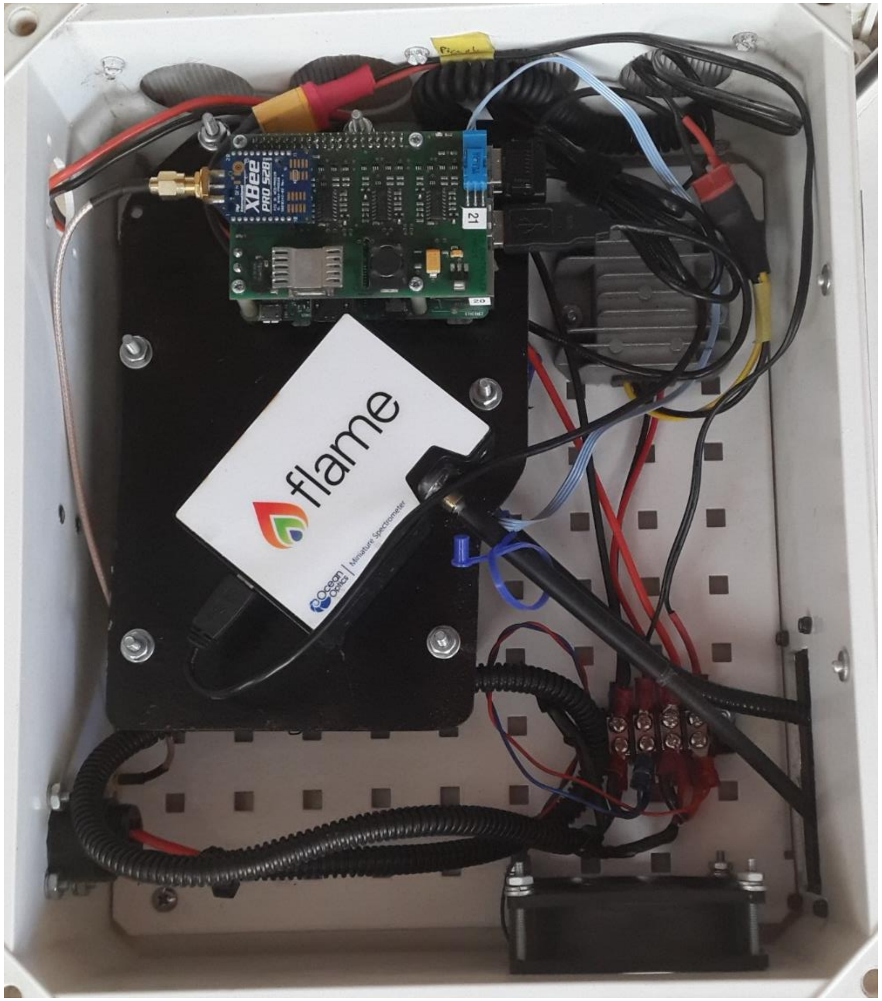


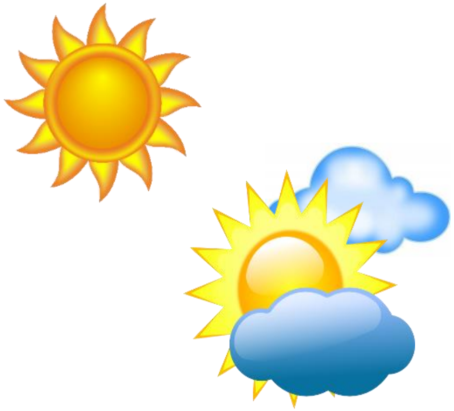
Figure 2 Piccolo doppio schematic

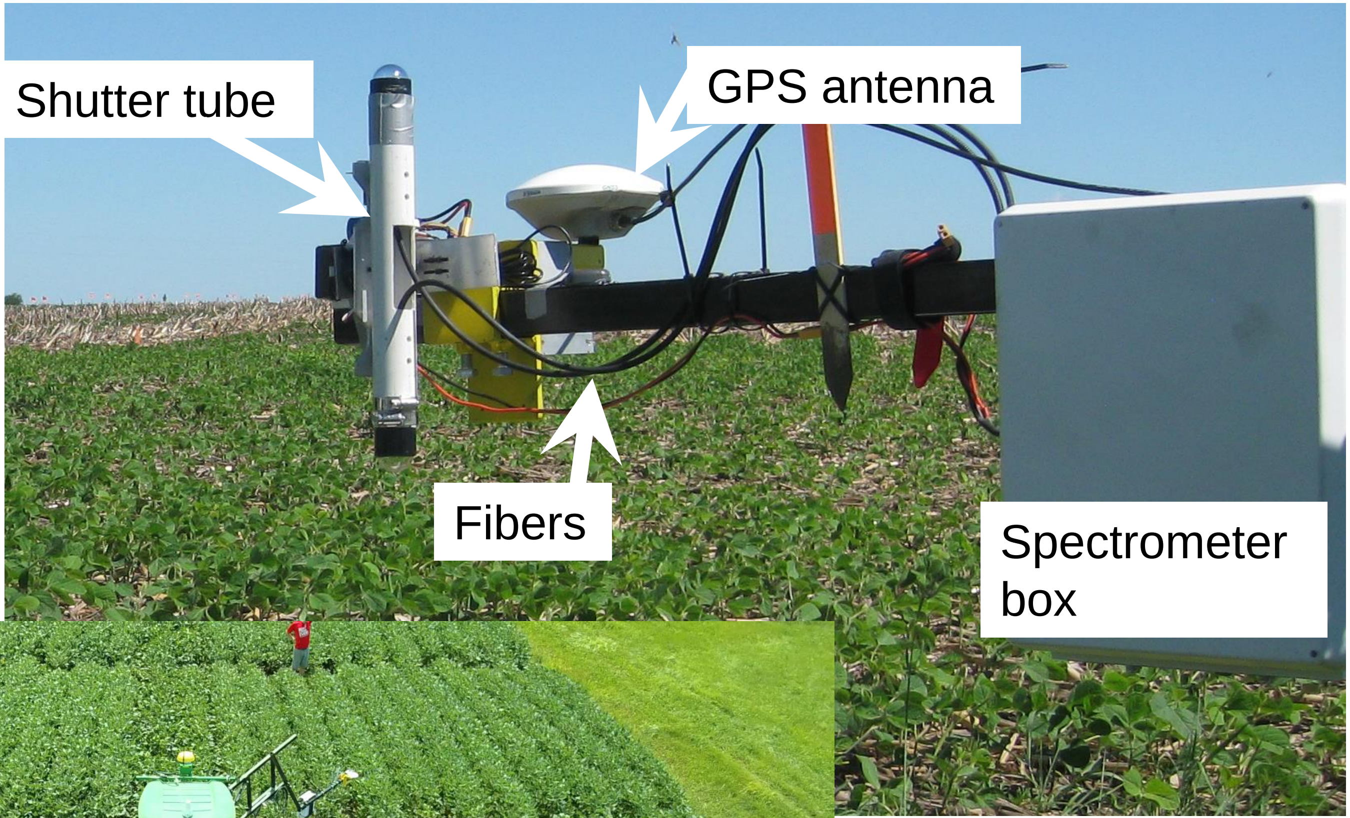
Mac Arthur et al. 2014



http://www.research.ed.ac.uk/portal/files/17385047/A_DFOV_spectrometer_system_for_reflectance_and_fluorescence_Piccolo_.pdf

Canopy data





Video by John Gaska

Leaf data - Arlington & Hancock – 500 plants

Ability to spectrally detect plants that are infected but not showing symptoms is attempted.
Roots sampled for qPCR

1 variety
1 planting date
2 inoculation treatments (250 plants each)
9 measuring dates along the season

https://www.asdi.com/products-and-services/accessories/leaf-clip

PLS - partial least squares

PLS models can deal efficiently with the multi-collinearity present among the wavelengths, and analyze spectra when the number of wavelengths is either larger or smaller than the number of observations (Atzberger et al., 2010; Wold et al., 2001).

- PLS-R - regression → assessment of quantitative trait.
- PLS-DA - discriminant analyses → classification.

Classification – canopy

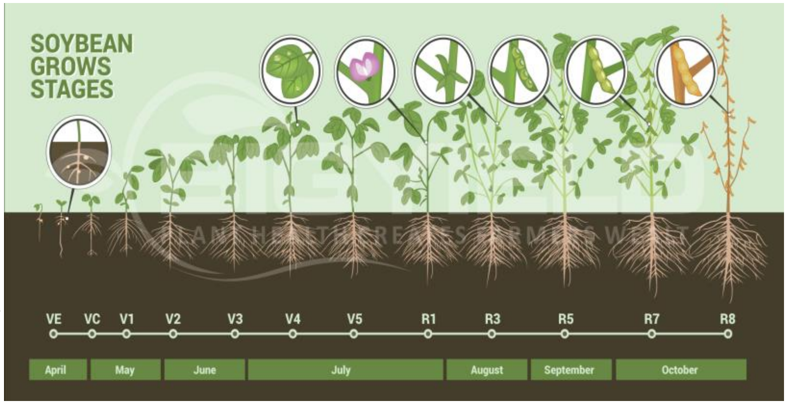
PLSDA model	% Total accuracy (# samples; Kappa)		
	Calibration	Cross-validation	Validation
All dates	62 (527;0.25)	58 (228; 0.17)	63 (252; 0.26)
All vegetative stages	76 (200; 0.52)	70 (88; 0.40)	77 (96; 0.55)
All reproductive stages	65 (326; 0.30)	59 (141; 0.17)	61 (156;0.21)
18-Jul-2016	88 (74; 0.77)	79 (34; 0.57)	82 (36; 0.66)
26-Jul-2016	86 (74; 0.72)	71 (34; 0.43)	82 (36; 0.65)
18 and 26-Jul-2016	85 (150; 0.70)	68 (66; 0.35)	79 (72; 0.59)

Prior to canopy symptoms

Independent validation	Inoculated	Control	Actual # of samples per class	Producer's accuracy %
Inoculated	29.53	6.47	36	82.03
Control	8.47	27.53	36	76.47
Total # of classified samples	38	34		
User's accuracy %	77.87	81.11		79.25

Producer’s accuracy – apples classified as apples.

User’s accuracy – classified as apples - really apples.



http://mashastudio.net/portfolio/soybean-grows-stages/

Classification – leaf

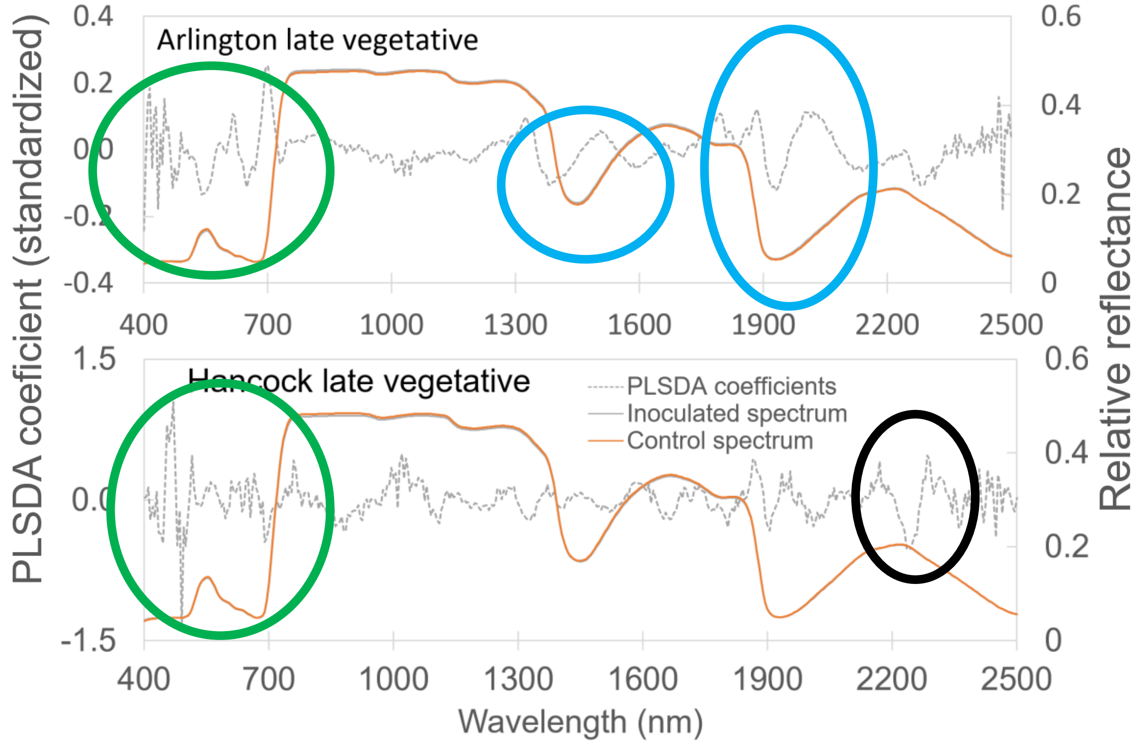
PLSDA model	Development stage	% Total accuracy (# samples; Kappa)		
		Calibration	Cross-validation	Validation
Arlington and Hancock				
All dates	V and R	67 (2531; 0.33)	63(1086; 0.25)	61 (1227; 0.21)
Vegetative stages	V	58 (903; 0.16)	56 (389; 0.12)	55 (430; 0.10)
Reproductive stages	R	76 (1626; 0.48)	70 (699; 0.40)	66 (797; 0.33)
Arlington				
All dates	V and R	76 (1255; 0.52)	71 (539; 0.43)	72 (589; 0.43)
Vegetative stages	V	74 (525; 0.48)	70 (226; 0.39)	67 (242; 0.34)
Reproductive stages	R	83 (729; 0.66)	77 (314; 0.53)	77 (347; 0.55)
Late vegetative stages	V_5 V_6	91 (263; 0.82)	87 (115; 0.74)	92 (120; 0.83)
Early reproductive stages	R_1 R_3	89 (254; 0.79)	81 (111; 0.63)	81 (131; 0.61)
Hancock				
All dates	V and R	78 (1275; 0.55)	74 (548; 0.46)	68 (616; 0.36)
Vegetative stages	V	71 (378; 0.42)	64 (163; 0.28)	63 (188; 0.26)
Reproductive stages	R	78 (897; 0.55)	75 (385; 0.48)	67 (428; 0.35)
Late vegetative stages	V_5 V_6	98 (265; 0.97)	90 (111; 0.81)	91 (132; 0.82)
Early reproductive stages	R_2 R_3	92 (263; 0.84)	82 (114; 0.64)	75 (121; 0.49)

V stands for vegetative; R stands for reproductive; numerical subscripts of V and R indicates the development stage.

Classification – leaf

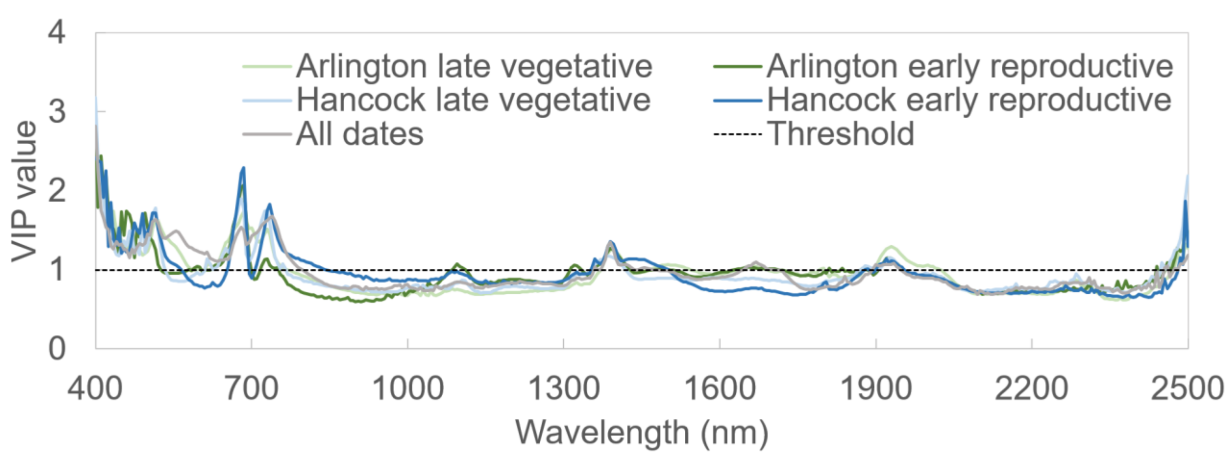
Arlington (silty and rain fed):
- Pigments & Red-edge
- Water

Hancock (sandy and irrigated):
- Pigments
- Protein & nitrogen

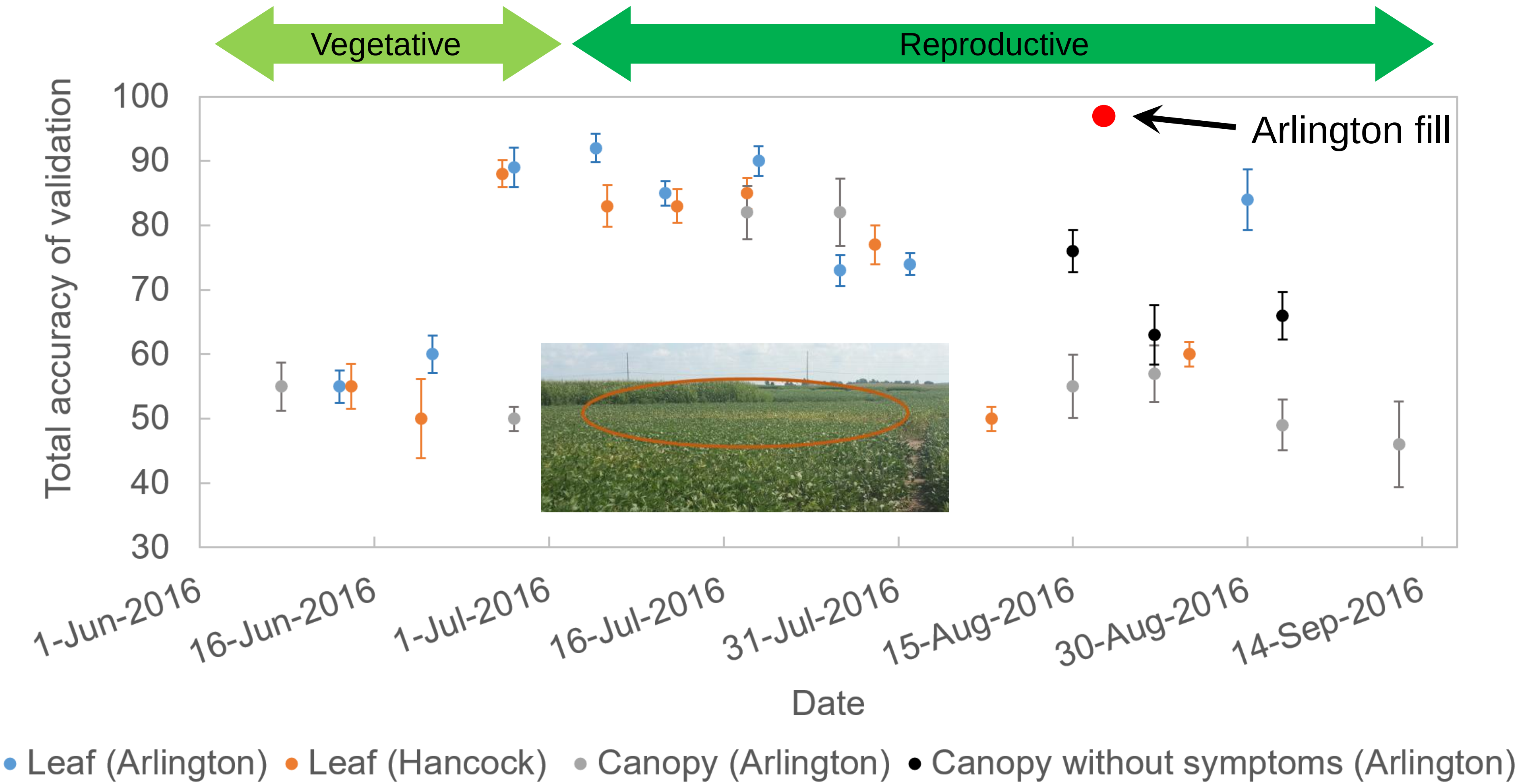


VIP:
- Pigments & Red-edge
- Water

Site specific breeding



Classification – canopy and leaf throughout the season

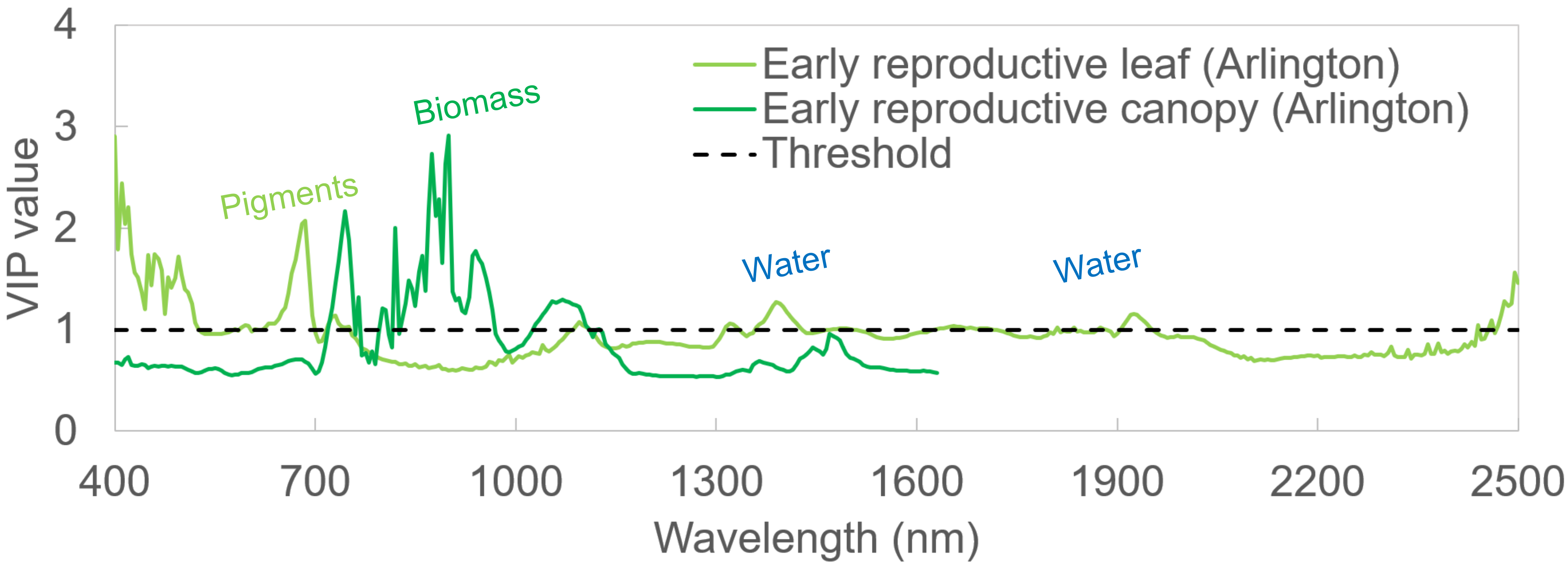


Random categorization

Classification - canopy and leaf - comparison

Canopy - classification models are mainly dependent on biomass.

Leaf - classification models are mainly dependent on pigments and water.

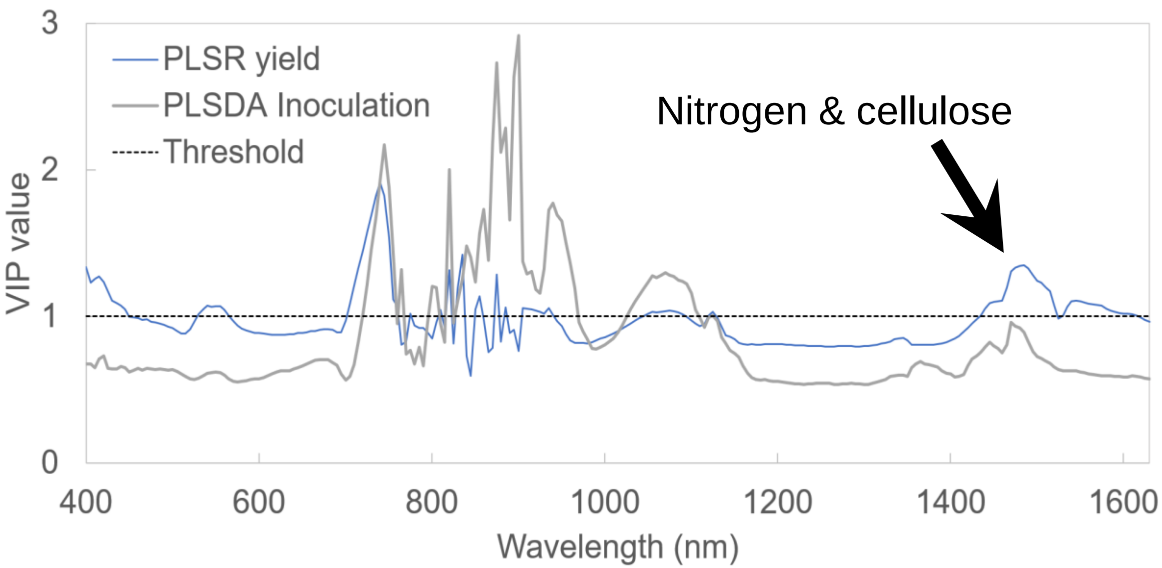


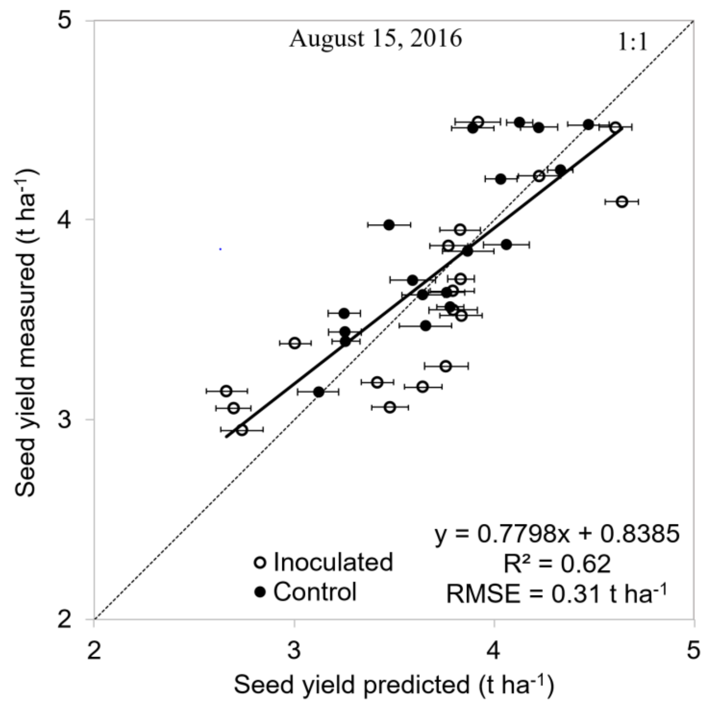
Biomass affects yield

Yield prediction – canopy

	R^2 (p<0.001)	RMSE (t ha^{-1})	# samples
Cal	0.71	0.35	73
CV	0.59	0.41	34
Val	0.62	0.31	36

Important bands for August 15, 2016

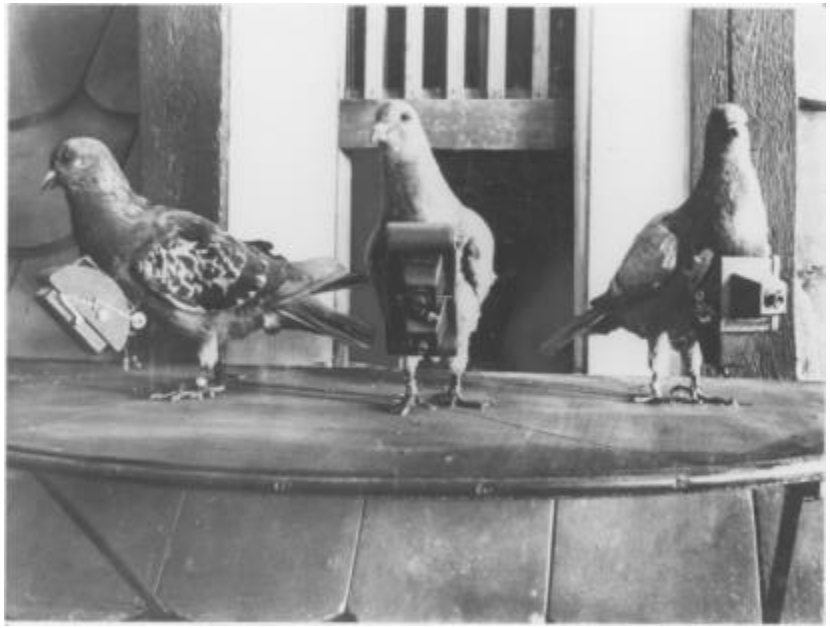




The yield prediction for non-symptomatic plots resulted in
R^2_{val} = 0.62
$RMSE_{val}$ = 0.29 t h^{-1}

Herrmann et al. 2018

Airborne imagery (1903)

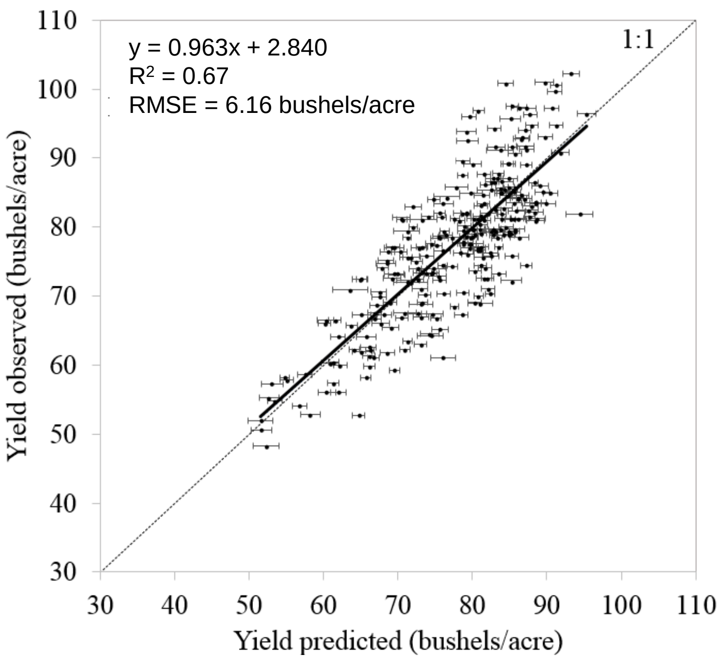


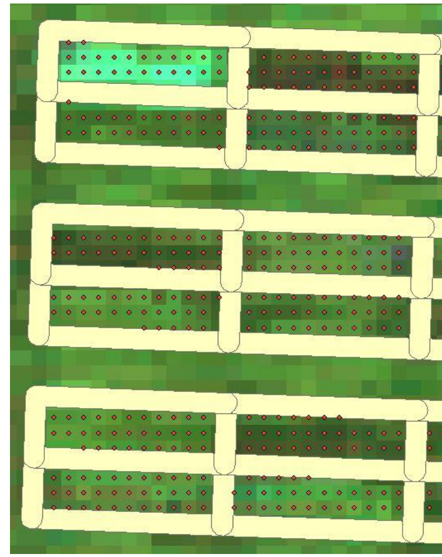
http://serc.carleton.edu/eyesinthesky2/week1/remote_sensing.html

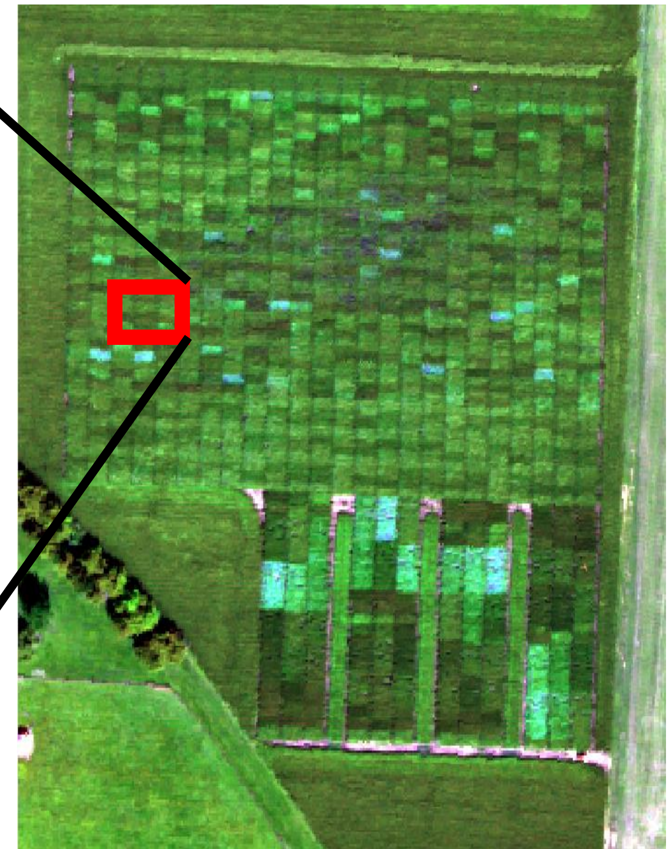
Site specific - yield prediction

AVIRIS NG – Arlington Sep. 01, 2015

Which pixel to pick?







Phil Townsend ; Shawn Conley

Can grain yield be predicted for several development stages of maize varieties under full and deficit irrigation treatments?

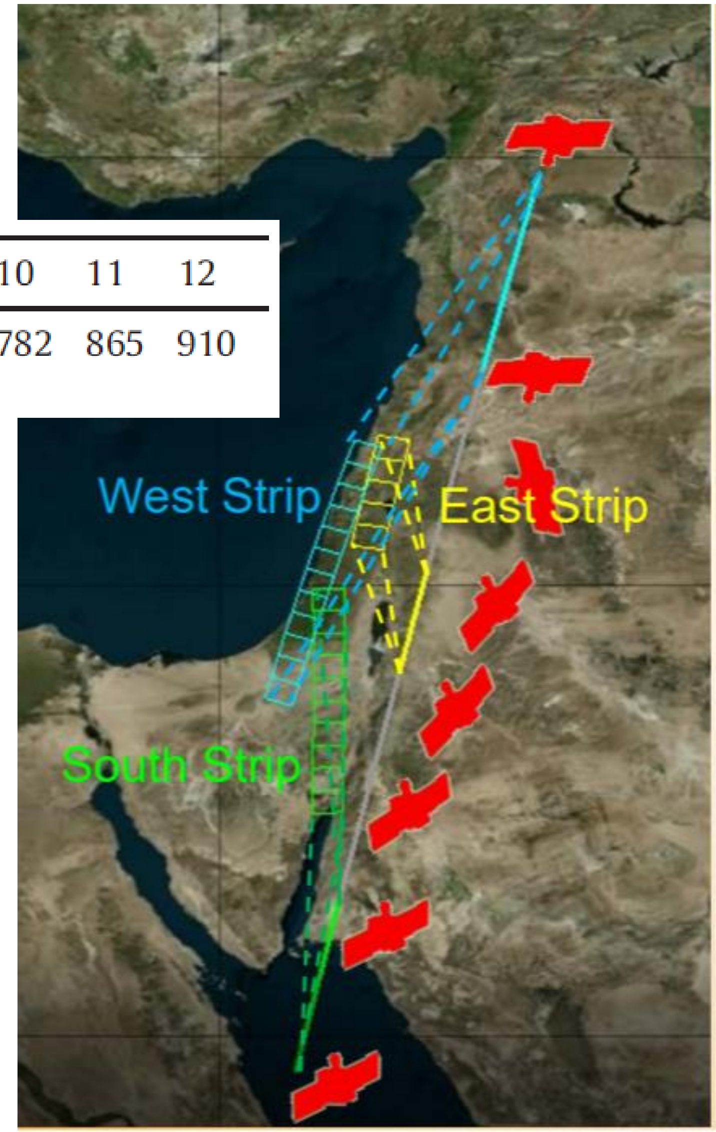
- Spectral – superspectral.
- Spatial – canopy (leaf).
- Temporal – weekly.

VENμS

Vegetation and Environmental New Micro Spacecraft

VENμS was launched in early August, 2017.

Band #	1	2	3	4	5	6	7	8	9	10	11	12
Band center (nm)	420	443	490	555	620	620	667	702	742	782	865	910

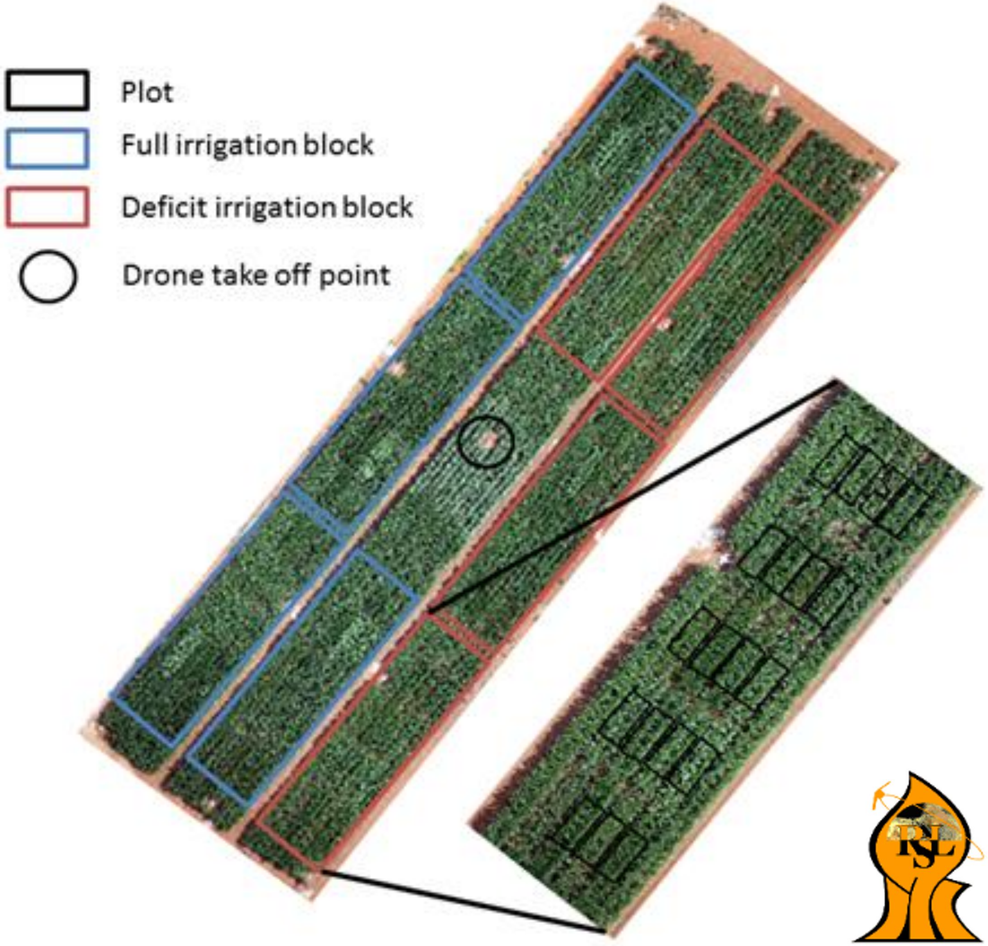


- West – 12 tiles
- East – 5 tiles
- South – 10 tiles
- **Total – 27 tiles 161 s**

Science from Above

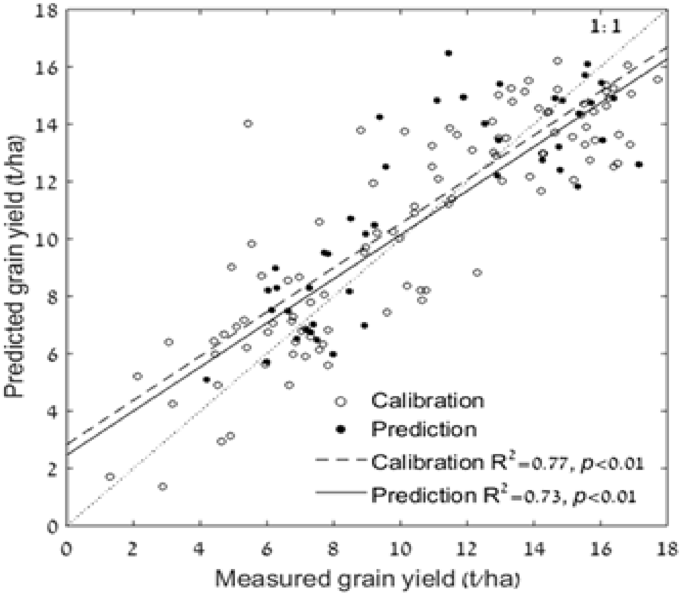
Grain yield prediction in maize

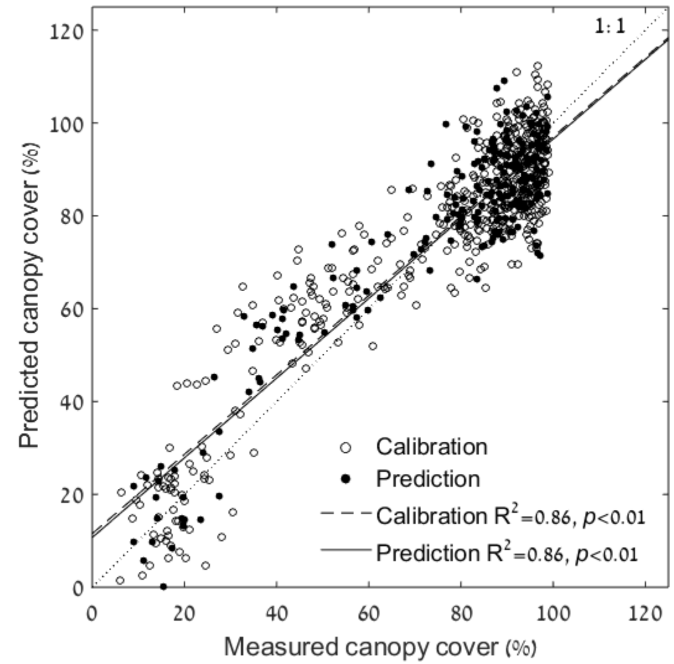
Can grain yield be predicted for several development stages of maize varieties under full and deficit irrigation treatments?

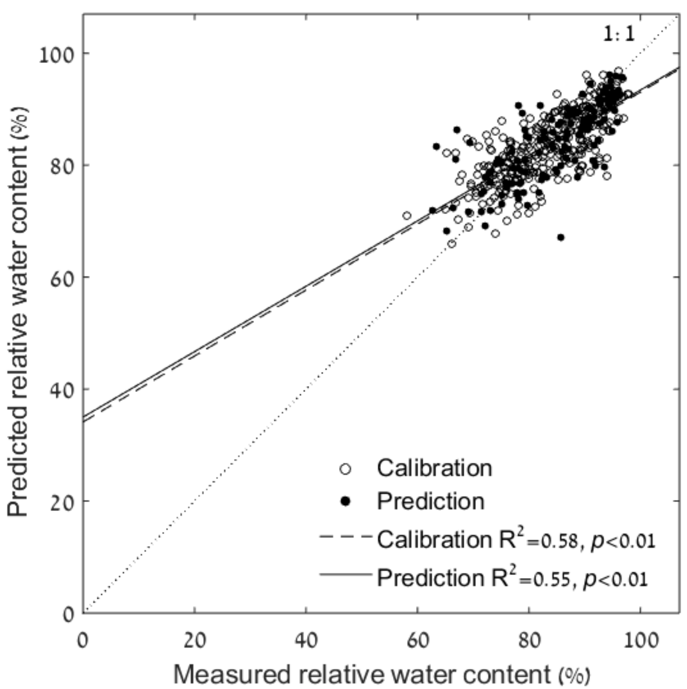


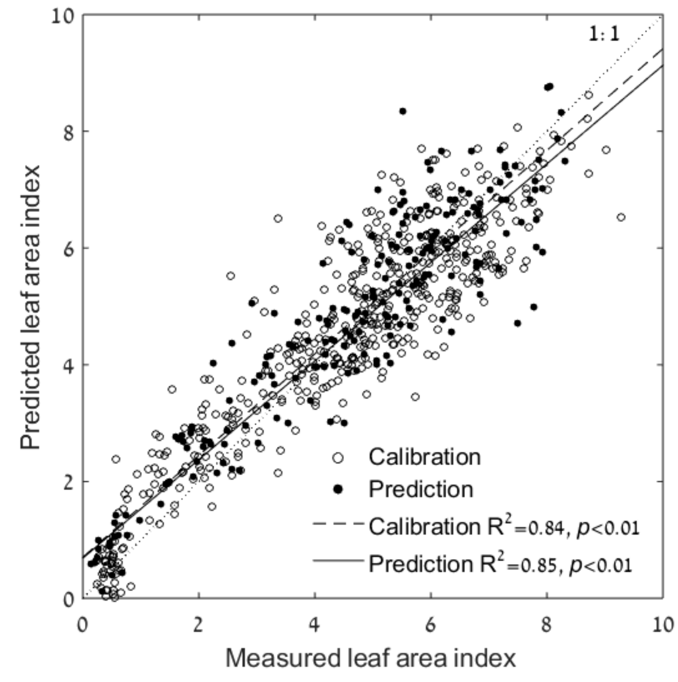
Herrmann et al. 2019

Traits spectral assessment





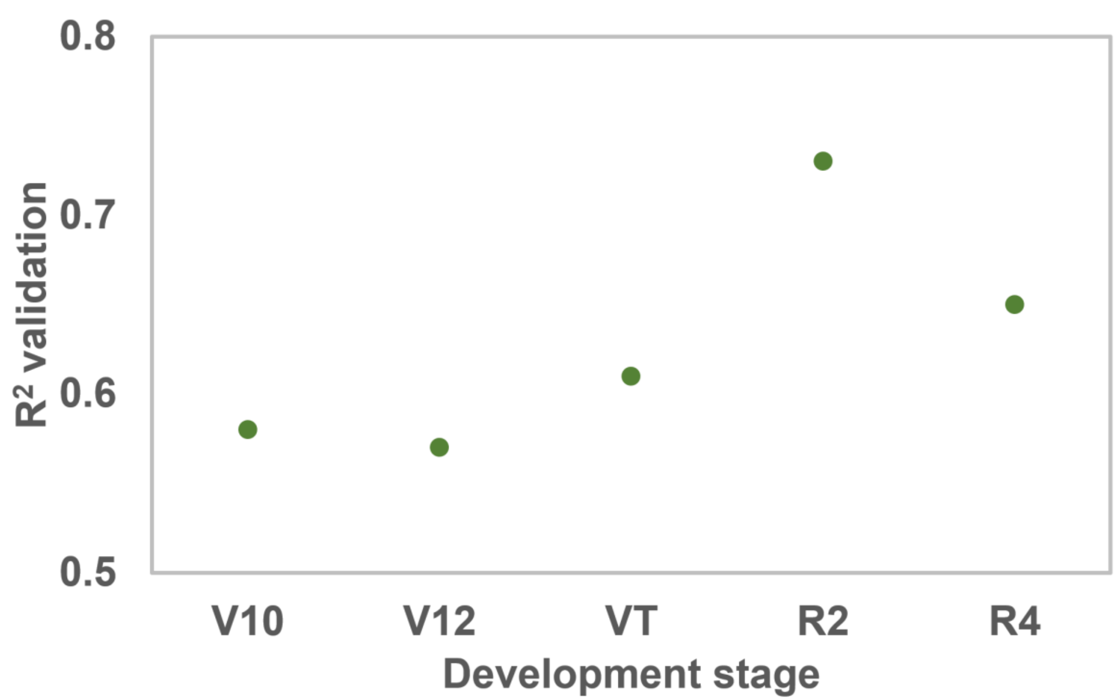




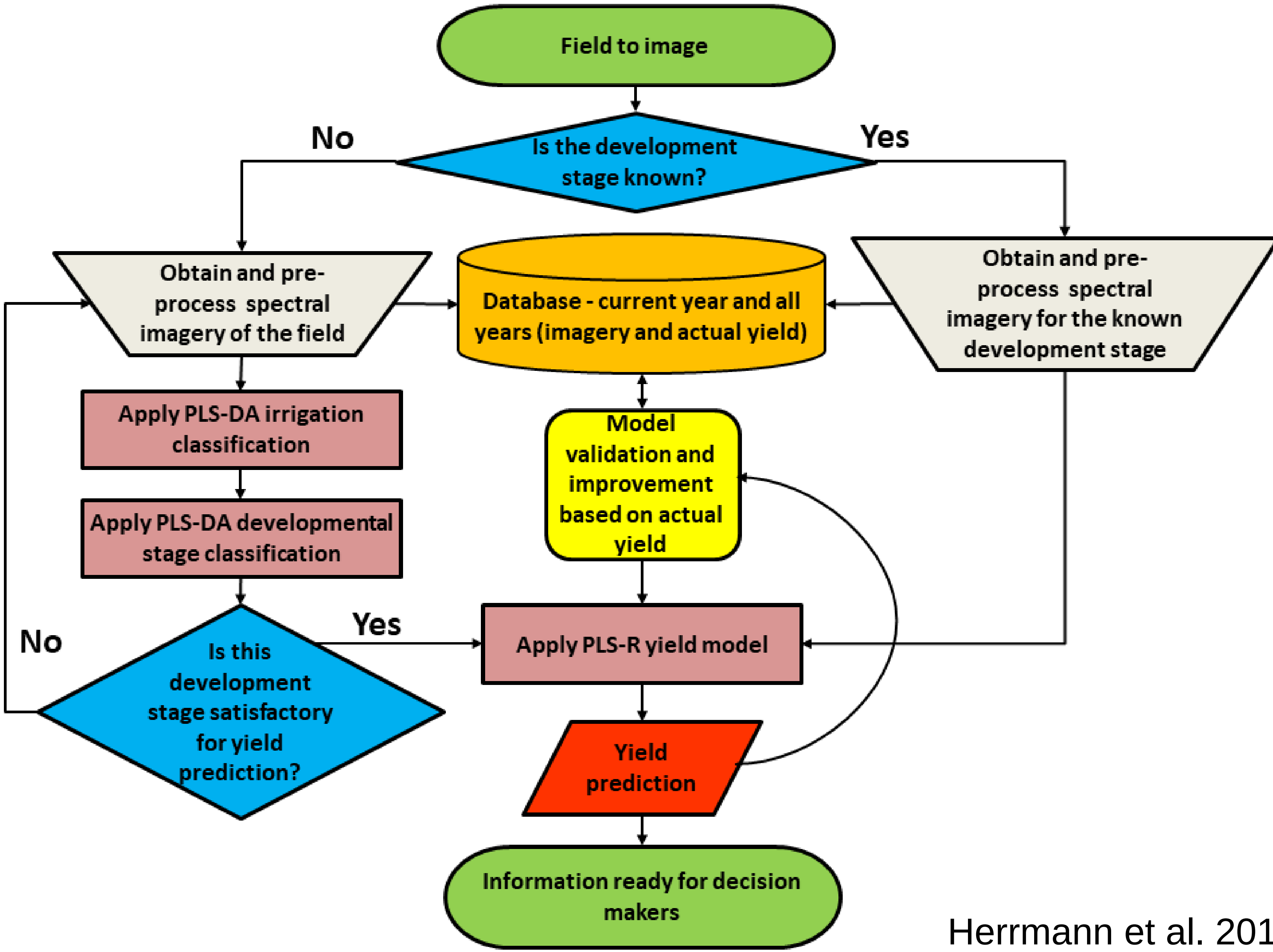
Maize traits spectral assessment

Development stage	Grain yield (t/ha)		
	CC	RWC	LAI
V10	0.17	0.08	0.17
V12	0.08	-	0.14
VT	0.02 ns	0.04	0.01 ns
R2	-	-	-
R4	0.00 ns	0.11	0.02 ns

Relation between other traits and yield

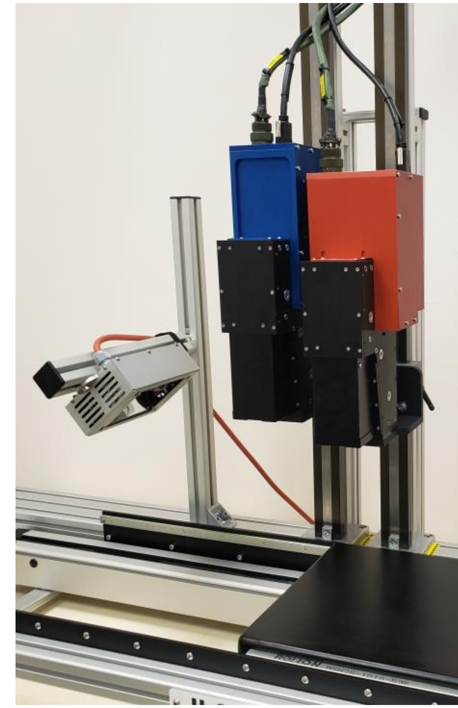


Grain yield prediction



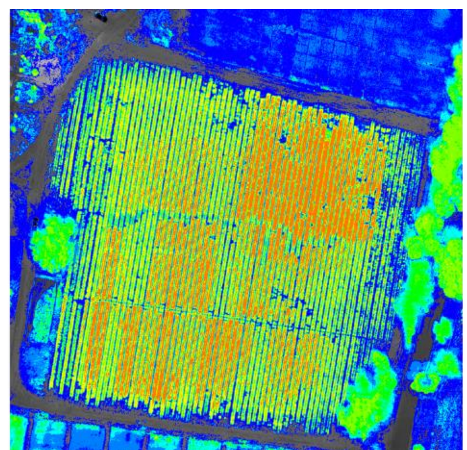
Herrmann et al. 2019

Plant Sensing Lab



Mainly interested in:

- Early stress detection.
- Sensors diversity.



Israel is an open lab for arid conditions

Looking forward for collaborations

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مختبر استشعار النبات

Pheno-IL

מוקד מחקר והוראה לפנומיקה של צמחים בתנאי עקה

Research & education facility for crop stress phenomics

منشأة الابحاث والتعليم لتشخيص النبات تحت ظروف الضرط البيئي

Acknowledgments

USA

- Steve Vosberg
- Ben Spaier
- John Gaska
- **Shawn Conley**
- **Phil Townsend**
- Clayton Kingdon
- Prabu Ravindran

Israel

- *Roy Sadeh*
- *Yaniv Tubul*
- *Rom Tarshish*
- *Prosperidad Abonete*
- *Gabriel Mulero*
- Zvi Peleg
- **Shimon Rachmilevitch**
- **Arnon Karnieli**
- Eyal Bdolach
- Yogev Montekio

Thank you

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Plant Innovation

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