New tools in plant disease assessments

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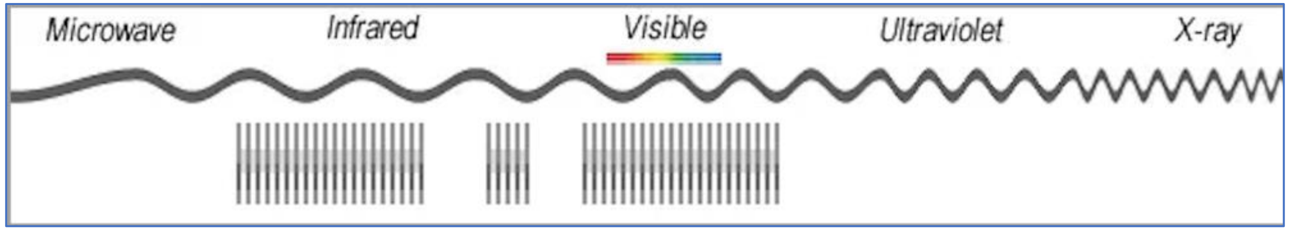
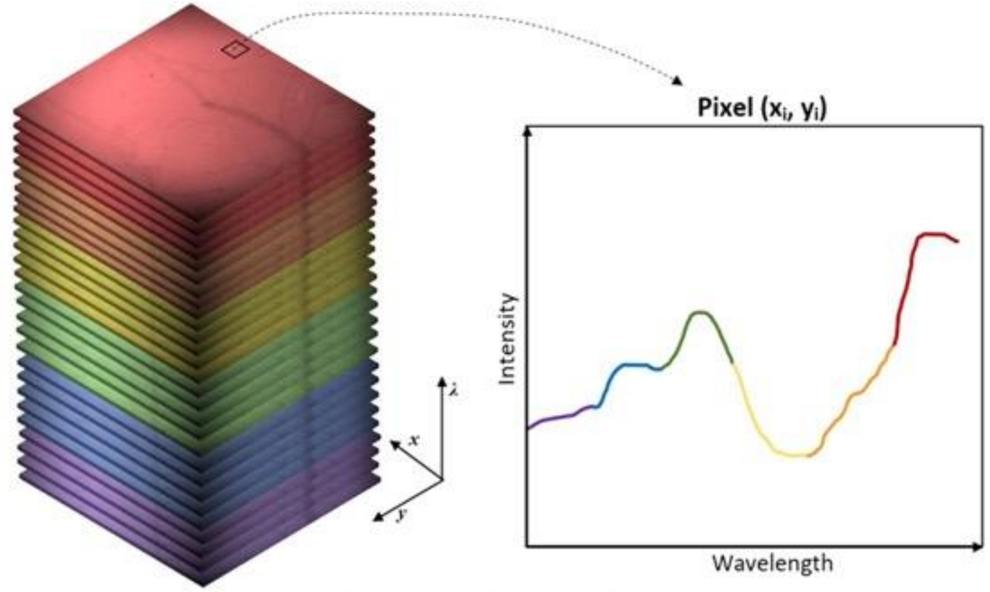
UF | IFAS
UNIVERSITY *of* FLORIDA

Hyperspectral sensor

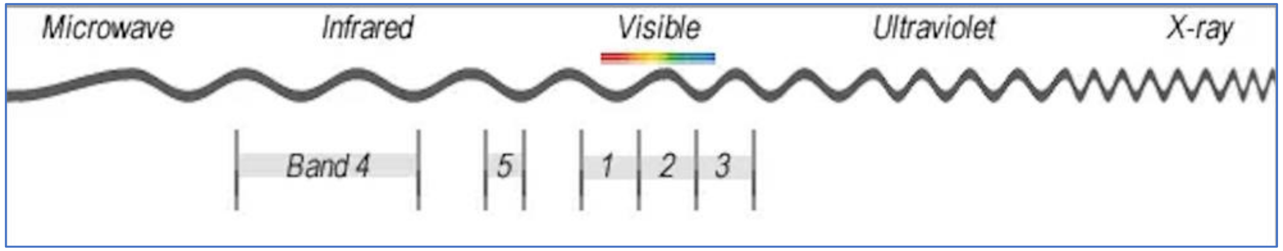


- Narrower bands (10-20 nm).
- Hundreds of bands

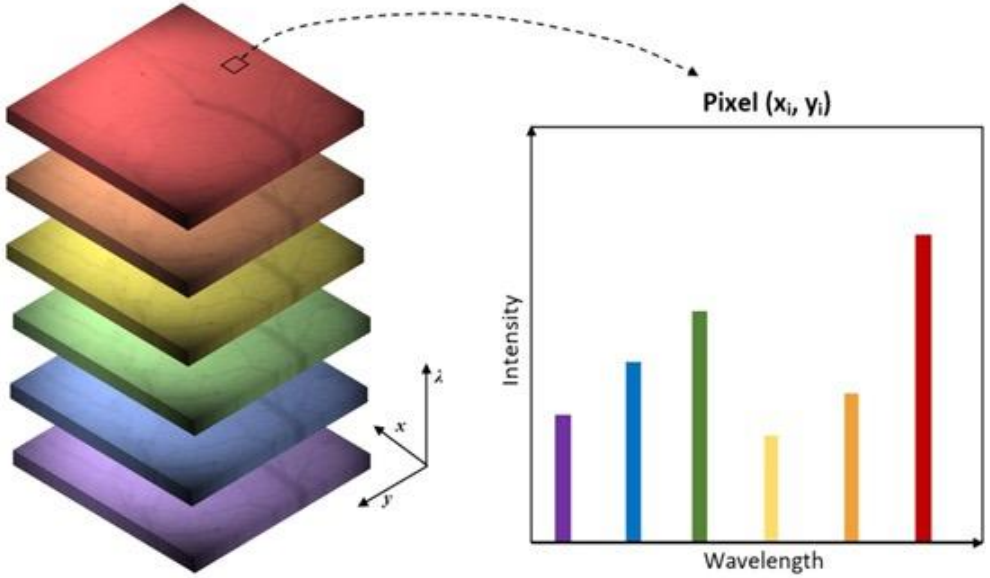


Hyperspectral imaging (HSI)

Multi-spectral sensor



- Three to ten bands
- Eg. red, green, blue, near-infrared, and short-wave infrared.



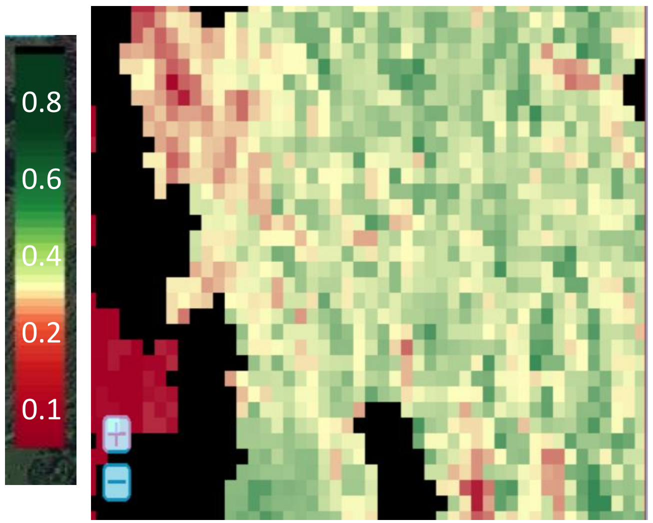
Multispectral imaging (MSI)

GISGeography.com

Giannoni et al. 2018

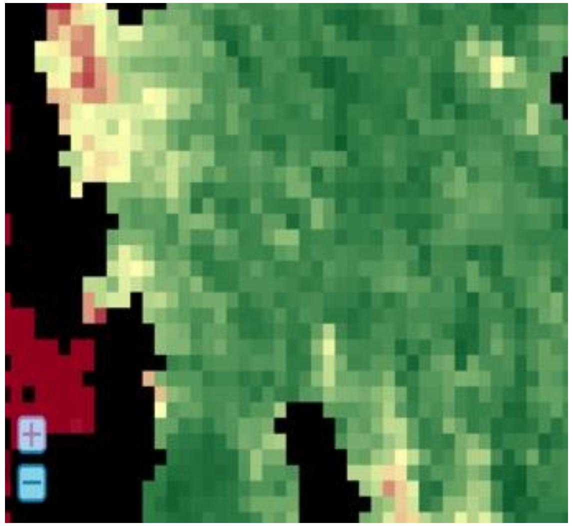
Multispectral sensor on UAV

Green NDVI - 550 nm



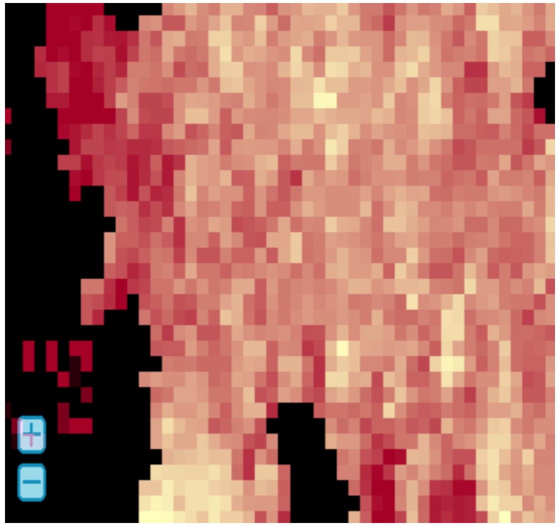
$$GNDVI = \frac{NIR - Green}{NIR + Green}$$

Red NDVI - 650 nm



$$RNDVI = \frac{NIR - Red}{NIR + Red}$$

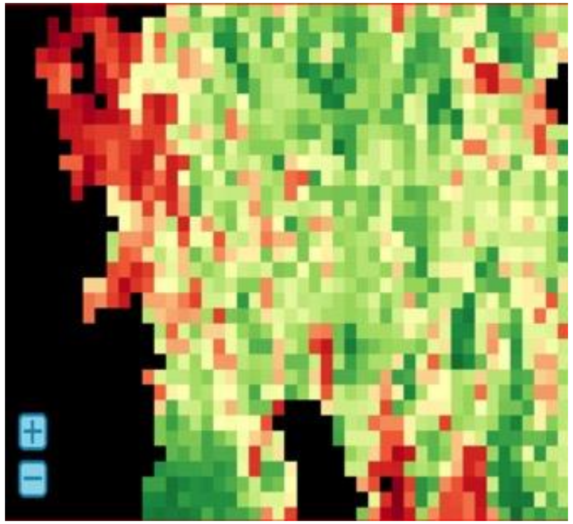
Red edge NDVI - 709 nm



$$RENDVI = \frac{NIR - Red\ edge}{NIR + Red\ edge}$$

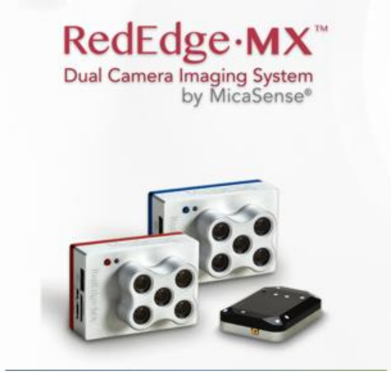
Slantrange 2p on a DJI Matrice 100

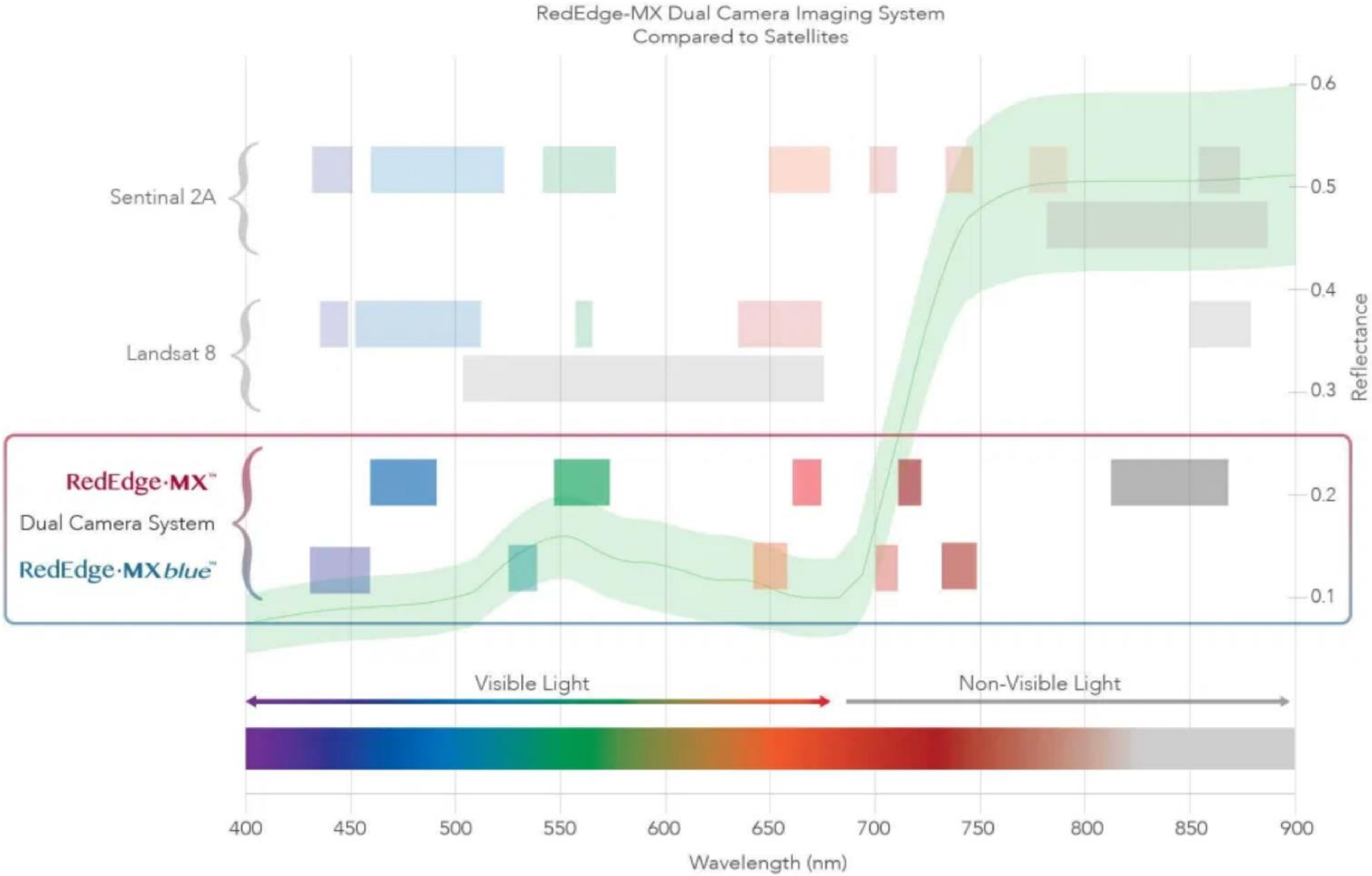
Stress Index



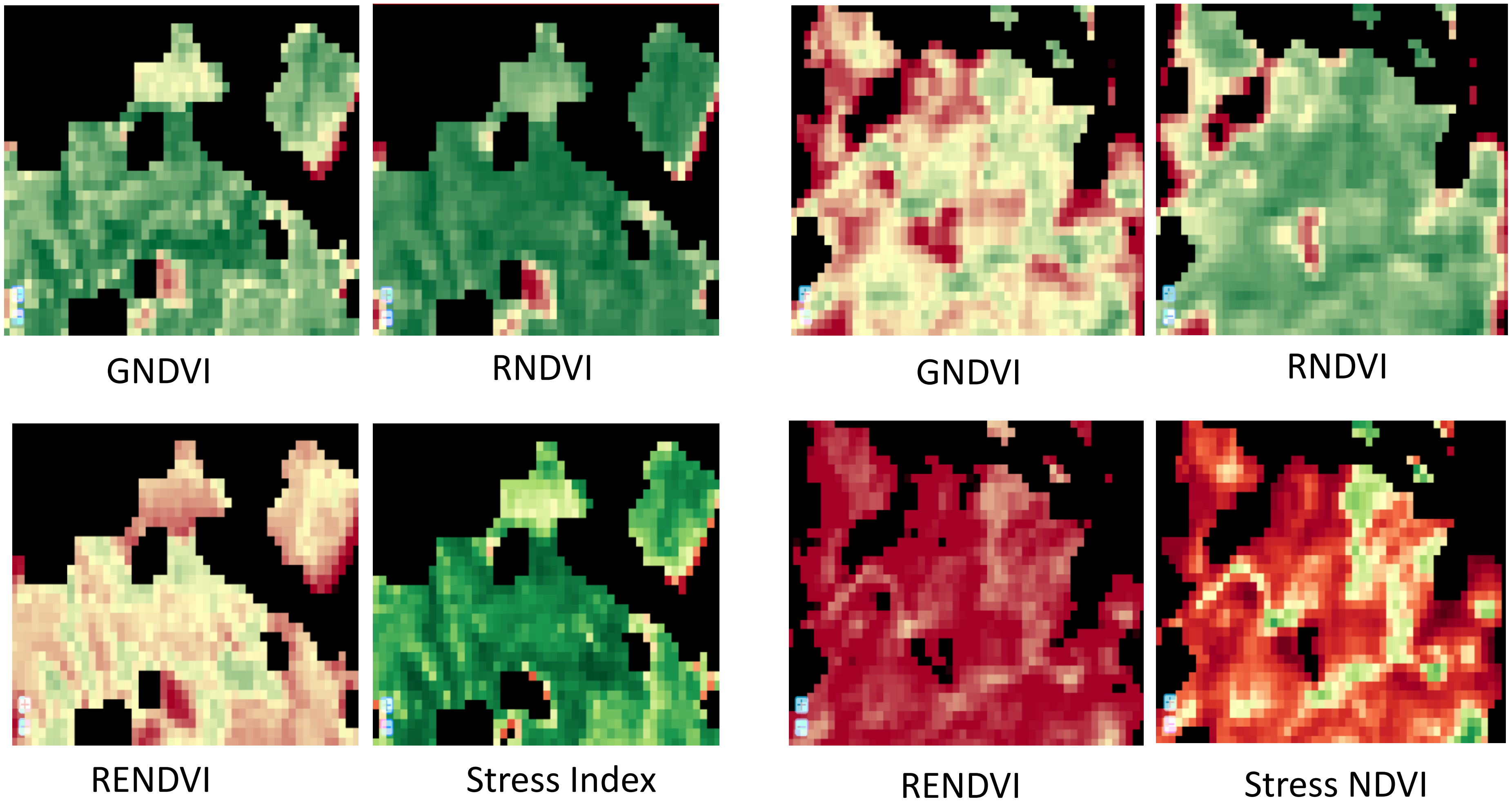
- **Vegetation Fraction (Canopy Closure)**
- Yield Potential
- and others

DIRECT DATA COMPARISON BETWEEN SATELLITE AND DRONE IMAGERY



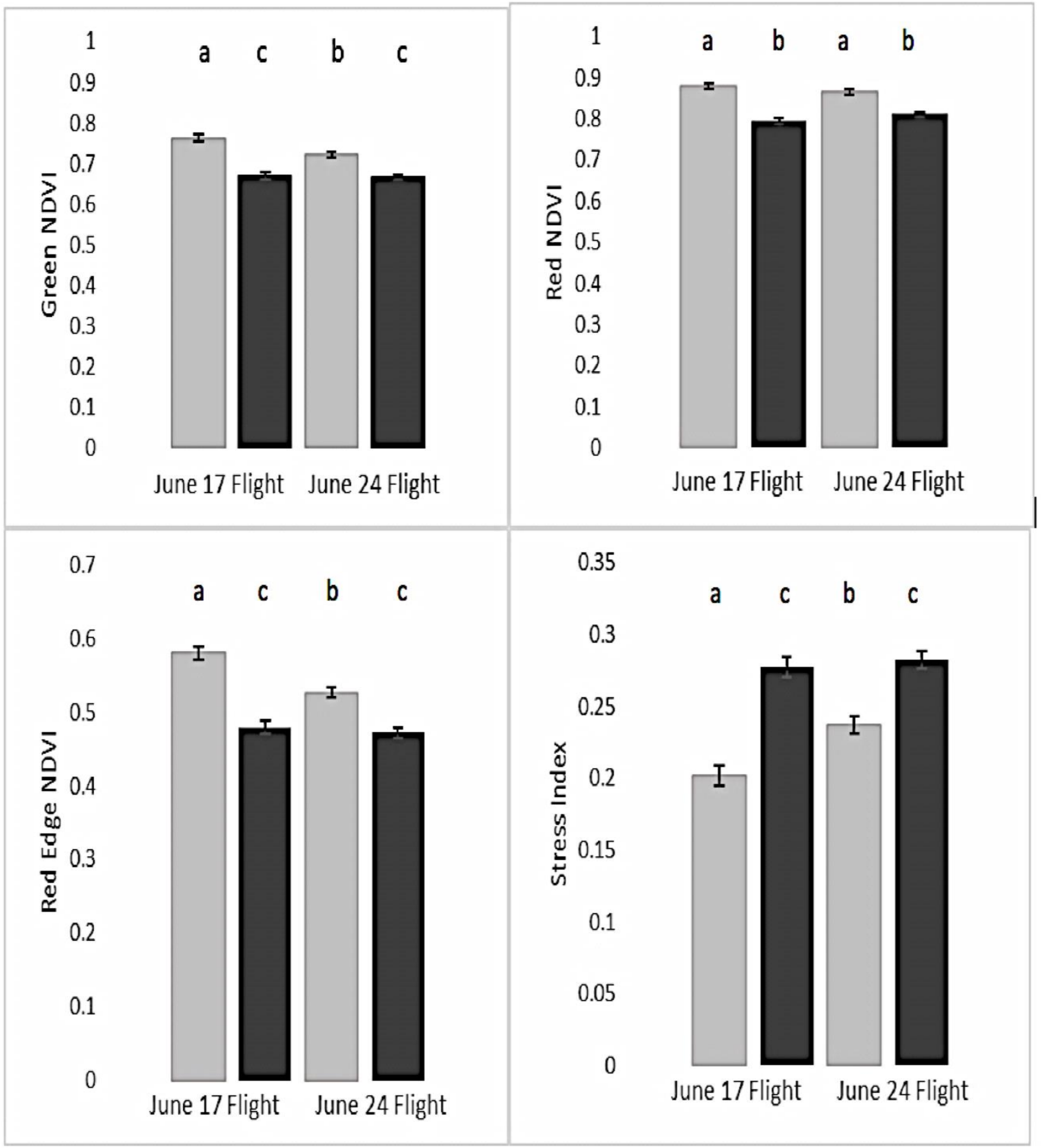


Healthy | Stressed



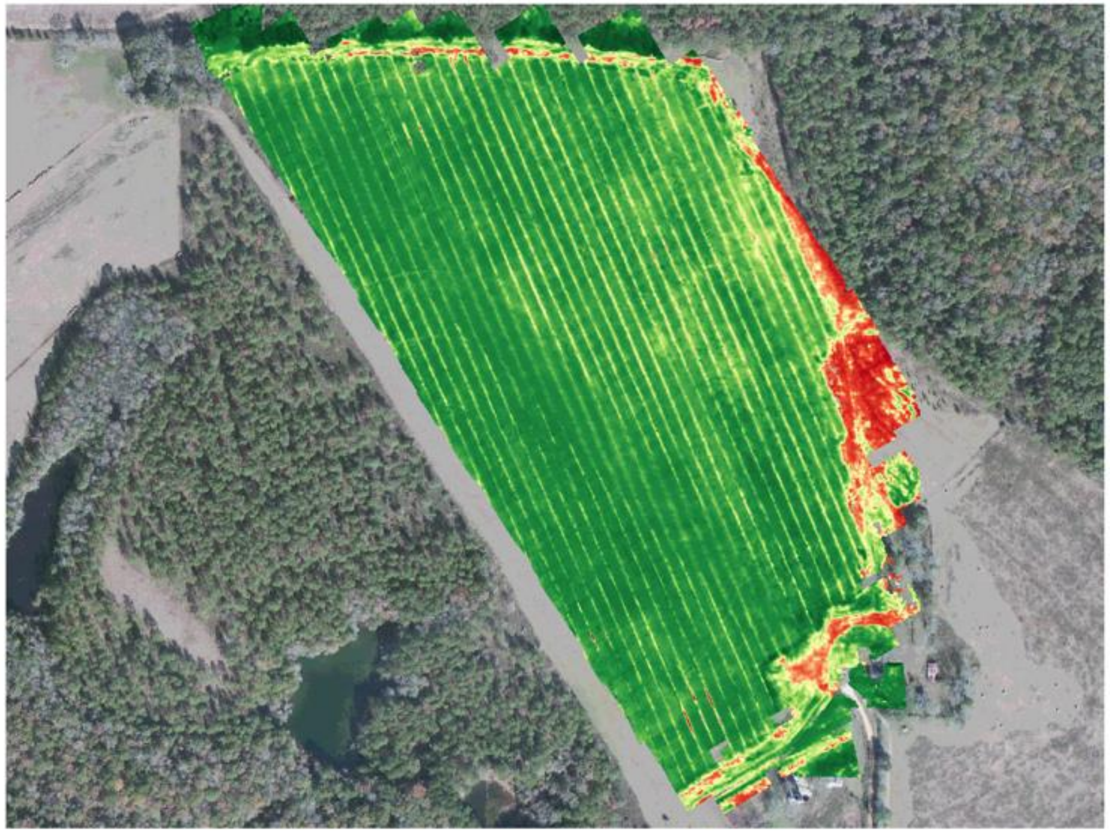
Green NDVI, Red NDVI, Red edge NDVI and Stress Index for **conventional (grey)** and **UAV-assisted (black) scouting** at two flight dates.

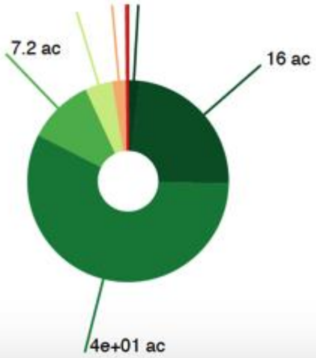
Different letter above the bar indicates significant difference at P= 0.05.



06/09/2017

STRESS Total map area: 130.0 acres, Vegetated area: 68.4 acres.

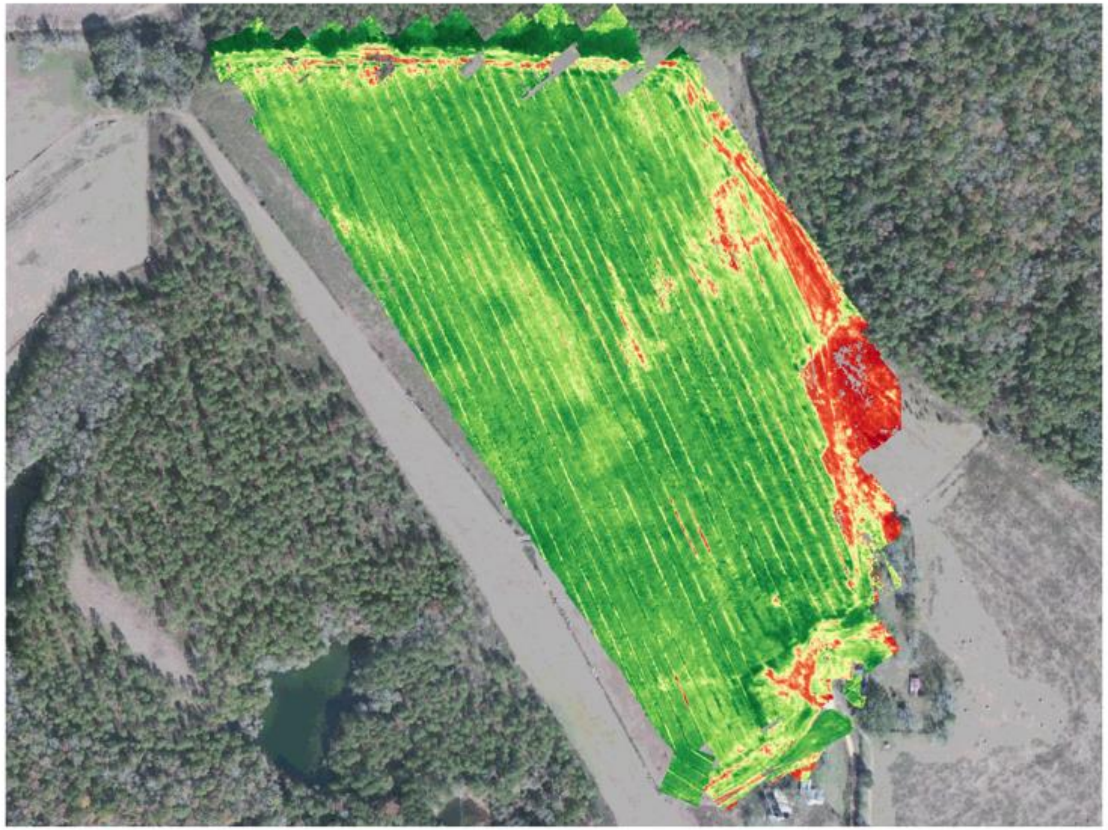


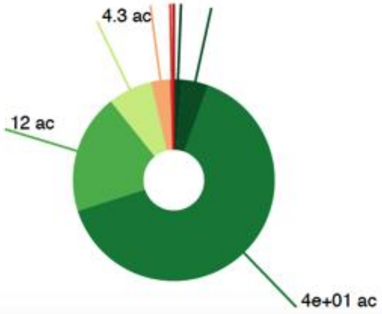


min - max	Area : acres	in %
0.001 - 0.050	Area : 0.02	0.04 %
0.050 - 0.100	Area : 1.22	1.78 %
0.100 - 0.150	Area : 16.10	23.55 %
0.150 - 0.200	Area : 39.08	57.16 %
0.200 - 0.250	Area : 7.23	10.58 %
0.250 - 0.300	Area : 3.00	4.39 %
0.300 - 0.350	Area : 1.45	2.13 %
0.350 - 0.400	Area : 0.25	0.37 %
0.400 - 0.450	Area : 0.01	0.01 %

06/17/2017

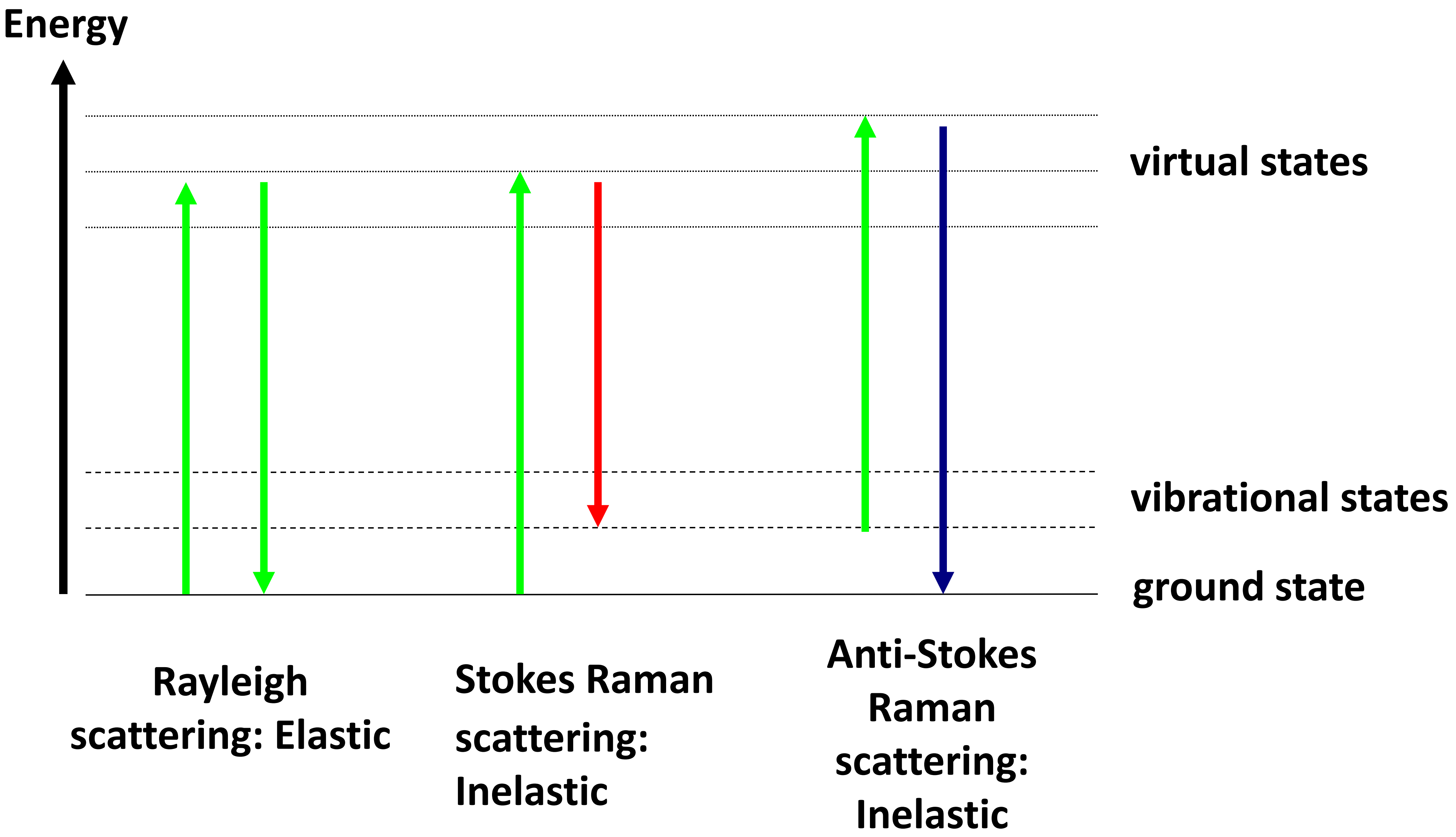
STRESS Total map area: 118.8 acres, Vegetated area: 60.3 acres.





min - max	Area : acres	in %
0.001 - 0.050	Area : 0.00	0.00 %
0.050 - 0.100	Area : 0.79	1.30 %
0.100 - 0.150	Area : 2.54	4.22 %
0.150 - 0.200	Area : 38.92	64.54 %
0.200 - 0.250	Area : 11.59	19.22 %
0.250 - 0.300	Area : 4.28	7.09 %
0.300 - 0.350	Area : 1.82	3.02 %
0.350 - 0.400	Area : 0.34	0.56 %
0.400 - 0.450	Area : 0.02	0.04 %

Raman spectroscopy



Raman spectroscopy as an early detection tool for rose rosette infection

Charles Farber[1] · Madalyn Shires[2] · Kevin Ong[2] · David Byrne[3] · Dmitry Kurouski[1,4]

Agilent Resolve spectrometer - 830 nm laser

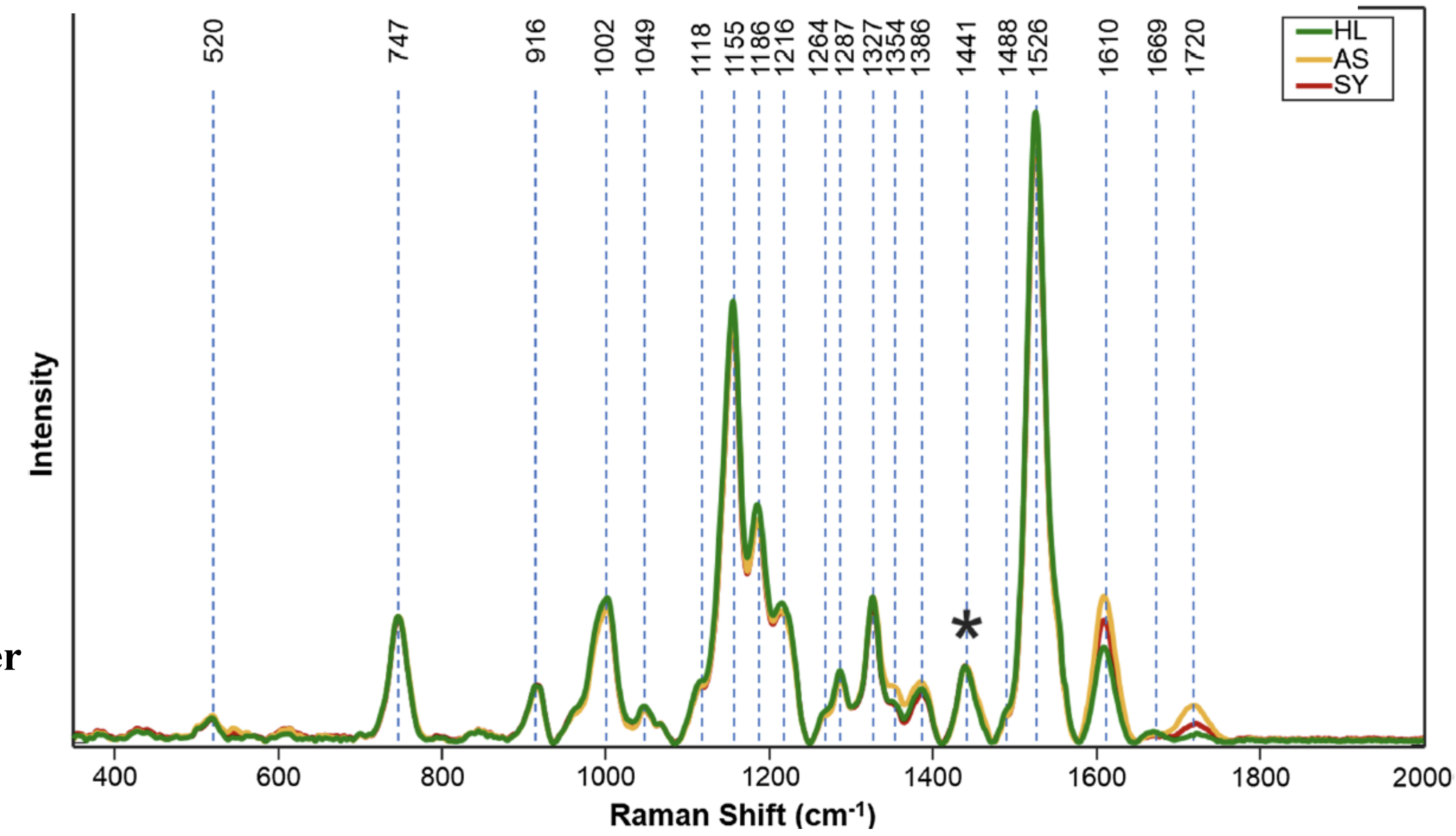


Table 1 Vibrational band assignments for rose leaf spectra

Band	Vibrational mode
520	ν(C–O–C) glycosidic
740–747	γ(C–O–H) of COOH
905–918	ν(C–O–C) in plane, symmetric
1000	In-plane CH_3 rocking of polyene
1048	ν(C–O) + ν(C–C) + δ(C–O–H)
1118	Sym ν(C–O–C), C–O–H bending
1157	C–C stretching; ν(C–O–C), ν(C–C) in glycosidic linkages, asymmetric ring breathing
1186	ν(C–O–H) next to aromatic ring + σ(CH)
1216	δ(C–C–H)
1264	Guaiacyl ring breathing, C–O stretching (aromatic)
1287	δ(C–C–H)
1327	δCH_2 bending
1354	$\delta(CH_2) + \delta(CH_3)$
1386	δCH_2 bending
1441	$\delta(CH_2) + \delta(CH_3)$
1488	$\delta(CH_2) + \delta(CH_3)$
1526	–C=C– (in-plane)
1610	ν(C–C) aromatic ring + σ(CH)
1669	=O stretching, amide I
1720	C=O stretching

Raman Spectroscopy *vs* Quantitative Polymerase Chain Reaction In Early Stage Huanglongbing Diagnostics

Lee Sanchez[1], Shankar Pant[2,5], Kranthi Mandadi[2,3] ✉ & Dmitry Kurouski[1,4] ✉

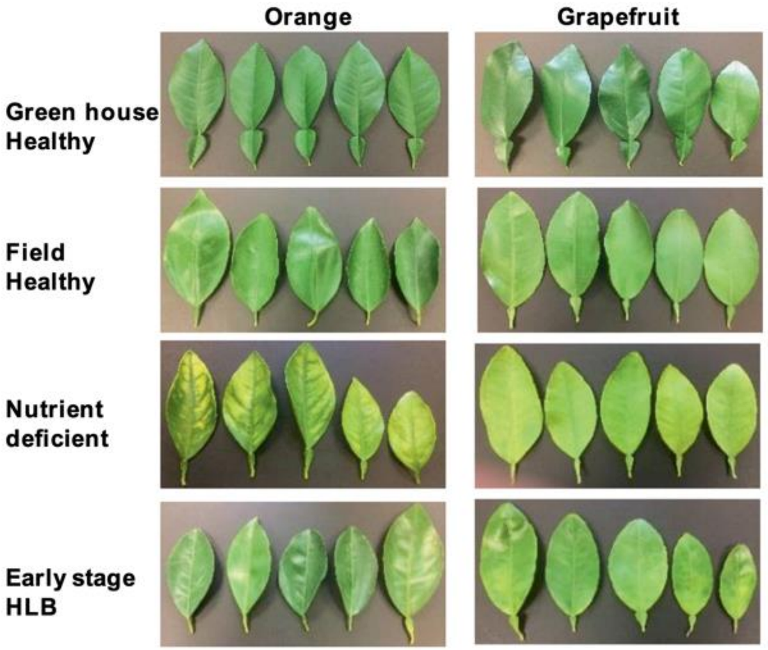


Figure 1. Leaf samples collected from greenhouse healthy (GHH) and field healthy leaves (IFH), as well leaves from both orange and grapefruit trees with nutrient deficit (ND) symptoms and asymptomatic HL (Figure panels for ND and asymptomatic HLB were adapted from Sanchez *et al.*, 2019, Anal. Bioanal. Ch

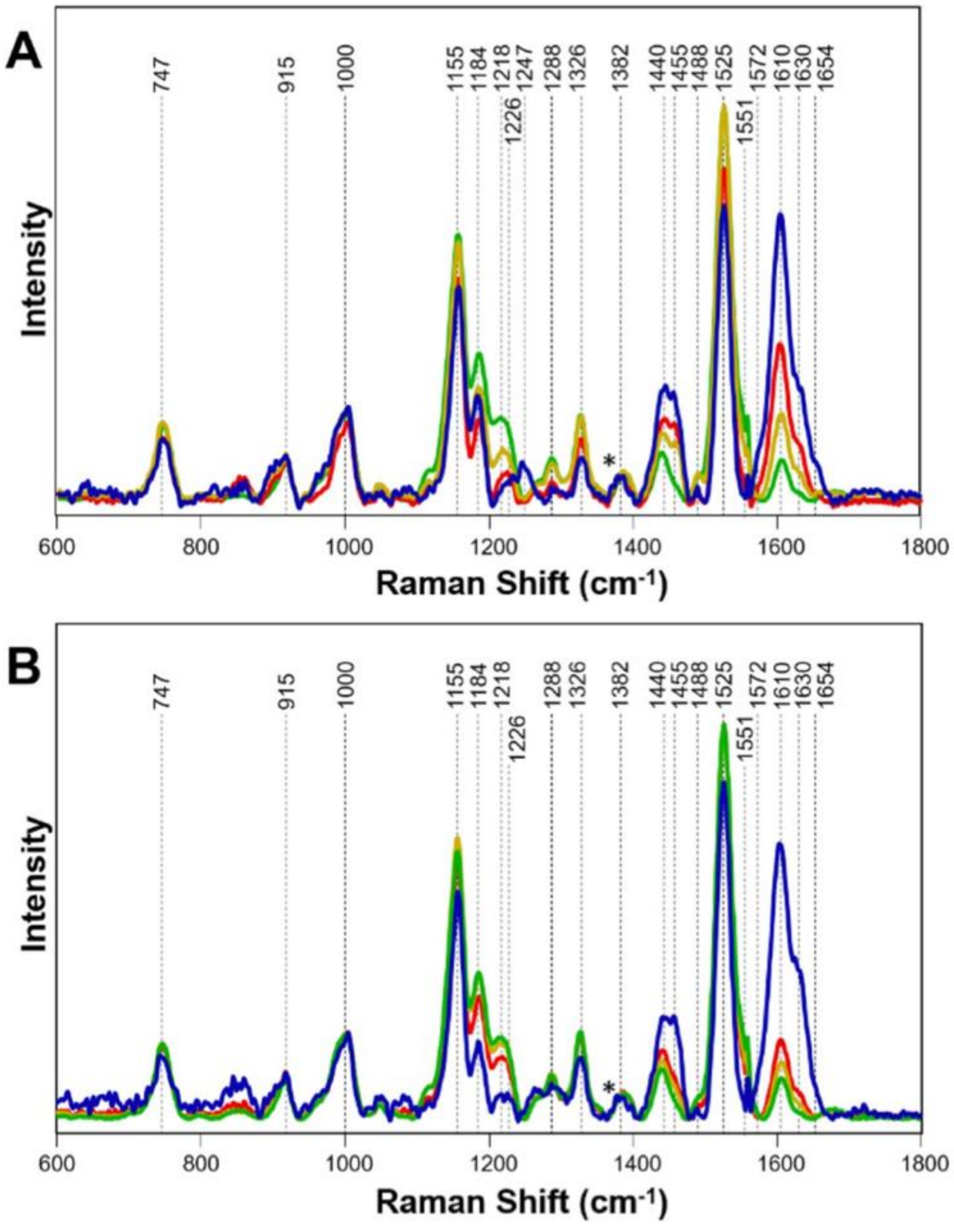
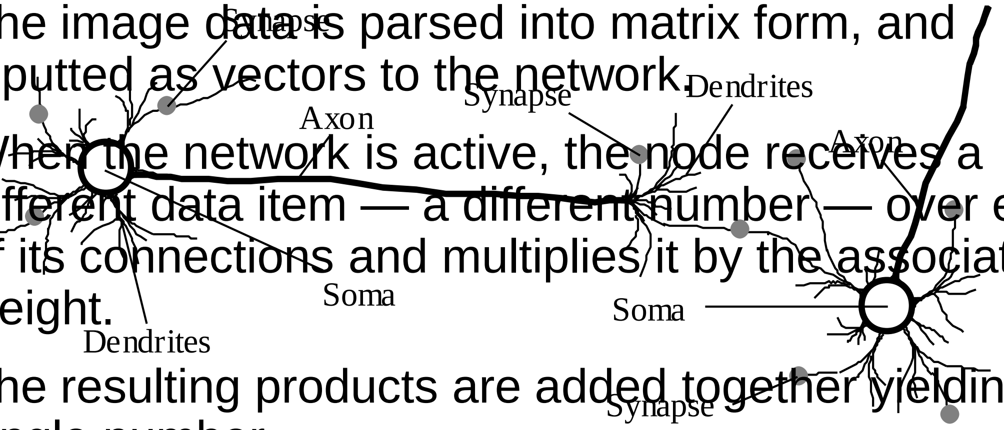


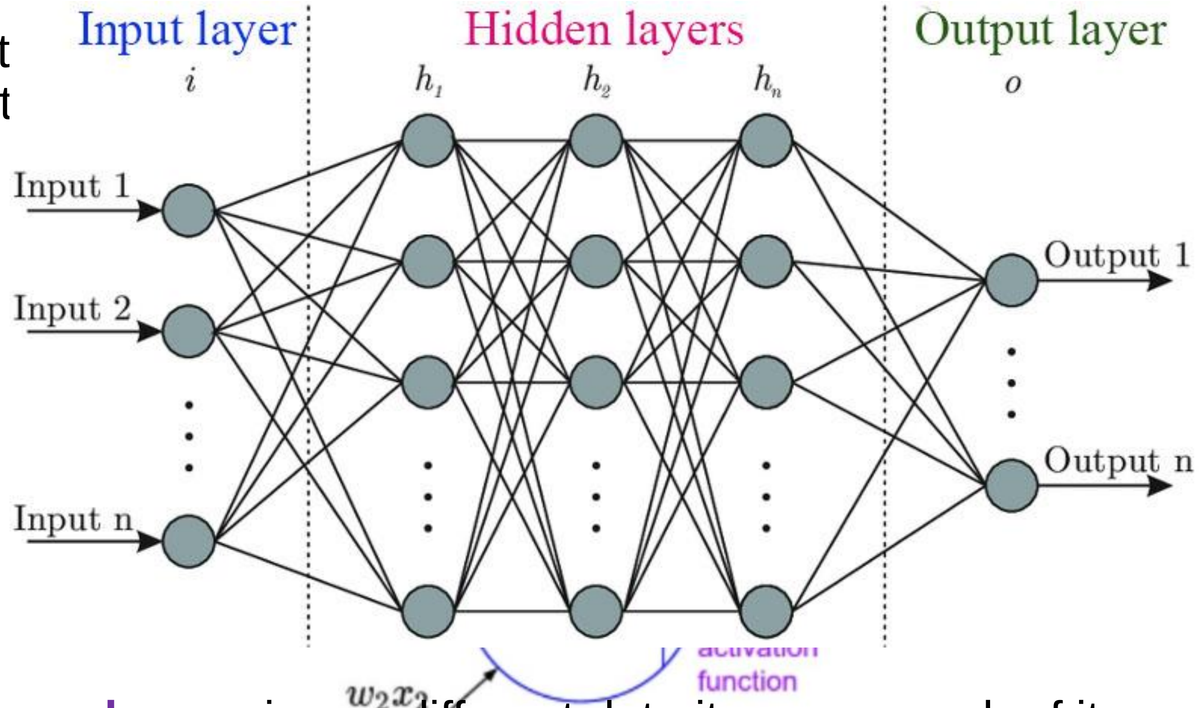
Figure 4. Raman spectra collected from leaves of GHH (green), IFH (gold), asymptomatic HLB infection (red), and nutrient-deficit (blue) symptoms in (**A**) grapefruit and (**B**) orange trees. Spectra are normalized on the CH_2 vibrational band that is present in nearly all classes in biological molecules (marked by asterisks (*)).

Introduction to Neural Networks

Neural Network: a type of machine learning model ut
network of functions to understand and translate a dat
from biological neurons

1. **Nodes** form connections based on the respective layers the connections are being established for
2. To each of these connections, the node randomly assigns a number (**weight**)
3. The image data is parsed into matrix form, and inputted as vectors to the network.
4. When the network is active, the node receives a different data item — a different number — over each of its connections and multiplies it by the associated weight.
5. The resulting products are added together yielding a single number
6. The weights and thresholds are continually adjusted during each **epoch** until training data with the same labels consistently yield similar outputs.





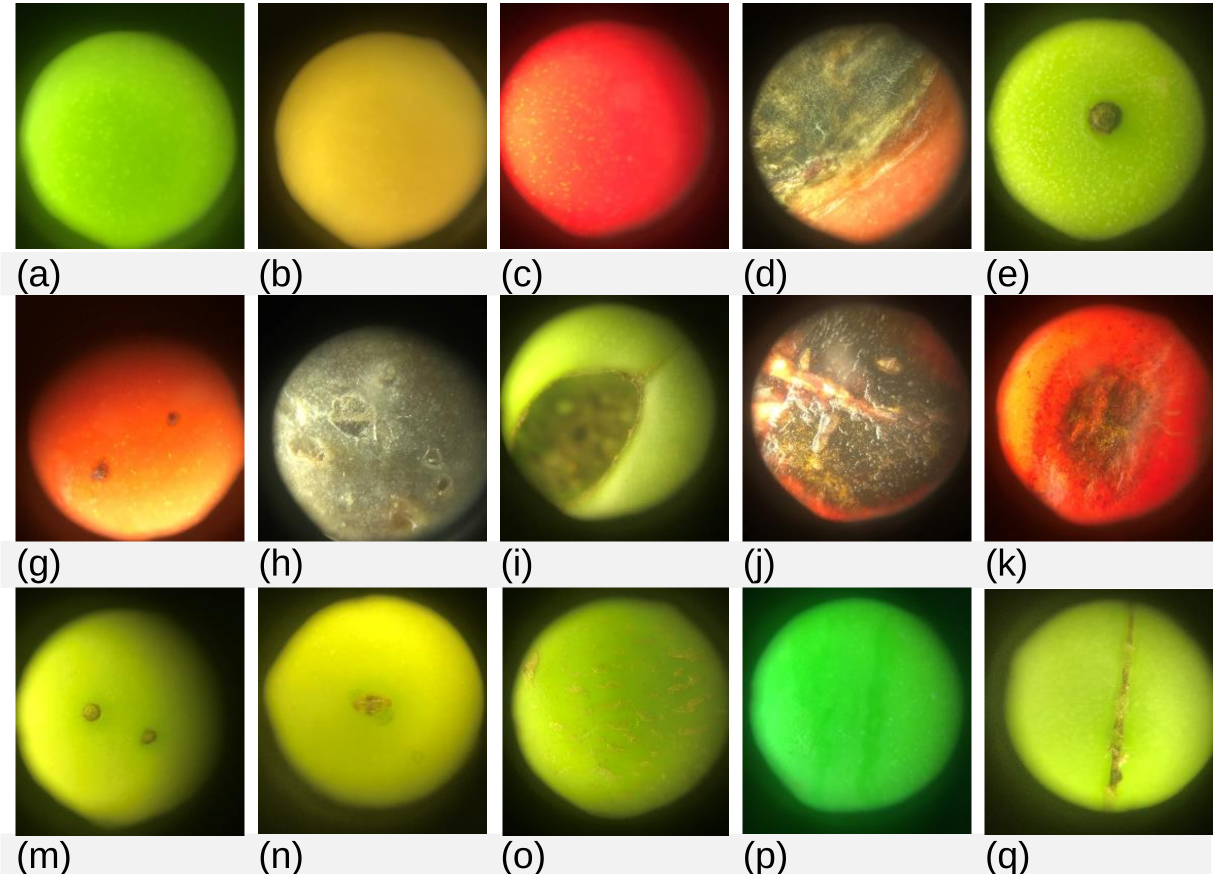
node: receives a different data item over each of its connections and multiplies it by the associated weight

- denoted by the symbol, ● in the diagram above

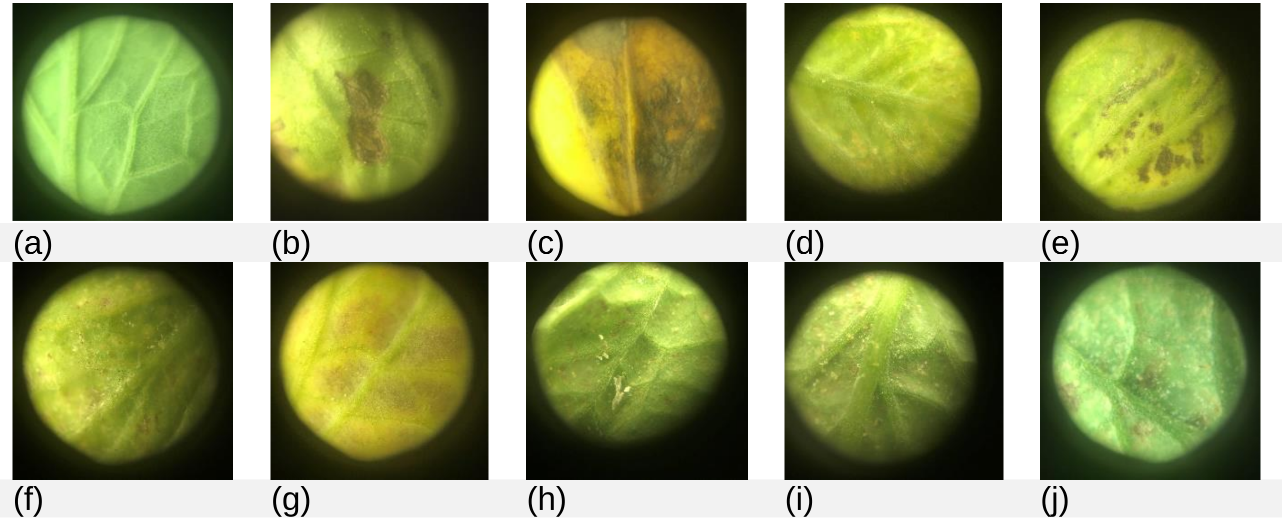
weight: the parameter within a neural network that transforms input data within the network's hidden layers

epoch: A full training pass over the entire dataset such that each example has been seen once

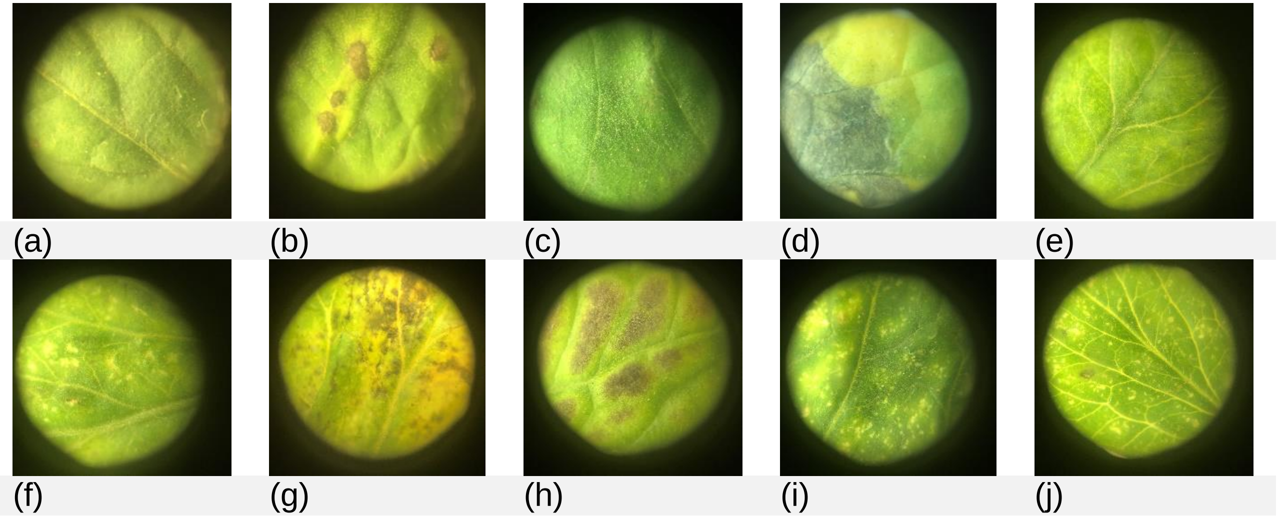
Raw Dataset



Sample fruit images. (a-c) Healthy tomato. (d) Anthracnose. (e-g) Bacterial spot. (h) Buckeye rot. (i) Catface-zippering. (j and k) Cladosporium fruit rot. (m) Pox-fleck. (n) Catface-Zippering-Zebra Stripe. (o) Rain check. (p) Zebra stripe. (q) Zippering



Sample upperside leaf images. (a) Healthy tomato. (b) Bacterial spot. (c) Bacterial wilt. (d) Early blight. (e) Cold injury. (f and g) Little leaf. (h) Zn Nutritional disorder. (i and j) Spider mite damage.



Sample underside leaf images. (a) Healthy tomato. (b) Bacterial spot. (c) Early blight. (d) Cold injury. (e and f) Little leaf. (g) Zn Nutritional disorder. (h and (i) Spider mite damage. (j) Tomato yellow leaf curl.

Methods

Step 1: Imaging with 30X Smartphone Microscope

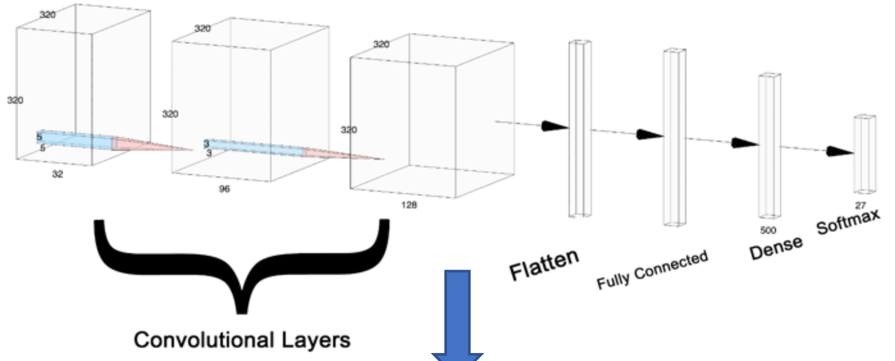
Step 2: Dataset

30X image database (5500 images)

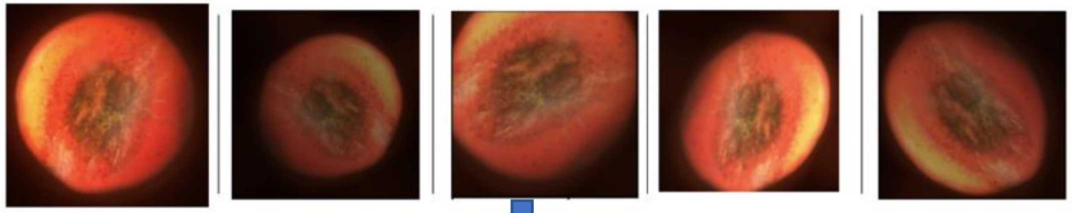
Partitioned from the complete dataset to test model performance when separated

- Fruit
- Leaf lower surface
- Leaf upper surface

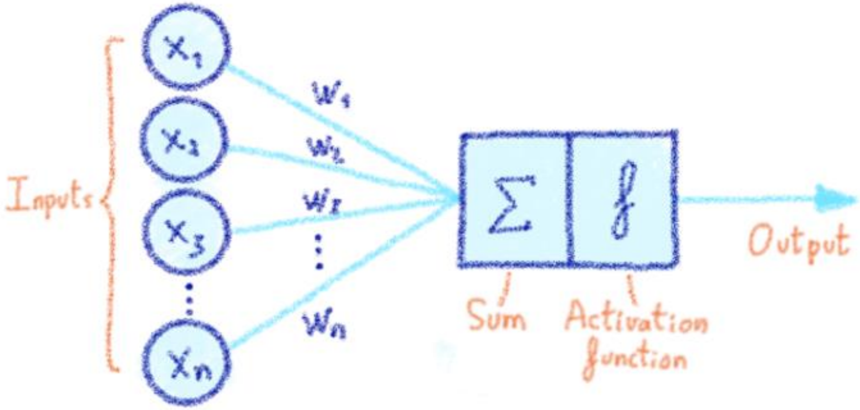
Step 3: Building of CNN



Step 4: Data Augmentation

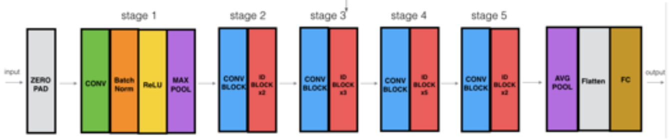


Step 5: Training the Model



Step 6: External Models

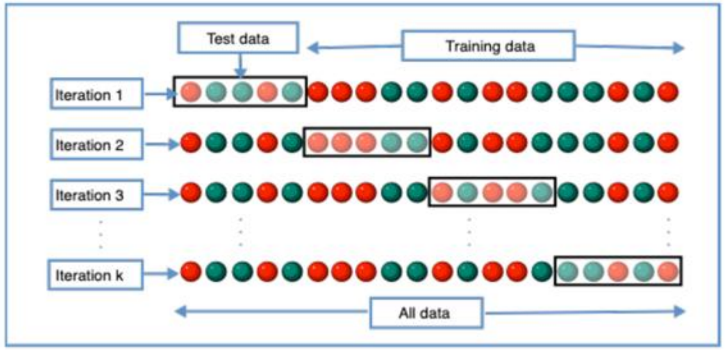
ResNet50



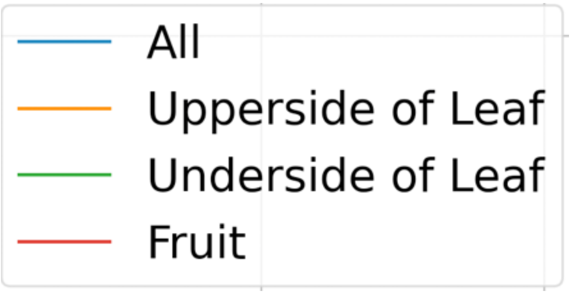
VGG16

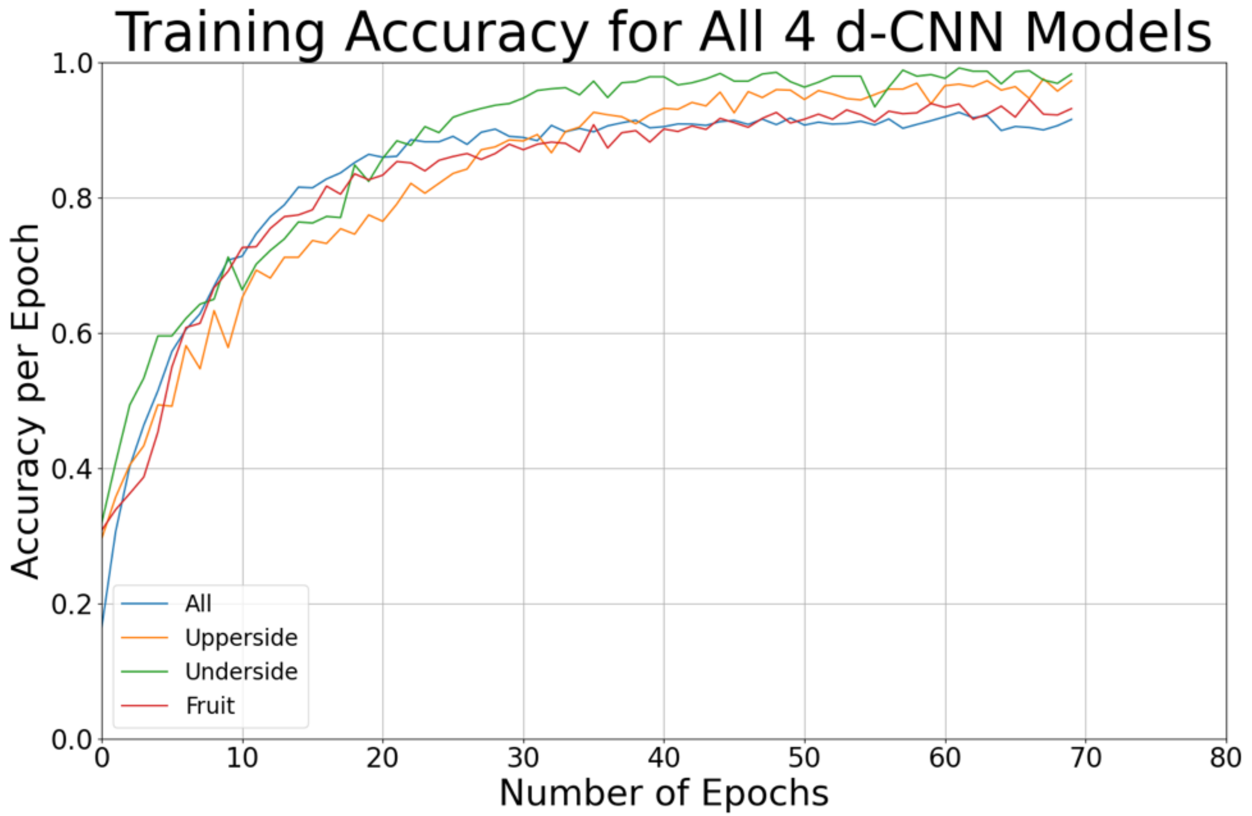
Step 7: Performance Measures

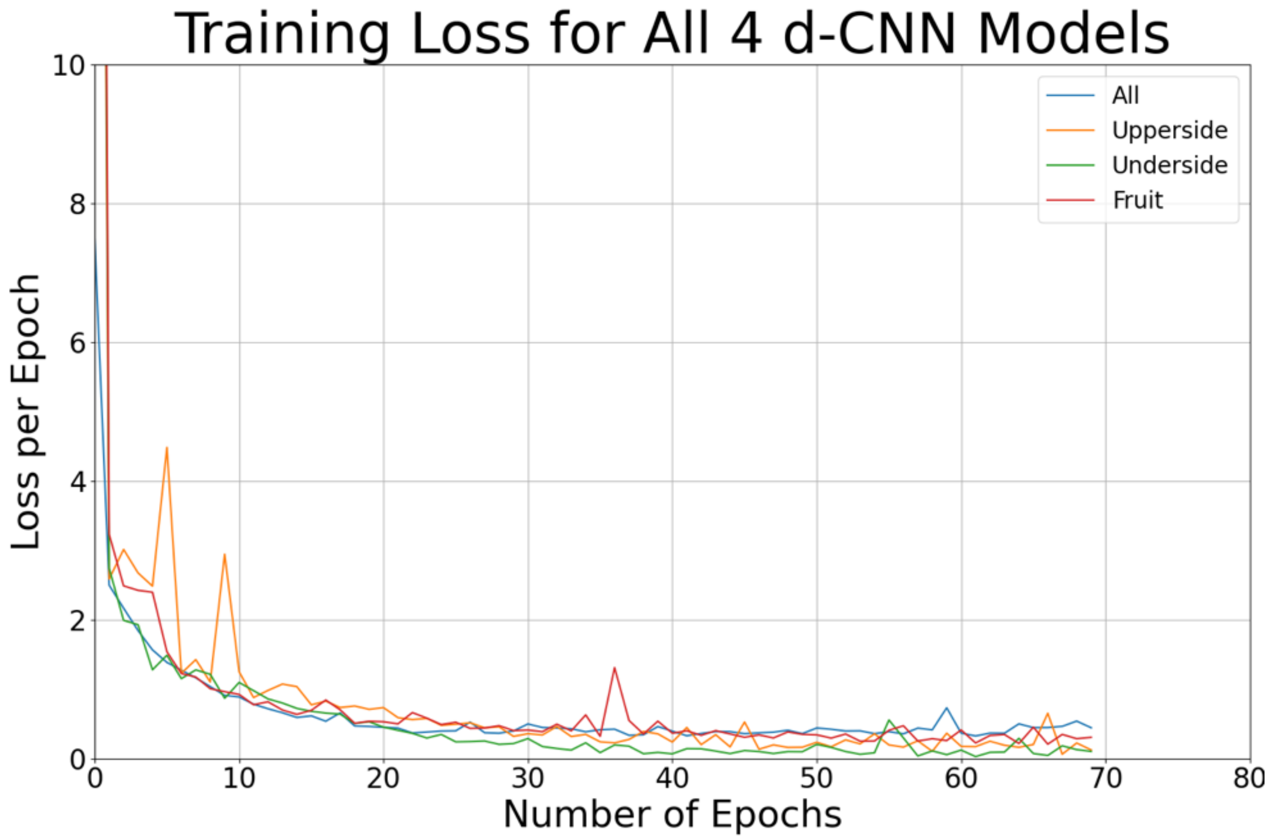
KFold Cross Validation

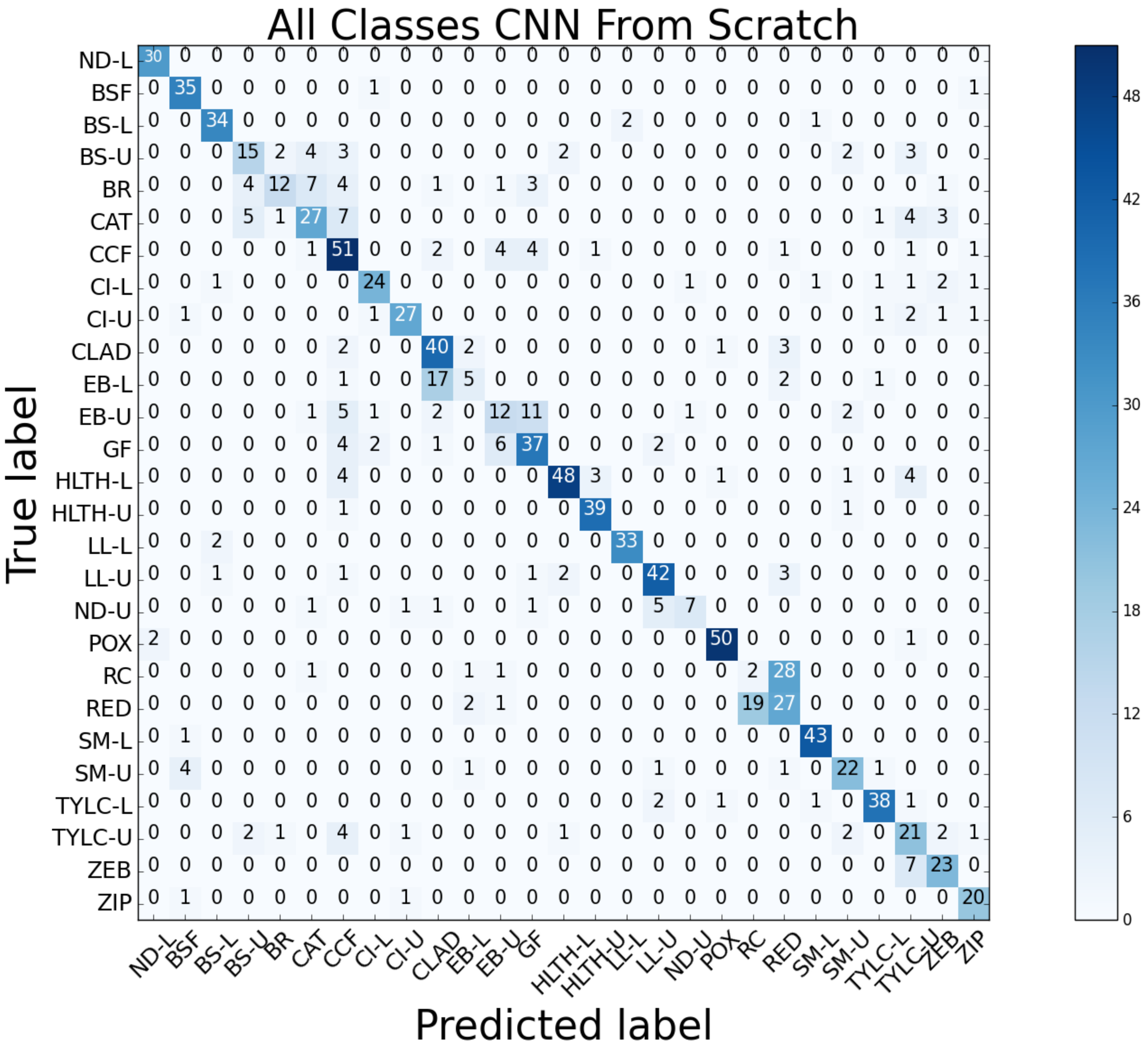


CNN: Training Accuracy and Loss









Qualitative Analysis: Confusion Matrices

Part of Plant		Accuracy	Loss
All		90.46% (+- 2.12%)	0.64
Separated by part of Plant	Fruit	97.05 (+- 1.04%)	0.26
	Under side leaf	96.50 %(+- 1.09%)	0.29
	Upper side leaf	95.57% (+- 1.14%)	0.48

KFold Average Scores for All CNN Models From Scratch

Recombinase Polymerase Amplification (RPA)

Analytical Biochemistry 546 (2018) 72–77

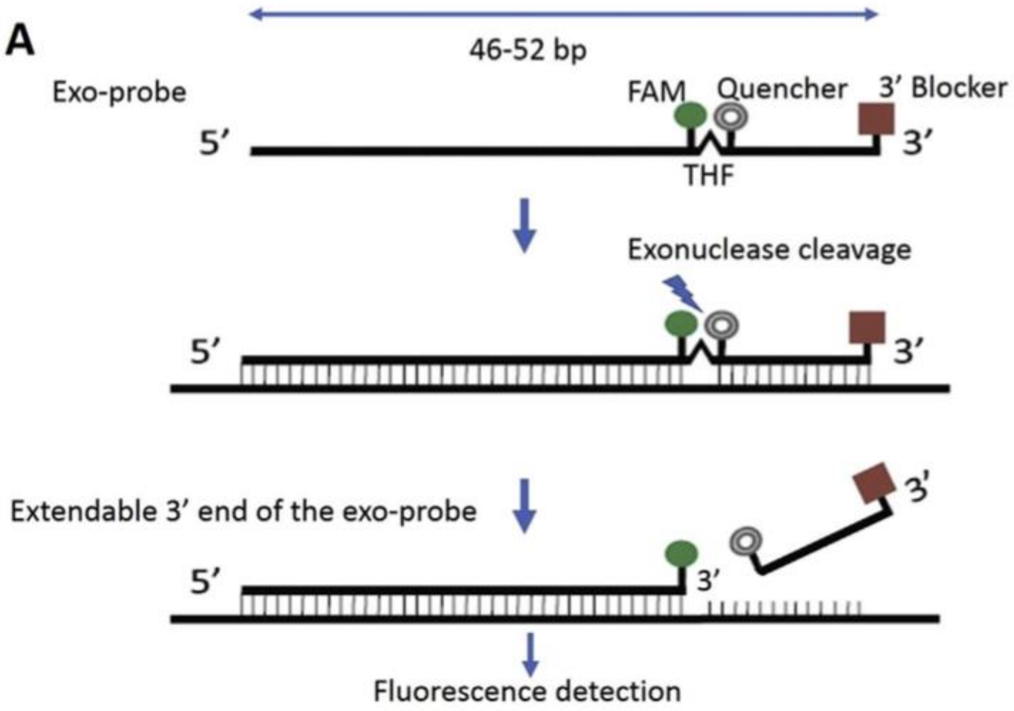
Contents lists available at ScienceDirect

Analytical Biochemistry

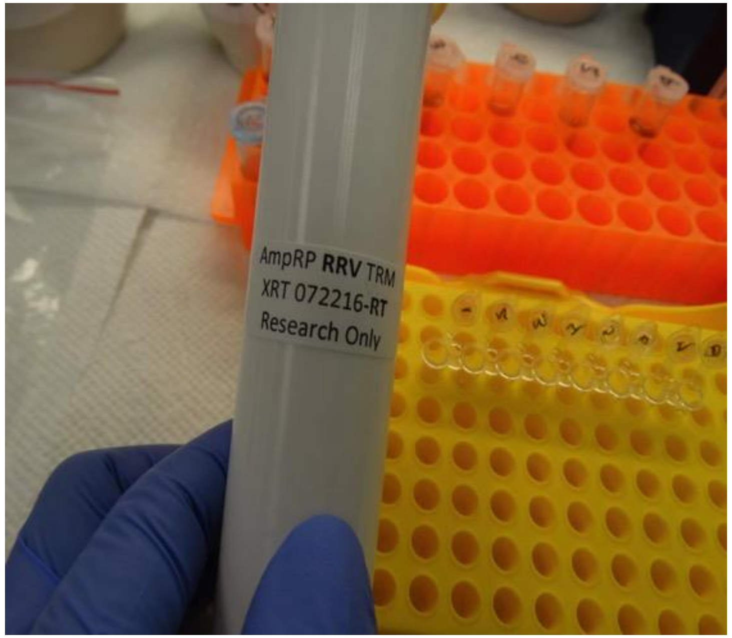
journal homepage: www.elsevier.com/locate/yabio

Recombinase polymerase amplification applied to plant virus detection and potential implications

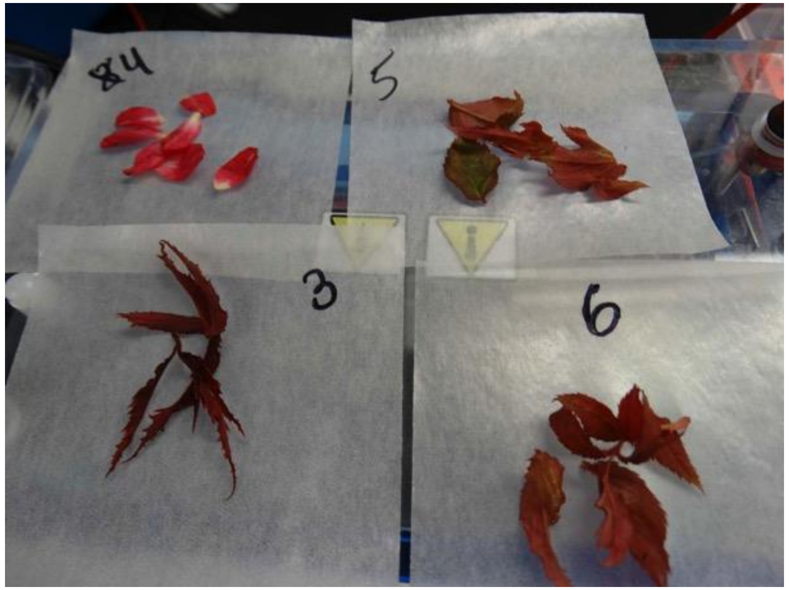
Binoy Babu[a,b,**], Francisco M. Ochoa-Corona[c], Mathews L. Paret[a,d,*]

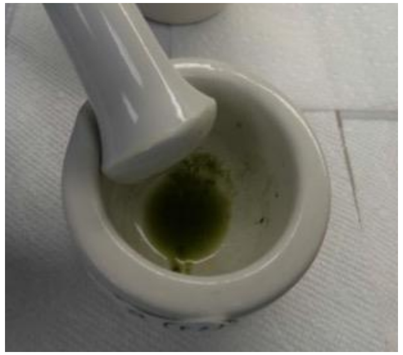


Sample Preparation for RPA



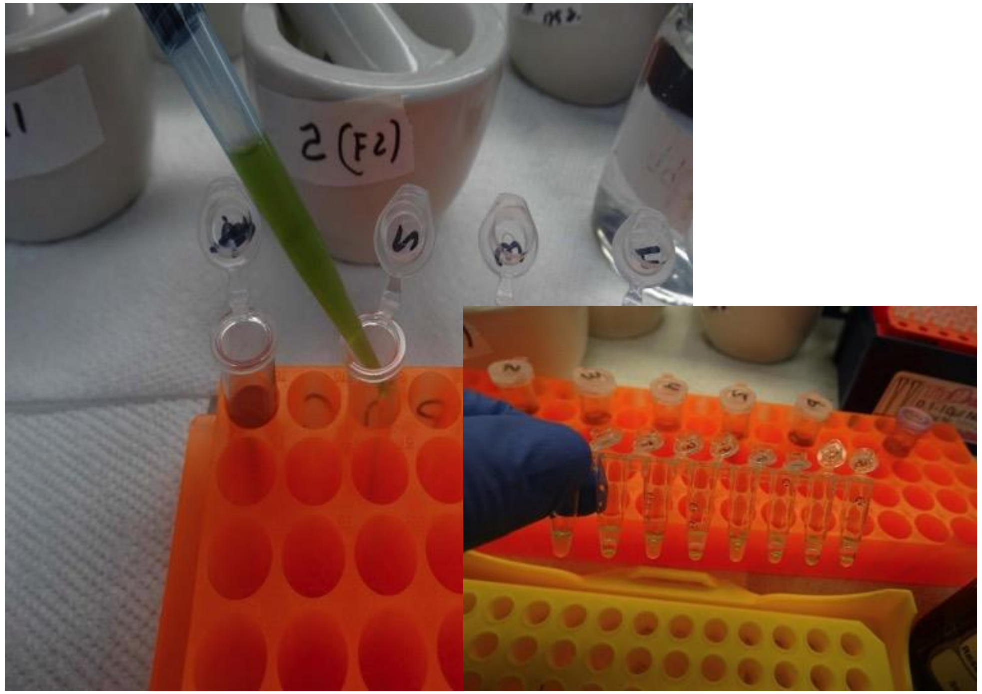
Ready to use Agdia "AmplifyRP XRT" RRV Pellet which includes all amplification reagents





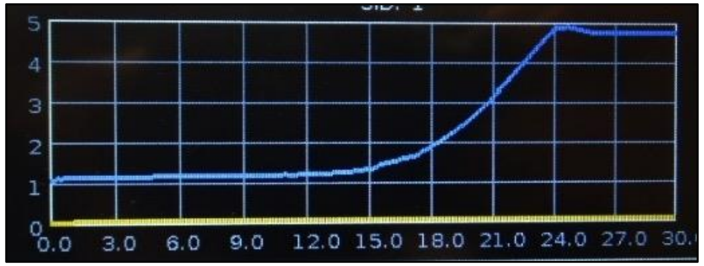
Grind plant samples (0.1 g) with 1:1 (w:v) GE ELISA Buffer. Extract diluted 1:4 in sterile deionized water

Add 23 µL of PD1 Buffer into the RPA pellet (Rehydration step – 1min)

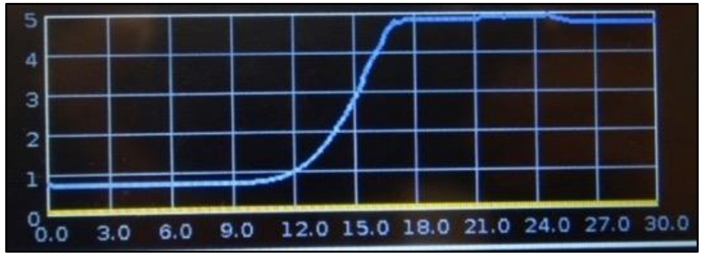


Add 1 µL of diluted sample to the PCR tubes with RPA reaction.

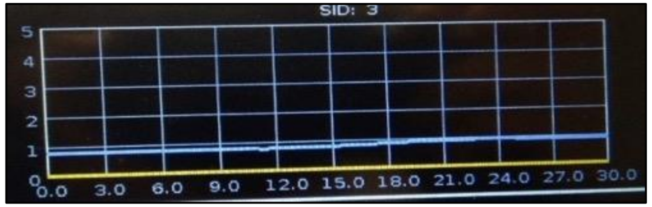
Run RPA (39 C, 15-30 min)
Battery powered to last 4 h and portable
8 samples at a time



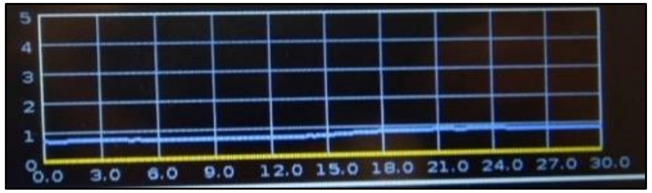
RRV infected plant 1



RRV infected plant 2

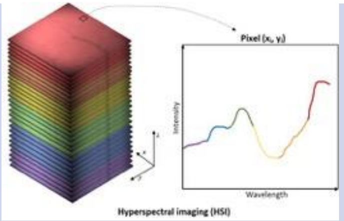
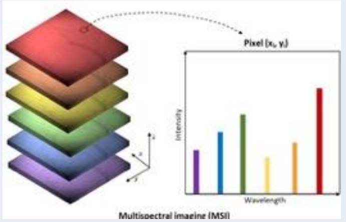
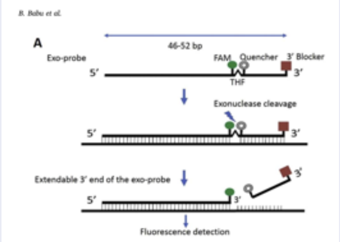


Healthy plant control



Negative control

Summary

Method	Approach	
Multi-spectral sensor	Reflectance from light for identifying areas with reflectance differences indicating hotspots of biotic and abiotic issues	
Hyper-spectral sensor	Above + identifying areas with unique reflectance differences for certain diseases.	
Raman spectroscopy	Laser induced vibrational spectra identifying chemical differences in plants that could be unique to certain diseases	
Recombinase Polymerase Amplification	Very specific and sensitive field-based DNA/RNA detection of pathogens	
Machine Learning and Artificial Intelligence (AI)	Neural network and image/object-based detection for disease identification