

Agricultural Sensing

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ENV-530 Sustainability Robotics

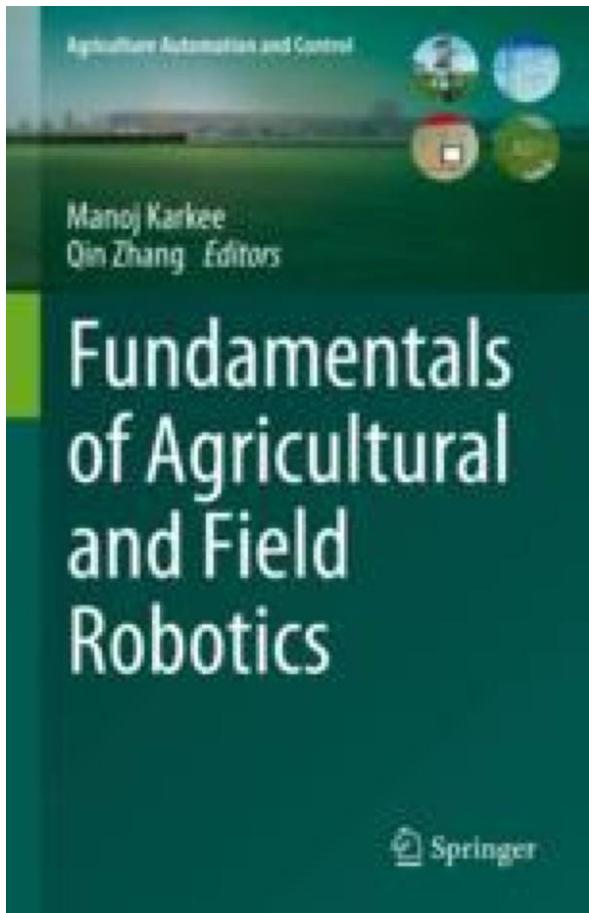


Lecture goals revisited

- Understand what **multi- and hyper- spectral sensing** is and how it can be used for precision agriculture
- Learn how robots can improve biodiversity sensing through automated collection of **eDNA**
- How can drones and robots contribute to **rapid phenotyping**

Reference material

- Fundamentals of agricultural and field robotics.
 - <https://link.springer.com/book/10.1007/978-3-030-70400-1>
 - Chapters 2, 3
 - Access through EPFL bibliography
 - Karkee M, Zhang Q, editors. Fundamentals of agricultural and field robotics. USA: Springer; 2021 Jul 27.
- Agricultural robotics: the future of robotic agriculture.
 - <https://arxiv.org/pdf/1806.06762>
 - Duckett T, Pearson S, Blackmore S, Grieve B, Chen WH, Cielniak G, Cleaversmith J, Dai J, Davis S, Fox C, From P. Agricultural robotics: the future of robotic agriculture. arXiv preprint arXiv:1806.06762. 2018 Jun 18.



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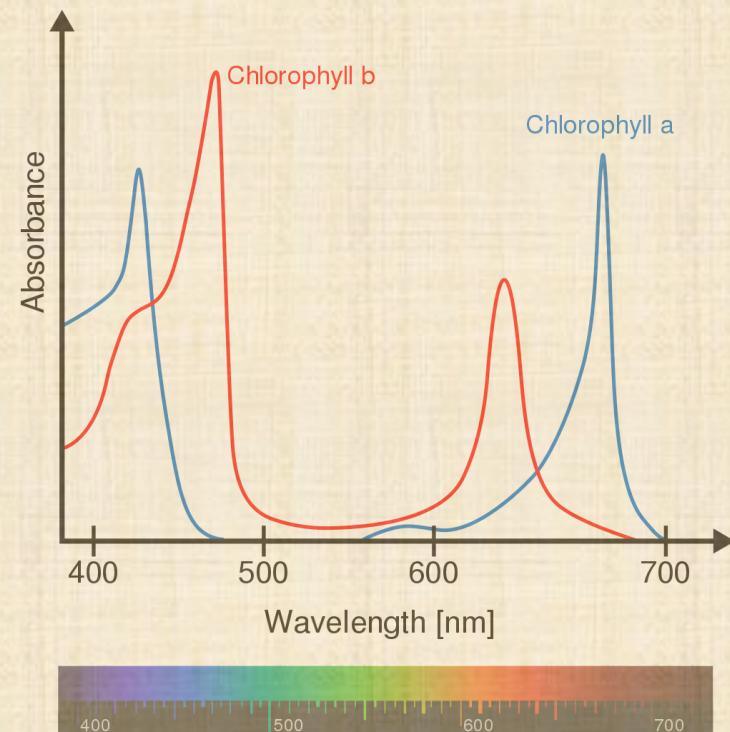
Agricultural Robotics:
The Future of Robotic Agriculture



2 weeks ago: Plant response to light

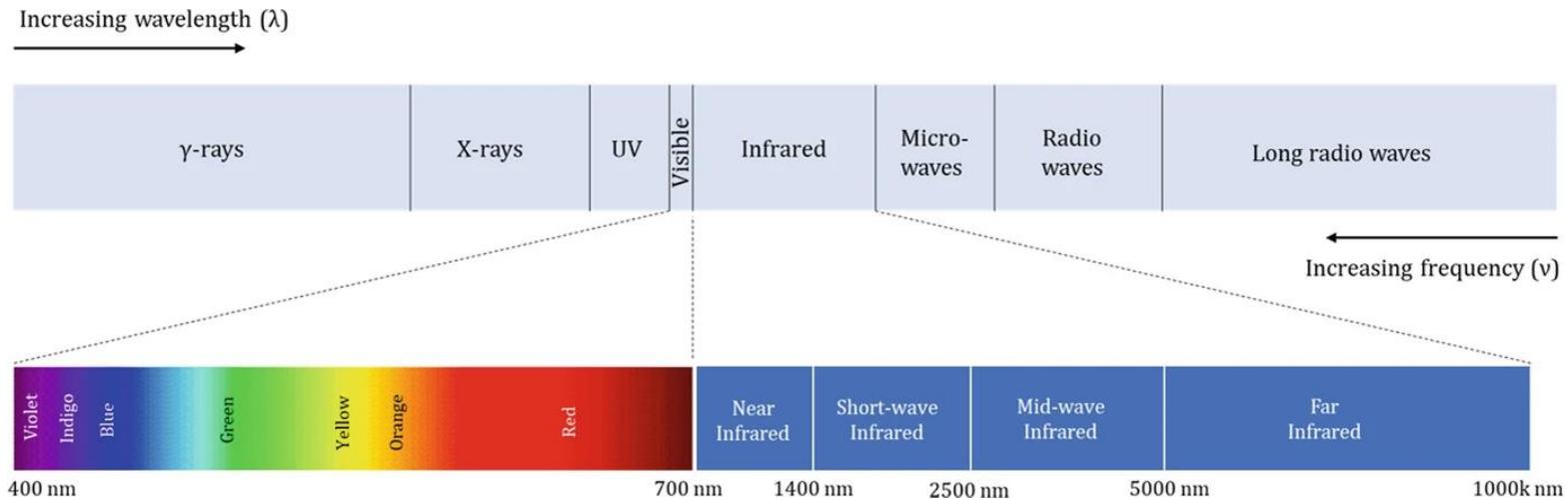
- Photosynthesis
 - Sun provides white light
 - White light: all wavelengths in visible light spectrum
- Chlorophyll has uneven absorption
 - Red and blue more sensitive
- Grow lights of only red and blue LED light save energy

How did this graph get generated?



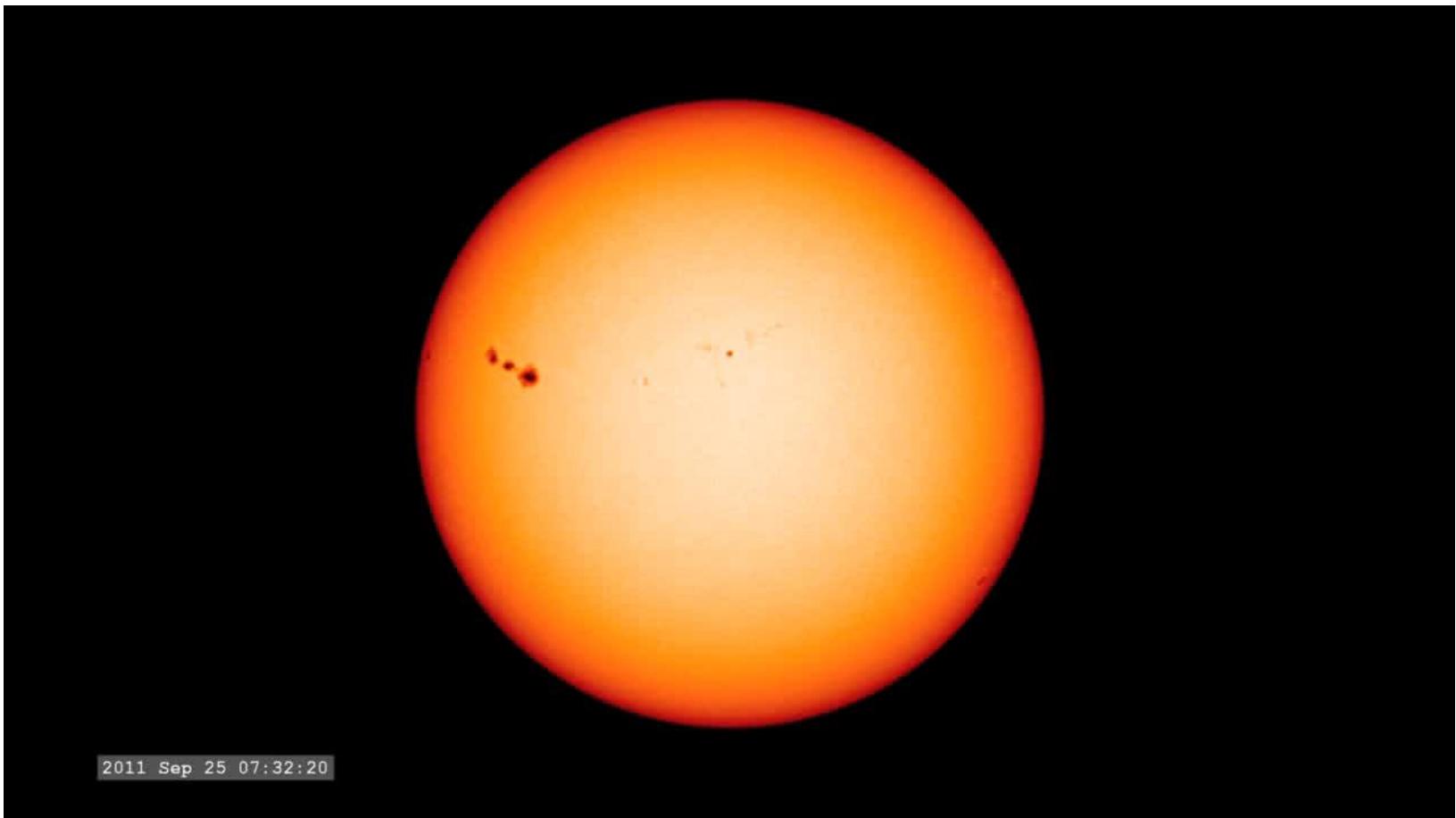
1) Source: Parke WC, Parke WC. Light in Biology and Medicine. Biophysics: A Student's Guide to the Physics of the Life Sciences and Medicine. 2020:205-77.
<https://en.wikipedia.org/wiki/Chlorophyll>

Spectral sensing



- Optical sensing
 - Visible
 - Near-infrared
 - Short-wave infrared
- Spectral sensing:
 - Beyond the visible light spectrum

Multispectral imaging

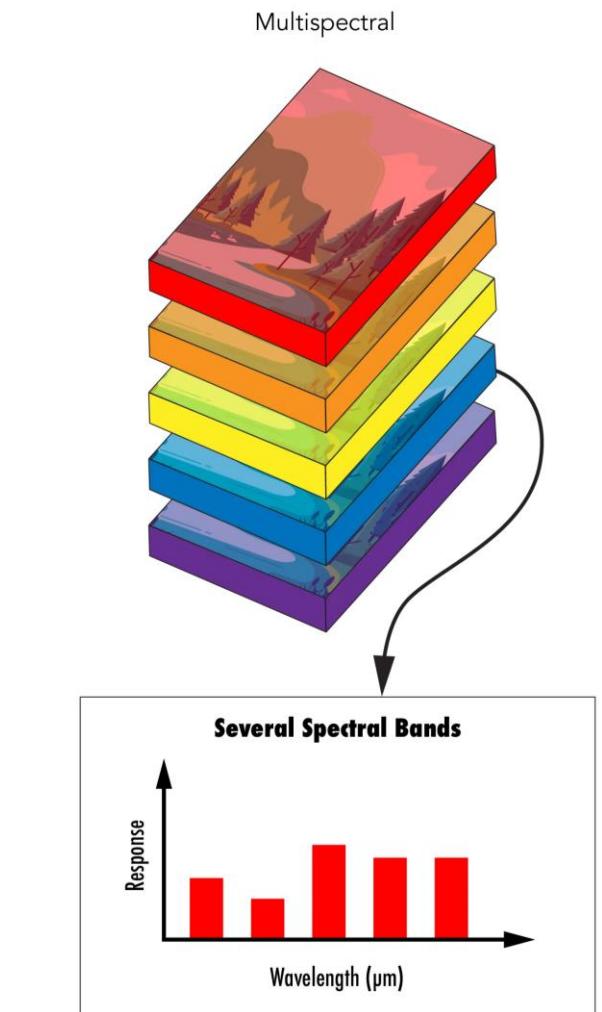


Different wavelengths give different information

1) https://en.wikipedia.org/wiki/Multispectral_imaging

Multispectral imaging

- Spectral power distribution
 - Relative wavelength power concentration
- Different matter reacts with light to emit different wavelengths
- Evaluating wavelengths gives insight as to composition of an object
 - E.g., water concentration in biological matter

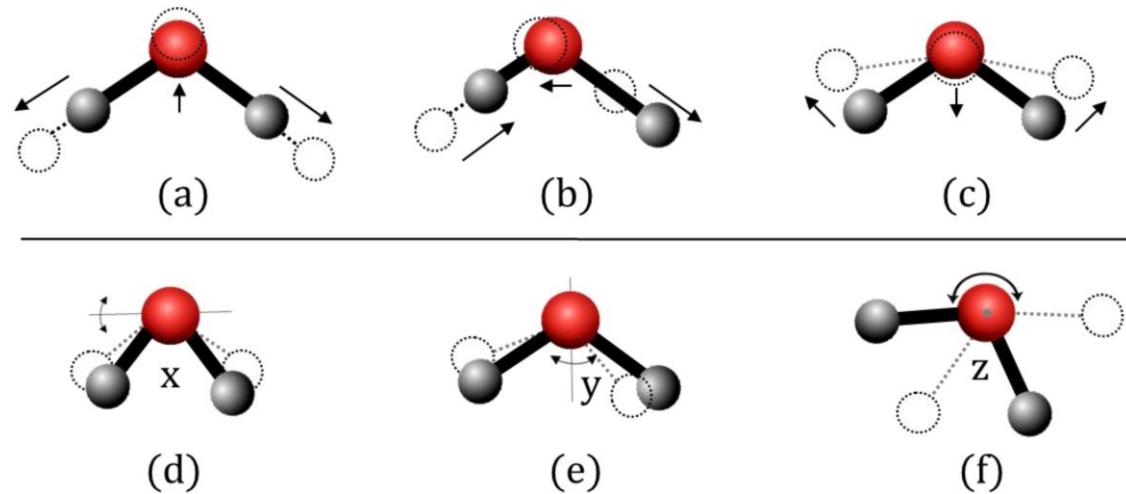


1) <https://en.wikipedia.org/wiki/Spectroradiometer>

2) <https://www.prophotonix.com/blog/hyperspectral-vs-multispectral-imaging-whats-the-difference/>

Water detection in multispectral imaging

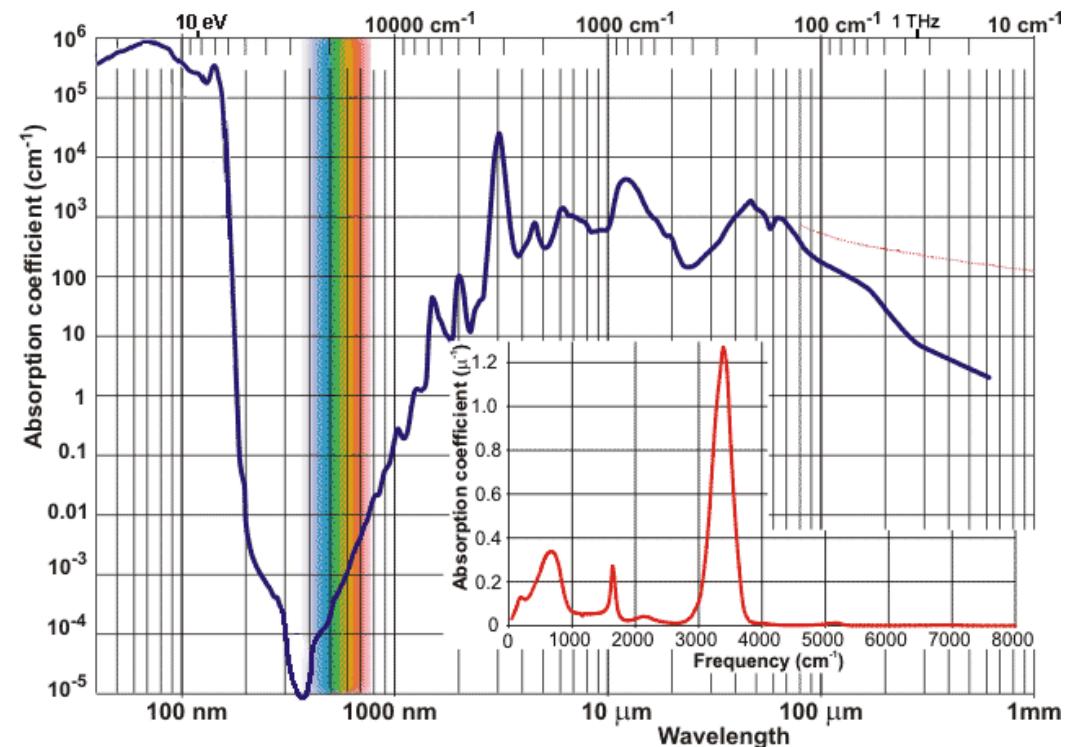
- Different chemicals absorbs light and convert to vibrations
 - Resonance with different light
- Measure light wavelengths
 - Wavelengths absorbed = molecular resonance
 - Clues to chemical composition
- E.g., different ways water can vibrate
 - Different modes of vibration react with different wavelengths



1) Raj R, Walker JP, Vinod V, Pingale R, Naik B, Jagarlapudi A. Leaf water content estimation using top-of-canopy airborne hyperspectral data. International Journal of Applied Earth Observation and Geoinformation. 2021 Oct 1;102:102393.

Methods for hyperspectral imaging

- Water absorption
 - x-axis: wavelength
 - y-axis: absorption coefficient
- Absorbency dips and peaks depending on vibration
- Nearly invisible in the visible light spectrum (380-700 nm)
 - Going beyond visible light spectrum gives more visibility
- Water absorbs more red -> Appears blue

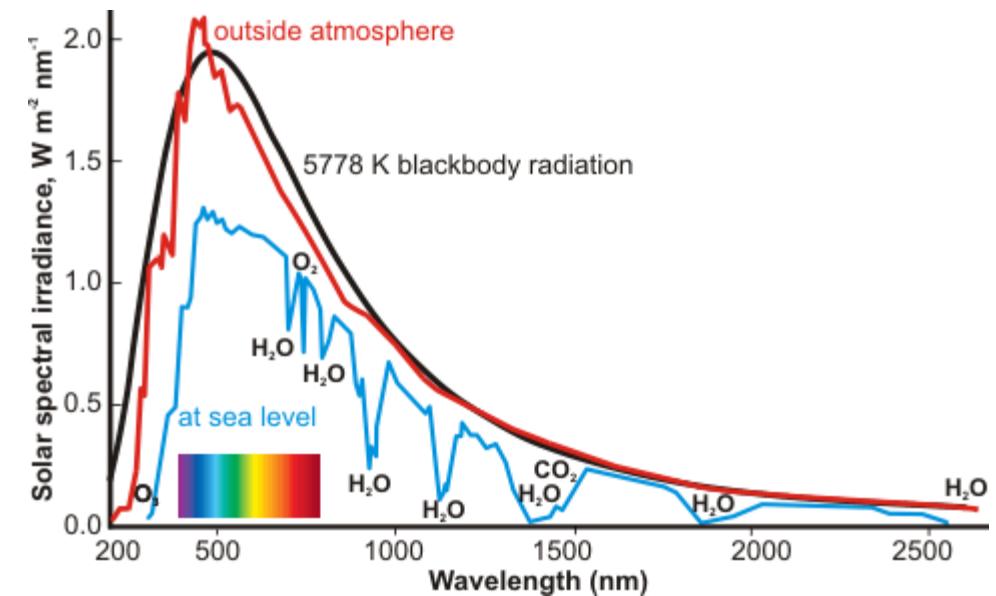


Light from the sun detecting presence of water
(Nested graph continuation of x axis)

1) https://water.lsbu.ac.uk/water/water_vibrational_spectrum.html

Methods for Water in multispectral

- Example: Presence of water detected from sunlight
 - Dips indicate water
 - Vibration overtones (harmonics)
- Compare absorption peaks with known water composition
 - Able to detect water from spectral imaging
 - Aerial and satellite imagery

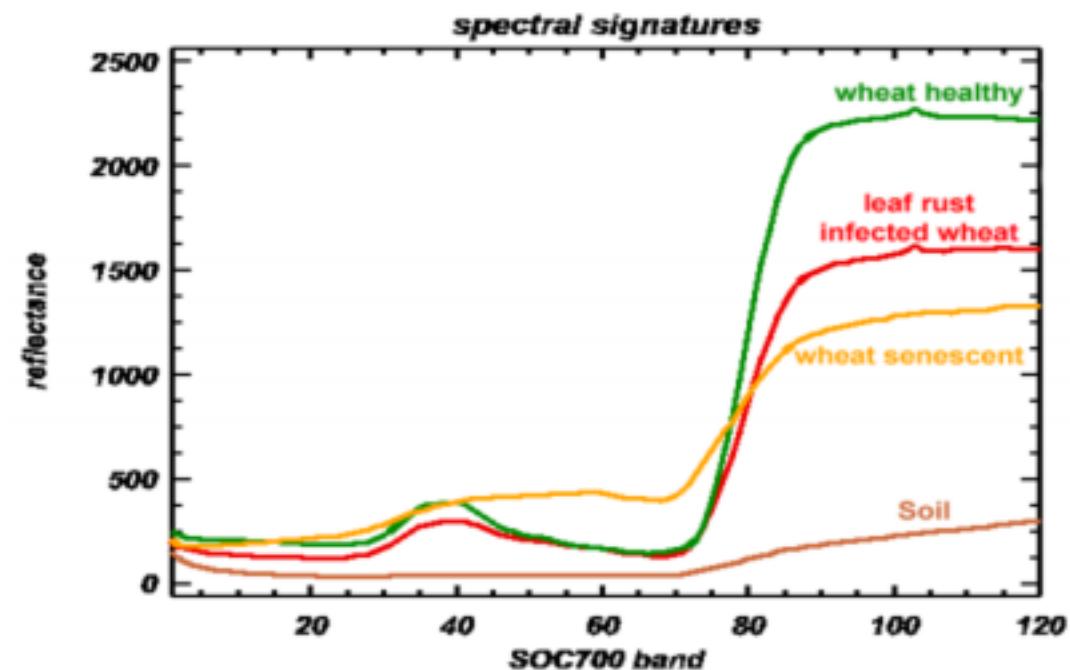


Light from the sun detecting presence of water

1) https://water.lsbu.ac.uk/water/water_vibrational_spectrum.html

Spectral sensing: agriculture

- Bio matter absorbs different wavelengths
- Comparing in red and near-infrared can estimate:
 - Normalized difference vegetation index
 - Used to calculate crop health (including red edge chlorophyll)
 - Water concentration
- Fungi detection
 - Figure: Leaf rust detection



1) Franke J, Menz G, Oerke EC, Rascher U. Comparison of multi-and hyperspectral imaging data of leaf rust infected wheat plants. In *Remote Sensing for Agriculture, Ecosystems, and Hydrology VII* 2005 Oct 19 (Vol. 5976, pp. 349-359). SPIE.

Spectroradiometers

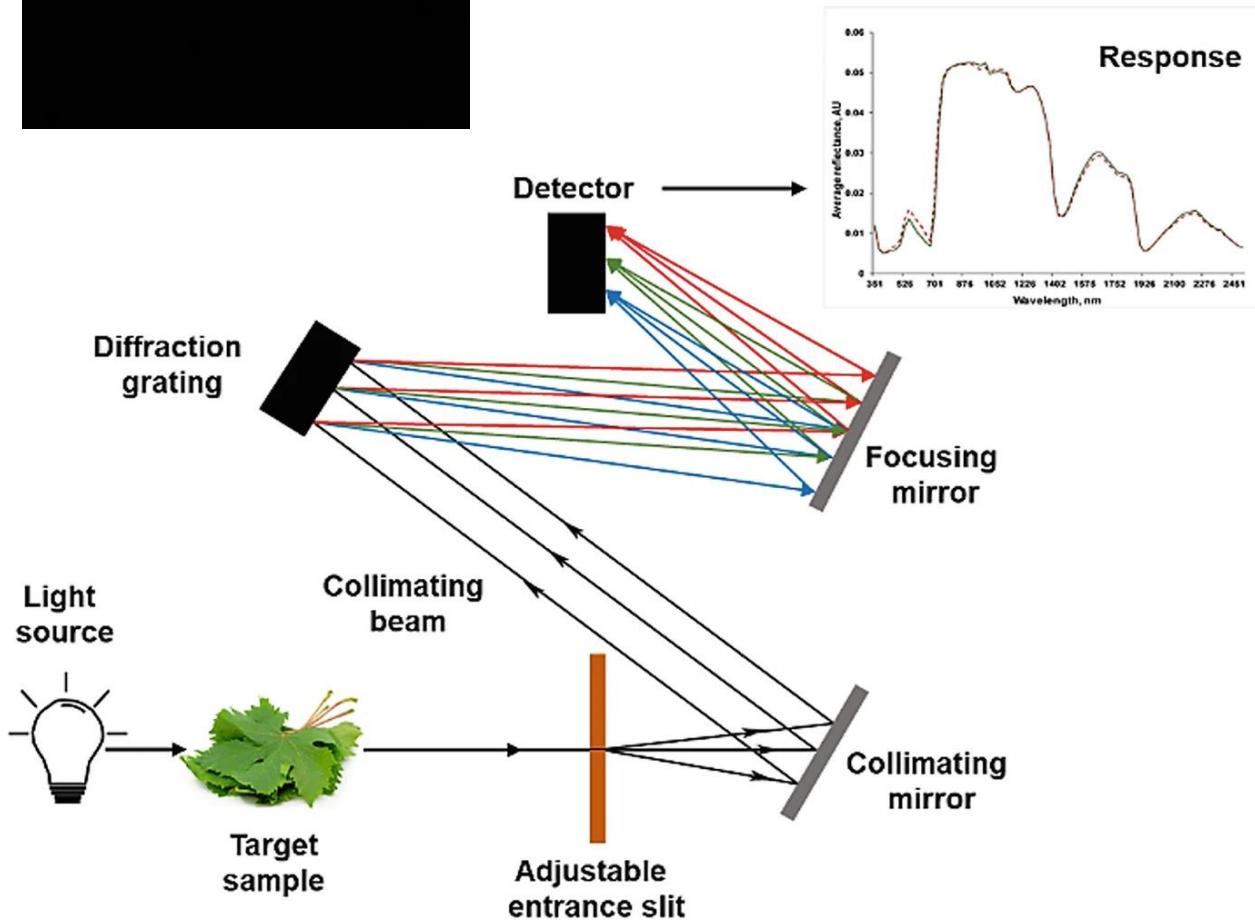
- Optical measurement unit measure wavelength and amplitude of light
 - Breaks light down into wavelengths
- When calibrated, can compare light and material absorbency
 - Can evaluate what materials are present in matter



1) <https://www.ci-systems.com/SR-5000N-Spectroradiometer>
2) <https://www.jeti.com/Products/Spectroradiometer/spectraval1511>

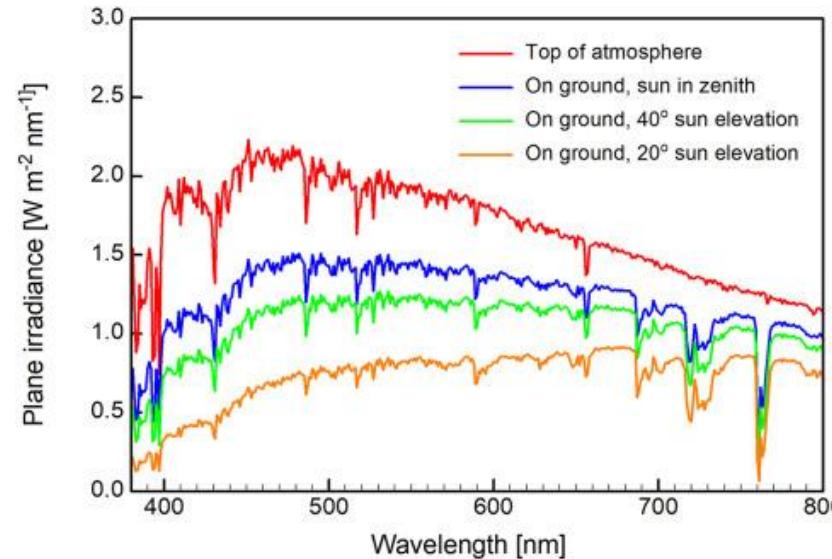
Spectroradiometer

- Components
 - Light source
 - Mirrors
 - Detector array
- Working principle
 - Light diffracts to separate beams
 - Each beam has a different wavelength
 - Beams focus on detector array



Spectroradiometer: Measurements

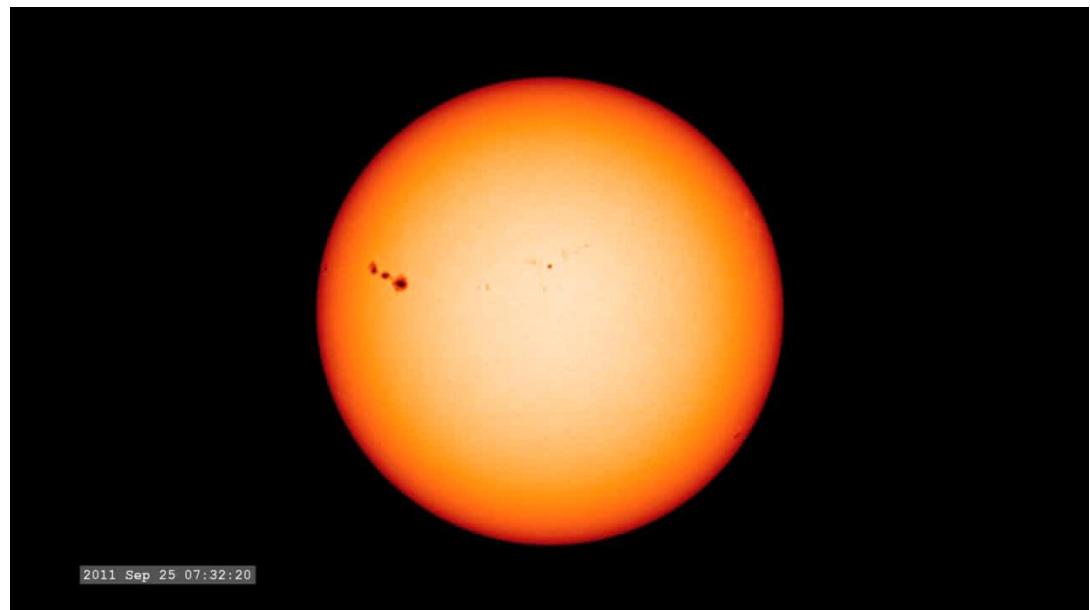
- Irradiance (W/cm²)
- Illuminance (lux or fc)
- Radiance (W/sr)
- Luminance (cd)
- Flux (Lumens or Watts)
- Chromaticity
- Colour Temperature
- Peak Wavelength
- Dominant Wavelength



- 1) Franke J, Menz G, Oerke EC, Rascher U. Comparison of multi-and hyperspectral imaging data of leaf rust infected wheat plants. In *Remote Sensing for Agriculture, Ecosystems, and Hydrology VII* 2005 Oct 19 (Vol. 5976, pp. 349-359). SPIE.
- 2) <https://www.sciencedirect.com/topics/earth-and-planetary-sciences/spectroradiometers>

Multispectral imaging

- Spectral measurement
 - 1 line – a pixel
- Spectral imaging
 - With spatial information
 - I.e., pixel arrangement on an image
- RGB camera with spectral data and special data

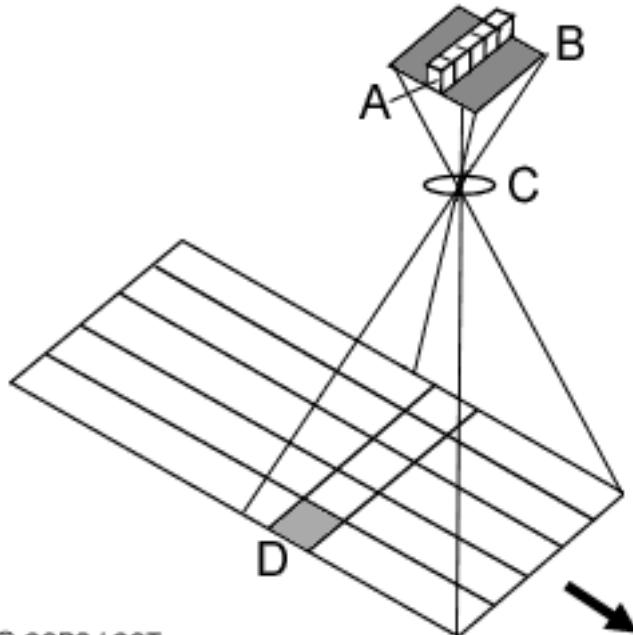


Actually a multispectral *image*

1) https://en.wikipedia.org/wiki/Multispectral_imaging

Multispectral imaging

- Approach:
 - Evaluate each pixel and scan
 - Break into x, y
 - Creates an image of pixels!
- Alternative approach:
 - Build an a camera with an ultrawide CMOS sensor
 - Use a filter to limit to a spectral range
 - Pros: Quick, easy,
 - Cons: Limited spectral resolution, lower spectral range, lower accuracy

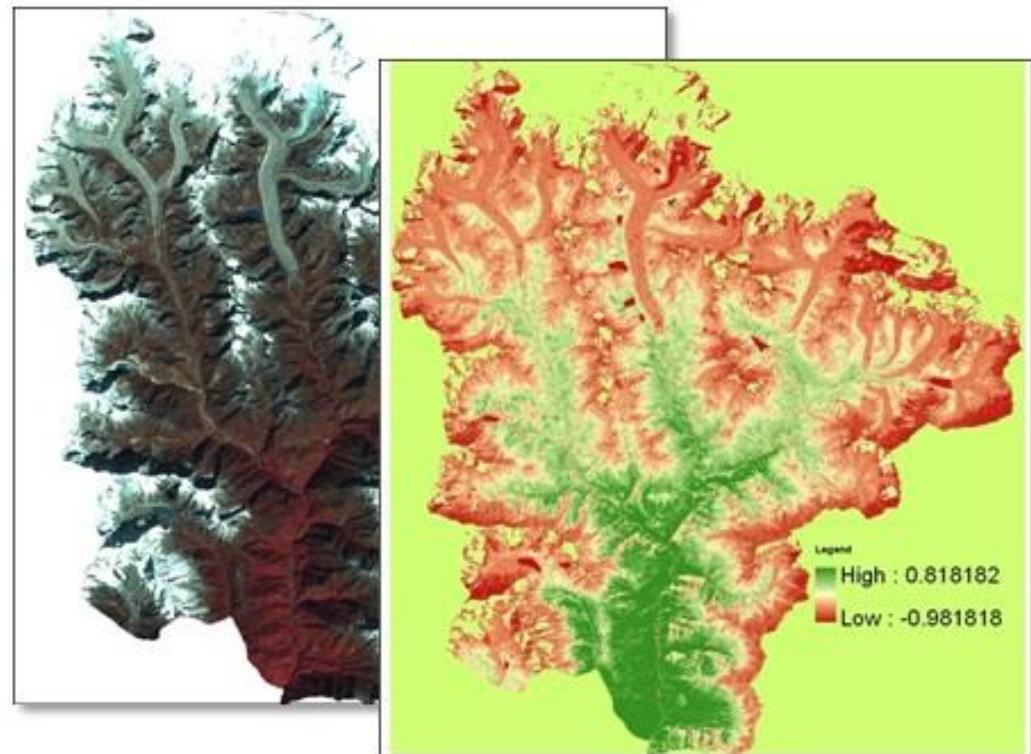


© CCRS / CCT

1) <https://natural-resources.ca/maps-tools-publications/satellite-elevation-air-photos/multispectral-scanning>

Multispectral imaging

- Multispectral imaging applications
 - Widely used
 - Asses biotic and abiotic stressors
 - Nutrient deficiencies
 - Heat and water stress
 - Disease
 - Pest infestations
- Normalized Difference Vegetation Index (NDVI)



1) https://en.wikipedia.org/wiki/Normalized_difference_vegetation_index

Normalized Difference Vegetation Index (NDVI)

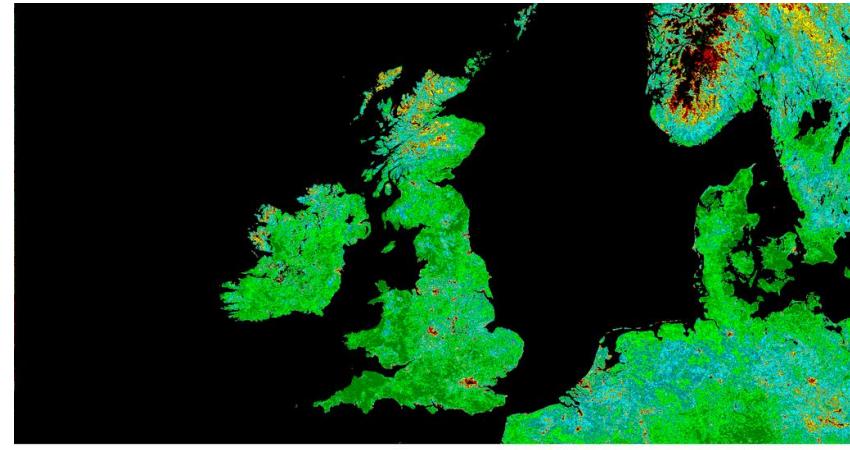
- Method to measure vegetation from aerial images

- Between -1 and 1
- 1: Healthy plants
- 0: No vegetation
- -1: Ocean / no dry land

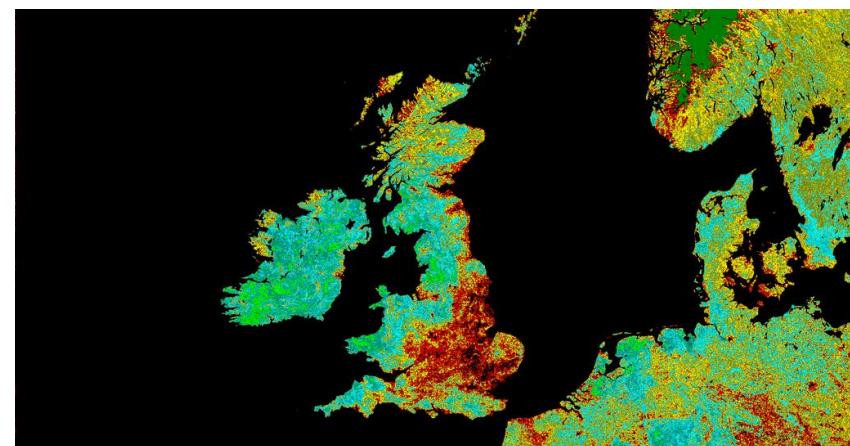
$$\text{NDVI} = \frac{(\text{NIR} - \text{Red})}{(\text{NIR} + \text{Red})}$$

- Reasoning:

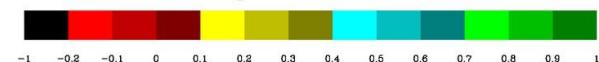
- Plants appear:
 - Dark in the red band, due to photosynthesis
 - Relatively bright in the near-infrared
- Clouds and snow appear:
 - Bright in the red
 - Dark in the near-infrared



average NDVI of June 2003



average NDVI of October 2003



1) https://en.wikipedia.org/wiki/Normalized_difference_vegetation_index

Spectroradiometers vs cameras

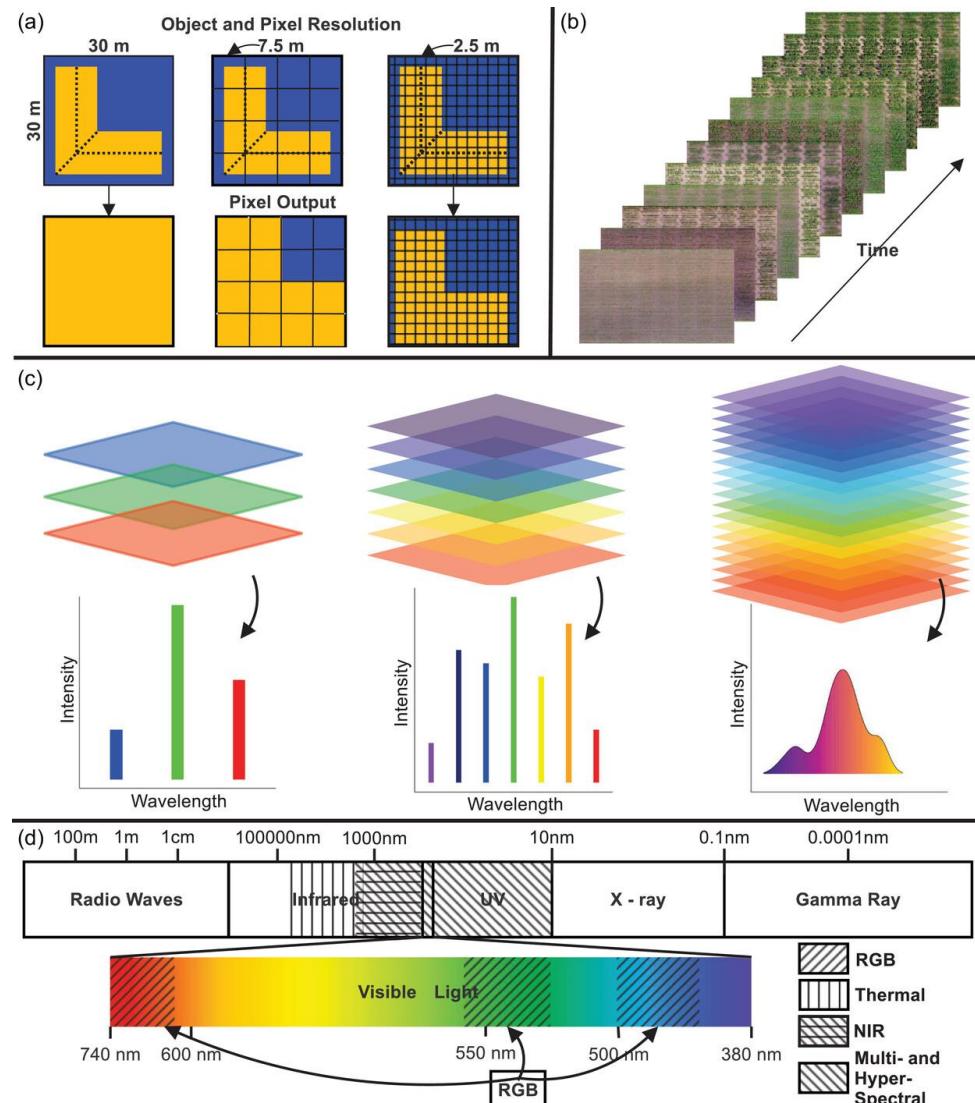
- Spectroradiometers vs cameras
 - Finer resolution
 - Specific wavelength range
 - Sensors measure individual wavelengths
 - Larger potential range
 - UV, Infra-red, Near-infra-red
- Spectral resolution prioritised over spatial information
 - Cameras: R, G, B + spatial



Image from ChatGPT

Spectral imaging

- Different possible levels of data resolution in agriculture
 - (a) Spatial resolution
 - (b) Temporal resolution
 - (c) Spectral resolution
 - (d) Locations of spectral wavelengths
- Upscaling spectral resolution:
 - Hyperspectral imaging

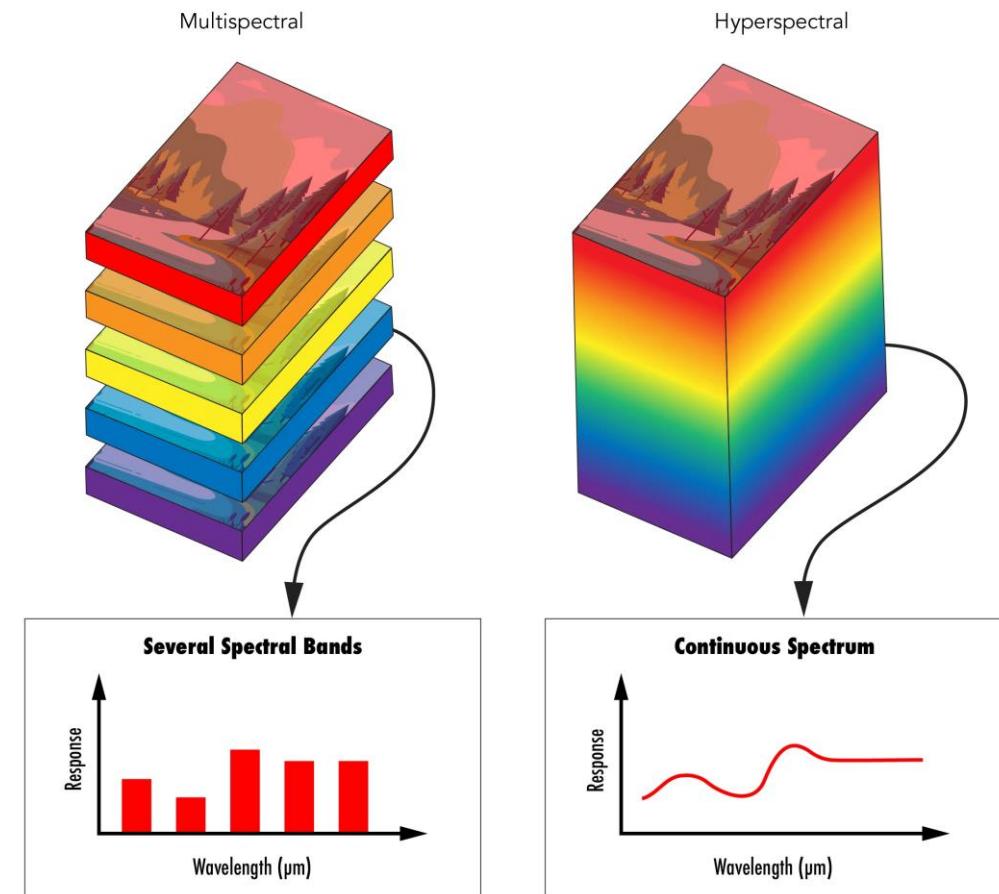


1) Source: <https://acsest.onlinelibrary.wiley.com/doi/full/10.1002/ppj2.20044>

Hyperspectral imaging

- Multispectral vs hyperspectral
 - Bands of wavelength
 - Multispectral: Appx 3-15
 - Hyperspectral: 100+
- Discrete vs “continuous”
 - *Note: not truly continuous, but interpolated*
- Significantly more complex data processing
 - More expensive sensing as well

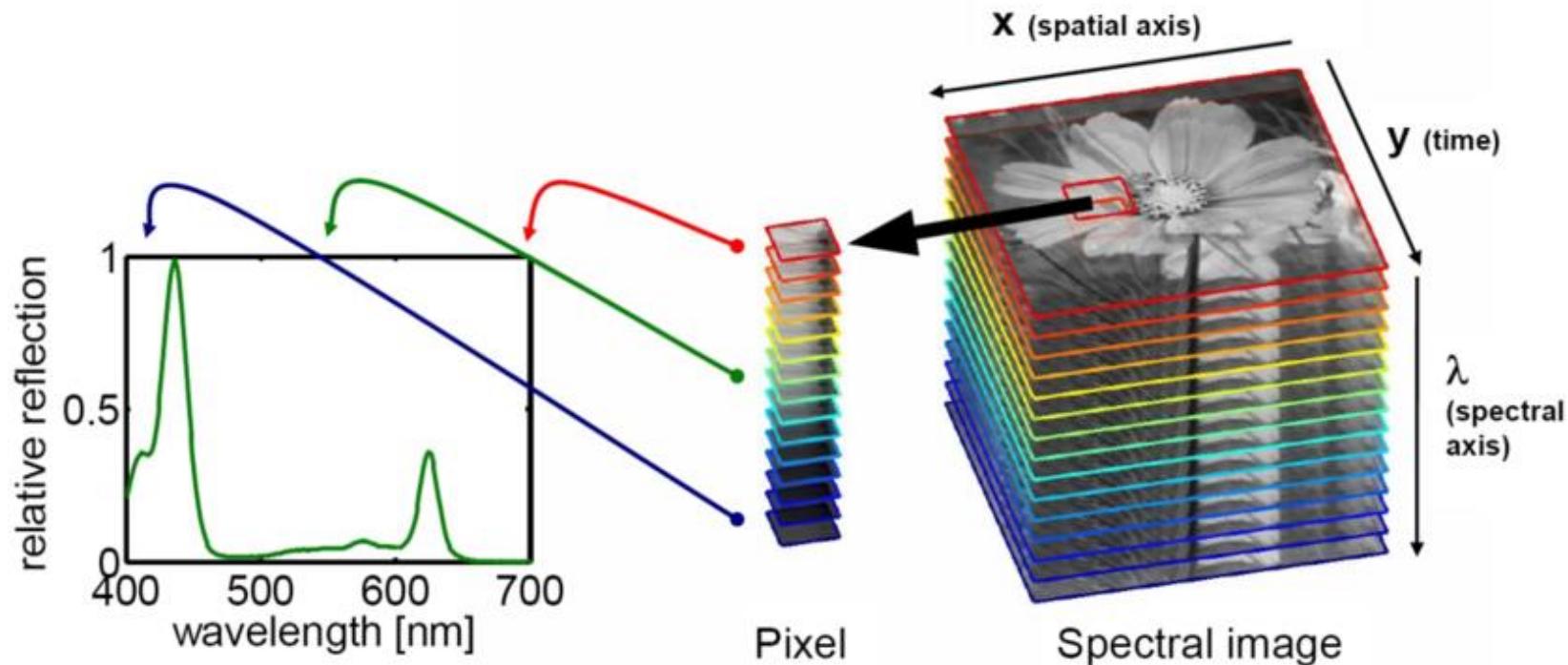
MULTISPECTRAL/ HYPER SPECTRAL COMPARISON



1) <https://www.prophotonix.com/blog/hyperspectral-vs-multispectral-imaging-whats-the-difference/>

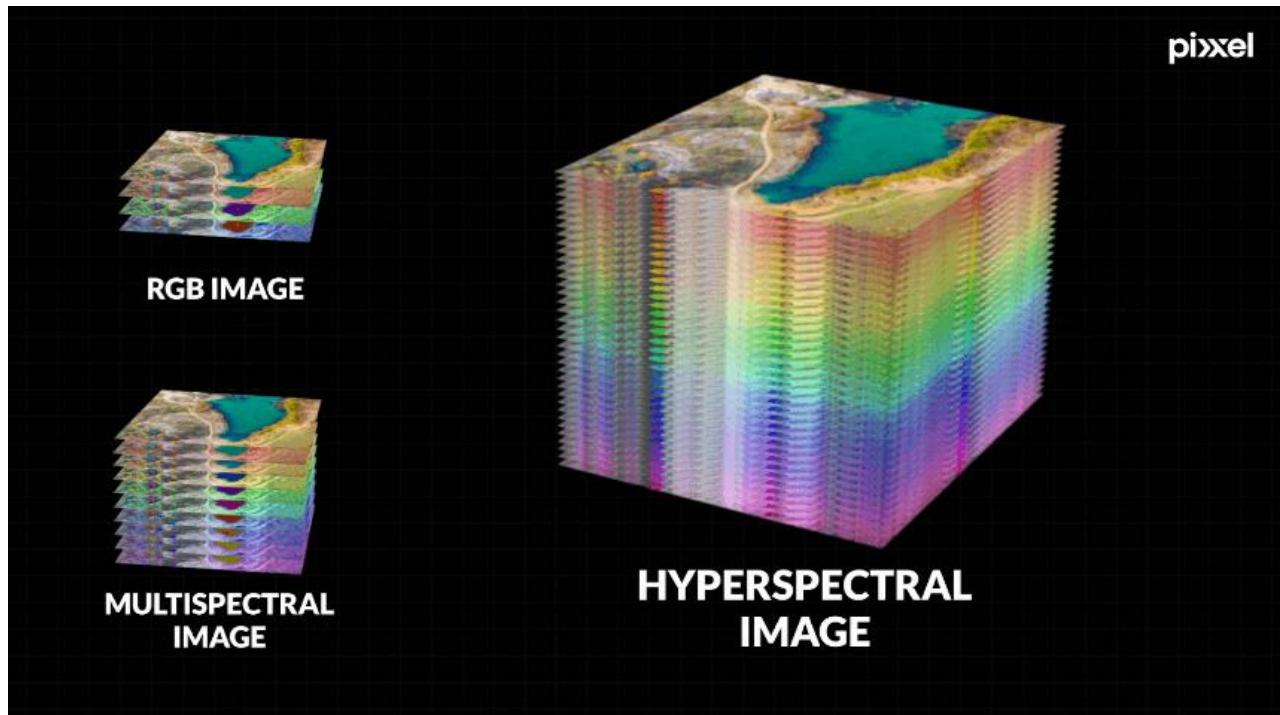
Hyperspectral imaging

- Hyperspectral data
 - One image for each wavelength
 - Each pixel covers whole spectral range
- Image contains 3D data (x , y , λ)
 - “Hyperspectral data cube”

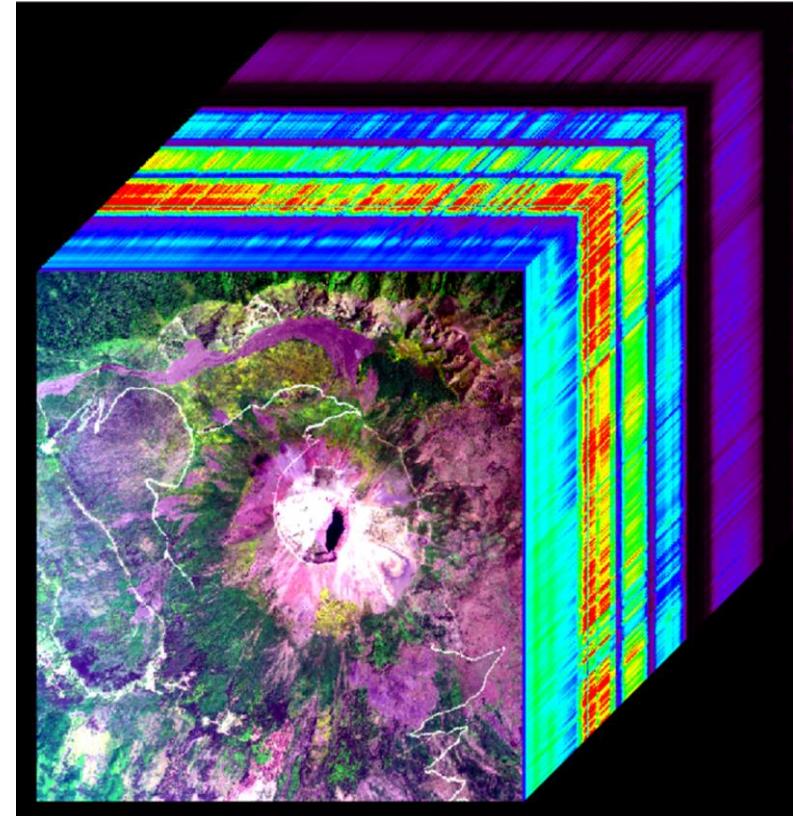


1) https://www.esa.int/ESA_Multimedia/Images/2021/09/Hyperspectral_image_cube_showing_Mount_Vesuvius_Italy

Hyperspectral imaging – data cubes



RGB vs Multispectral vs Hyperspectral

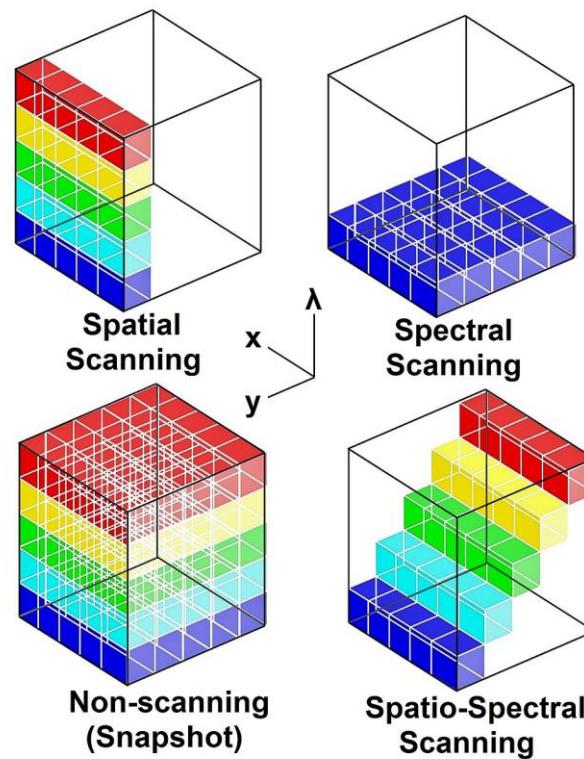


Hyperspectral cube of Mount Vesuvius

- 1) https://www.esa.int/ESA_Multimedia/Images/2021/09/Hyperspectral_image_cube_showing_Mount_Vesuvius_Italy
- 2) <https://www.pixxel.space/blogs/monitoring-water-quality-with-pixxels-hyperspectral-imaging-satellites>

Methods for hyperspectral imaging

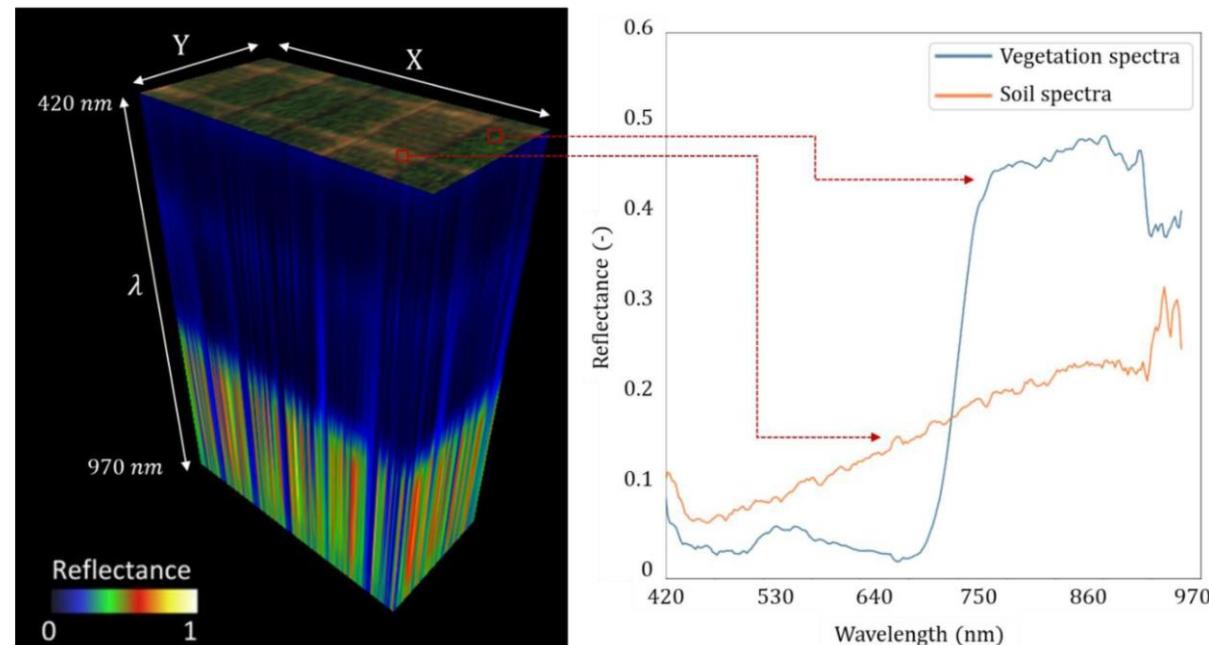
- Spatial Scanning
 - Stacked 2D image of x, λ
- Spectral Scanning
 - Stacked 2D image of x, y
- Non-Scanning
 - Single sensor for x, y, λ
- Spatio-Spectral Scanning
 - Each sensor specific to one x, y, λ



1) https://en.wikipedia.org/wiki/Hyperspectral_imaging

Hyperspectral imaging – data cube example

- Hyperspectral data
 - Can view between soil and vegetation
- Can compare spectral data between:
 - Soil and vegetation
 - Different areas of the farm
- Find what areas absorb more and less water

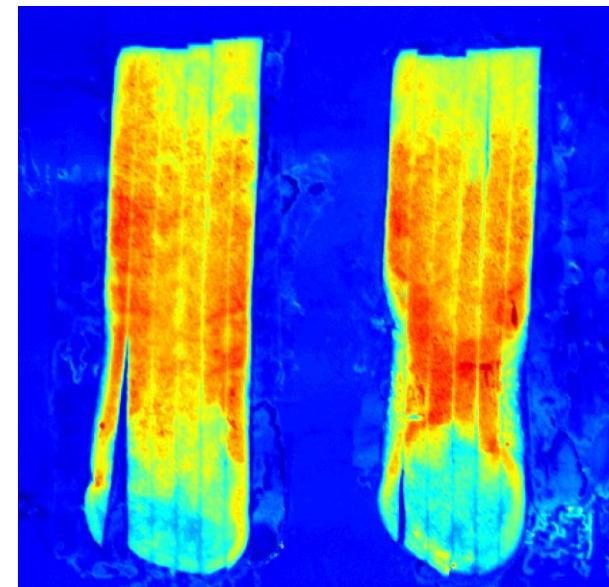


Hyperspectral cube of farm with vegetation and soil

1) Source: Raj R, Walker JP, Vinod V, Pingale R, Naik B, Jagarlapudi A. Leaf water content estimation using top-of-canopy airborne hyperspectral data. International Journal of Applied Earth Observation and Geoinformation. 2021 Oct 1;102:102393.

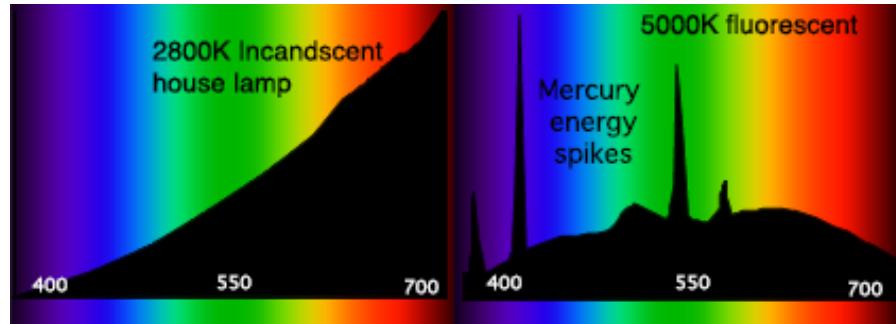
Hyperspectral imaging – factory automation

- Food screening:
 - Invisible defects
- “Sugar end” defect in potatoes:
 - Invisible until cooked
- Hyperspectral image capable of detecting in raw potato



Hyperspectral imaging – Light

- Light source important!
 - Lightbulbs do not emit uniform light
 - Some emit more wavelengths than others
- Choice of radiation source (light) important!
 - Light choice can activate certain peaks
 - More important is to calibrate
- Applies to the atmosphere
 - Have rough baselines to sun's lighting conditions
 - Can really only compare relative amounts of absorbance

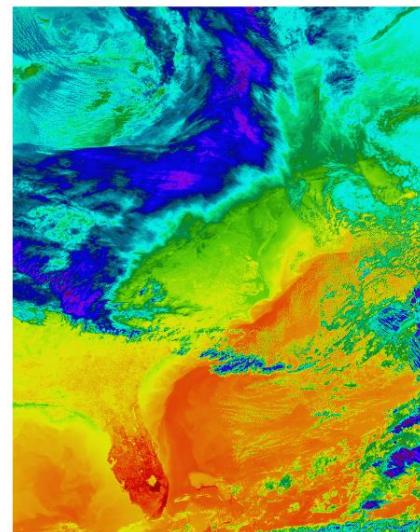
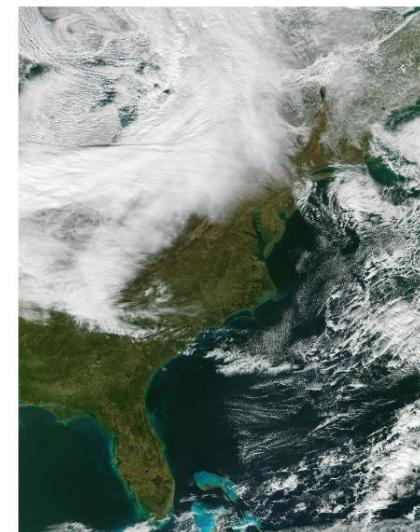


1) https://en.wikipedia.org/wiki/Compact_fluorescent_lamp
2) https://en.wikipedia.org/wiki/Hyperspectral_imaging

Hyperspectral analysis of cheese, with halogen light

Multi-spectral satellite: VIIRS

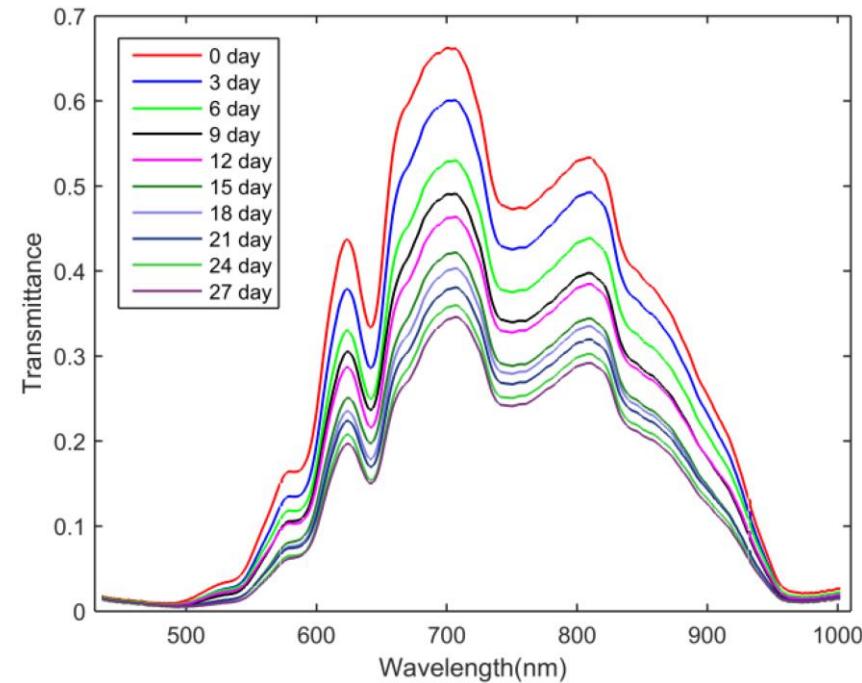
- VIIRS: Visible Infrared Imaging Radiometer Suite
 - Multi-spectral NASA satellites in orbit
- Measures different spectral bands 22 in total
 - Ocean Color Aerosol (x6)
 - Imagery band
 - Day/Night Band
 - Atmospheric Correction
 - **NDVI**
 - Cloud Particle Size
 - Cirrus Cloud Cover
 - Binary Snow Map
 - Snow Fraction
 - Clouds
 - Imagery band Clouds
 - Sea Surface Temperature
 - Sea Surface Temperature/Fires
 - Cloud Top Properties
 - Sea Surface Temperature
 - Imagery band Clouds
 - Sea Surface Temperature



1) <https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/viirs/>
2) https://cimss.ssec.wisc.edu/dbs/Hawaii2013/Day1/Gumley_VIIRS.pptx.pdf

Hyperspectral imaging

- Data analysis methods
 - Preprocessing (normalising)
 - Feature selection (what feature, e.g., size, colour, texture of the object)
 - Classification/Prediction Models
- Compare derivatives of spectral data to reference data set
 - E.g., amount of cholesterol in eggs
- High dimensionality – lots of data!
 - Dimensionality reduction techniques necessary



Egg transmittance vs storage time

1) Textbook

2) <https://www.mdpi.com/2304-8158/11/14/2024>

Hyperspectral imaging - Applications

Table 4.1 Commonly used classification/prediction models with Vis-NIR/NIR spectral datasets in agricultural applications

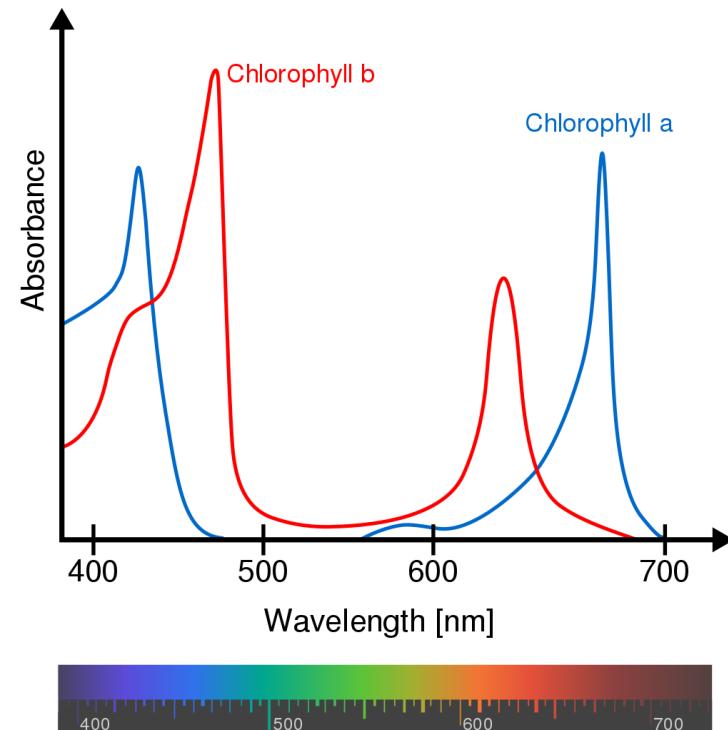
Model	Application	Spectral range, nm	Spectral features	References
LR	Citrus greening detection	350–2500	PCs, >95% variance	Mishra et al. (2012)
	Maize yield prediction	350–2500	Full spectrum	Ferreiro-González et al. (2017)
	Blood spot detection in eggs	200–1100	576.94, 600.31 nm	Chen et al. (2015)
LDA	Tea-type classification	190–800	PCs, first 7	Dankowska and Kowalewski (2019)
	Wine grape quality assessment	350–2500	Full spectrum	Costa et al. (2019)
	Adulteration in processed meat	400–1000, 900–1700	PCs, >99% variance	Rady and Adedeji (2018)
QDA	Citrus greening detection	350–2500	PCs, >99.9% variance	Sankaran et al. (2011)
	Grapevine leafroll disease detection	350–2500	626, 701, 726, 901, 976, 1001, 1027, 1052, 1101 nm	Sinha et al. (2019)
	Bitter pit detection in apples	800–2500	971.2, 978, 986.1, 987.3, 995.4, 1131.5, 1135.3, 1139.1, 1142.8 nm	Kafle et al. (2016)
NB	Grapevine leafroll disease detection	350–2500	626, 701, 726, 901, 976, 1001, 1027, 1052, 1101 nm	Sinha et al. (2019)
	Unfertilized duck eggs detection	330–1030	500–940 nm	Dong et al. (2019)
	Adulteration in processed meat	400–1000, 900–1700	PCs, >99% variance	Rady and Adedeji (2018)
SIMCA	Citrus greening detection	350–2500	PCs, >99.9% variance	Sankaran et al. (2011)
	Nutrient estimation in oil palm leaf	350–2500	354, 732, 2129, 2292 nm for N, 352, 356, 568 nm for P, 356 nm for K	Khorramnia et al. (2014)
	Weed species discrimination	920–2500	1078, 1435, 1490, 1615 nm	Shirzadifar et al. (2018)
kNN	Citrus greening detection	350–2500	PCs, >99.9% variance	Sankaran et al. (2011)
	Adulteration in processed meat	400–1000, 900–1700	PCs, >99% variance	Rady and Adedeji (2018)
	Blood spot detection in eggs	200–1100	576.94, 600.31 nm	Chen et al. (2015)

Model	Application	Spectral range, nm	Spectral features	References
ANN	Soil lead and zinc content estimation	350–2500	460, 900, 1400, 1900, 2200 nm for Pb, 600, 900, 1100, 1400, 1900, 2200 nm for Zn	Khosravi et al. (2018)
	Nutrient estimation in oil palm leaf	350–2500	354, 732, 2129, 2292 nm for N, 352, 356, 568 nm for P, 356 nm for K	Khorramnia et al. (2014)
DT	Discrimination of apple varieties	325–1075	500–700, 720–960 nm	He et al. (2007)
	Classification of orange growing locations	1000–2500	Full spectrum	Dan et al. (2015)
	pH-based classification of meat quality grades	400–2500	400, 448, 482, 540, 568, 600, 602, 604, 606, 608, 622, 626, 654, 666, 684, 698, 968, 1376, 1710, 1874, 2476, 2494 nm	Jr et al. (2018)
SVM	Bitter pit detection in apples	800–2500	971.2, 978, 986.1, 987.3, 995.4, 1131.5, 1135.3, 1139.1, 1142.8 nm	Kafle et al. (2016)
	Nutrient estimation in oil palm leaf	350–2500	354, 732, 2129, 2292 nm for N, 352, 356, 568 nm for P, 356 nm for K	Khorramnia et al. (2014)
	Adulteration in processed meat	400–1000, 900–1700	PCs, >99% variance	Rady and Adedeji (2018)
RF	Soil nitrogen and carbon assessment	305–2200	Full spectrum	Nawar and Mouazen (2017)
	Soil organic carbon estimation	350–2500	Full spectrum	Vásá et al. (2017)
	Soil quality parameters	400–2500	Full spectrum	de Santa et al. (2018)
PLSR	Wine grape quality assessment	350–2500	Full spectrum	Costa et al. (2019)
	Bitter pit development prediction in apples	935–2500	PLS components, >95% variance	Jarolmajed et al. (2017)
	Adulteration in processed meat	400–1000, 900–1700	PCs, >99% variance	Rady and Adedeji (2018)
PCR	Egg yolk cholesterol quantification	190–2500	Full spectrum	Puertas and Vázquez (2019)
	Winter wheat biomass estimation	350–2500	5 vegetation indices	Yue et al. (2018)
	Soil properties assessment	1300–2500	20 PCs, smallest RMSECV	Chang et al. (2001)

LR Logistic regression, LDA Linear discriminant analysis, QDA Quadratic discriminant analysis, NB Naive Bayes, SIMCA Soft independent modeling by class analogy, kNN k-Nearest neighbors, ANN Artificial neural networks, DT Decision tree, SVM Support vector machines, RF Random forest, PLSR Partial least square regression, PCR Principal component regression

Revisit: Plant response to light

- Chlorophyll resonates differently with light
 - This resonance has been classified using spectroscopy
- Findings from spectroscopy
 - Red and blue more sensitive
 - Grow lights of only red and blue LED light save energy
- Rather than absorption, **emission** is used
 - Chlorophyll fluorescence imaging



1) Parke WC, Parke WC. Light in Biology and Medicine. Biophysics: A Student's Guide to the Physics of the Life Sciences and Medicine. 2020:205-77.
<https://en.wikipedia.org/wiki/Chlorophyll>

Chlorophyll fluorescence imaging

- Flash a light at the leaves
 - Leaves glow in the dark
 - Red and near-infra-red light
 - Intensity indicates chlorophyll concentration
- Challenge: ambient light

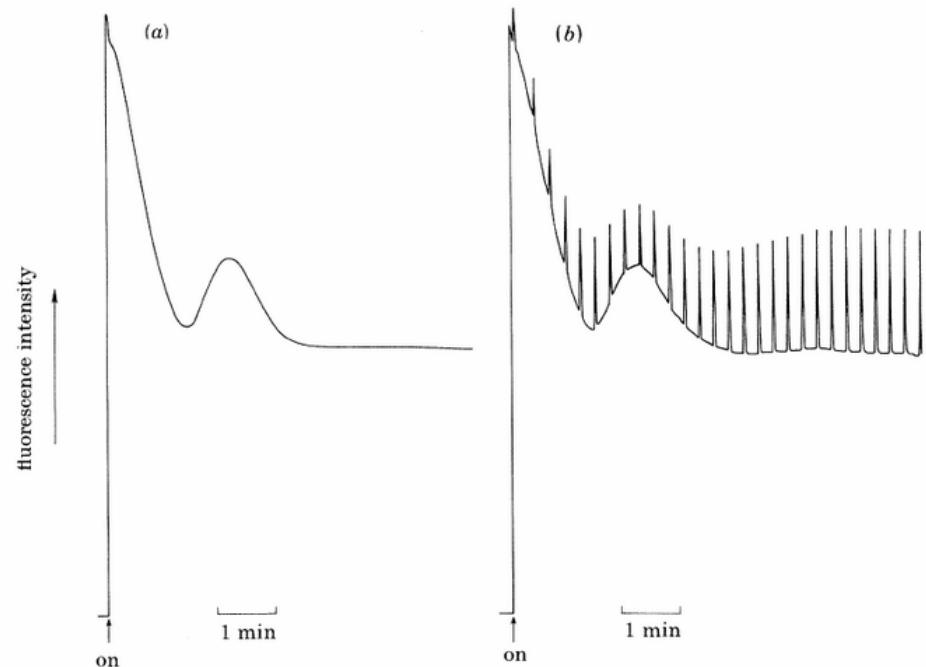


Chlorophyll extract in alcohol under white light and UV light (below)

1) https://en.wikipedia.org/wiki/Chlorophyll_fluorescence

Chlorophyll fluorescence imaging

- Ambient light
 - Fluorescence from chlorophyll drops to baseline conditions
- Pulsing the light source
 - Able to separate the fluorescence signal from background light



Fluorescence induction curve of barley with and without light pulses

1) Quick WP, Horton P. Studies on the induction of chlorophyll fluorescence in barley protoplasts. II. Resolution of fluorescence quenching by redox state and the transthylakoid pH gradient. Proceedings of the Royal society of London. Series B. Biological sciences. 1984 Jan 23;220(1220):371-82.

Fluorometer

- Sensor to measure photosynthetic efficiency
- Usually has a specific source wavelength, rather than a spectrum
 - E.g., 660 nm
- Small enough to be handheld



Chlorophyll fluorescence imaging (CFI) vs Hyperspectral imaging (HSI)

- Measures
 - CFI: light emission (fluorescence).
 - HIS: light reflection across a spectrum.
- Both detect plant stress
 - CFI: Reduced photosynthetic efficiency.
 - HSI: Properties related to stress
 - E.g., Pigment concentrations, water content
 - Chlorophyll-related signals:
 - HSI can capture reflectance changes influenced by chlorophyll,
 - CFI directly quantifies fluorescence from chlorophyll.
- Complement to plant health
 - CFI offers functional insights into photosynthesis
 - HSI provides structural and compositional information

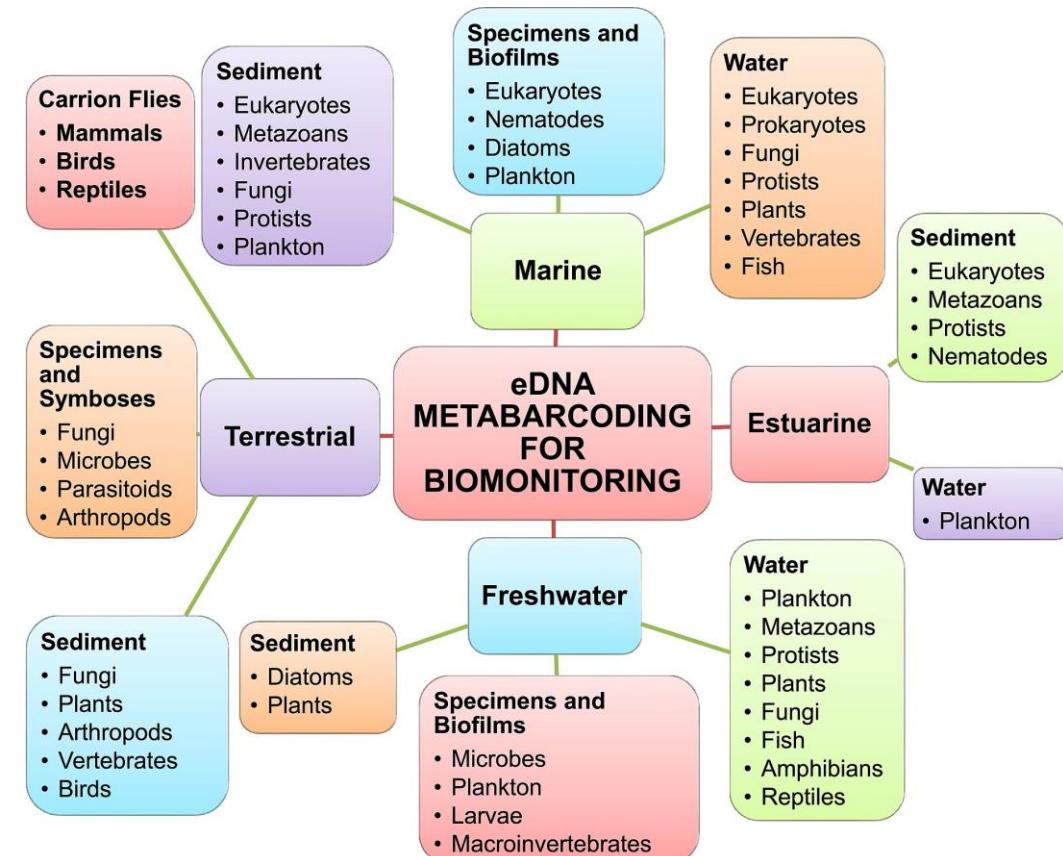


Image from ChatGPT

1) Image source: ChatGPT

eDNA

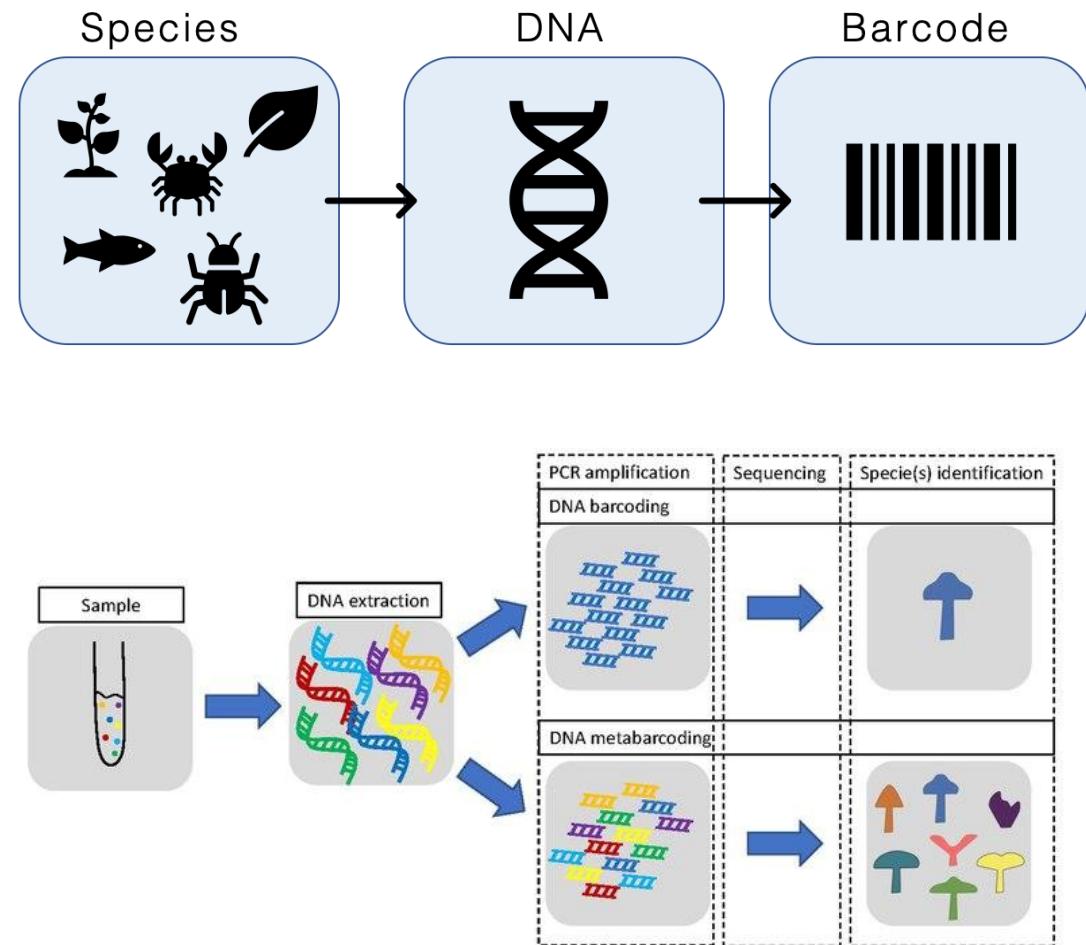
- eDNA: Environmental DNA
 - DNA collected from environment
 - Not from organism specifically
- DNA lost through interaction with environment
 - Skin, mucus, feces, hair, gams, carcasses
- eDNA detects what species are present
 - Does not measure quantity



• Source: Ruppert KM, Kline RJ, Rahman MS. Past, present, and future perspectives of environmental DNA (eDNA) metabarcoding: A systematic review in methods, monitoring, and applications of global eDNA. *Global Ecology and Conservation*. 2019 Jan 1;17:e00547.

eDNA

- eDNA maps what species are present
 - DNA sequenced, matched to reference library
 - “DNA barcoding”
- Simultaneous identification of different species from a single sample
 - “Metabarcoding”
 - Aims to determine species composition within a sample



1) https://en.wikipedia.org/wiki/DNA_barcode, <https://en.wikipedia.org/wiki/Metabarcoding>

eDNA – Challenges in acquisition

- Manual acquisition
 - Labourious
 - Time expensive
 - Difficulty depends on the environment!
- Accessibility
 - Tree canopies
 - Open oceans
- Temporal changes
 - Repeated measurements over time
 - Repetitive, difficult to acquire
- Invasiveness
 - Stress local wildlife
 - Repeated stress alters experiment



1) <https://www.ari.vic.gov.au/research/field-techniques-and-monitoring/edna-technology-an-innovative-survey-method>

Examples - ESP

- Monterey Bay Aquarium Research Institute
 - Environmental Sample Processor
 - Robotic sampler
- Sampled in a creek 3 times for a year
 - Monitored species of salmon and trout



1) <https://www.youtube.com/watch?v=OYDnqR3KLzQ>

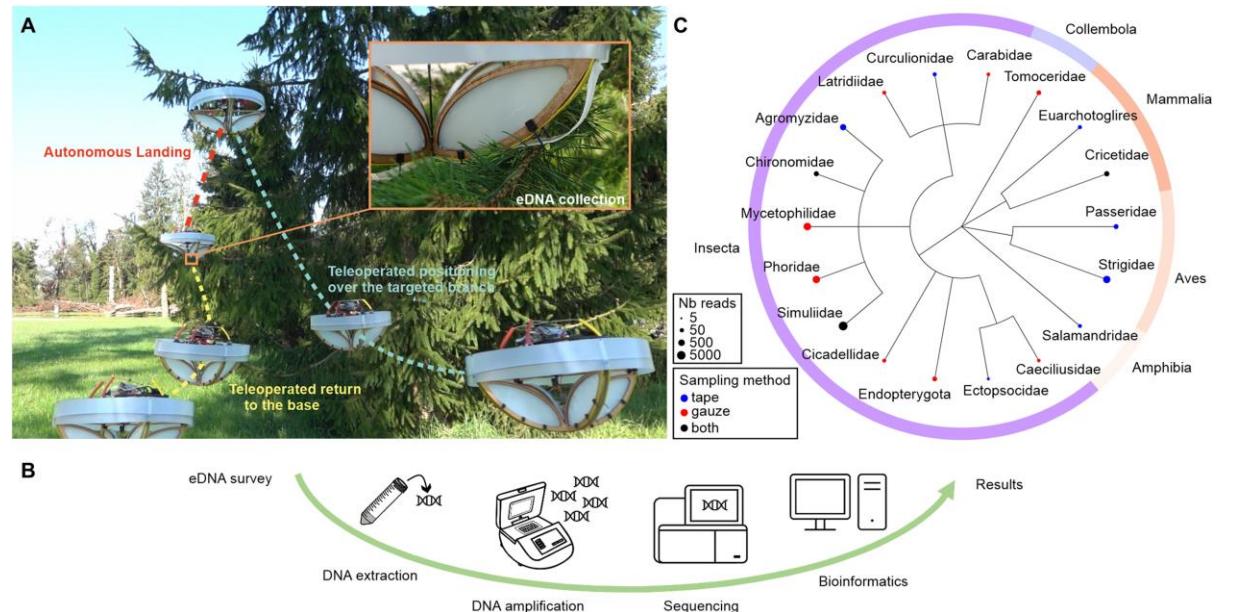
Examples – SURF eDNA

- Soft fish
 - ETH student group / startup
- Shape
 - Less stressful to wildlife
 - Less invasive



Examples - Drone

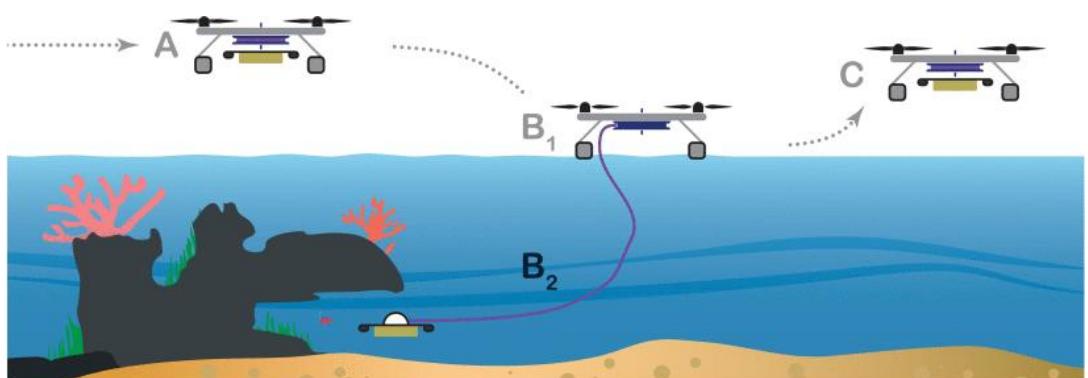
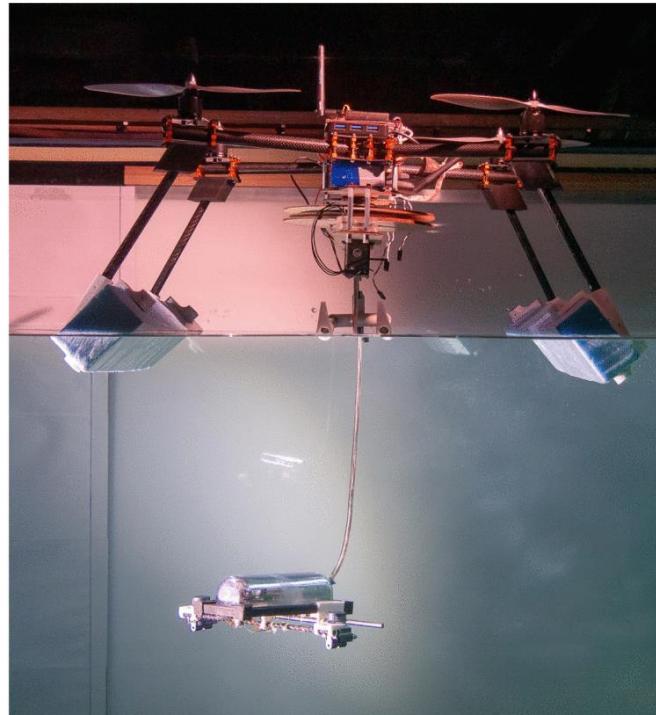
- Drones for eDNA sampling
- Tree canopies hard to reach
 - Needs to rest in contact with tree branch
- Retrieval for sequencing



1) <https://www.science.org/doi/10.1126/scirobotics.add5762>

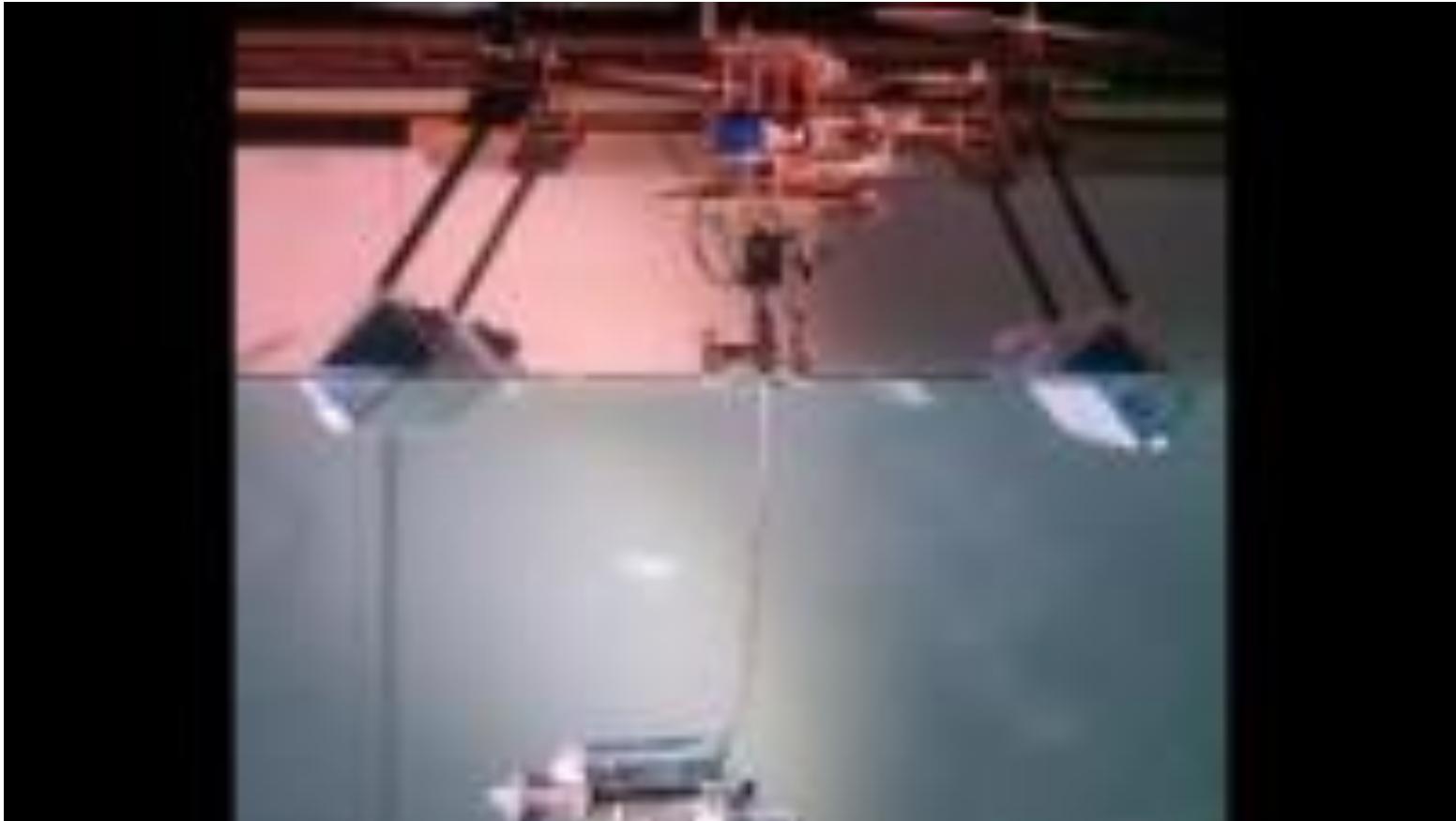
Examples - MEDUSA

- MEDUSA:
 - Multi-Environment Dual-Robot for Underwater Sample Acquisition
- Floating drone with maneuverable tether
 - Able to navigate to difficult areas



1) MEDUSA: A Multi-Environment Dual-Robot for Underwater Sample Acquisition

Examples – MEDUSA (2)



1) MEDUSA: A Multi-Environment Dual-Robot for Underwater Sample Acquisition

Phenotype

- Phenotype: set of observable characteristics of an organism
- Characteristics
 - Organism's morphology
 - Physical form and structure
 - Developmental processes
 - Biochemical and physiological properties
 - Behaviour
- Polymorphism:
 - Two or more different phenotypes exist in the same population
 - E.g., Labrador retriever fur

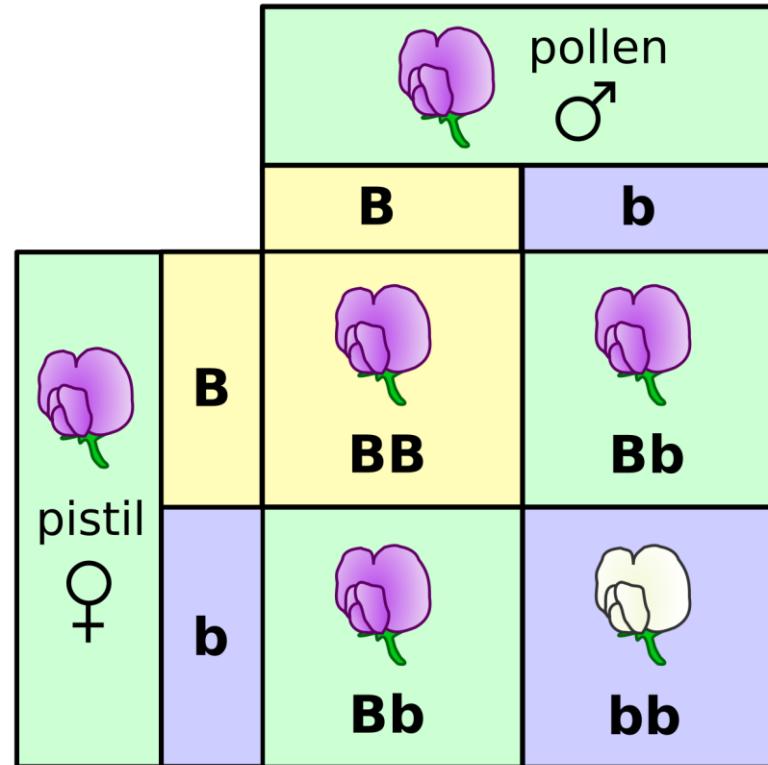


1) <https://en.wikipedia.org/wiki/Phenotype>

2) https://en.wikipedia.org/wiki/Labrador_retriever_coat_colour_genetics

Plant Phenotyping

- Obtaining observable traits jointly affected by
 - Genotypes
 - The Environment
- Phenotype formed during plant growth and development
 - Nature and nurture
- DNA sequencing and genotyping improved plant prediction



1) <https://en.wikipedia.org/wiki/Phenotype>

2) <https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2023.1215899/full>

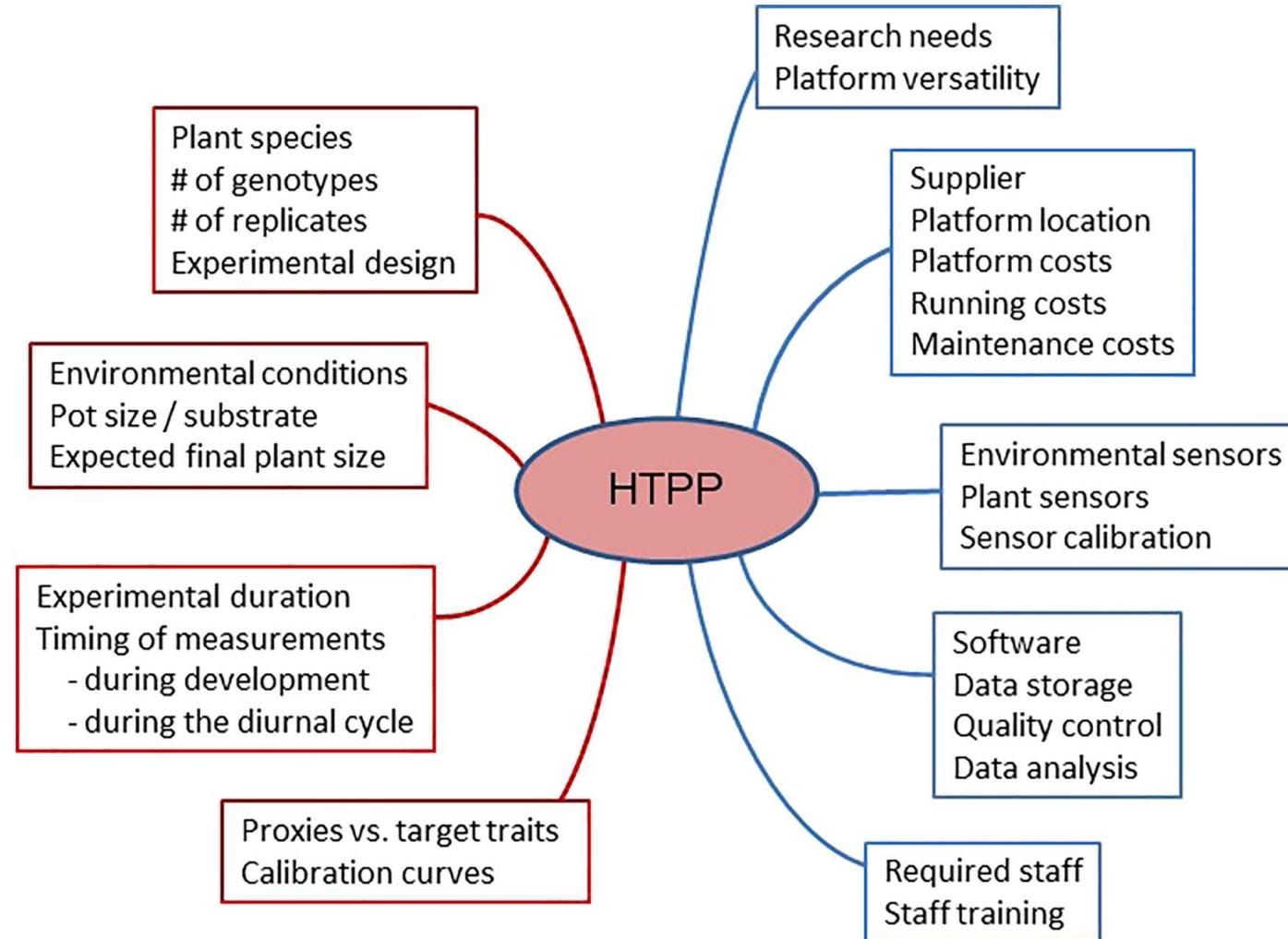
High-Throughput plant phenotyping

- Large and high quality plant phenotypic datasets are needed to relate genetic traits to quantitative results
 - Related to growth, yield, adaptation to stresses
- Robotics and technology to rapidly phenotype
 - High-throughput
- Enables:
 - Phenotyping over time
 - Phenotyping over larger areas



1) <https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2021.611940/full>
2) <https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2021.611940/full>

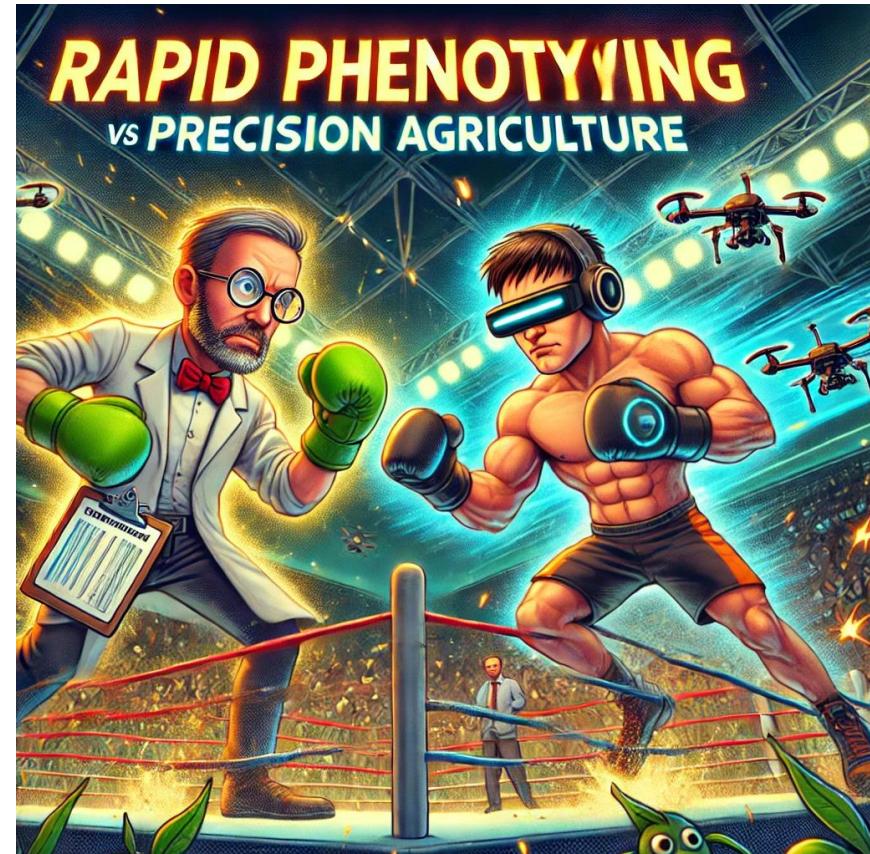
High-Throughput plant phenotyping aspects



1) <https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2023.1233794/full>

Rapid phenotyping vs precision agriculture

- Similarities
 - Monitor plant characteristics
 - Health, growth, stress responses
 - Non-destructive monitoring
 - Data-driven decision making
- Similar technology for data
 - Images, hyperspectral cameras, thermal cameras, LiDAR
- Robotic technology to improve data acquisition
 - Drones, ground-based robotics



1) <https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2023.1215899/full>
2) Image source: ChatGPT

Plant phenotyping vs precision agriculture

	High-throughput plant phenotyping	Precision agriculture
Goal	Research and trait measurement	Farm management and yield optimization
Setting	Research	Operational farms
Focus	Genetics, plant traits, stress studies	Resource management, input efficiency
Data Usage	Breeding programs	Farmer Decision-making

- Source: <https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2023.1215899/full>

Phenomobile

- Phenomobile
 - Sensorised robot platform for phenotyping measurement
- Land based, navigates between crop rows
- Closer imaging to crops, heavy payload

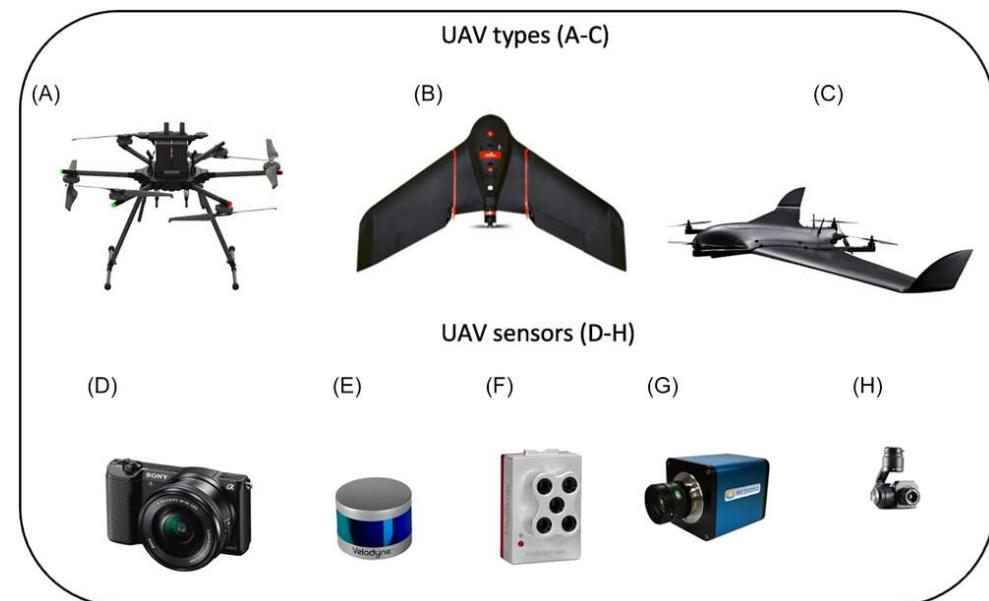


- Source: <https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2018.00237/full>, <https://www.hs-osnabrueck.de/fileadmin/HSOS/Homepages/COALA/Veroeffentlichungen/2009-JIAC-BoniRob.pdf>

Drones for phenotyping

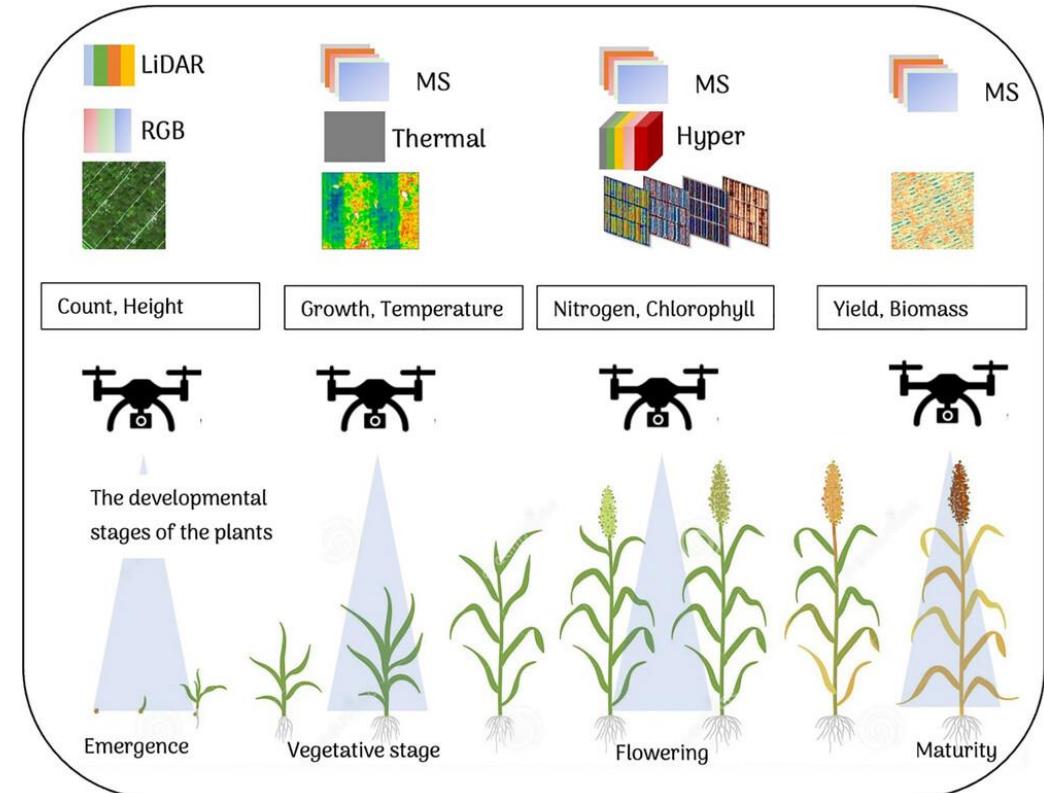
- Drones
 - Smaller payload
 - Larger areas
 - Faster
- Choice of aerial vehicle
 - Multirotor – good for fixed & high images
 - Fixed wing – longer distance
 - Hybrid – Benefits of both, less efficient an each

• Source: <https://acsess.onlinelibrary.wiley.com/doi/full/10.1002/ppj2.20044>,
<https://acsess.onlinelibrary.wiley.com/doi/full/10.1002/ppj2.20100>



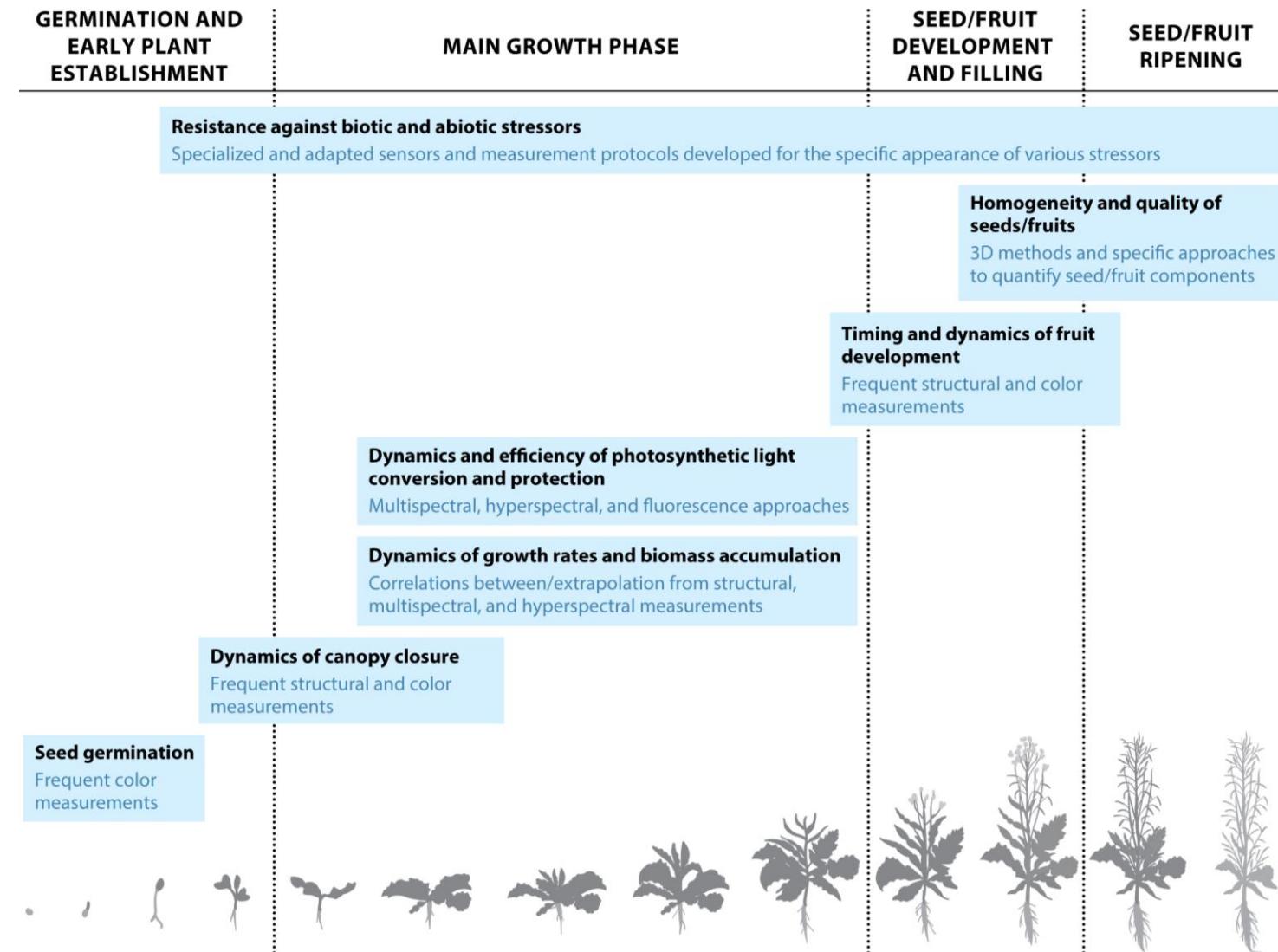
Drones for rapid phenotyping

- Choice of sensor determines phenotype
 - Trade off between power, weight, data collection, expense



- Source: <https://acsest.onlinelibrary.wiley.com/doi/full/10.1002/ppj2.20100>

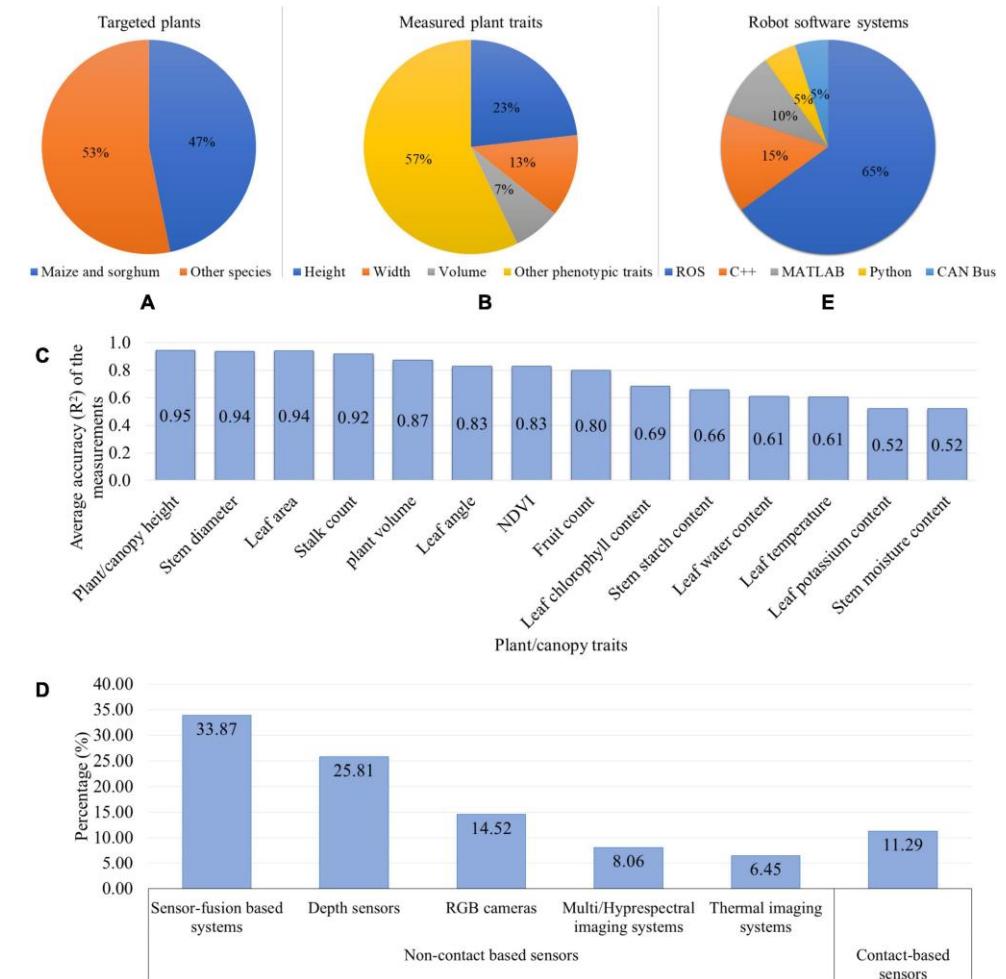
Growth stage and sensing



1) <https://www.annualreviews.org/content/journals/10.1146/annurev-arplant-042916-041124>

High-Throughput plant phenotyping

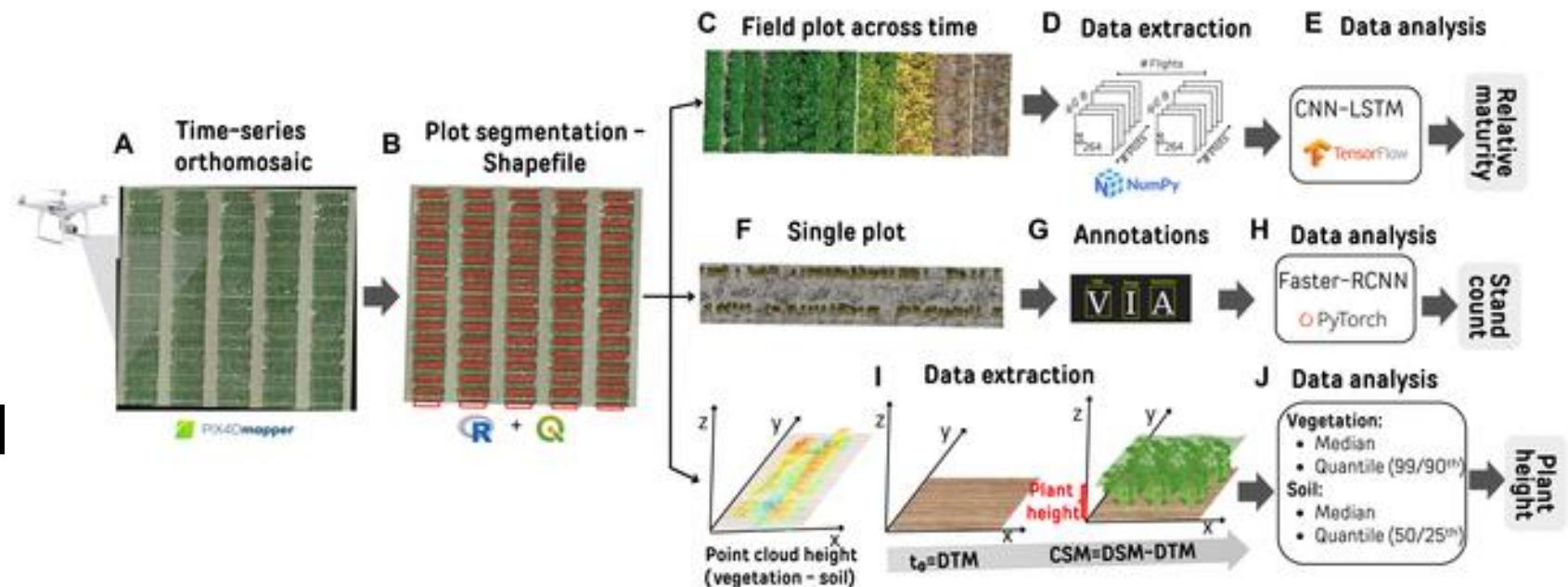
- Target plants:
 - Mostly maize and sorghum
- Most accurate
 - Plant height, stem, leaf area
- Least accurate
 - Internal characteristics (e.g., moisture, potassium)
- Sensor fusion most popular method



1) <https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2021.611940/full>

Aerial plant phenotyping

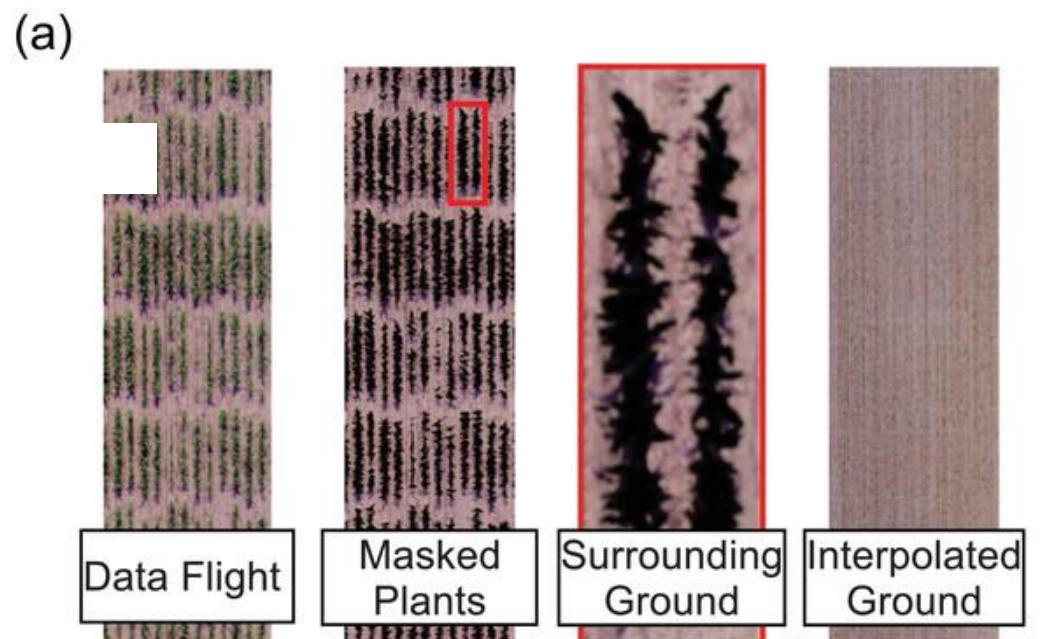
- From the same image, able to extract:
 - Maturity
 - Stand count
 - Plant height
- Different method for each



1) <https://spj.science.org/doi/full/10.34133/plantphenomics.0278>

Example: model to measure plant height

- Digital terrain model
 - Way to measure plant height
- Method
 - Localisation techniques to estimate heights of all pixels
 - E.g., SLAM
 - Use computer vision to mask plants
 - Remaining area is ground
 - Interpret as a plane
 - Subtract unmasked plants to get height



Plant height = Data height - Interpolated ground height

1) <https://acsest.onlinelibrary.wiley.com/doi/full/10.1002/ppj2.20044>

Lecture goals revisited

- Understand what **multi- and hyper- spectral sensing** is and how it can be used for precision agriculture
 - Methods to detect intensity of spectral power
- How robots can improve biodiversity sensing through collecting **eDNA**
 - Automated sampling and collection in difficult environments
- How can drones and robots contribute to **rapid phenotyping**
 - Scanning of fields and quantifying crop growth