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High-resolution hyperspectral and thermal imaging for the early detection of plant diseases

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@ZarcoTejada

The University of Melbourne

Vegetation Indices – 50 years ago

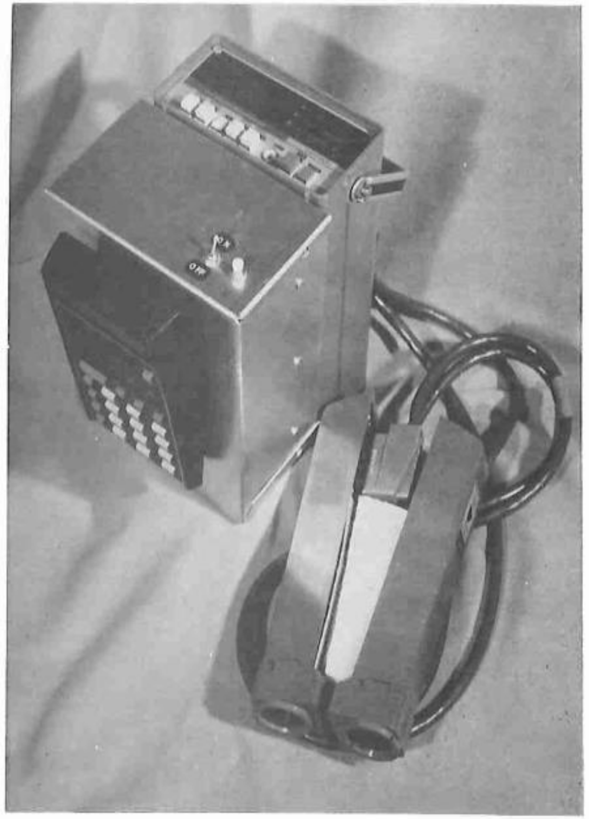

Figure 9. The prototype hand-held biomass meter consisting of a radiometer with two probes interfaced to a pocket calculator through a programmable data collection digital interface.

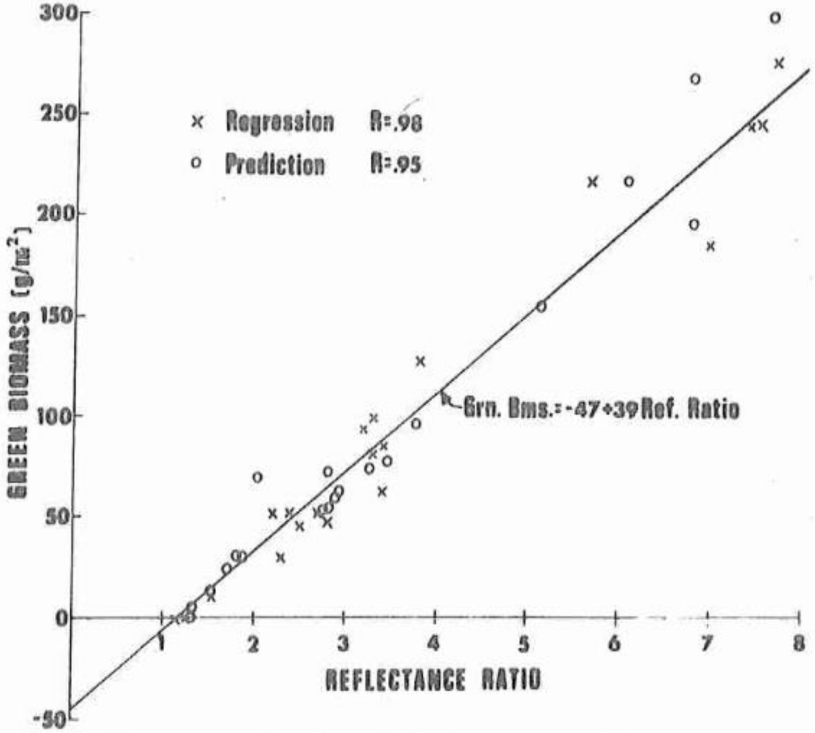

Figure 8. The linear relationship between biomass of a sample plot and the ratio of the reflectance of that plot at .800 µm to that at .680 µm was established on 20 plots using regression methods. Next, this linear relationship was used to predict the biomass on 20 new sample plots. The same plots measured in September were used here.

Tucker, Miller and Pearson (1973)

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50 years of progress

Vegetation indices

- NDVI, MTVI, RDVI …
- CARI, MCARI, TCARI
- NDWI, SRWI …
- PRI, BG1, BR1 …
- …

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50 yea

Vegetation indices

- NDVI, MTVI, RDVI …
- CARI, MCARI, TCARI
- NDWI, SRWI …
- PRI, BG1, BR1 …
- …

Structure

Chlorophyll

Water

Photochemical

Vegetation index	Equation
	Structural indices
Normal Difference Vegetation Index	$NDVI = (R_{NIR} - R_{red})/(R_{NIR} + R_{red})$
ngular Vegetation Index	$MTVI1 = 1.2 \times [1.2 \times (R_{800} - R_{550}) - 2.5 \times (R_{670} - R_{550})]$
riangular Vegetation Index VI2)	$MTVI2 = \frac{1.5 \times [1.2 \times (R_{800} - R_{550}) - 2.5 \times (R_{670} - R_{550})]}{\sqrt{(2 \times R_{800} + 1)^2 - (6 \times R_{800} - 5 \times \sqrt{R_{670}}) - 0.5}}$
Renormalized Difference Vegetation Index (RDVI)	$RDVI = (R_{800} - R_{670})/\sqrt{(R_{800} + R_{670})}$
Simple Ratio Index (SR)	$SR = R_{NIR}/R_{red}$
Modified Simple Ratio (MSR)	$MSR = \frac{R_{NIR}/R_{red} - 1}{(R_{NIR}/R_{red})^{0.5} + 1}$
Modified Chlorophyll Absorption in Reflectance Index ($MCARI_1$)	$MCARI1 = 1.2 \times [2.5 \times (R_{800} - R_{670}) - 1.3 \times (R_{800} - R_{550})]$
Modified Chlorophyll Absorption in Reflectance Index ($MCARI_2$)	$MCARI2 = \frac{1.5 \times [2.5 \times (R_{800} - R_{670}) - 1.3 \times (R_{800} - R_{550})]}{\sqrt{(2 \times R_{800} + 1)^2 - (6 \times R_{800} - 5 \times \sqrt{R_{680}}) - 0.5}}$
Soil Adjusted Vegetation Index (SAVI)	$SAVI = (1 + L) \times (R_{800} - R_{670})/(R_{800} + R_{670} + L)\ [L \varepsilon (0,1)]$
Improved SAVI with self-adjustment factor L (MSAVI)	$MSAVI = \frac{1}{2}[2 \times R_{800} + 1 - \sqrt{(2 \times R_{800} + 1)^2 - 8 \times (R_{800} - R_{670})}]$
Optimiz justed Vegetation Index (O	$OSAVI = (1 + 0.16) \times (R_{800} - R_{670})/(R_{800} + R_{670} + 0.16)$
	Chlorophyll indices
dex (G)	$G = R_{554}/R_{677}$
Chlorophyll Absorption in eflectance Index (MCARI)	$MCARI = [(R_{700} - R_{670}) - 0.2 \times (R_{700} - R_{550})] \times (R_{700}/R_{670})$
Transformed CARI (TCARI)	$TCARI = 3 \times [(R_{700} - R_{670}) - 0.2 \times (R_{700} - R_{550}) \times (R_{700}/R_{670})]$
Triangular ation Index (TVI)	$TVI = 0.5 \times [120 \times (R_{750} - R_{550}) - 200 \times (R_{670} - R_{550})]$
Zarco Miller	$ZTM = R_{750}/R_{710}$
	Water indices
erence Water Index	$NDWI = (R_{860} - R_{1240})/(R_{860} + R_{1240})$
Ratio Water Index (SRWI)	$SRWI = R_{858}/R_{1240}$
ant Water Index (PWI)	$PWI = R_{970}/R_{900}$
	Red edge spectral parameters
λ_p	$\lambda_{pr} = \lambda_{max(680-750)}$; $\lambda_{p1g} = \lambda_{max(500-600)}$; $\lambda_{p2g} = \lambda_{min(500-600)}$
R_o	$R_o = R_{min(650-700)}$
R_s	$R_s = R_{max(700-770)}$
σ	σ = shape parameter as defined by the inverted-Gaussian curve-fit model
	Other indices mentioned but not used in this study
Simple P SRPI)	$SRPI = R_{430}/R_{680}$
Nor zation Index	$NPQI = (R_{415} - R_{435})/(R_{415} + R_{435})$
eflectance Index (PRI)	$PRI_1 = (R_{528} - R_{567})/(R_{528} + R_{567})$ $PRI_2 = (R_{531} - R_{570})/(R_{531} + R_{570})$
Pigment Chlorophyll Index I)	$NPCI = (R_{680} - R_{430})/(R_{680} + R_{430})$
rter indices	$Ctr1 = R_{695}/R_{420}$ $Ctr2 = R_{695}/R_{760}$
Lichtenthaler indices	$Lic1 = (R_{800} - R_{680})/(R_{800} + R_{680})$; $Lic2 = R_{440}/R_{690}$; $Lic3 = R_{440}/R_{740}$; $Lic4 = \int_{450}^{680} R$
Structure Intensive Pigment Index (SIPI)	$SIPI = (R_{800} - R_{450})/(R_{800} + R_{650})$
Vogelmann indices	$Vog1 = R_{740}/R_{720}$; $Vog2 = (R_{734} - R_{747})/(R_{715} + R_{726})$; $Vog3 = (R_{734} - R_{747})/(R_{715} + R_{720})$; $Vog4 = D_{715}/D_{705}$
Gitelson and Merzlyak	$G\_M1 = R_{750}/R_{550}$ $G\_M2 = R_{750}/R_{700}$
Curvature Index (Fluorescence)	$CUR = (R_{675} \cdot R_{690})/(R_{683}^2)$
Double-Peak Ratio indices	$DPR1 = D_{\lambda p(680-750)}/D_{\lambda 0+12}$; $DPR2 = D_{\lambda p(680-750)}/D_{\lambda 0+22}$; $DP21 = D_{\lambda p(680-750)}/D_{703}$; $DP22 = D_{\lambda p(680-750)}/D_{720}$
Area Red Edge Peak (ADR)	$ADR = \int_{680}^{760} D$

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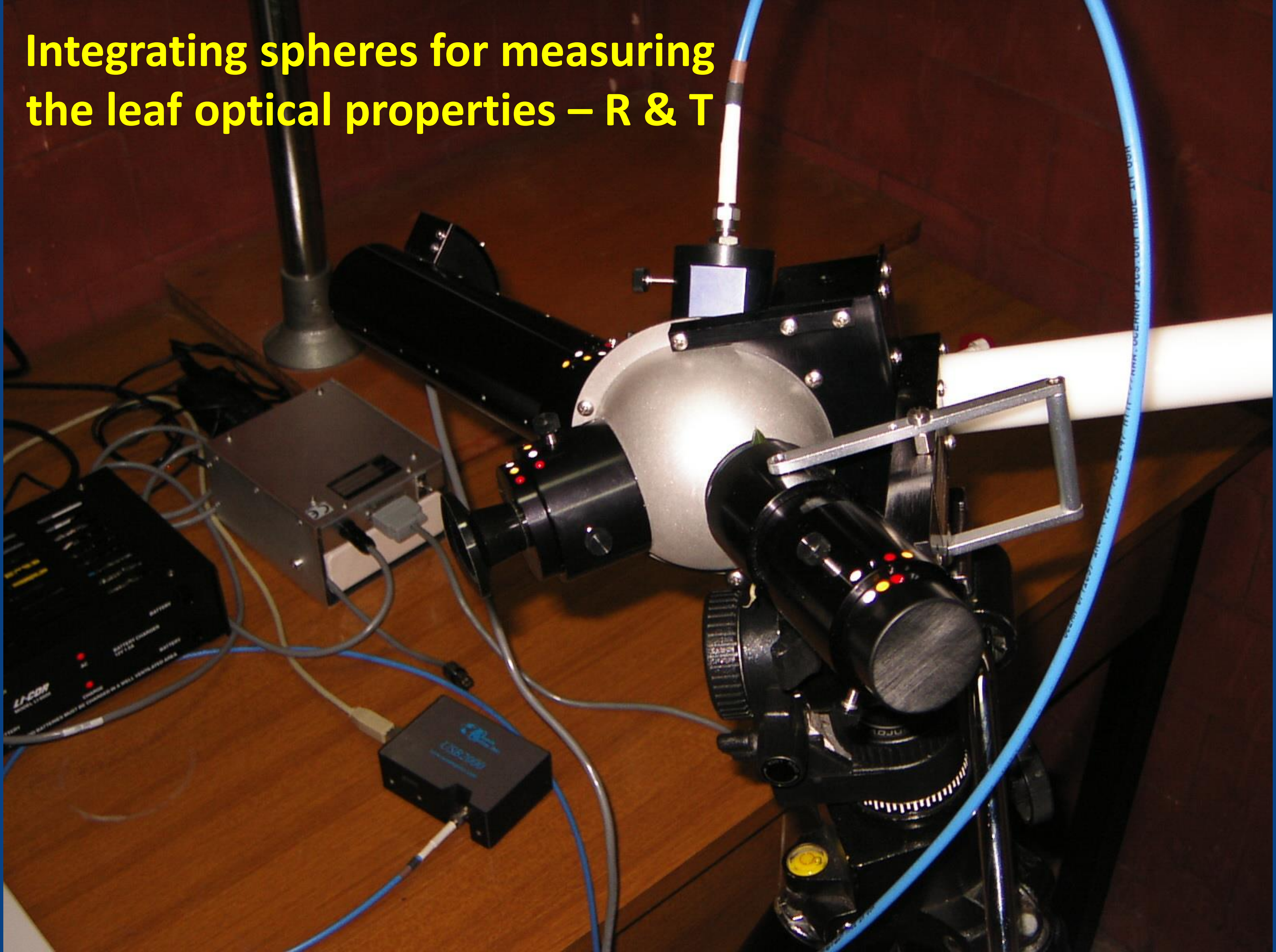
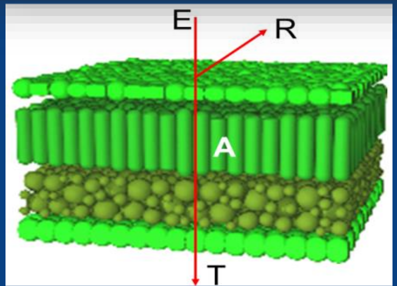
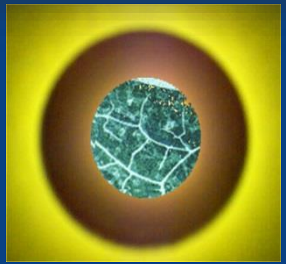
Hand-held spectral devices

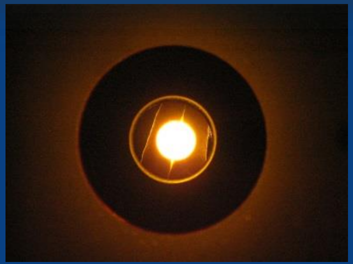
Integrating spheres for measuring the leaf optical properties – R & T

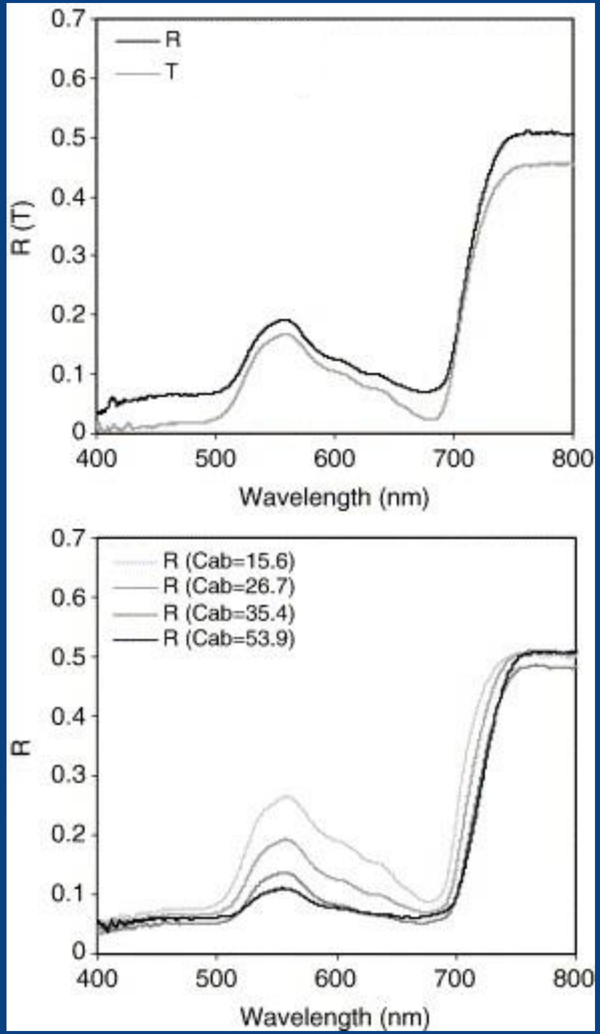


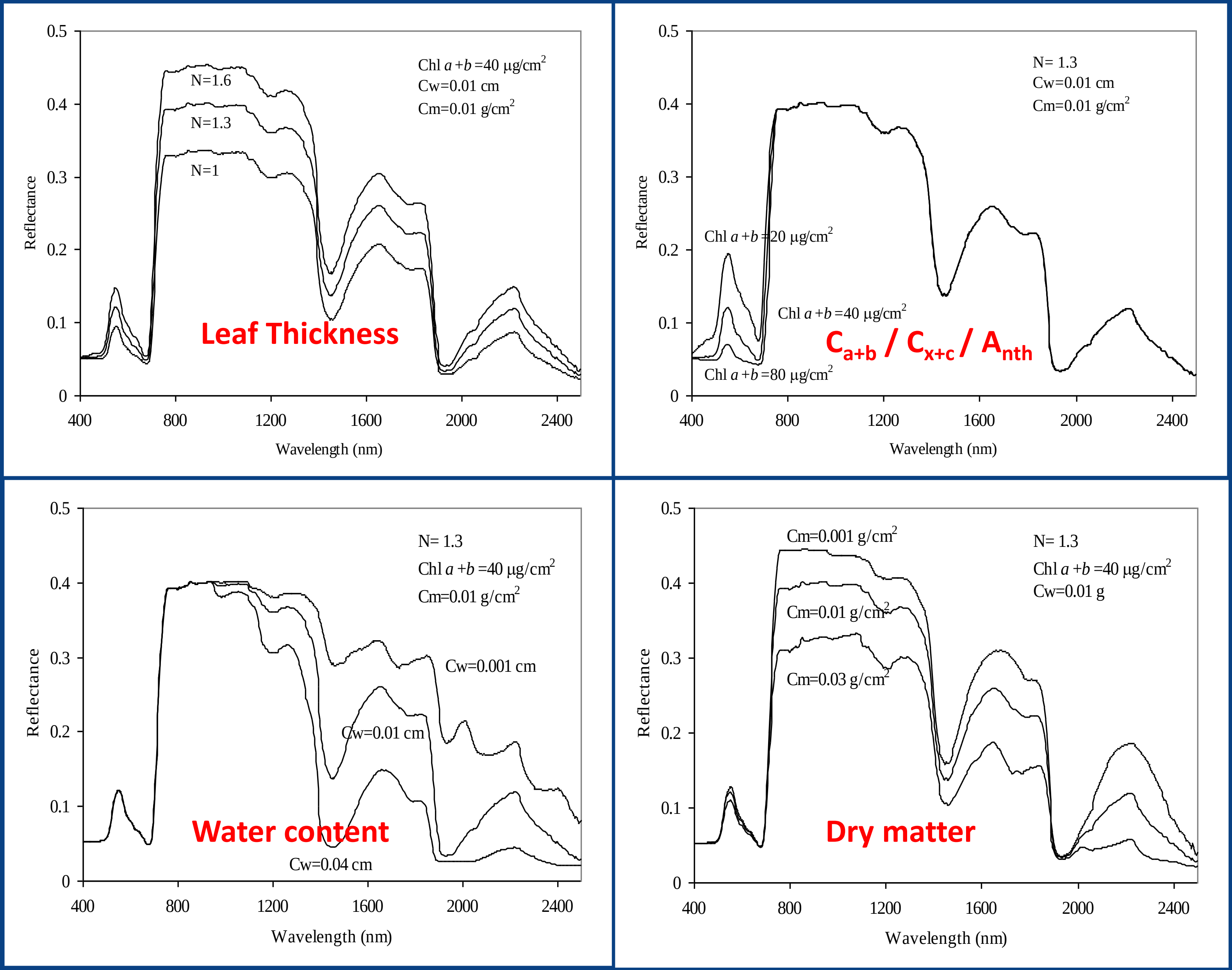
Leaf optical properties – R & T



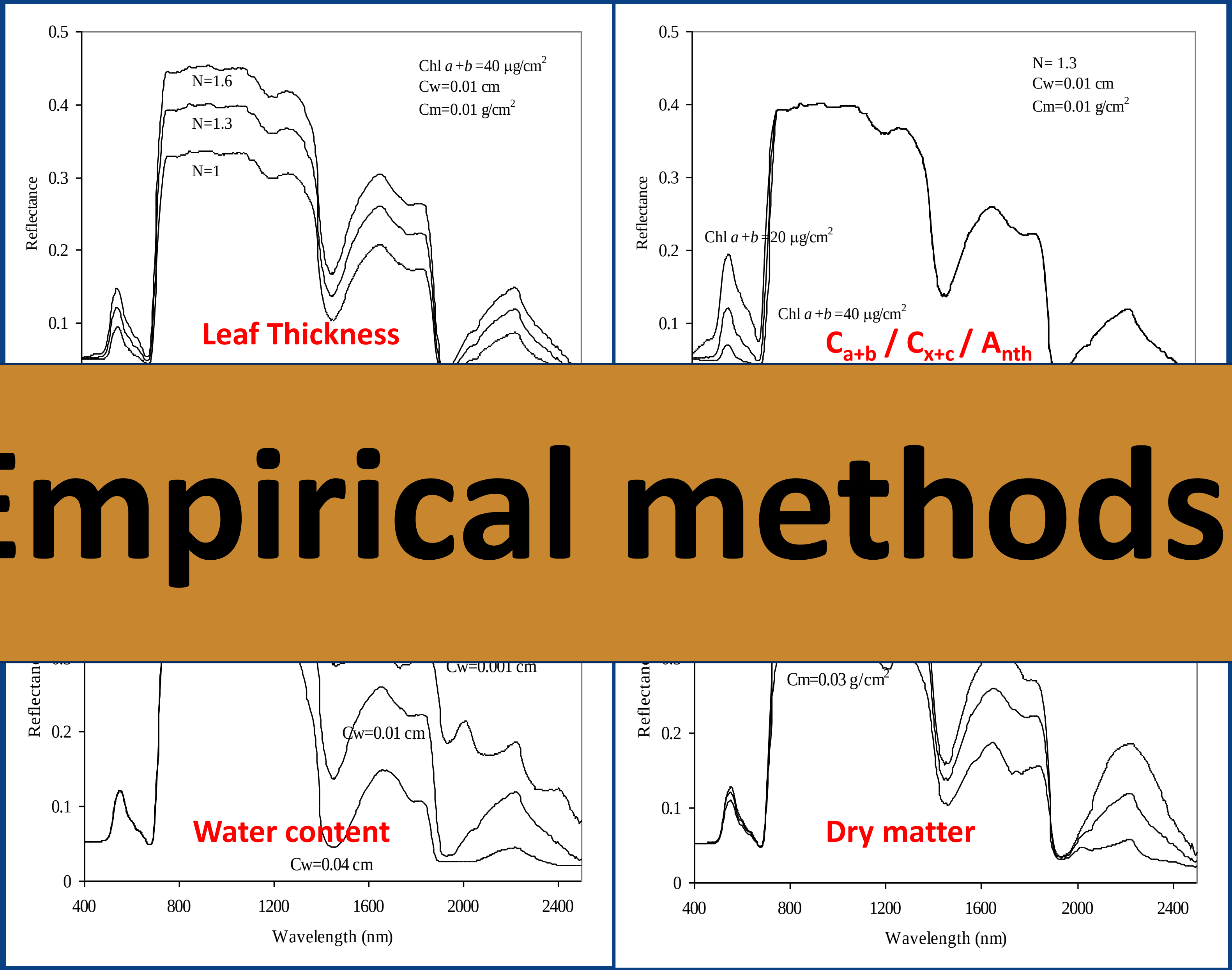




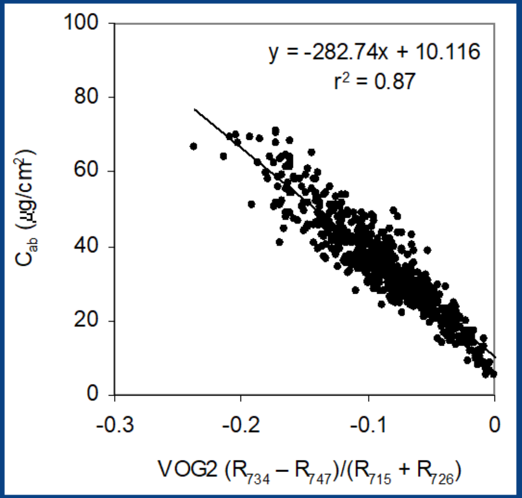


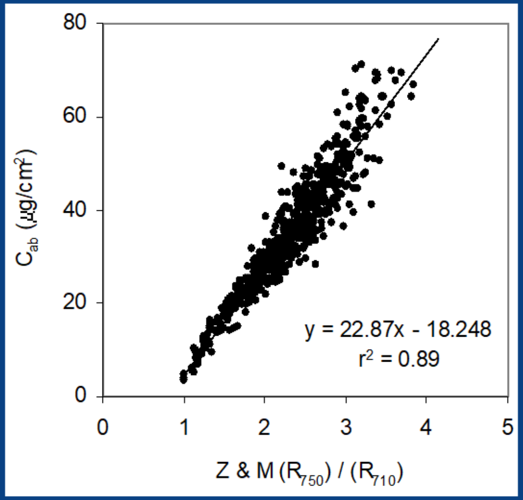

Leaf Thickness
Reflectance
Wavelength (nm)
N=1.6
N=1.3
N=1
Chl a +b =40 μg/cm2
Cw=0.01 cm
Cm=0.01 g/cm2
C a+b / C x+c / A nth
N= 1.3
Cw=0.01 cm
Cm=0.01 g/cm2
Chl a +b =20 μg/cm2
Chl a +b =40 μg/cm2
Chl a +b =80 μg/cm2
Water content
N= 1.3
Chl a +b =40 μg/cm2
Cm=0.01 g/cm2
Cw=0.001 cm
Cw=0.01 cm
Cw=0.04 cm
Dry matter
Cm=0.001 g/cm2
Cm=0.01 g/cm2
Cm=0.03 g/cm2
N= 1.3
Chl a +b =40 μg/cm2
Cw=0.01 g

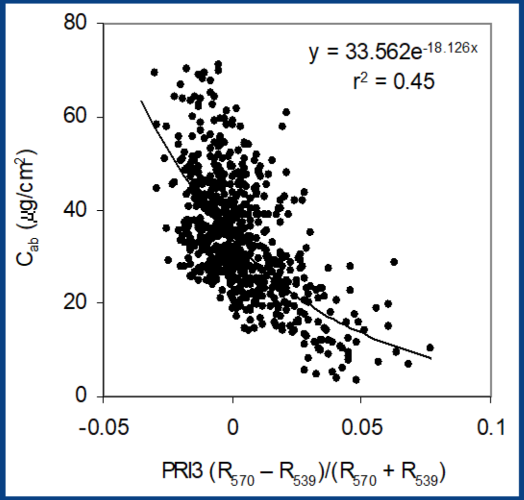
Empirical methods

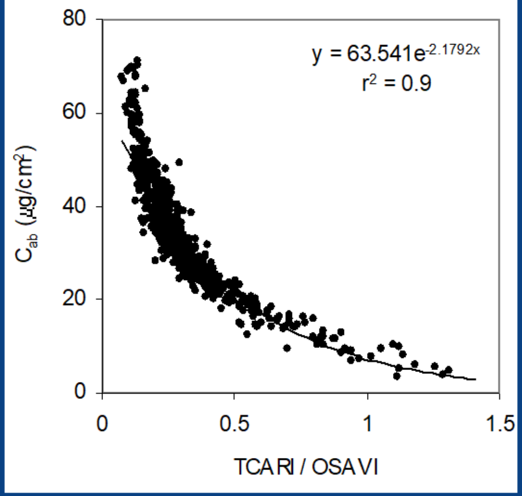


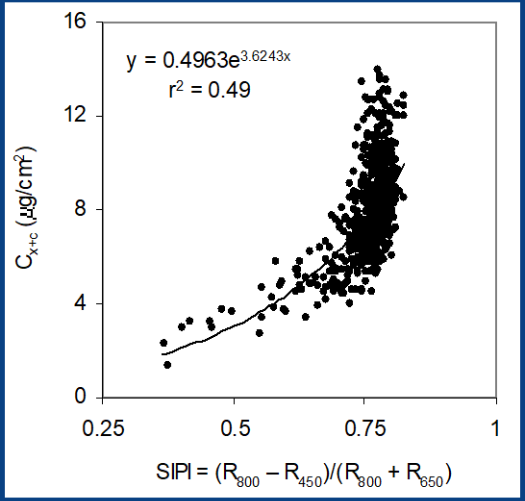
Empirical relationships: indices vs. leaf traits

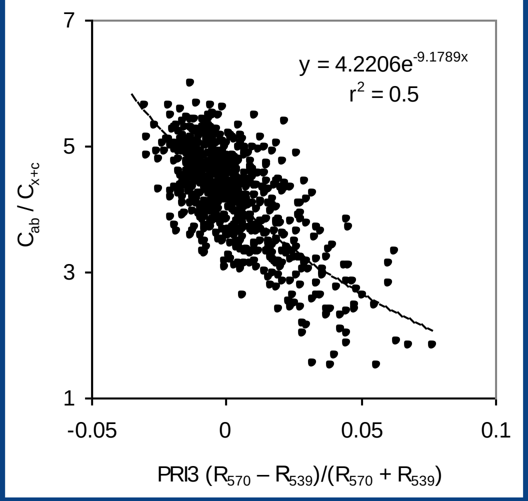












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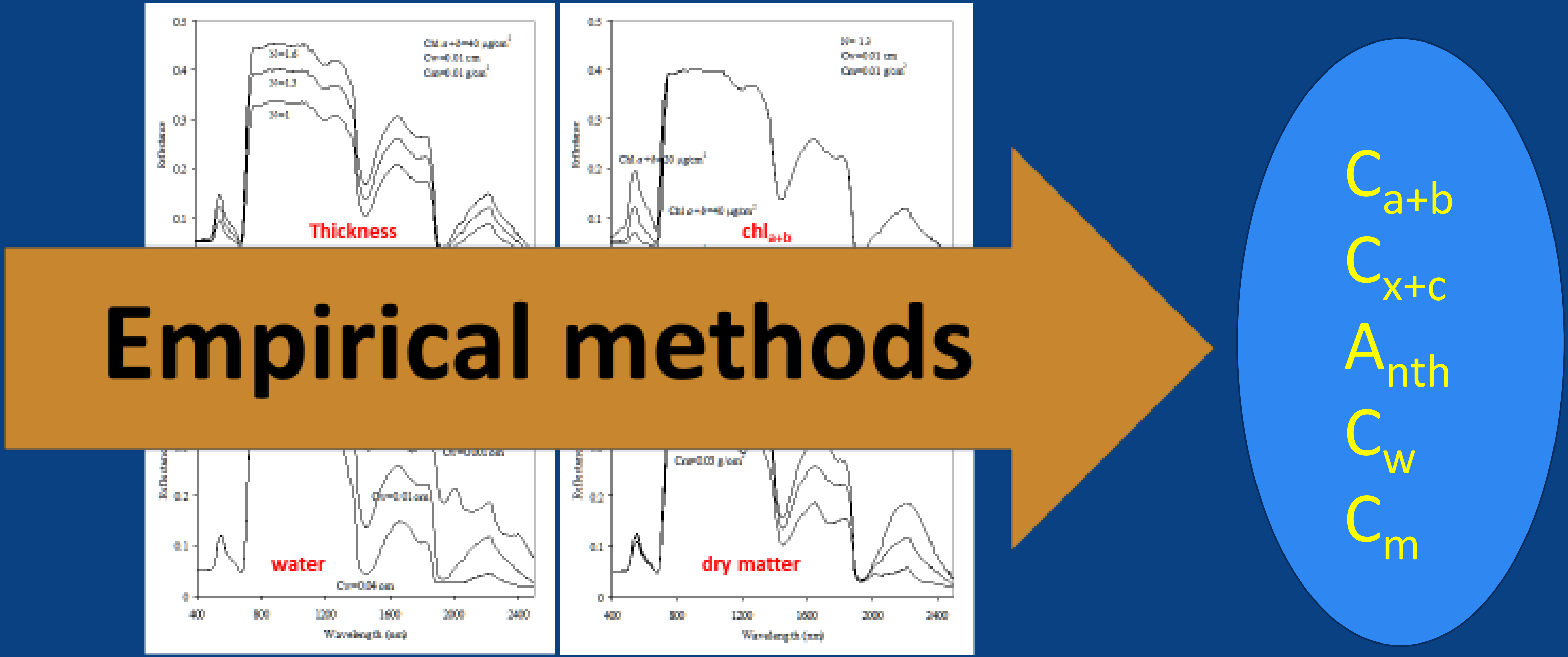
Empirical relationships: indices vs. leaf traits



Main limitations of empirical models

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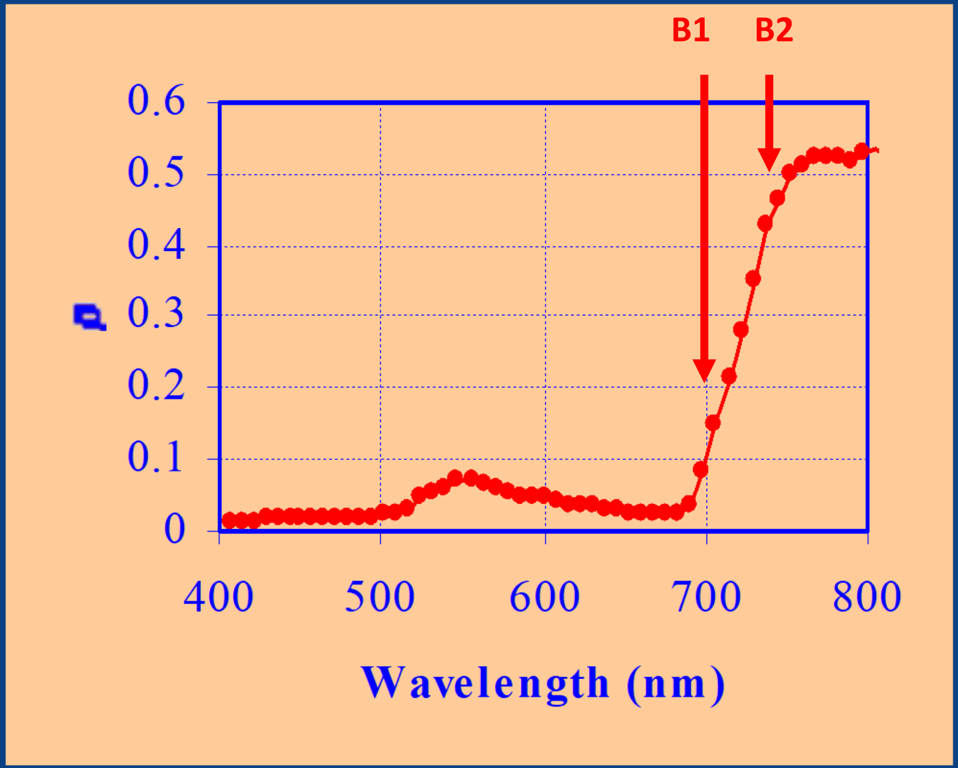
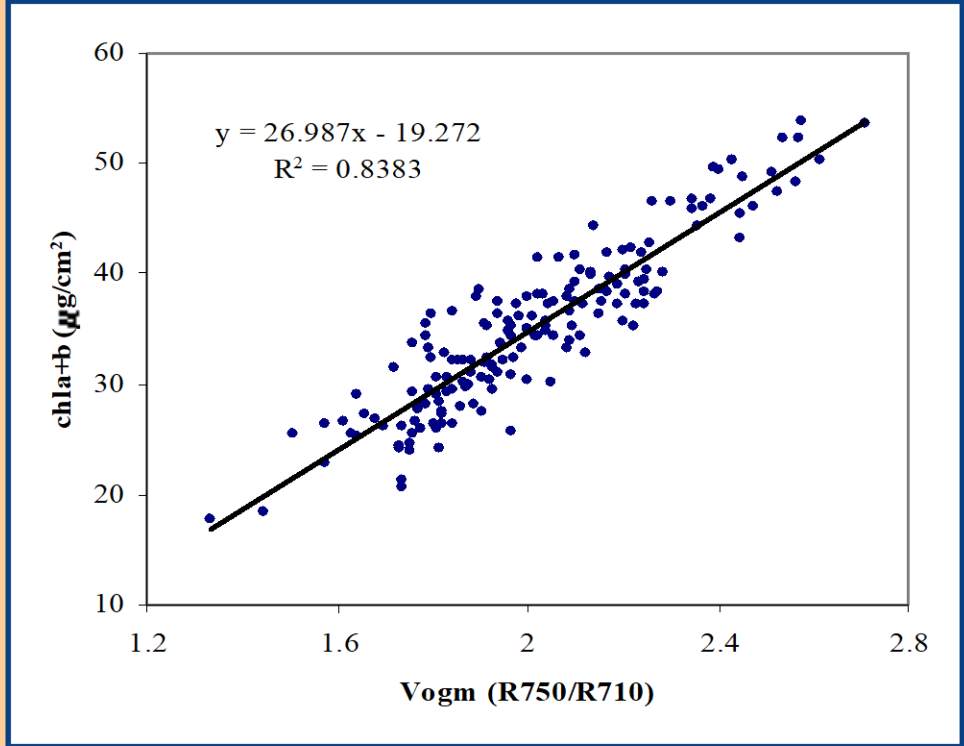
1. Robustness of empirical relationships

→ species / phenology / architecture

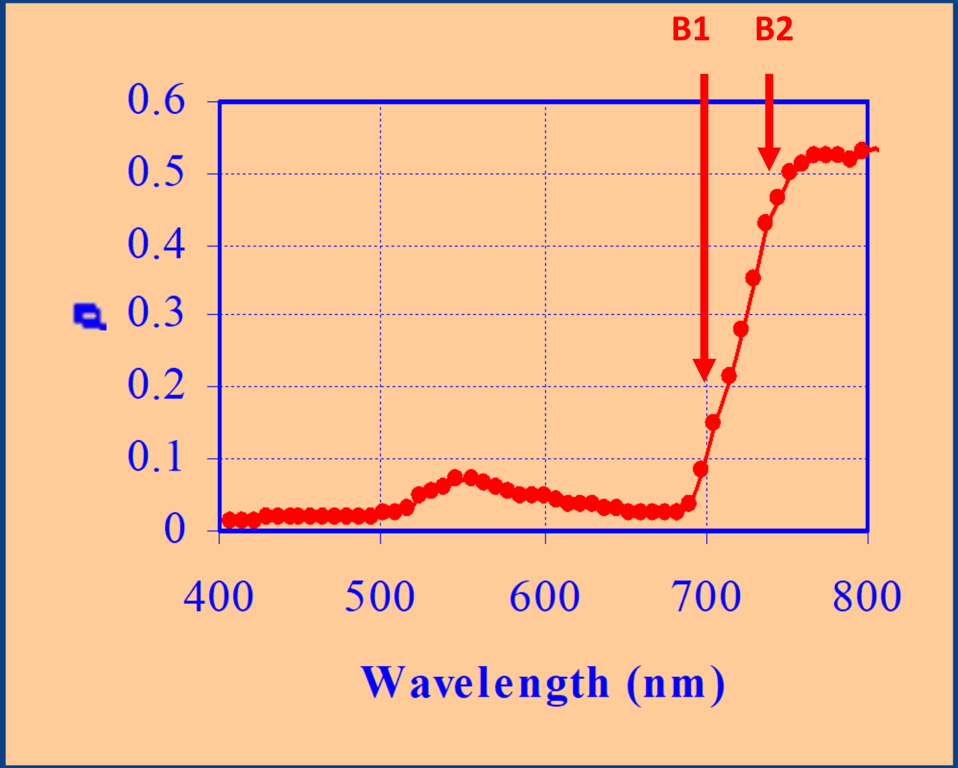
Empirical relationships indices vs. leaf traits

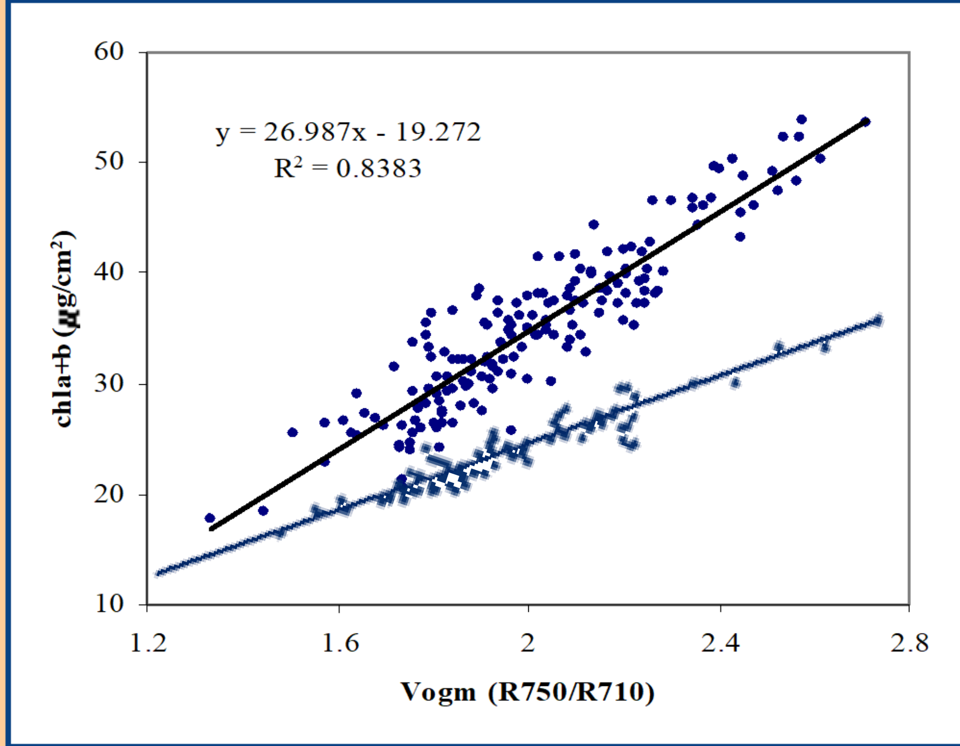




Red edge vs. C_{a+b}

Empirical relationships indices vs. leaf traits





Red edge vs. C_{a+b}

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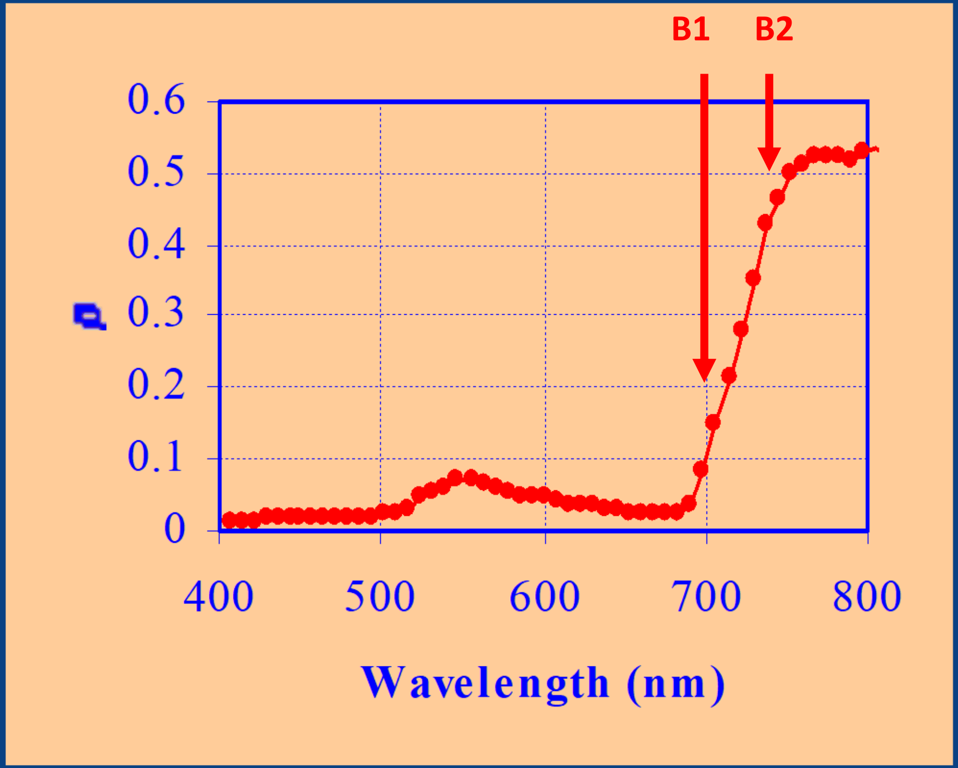
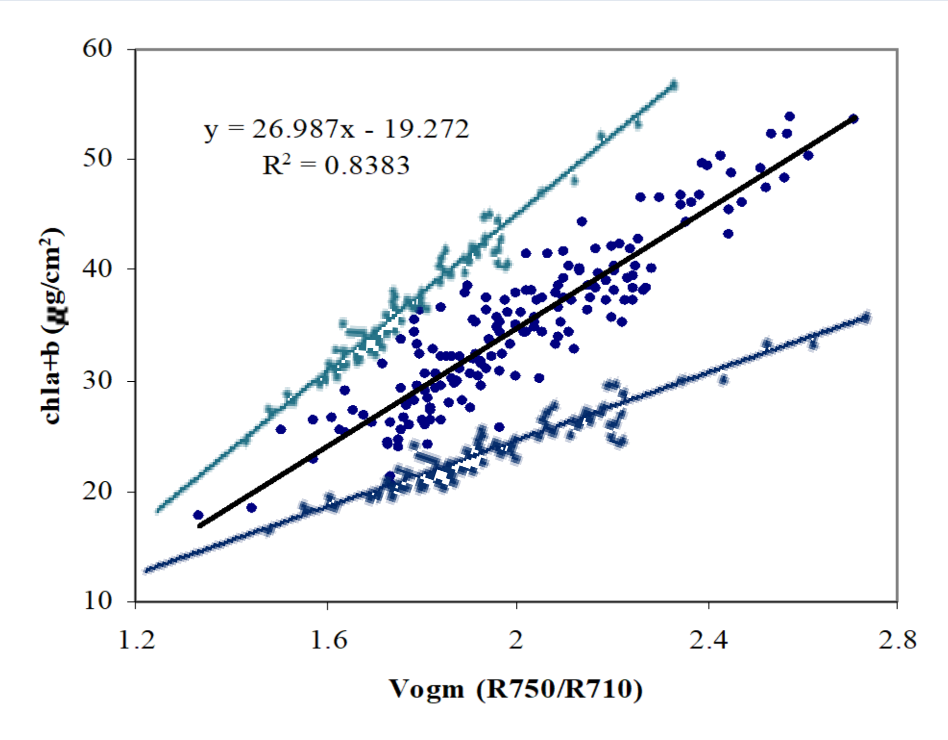
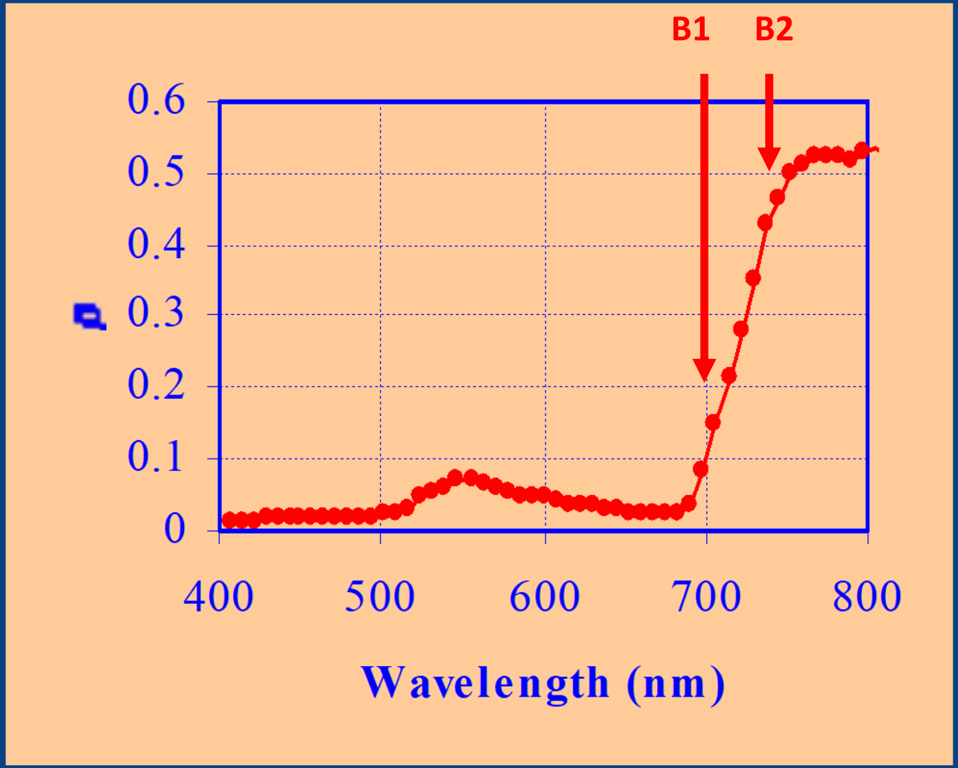
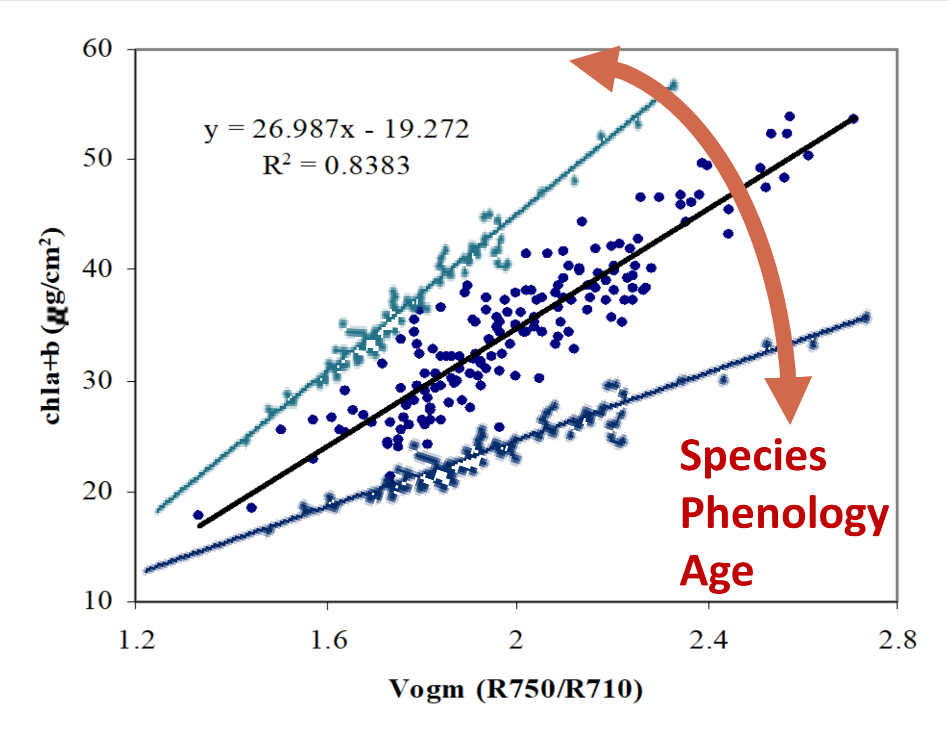




Red edge vs. C_{a+b}

Empirical relationships indices vs. leaf traits





Red edge vs. C_{a+b}

Main limitations of empirical models

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1. Robustness of empirical relationships

→ species / phenology / architecture

→ RS indices for disease detection are species- & site-specific

2. Account for the canopy structure

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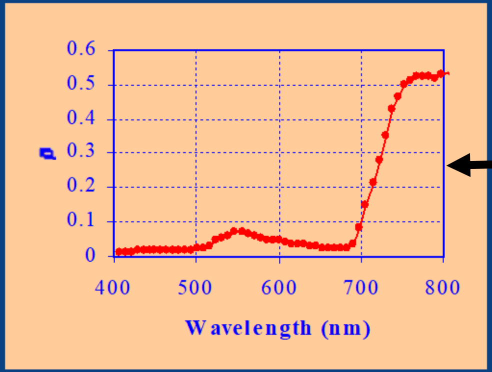
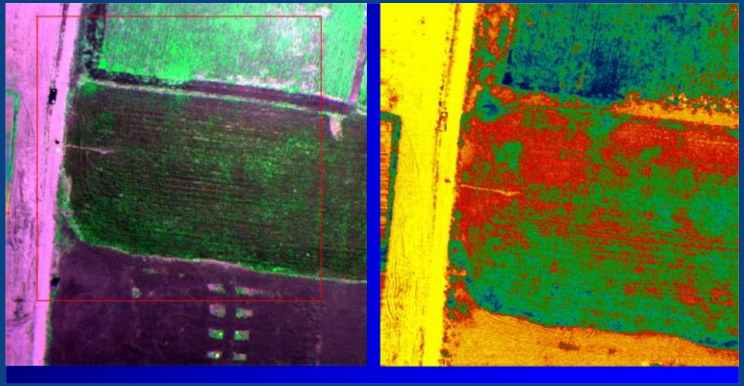
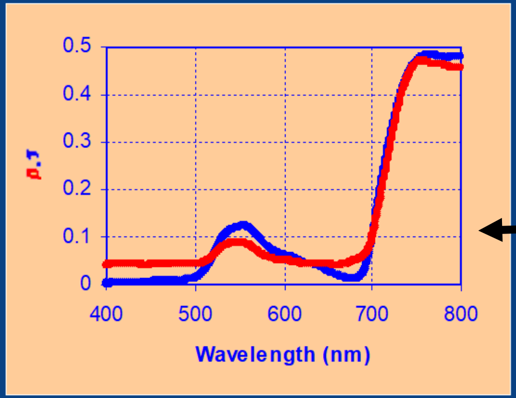




Canopy Level

Leaf ≠ Canopy



Leaf Level

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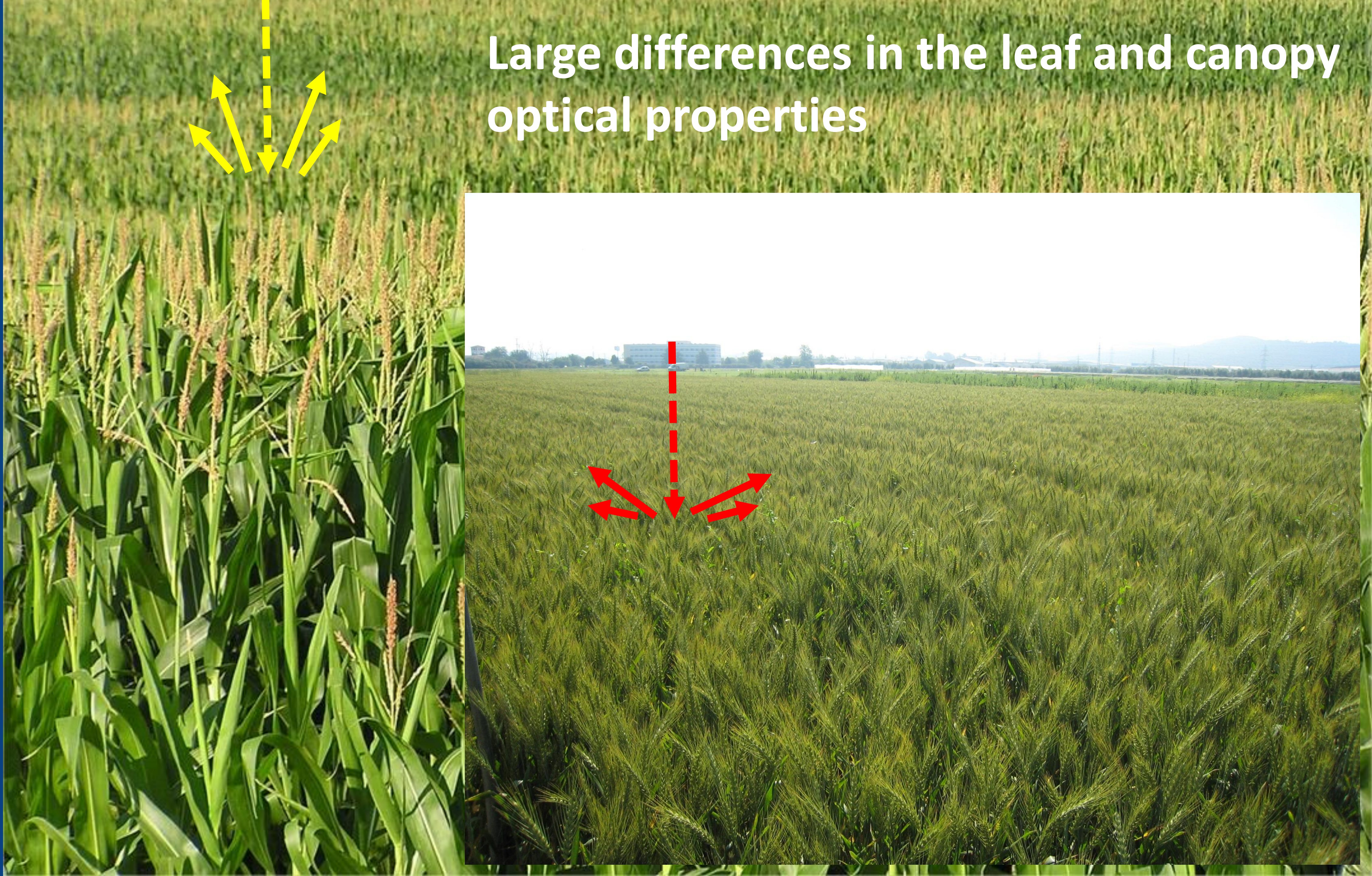
Large differences in the leaf and canopy optical properties



Large differences in the leaf and canopy optical properties

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Main limitations of empirical models

1. Ro ustness o
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2. Ac count for

Physically-based plant trait retrievals

50 years of progress

Vegetation indices

- NDVI, MTVI, RDVI …
- CARI, MCARI, TCARI
- NDWI, SRWI …
- PRI, BG1, BR1 …
- …

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50 years of progress

Vegetation indices

- NDVI, MTVI, RDVI …
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- …

Leaf & Canopy traits

- LAI, % cover, height
- C_{ab}, C_{x+c}, Anth
- C_w, C_m
- SIF
- …

50 years of progress

Vegetation indices

- NDVI, MTVI, RDVI …
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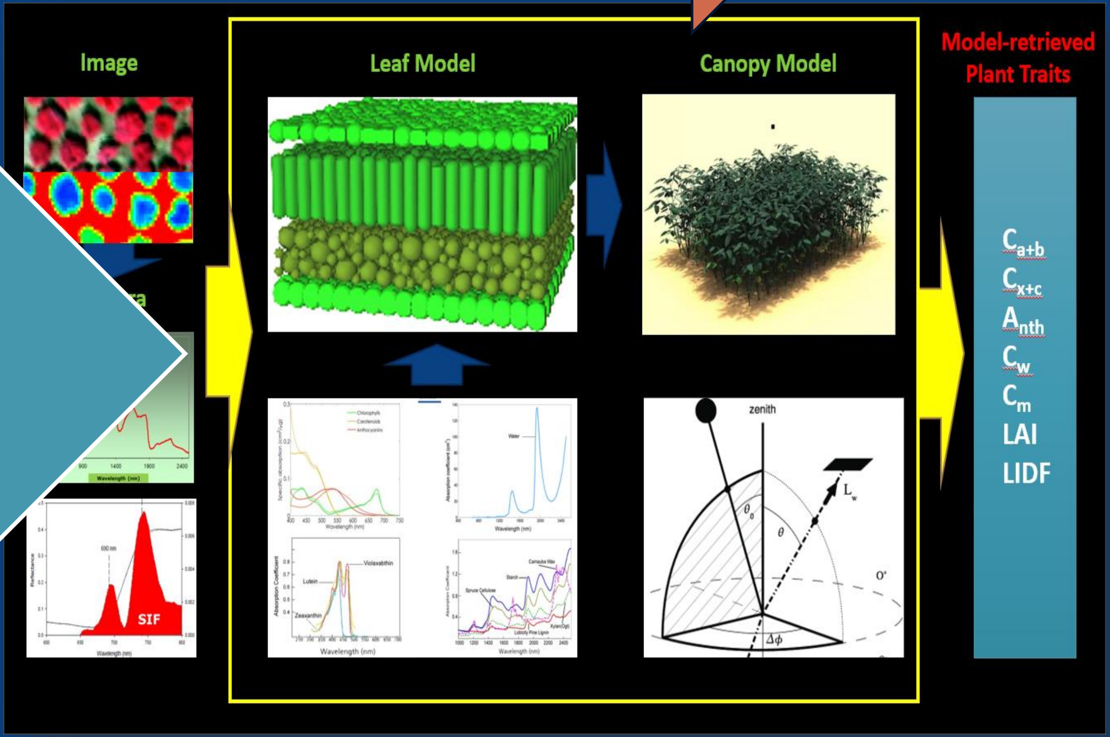
- …



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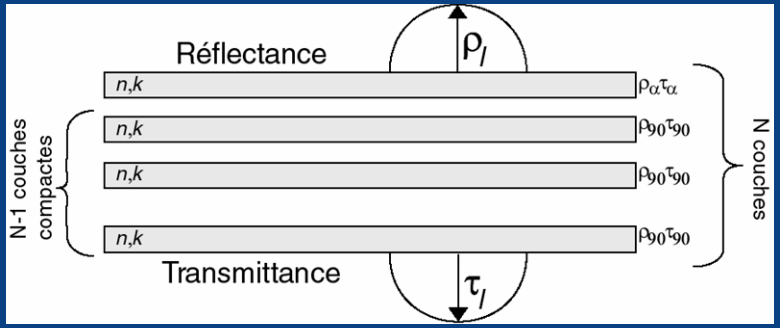
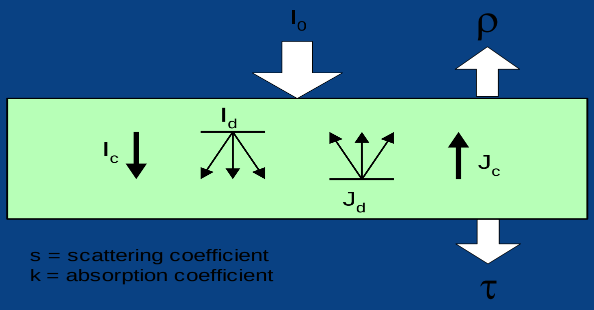
Progress on Leaf RT Models: from *plate* models to 3D simulations

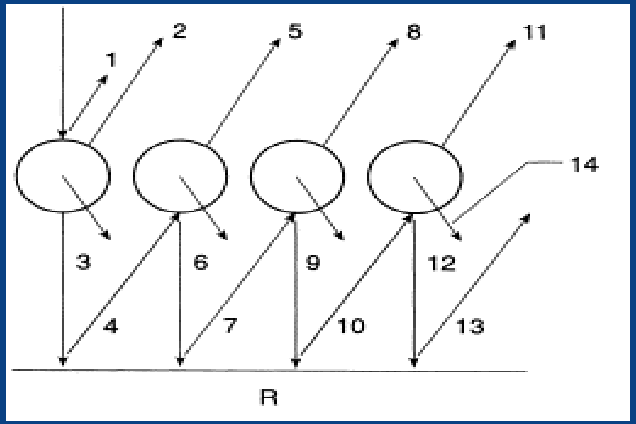
Plate Models



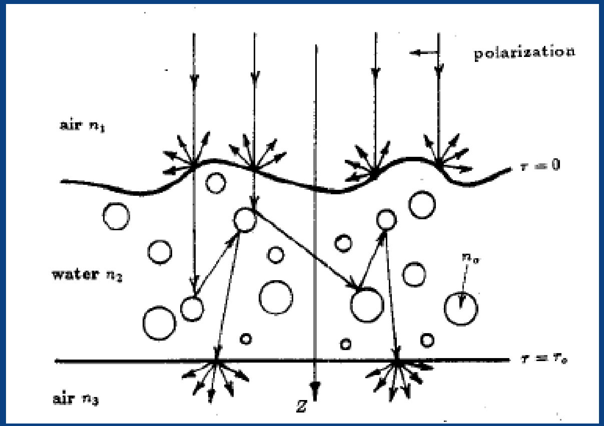
Models N-Flux



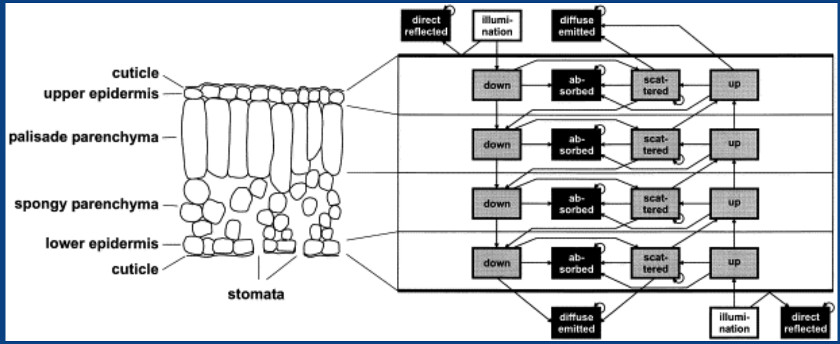
Models based on Spheric Particles



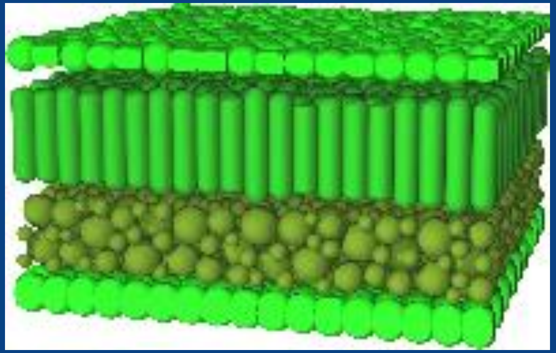
Radiative Transfer Theory



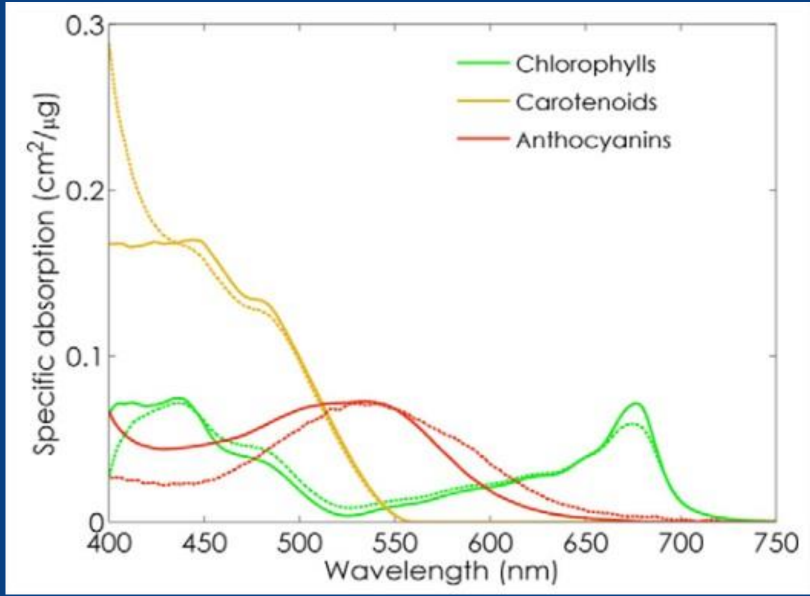
Stocastic Models

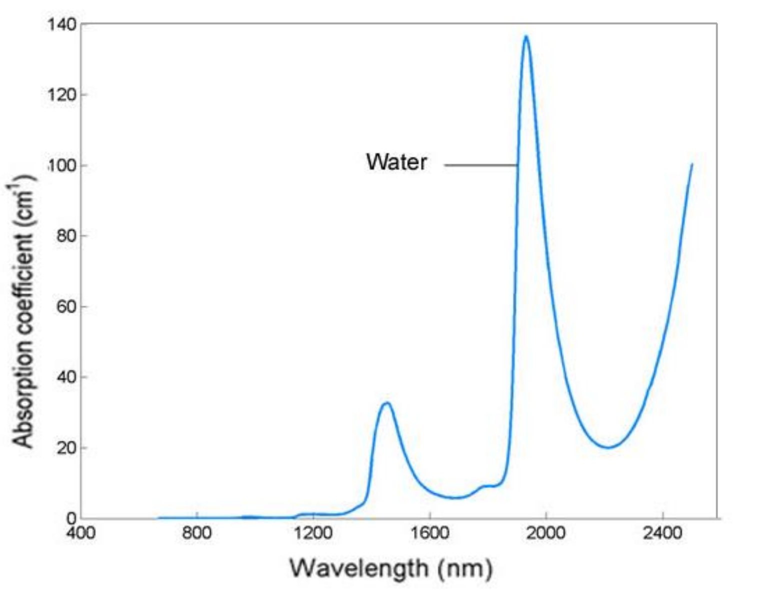


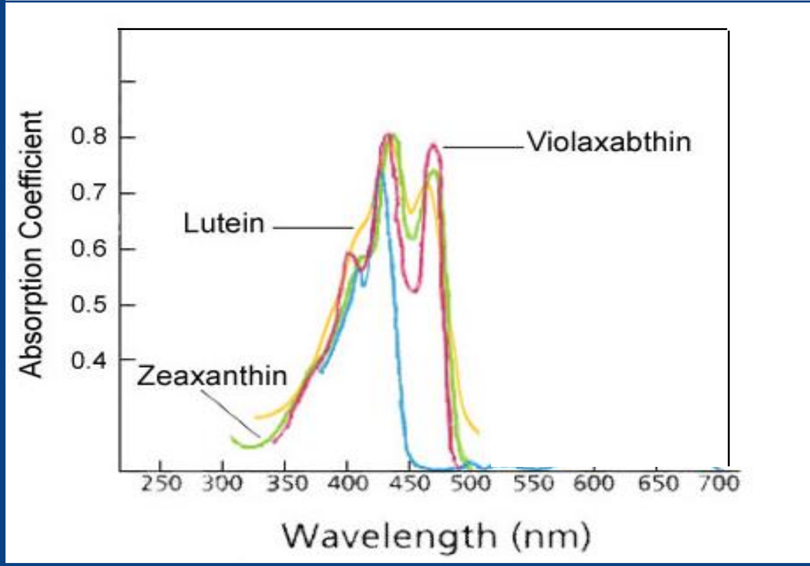
Ray Tracing Models (Monte Carlo)

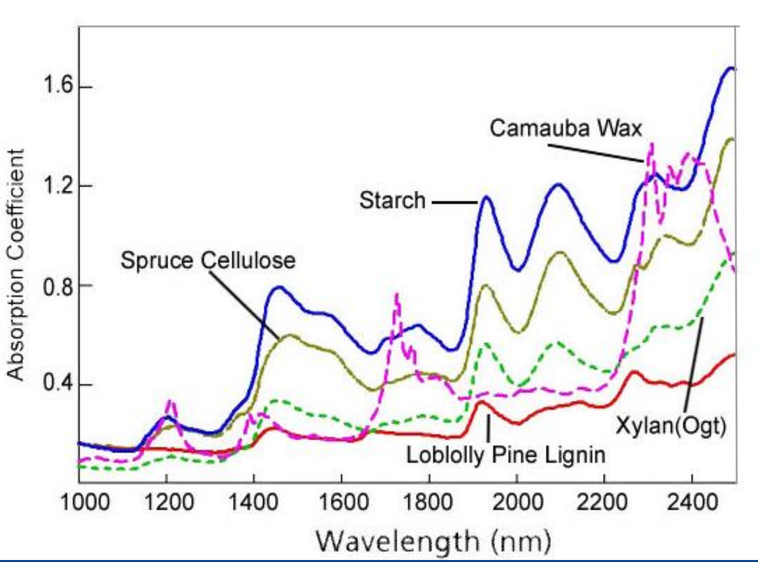


Progress on leaf Radiative Transfer modelling









PROSPECT
(Jacquemoud & Baret, 1990)

↓

Separation of total chlorophylls from total carotenoids
PROSPECT-5
(Feret *et al.*, 2008)

↓

Anthocyanins, chlorophylls and carotenoids
PROSPECT-D
(Feret *et al.*, 2017)

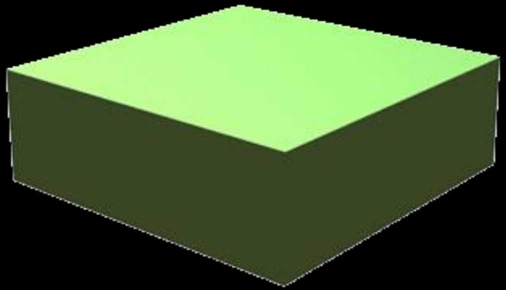
↓

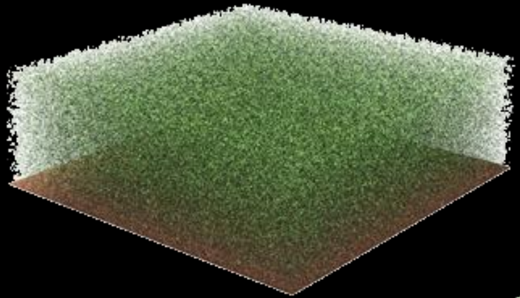
Xanthophyll dynamics
Fluspect-CX
(Vilfan *et al.*, 2018)

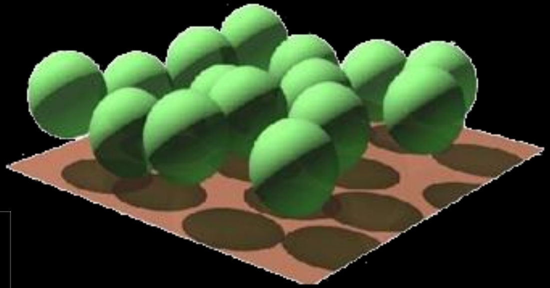
↓

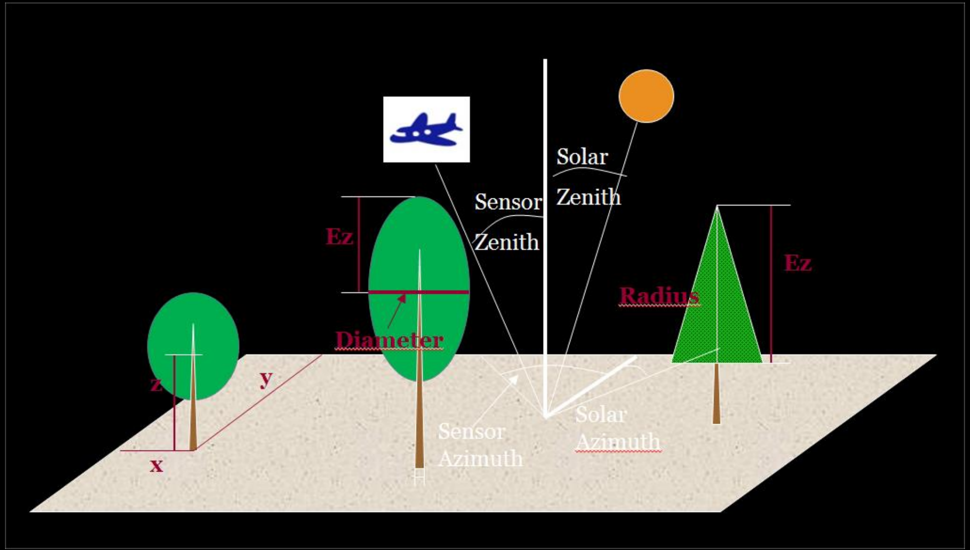
Leaf proteins and other carbon-based constituents
PROSPECT-PRO
(Feret *et al.*, 2021)

Canopy RT simulation models









From SAIL to DART / SCOPE RT models

Linked leaf-canopy simulation models

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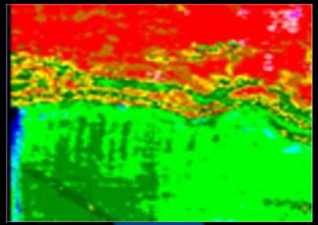
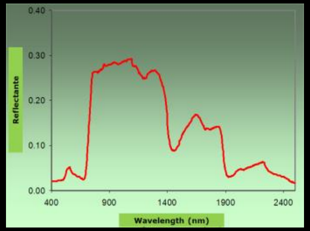
Image



Spectra

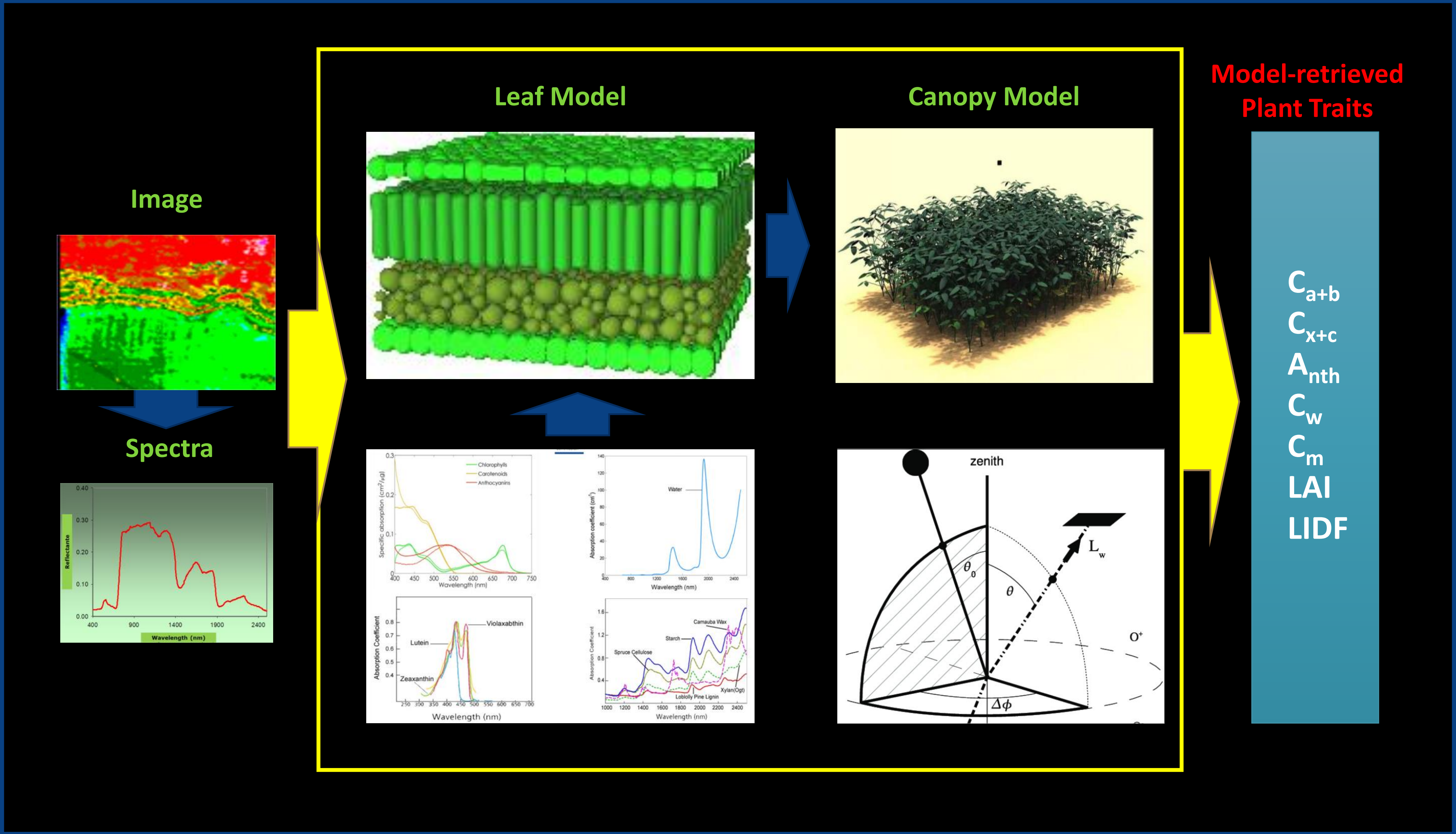


Index-based empirical models

Model-retrieved Plant Traits

C_{a+b}
C_{x+c}
A_{nth}
C_w
C_m
LAI
LIDF

Linked leaf-canopy simulation models



50 years of progress

Vegetation indices

- NDVI, MTVI, RDVI …
- CARI, MCARI, TCARI
- NDWI, SRWI …
- PRI, BG1, BR1 …
- …

Leaf & Canopy traits

- LAI, % cover, height
- C_{ab}, C_{x+c}, Anth
- C_w, C_m
- SIF
- …

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50 years of progress

Vegetation indices

- NDVI, MTVI, RDVI …
- CARI, MCARI, TCARI
- NDWI, SRWI …
- PRI, BG1, BR1 …
- …

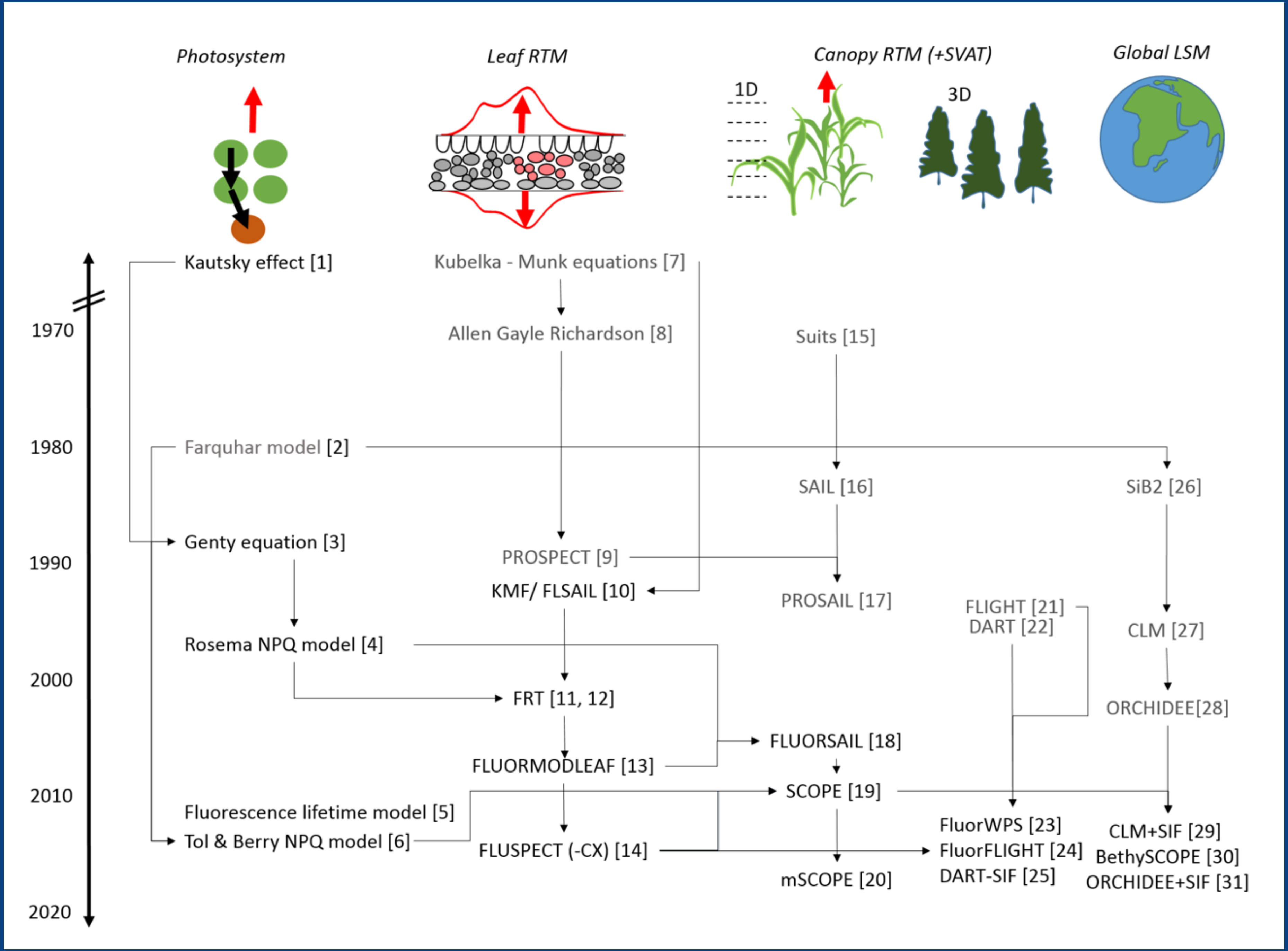
Leaf & Canopy traits

- LAI, % cover, height
- C_{ab}, C_{x+c}, Anth
- C_w, C_m
- SIF
- …

Functioning

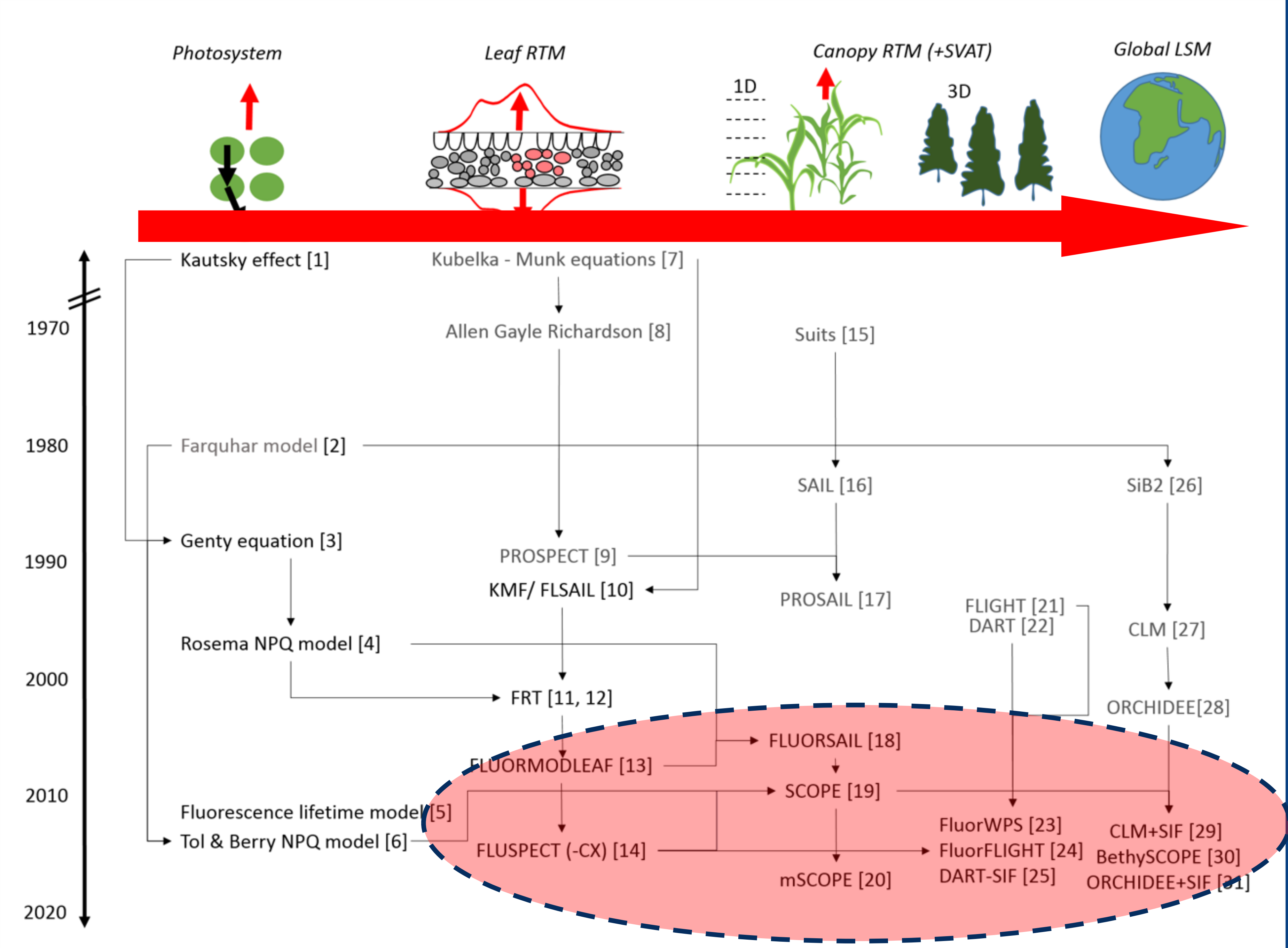
- Gs / Transpiration
- Assimilation rates

SIF quantification: 50 years of progress



Mohammed *et al.* (2019)

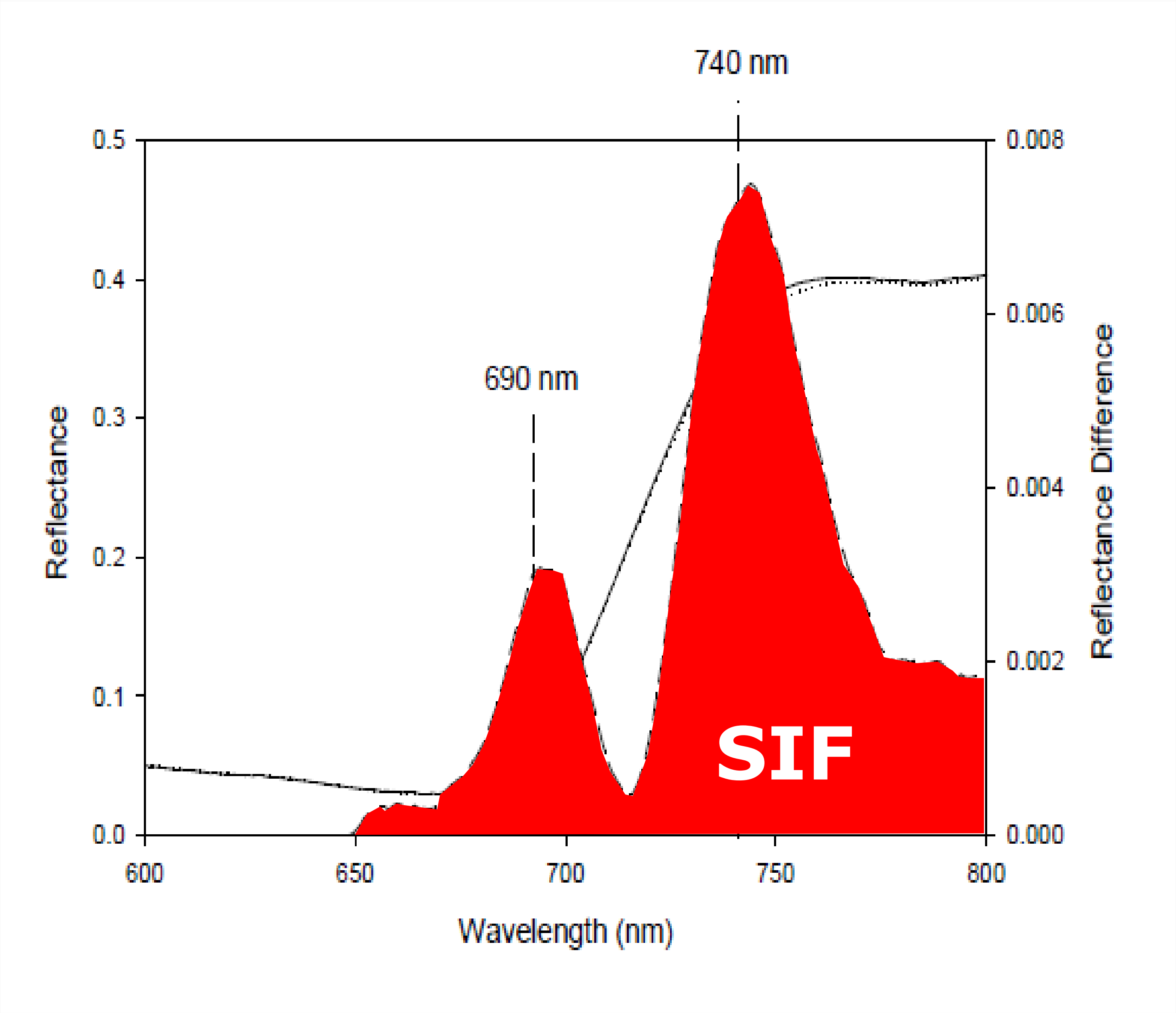
SIF quantification: 50 years of progress



Mohammed *et al.* (2019)

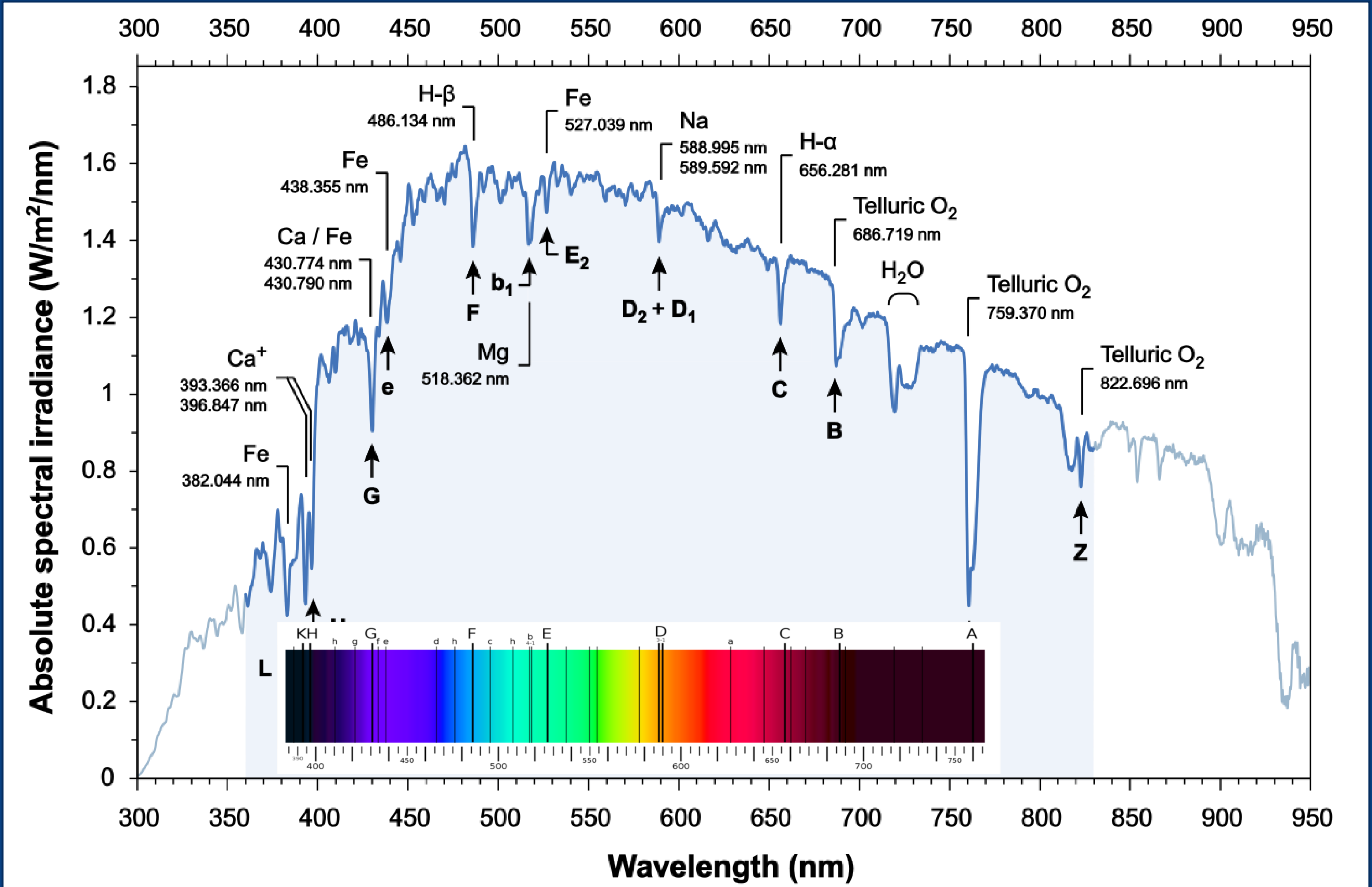
Solar-induced Chlorophyll Fluorescence (SIF)

→ ~2% of the total incoming radiation
→ Linked to photosynthesis
→ High spectral resolution required
→ Early indicator of stress



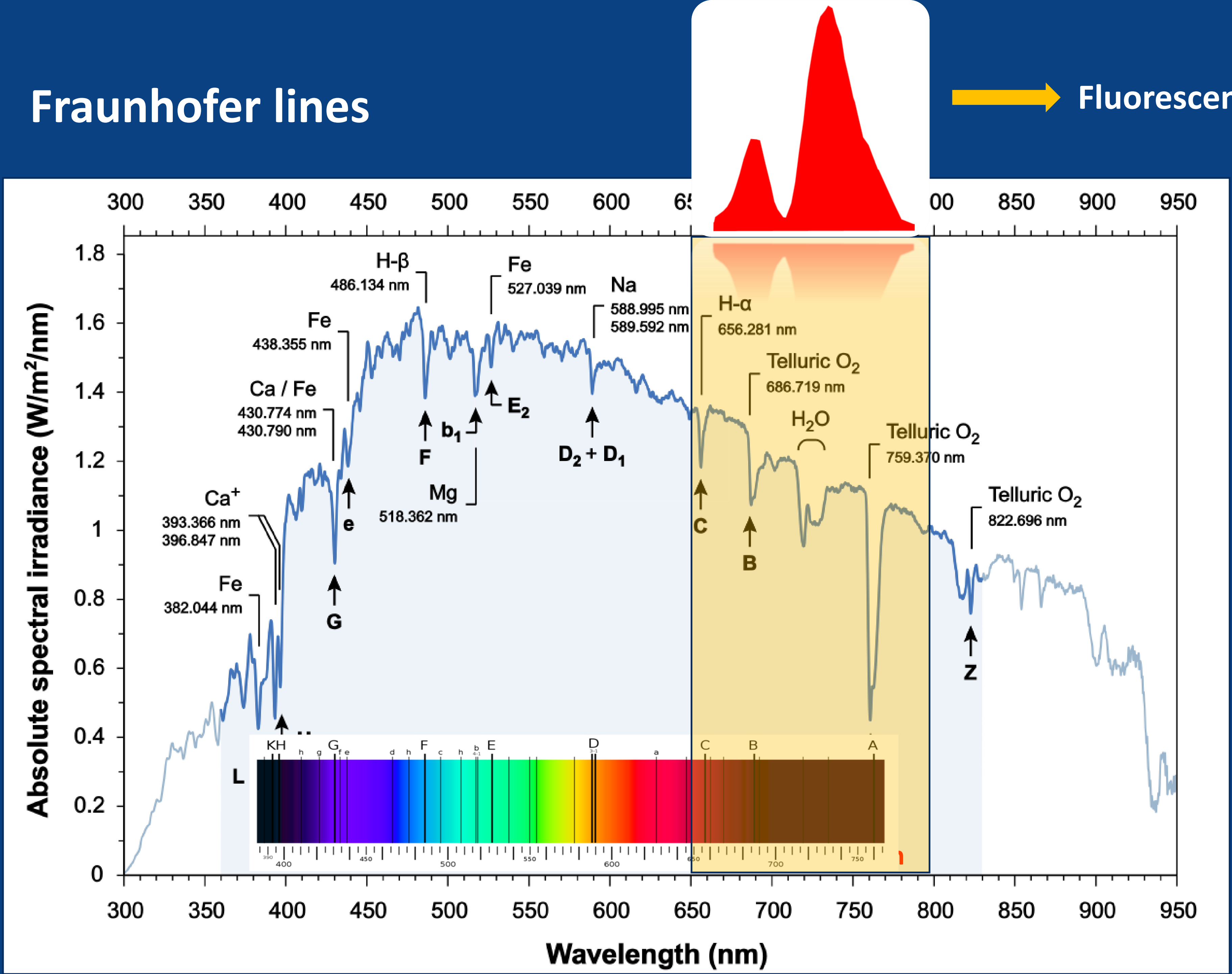
Fraunhofer lines

dark features (absorption lines) in the optical spectrum of the Sun



Fraunhofer lines

Fluorescence emission



Plant traits quantification using Radiative Transfer models

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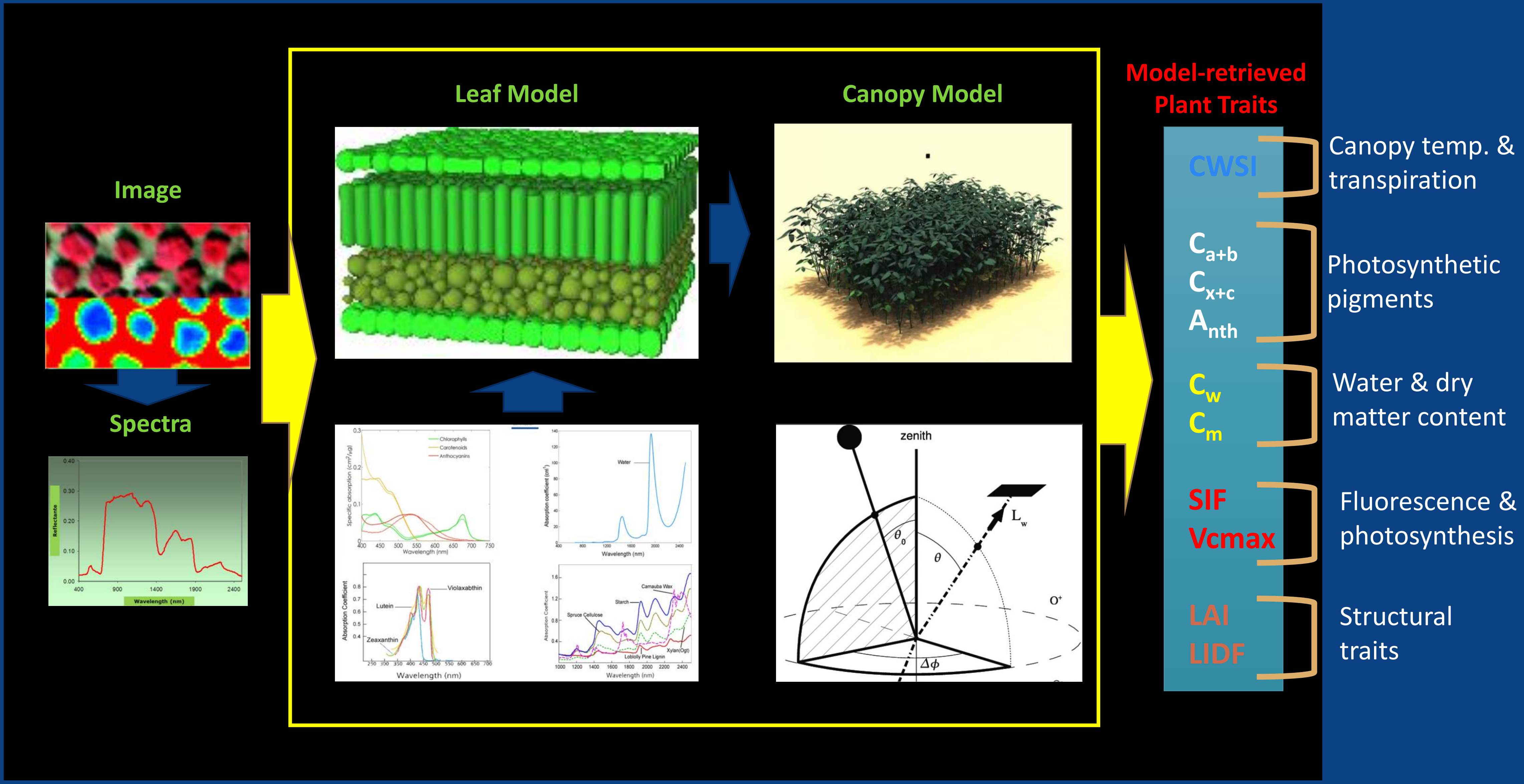

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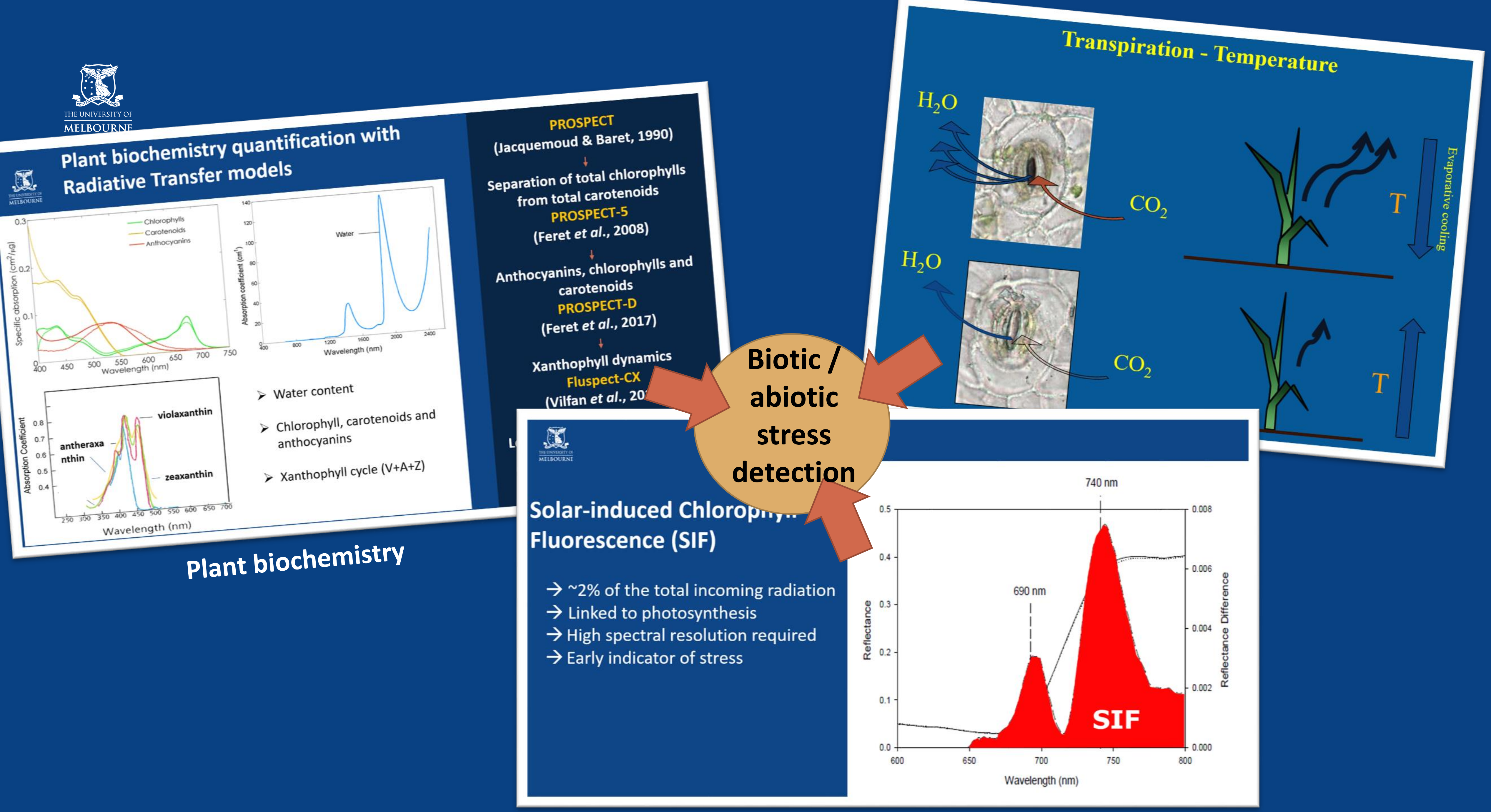
Main advantages of quantifying plant traits

1. Non site-specific algorithms
2. Robust across species
3. Measurable
4. Physiological meaning



Plant biochemistry

Fluorescence emission

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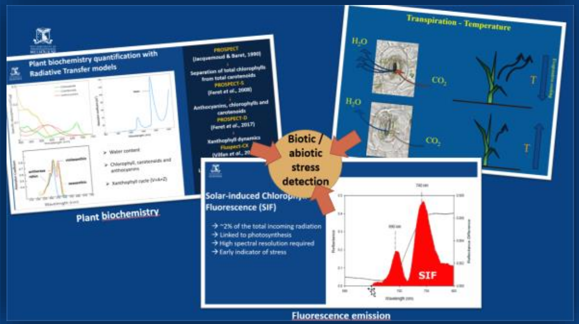
Using plant traits and plant functioning indicators for biotic-induced stress detection

- *Xylella fastidiosa*
- *Verticillium dahliae*
- Phytophtora
- Red leaf blotch
- Mildew
- Yellow rust
- Pine wood nematode (PWN)



→ Early detection vs damage

→ Disentangling Biotic vs Abiotic stress indicators

Spectral plant traits for biotic-induced detection

Asymptomatic — Initial — Severe

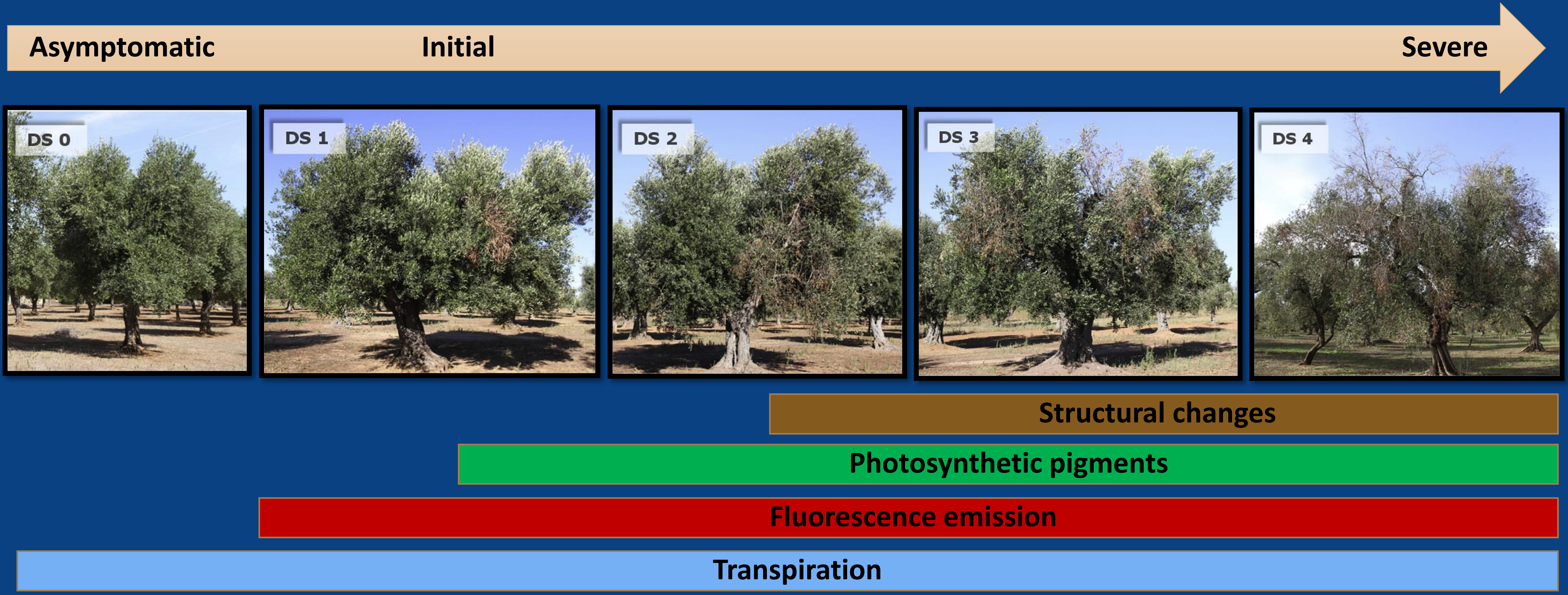
Structural changes

Photosynthetic pigments

Fluorescence emission

Transpiration

Spectral plant traits for biotic-induced detection



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Spectral plant traits for biotic-induced detection

Asymptomatic — Initial — Severe

Structural changes

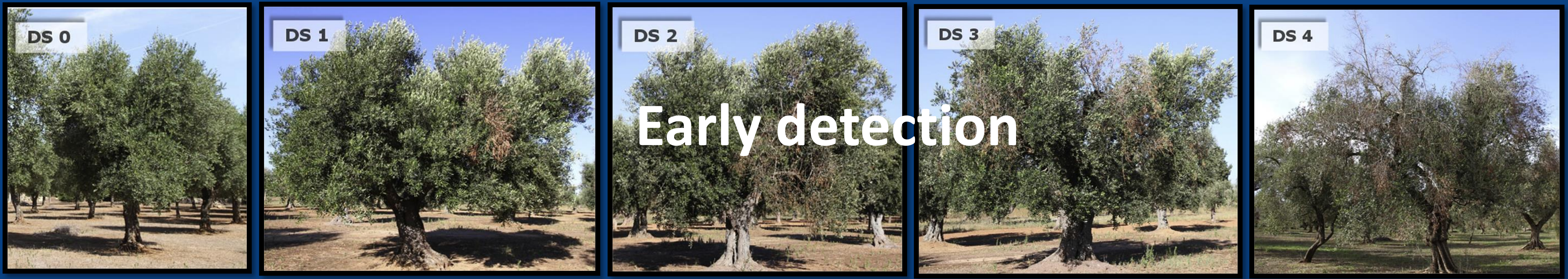
Photosynthetic pigments

Fluorescence emission

Transpiration

Spectral plant traits for biotic-induced detection

Asymptomatic → Initial → Severe



Structural changes

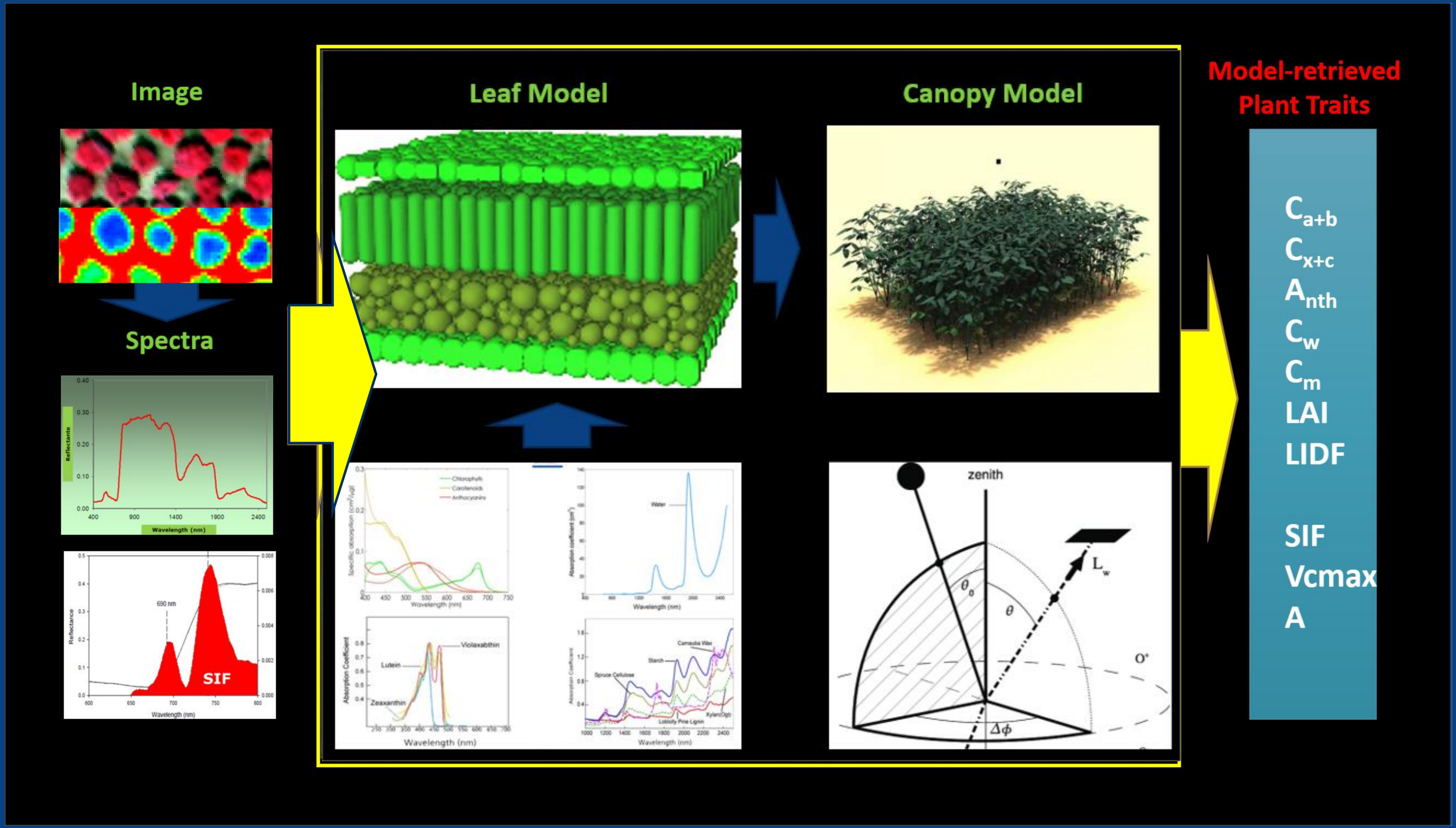
Photosynthetic pigments

Fluorescence emission

Transpiration

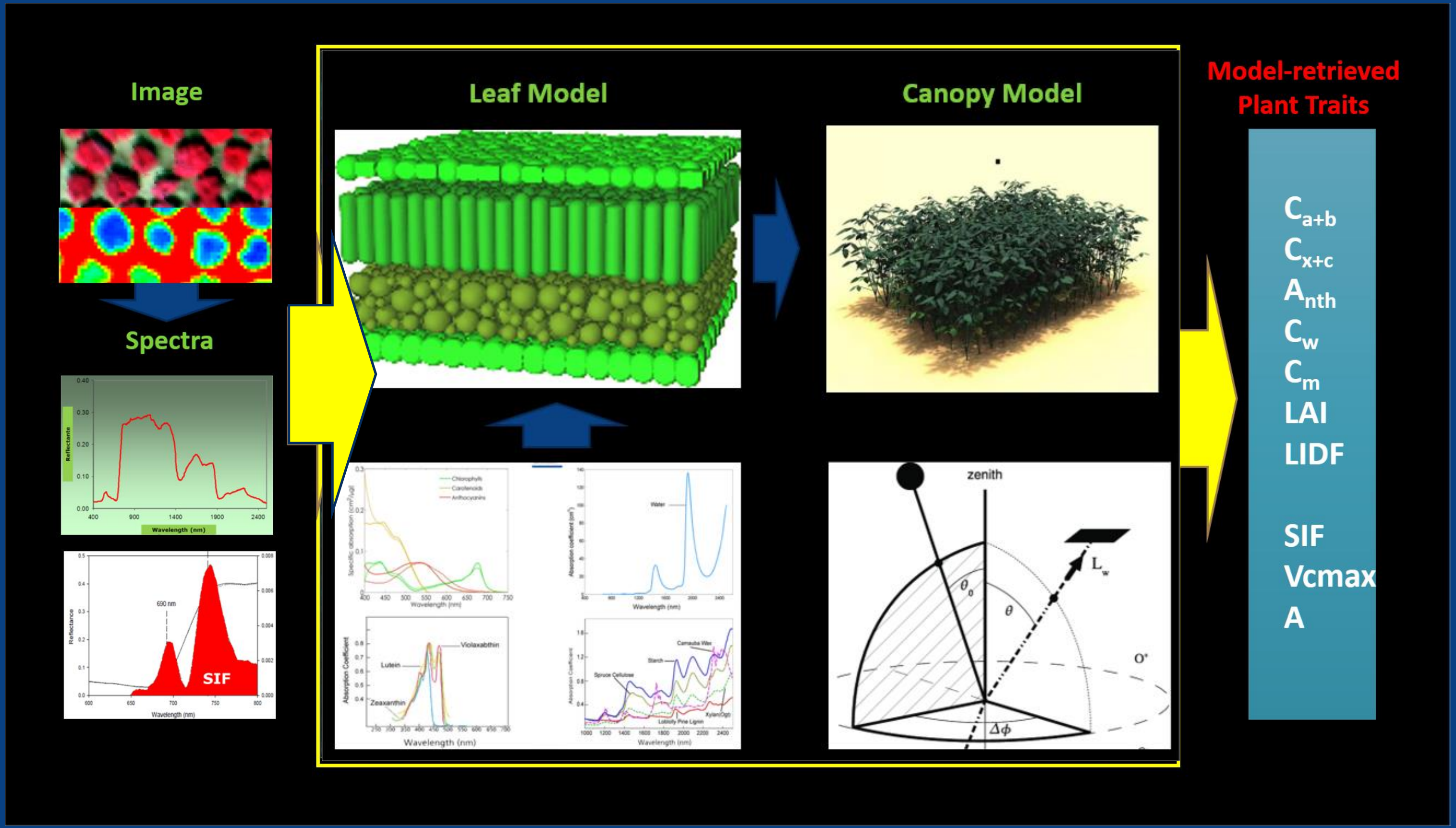
Disease detection framework from hyperspectral data

Mechanistic models



Disease detection framework from hyperspectral data

Mechanistic models



Importance of each RS-based indicator

Structural changes

Photosynthetic pigments

Fluorescence emission

Transpiration

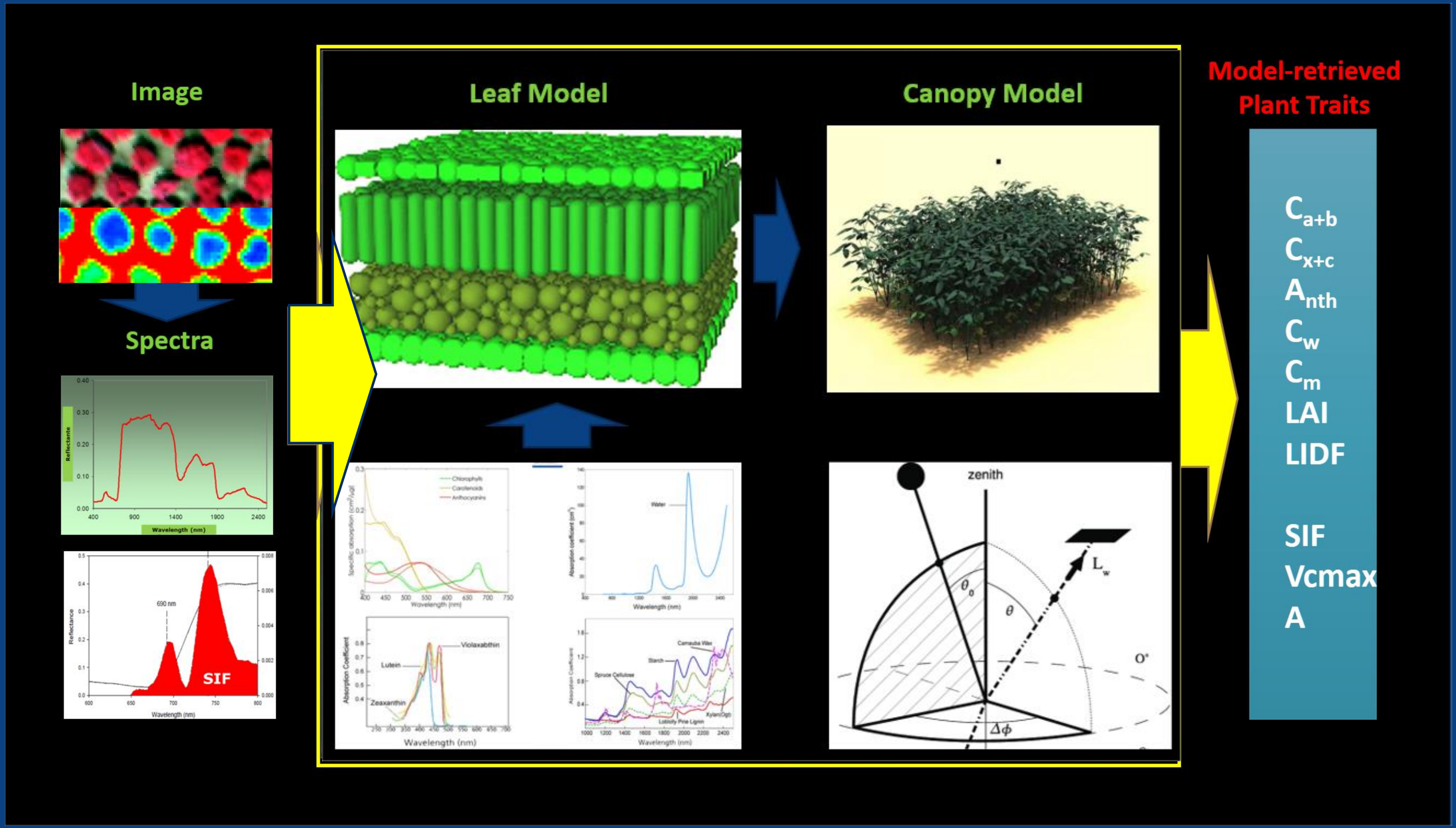
Spectral indicators

Disease detection framework from hyperspectral data

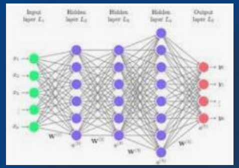
Importance of each RS-based indicator

- Structural changes
- Photosynthetic pigments
- Fluorescence emission
- Transpiration
- Spectral indicators

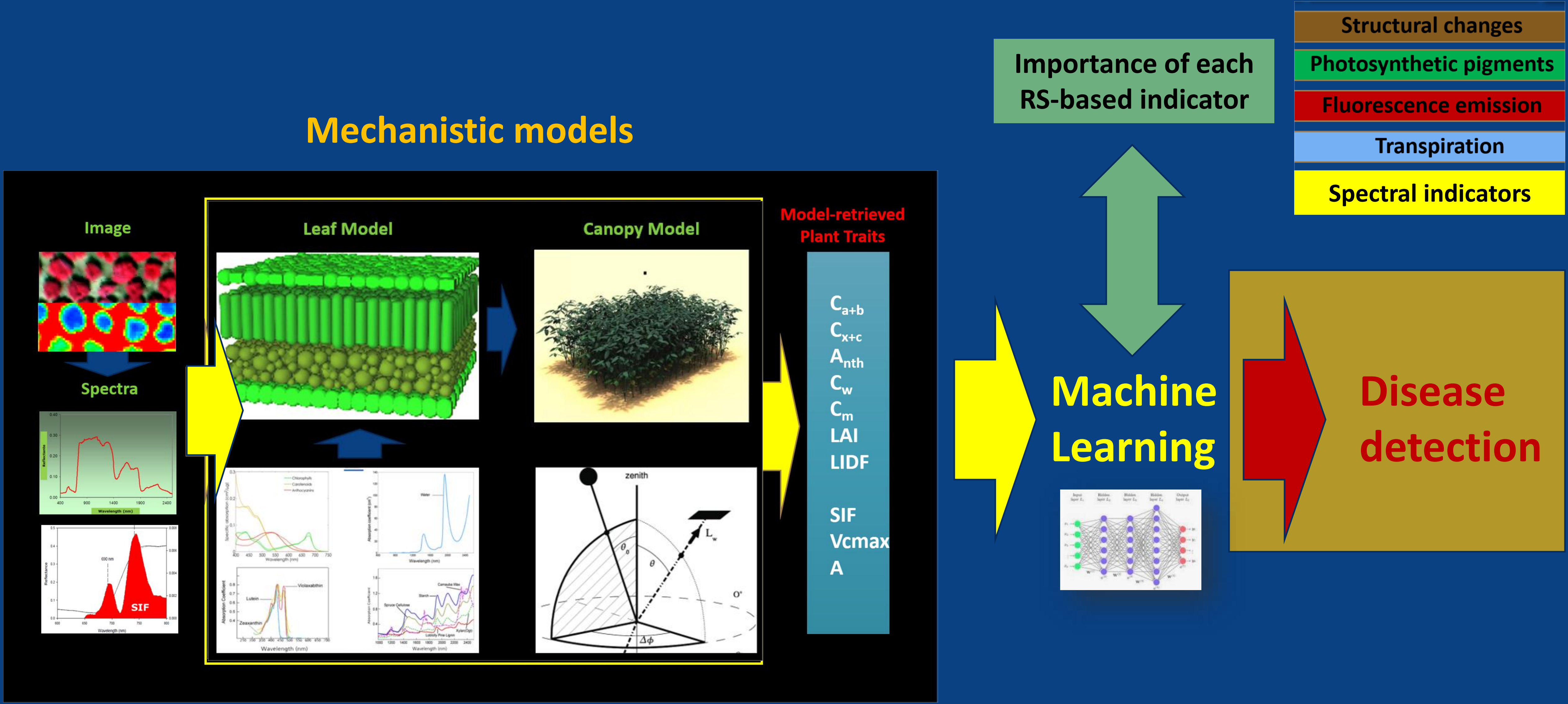
Mechanistic models



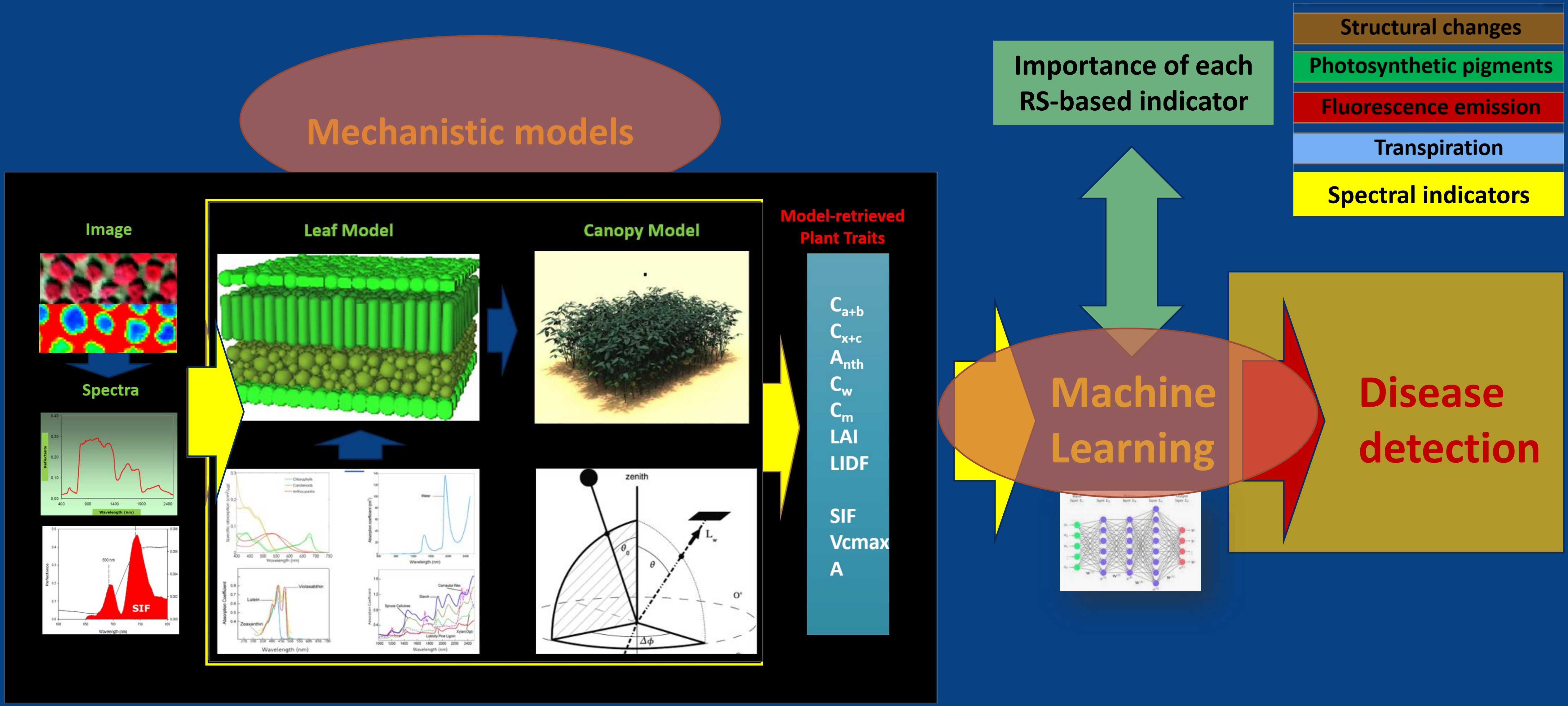
Machine Learning



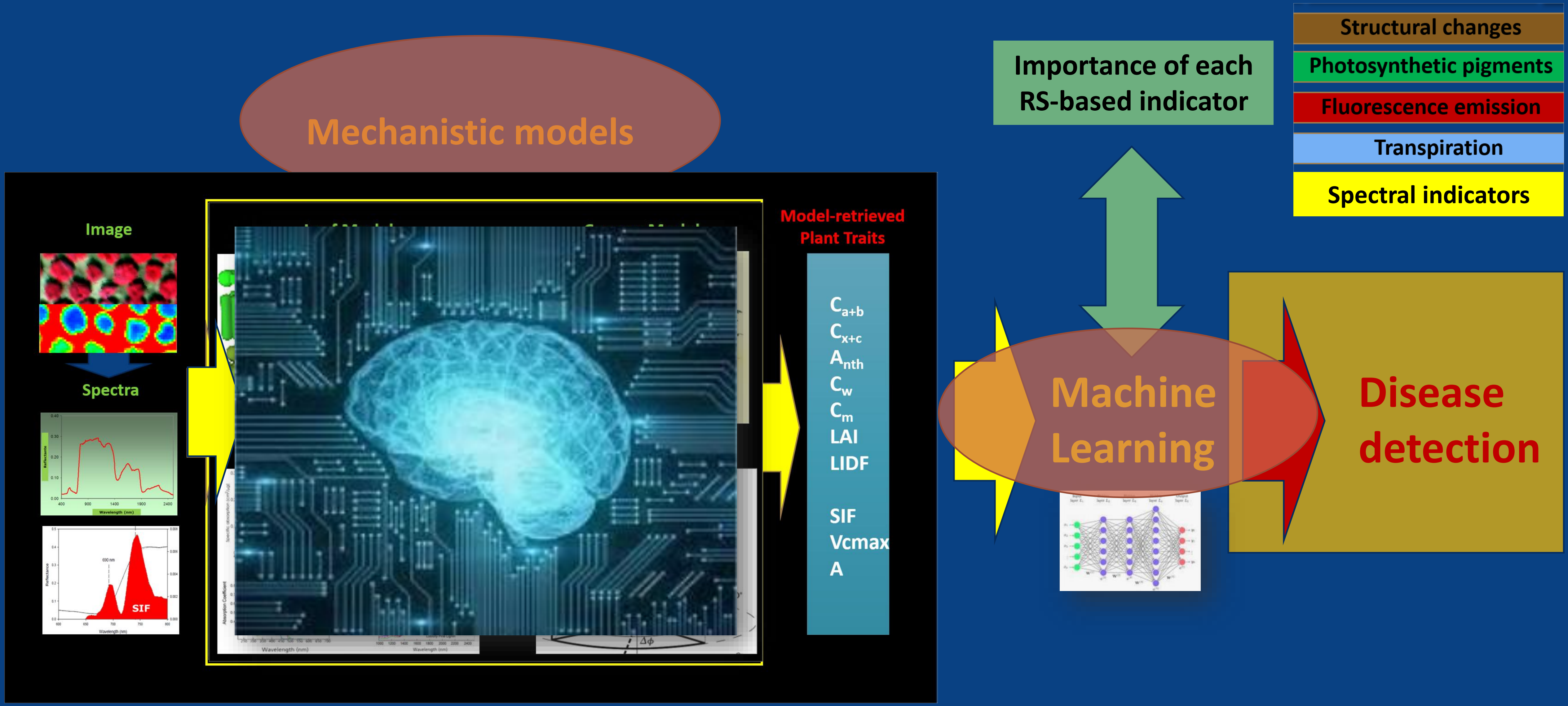
Disease detection framework from hyperspectral data



Disease detection framework from hyperspectral data



Disease detection framework from hyperspectral data



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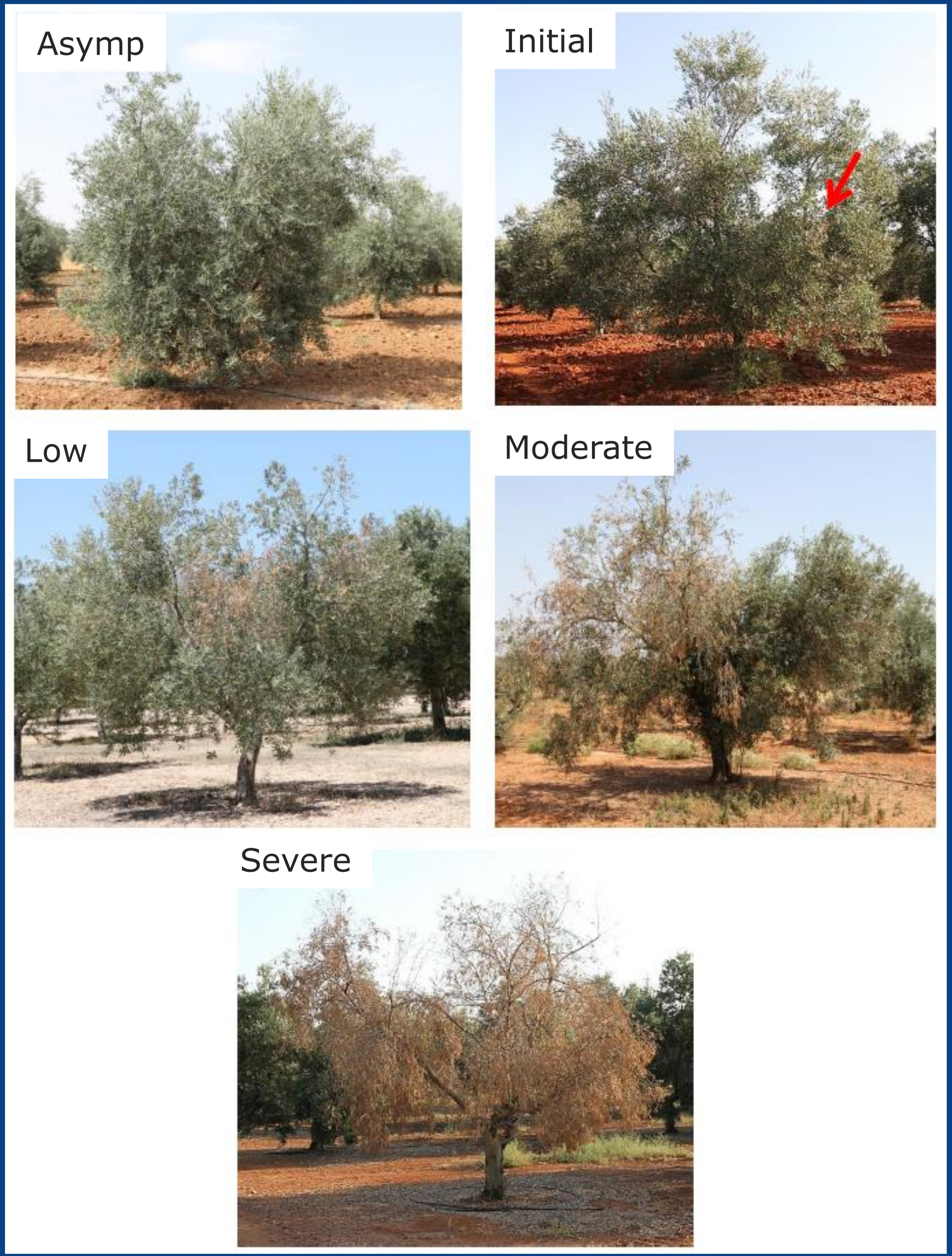
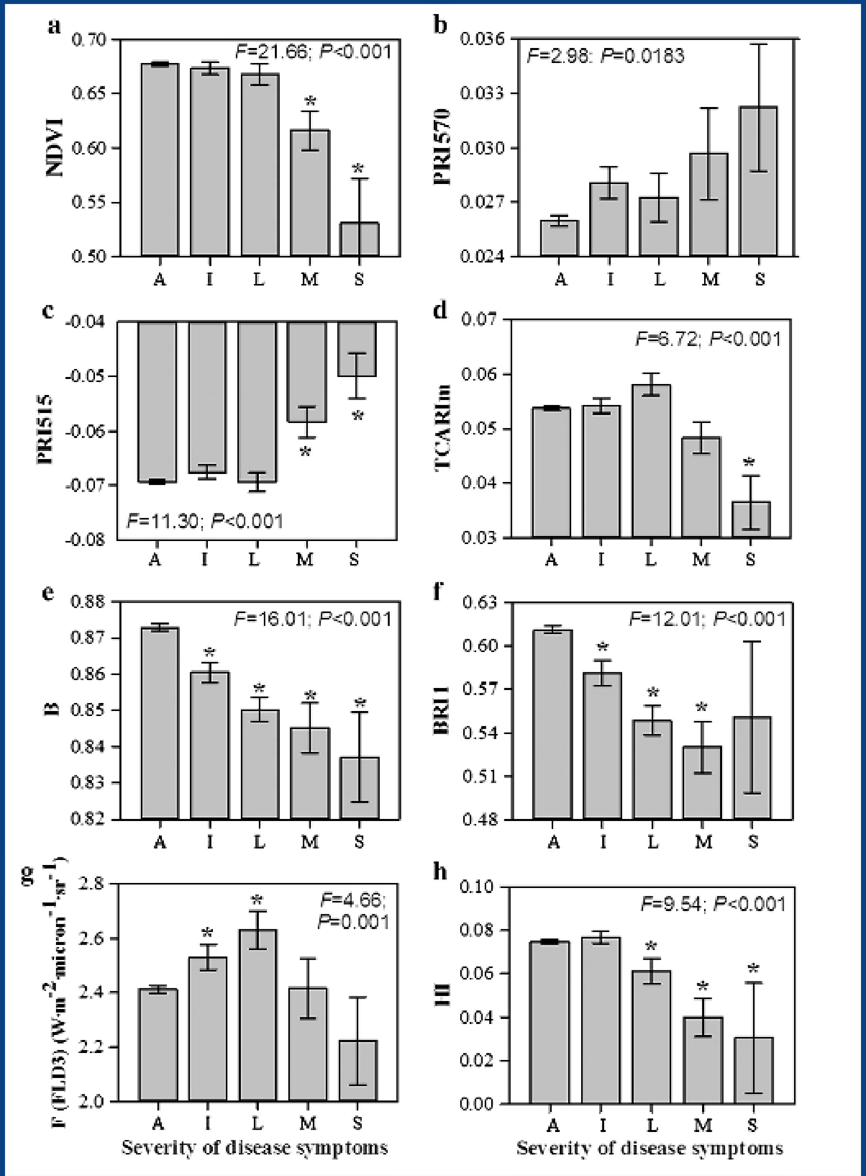
Early Detection of *Verticillium* wilt in Olive



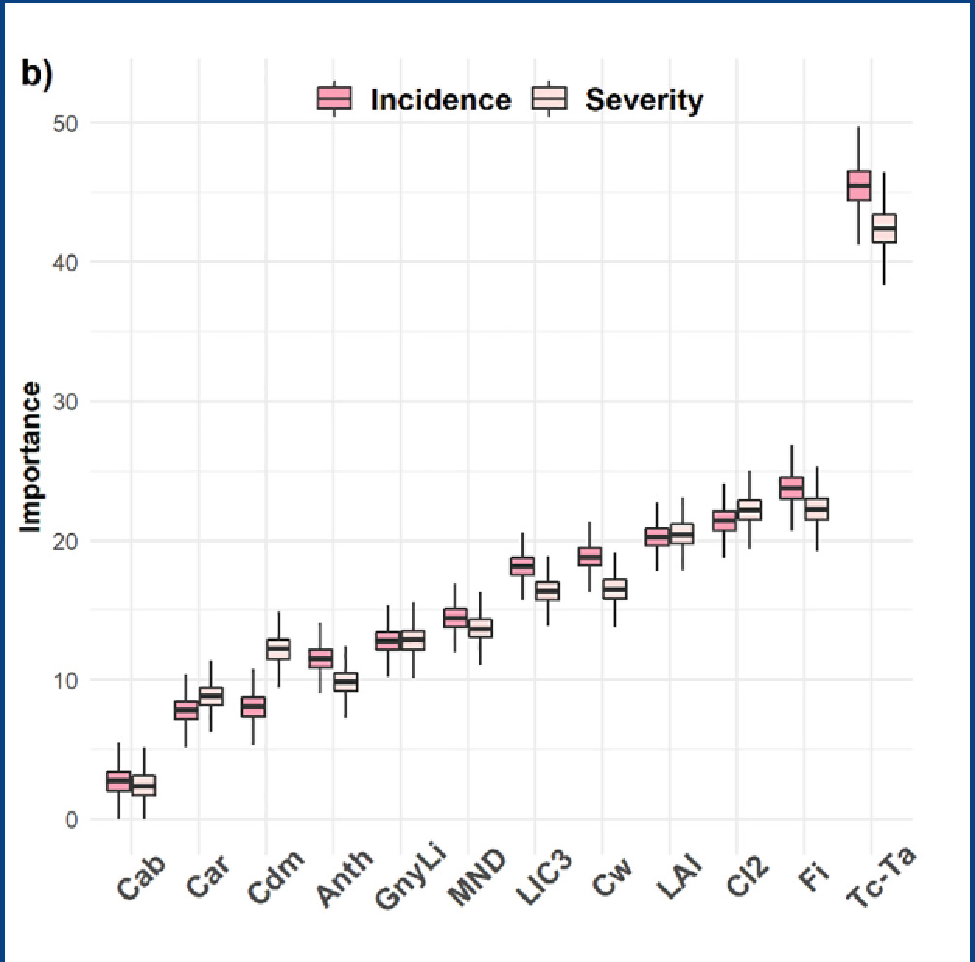


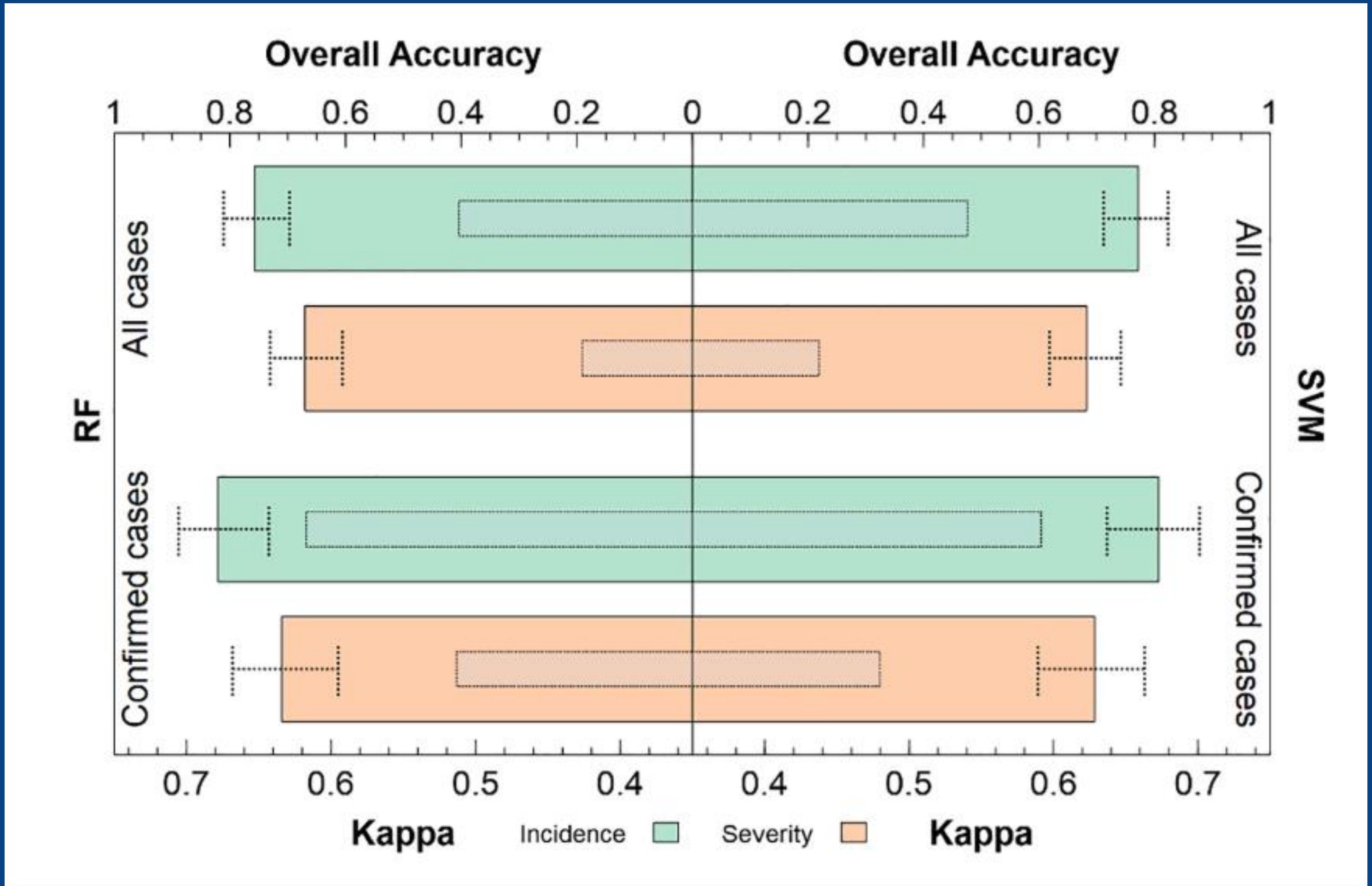
OA=70-80%

Calderon *et al.* (2013; 2015)

Phytophtora-induced symptoms detection

80% accuracy





Hornero *et al.* (2021)

Sensitivity of Plant Traits to *Xf* symptoms - olive

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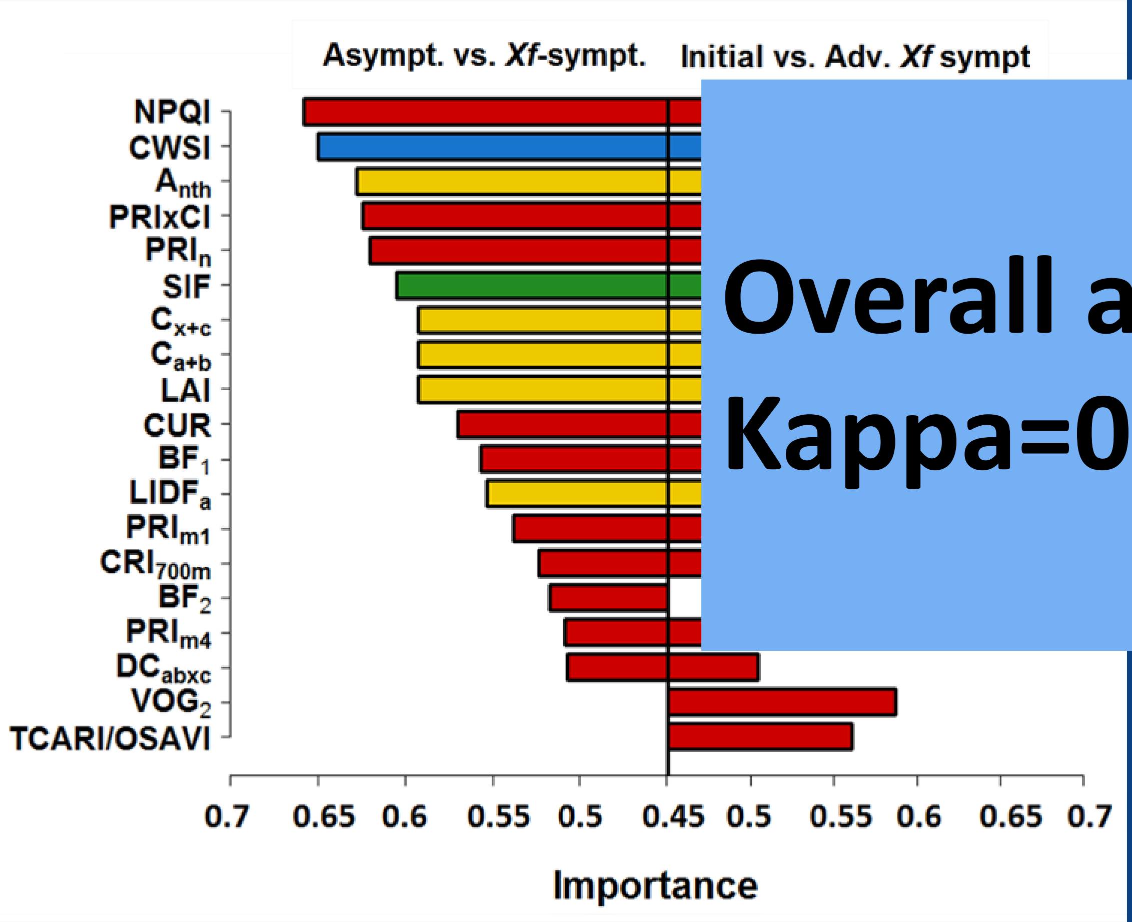
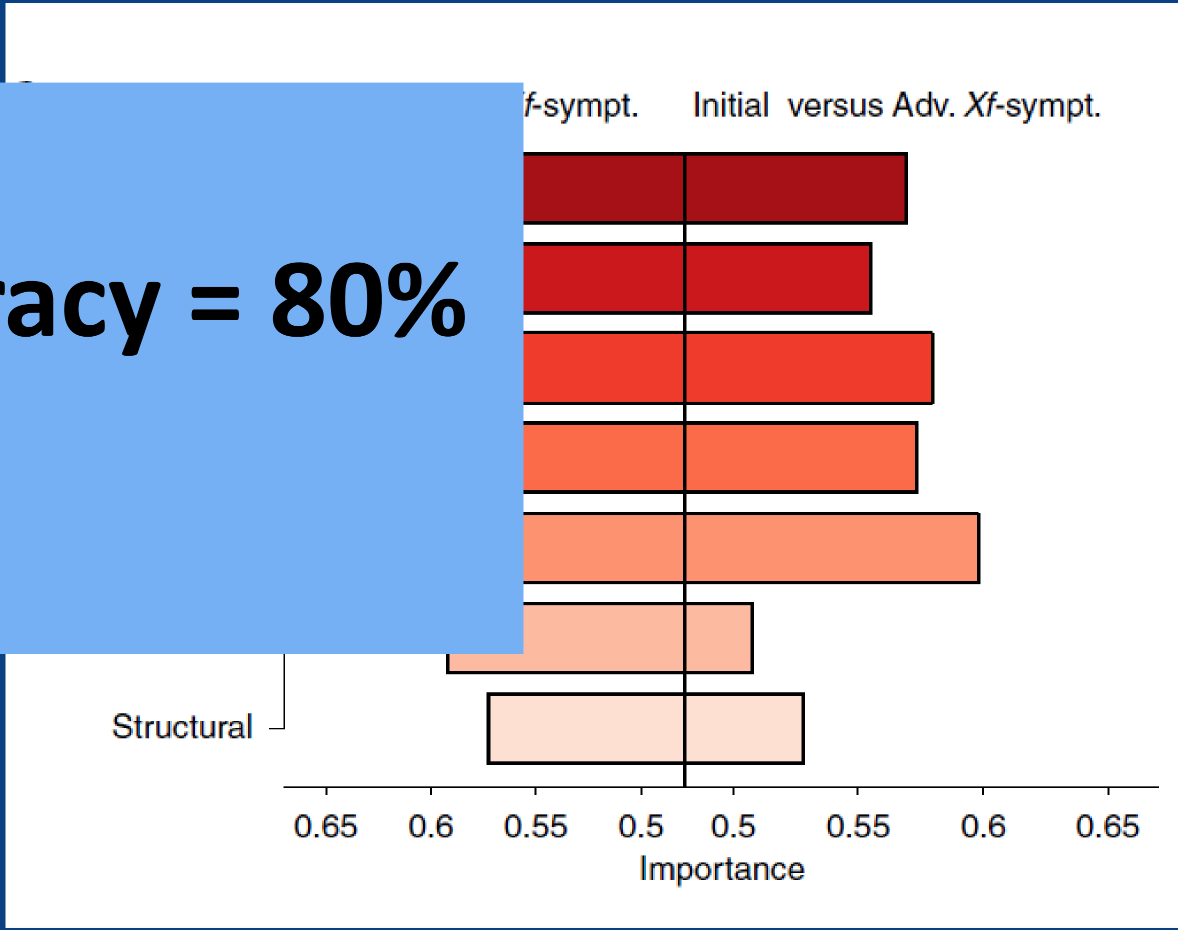
Spectral plant traits



Spectral functional groups

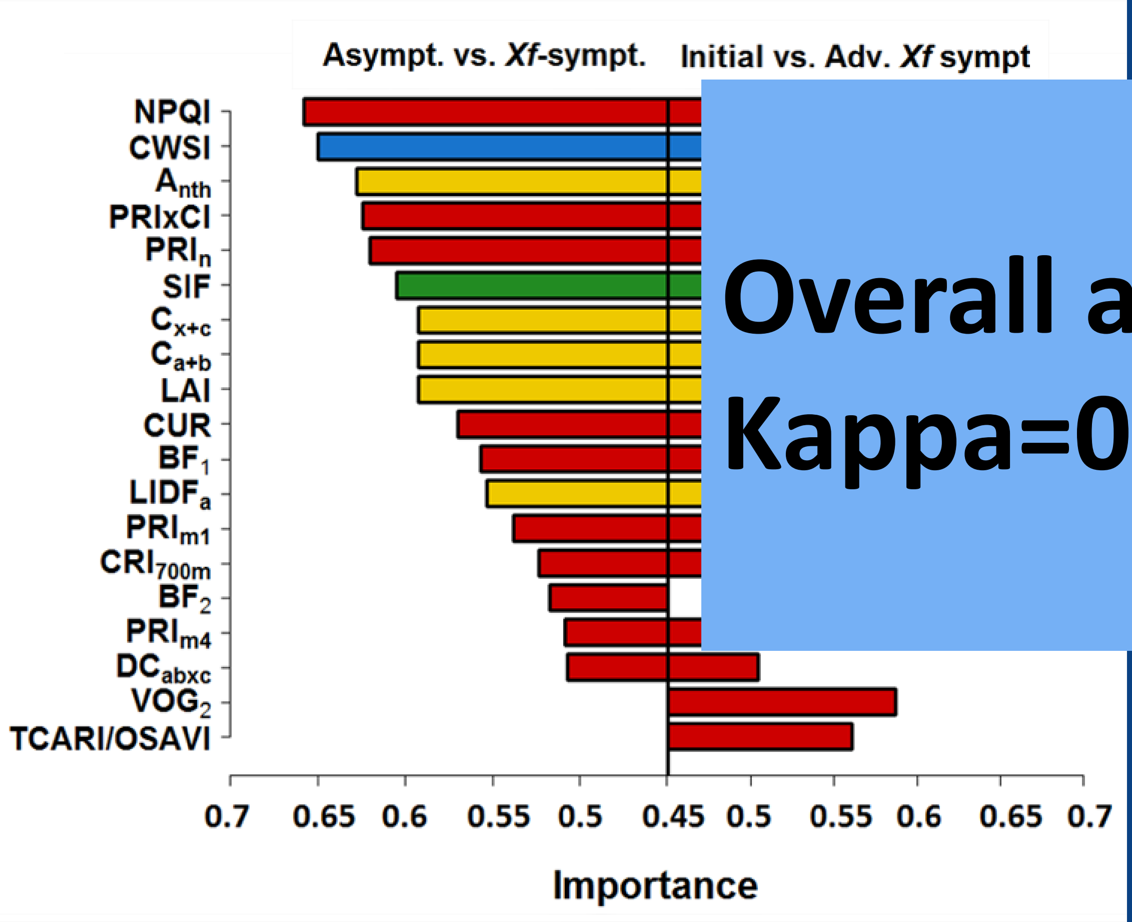


Overall accuracy = 80%

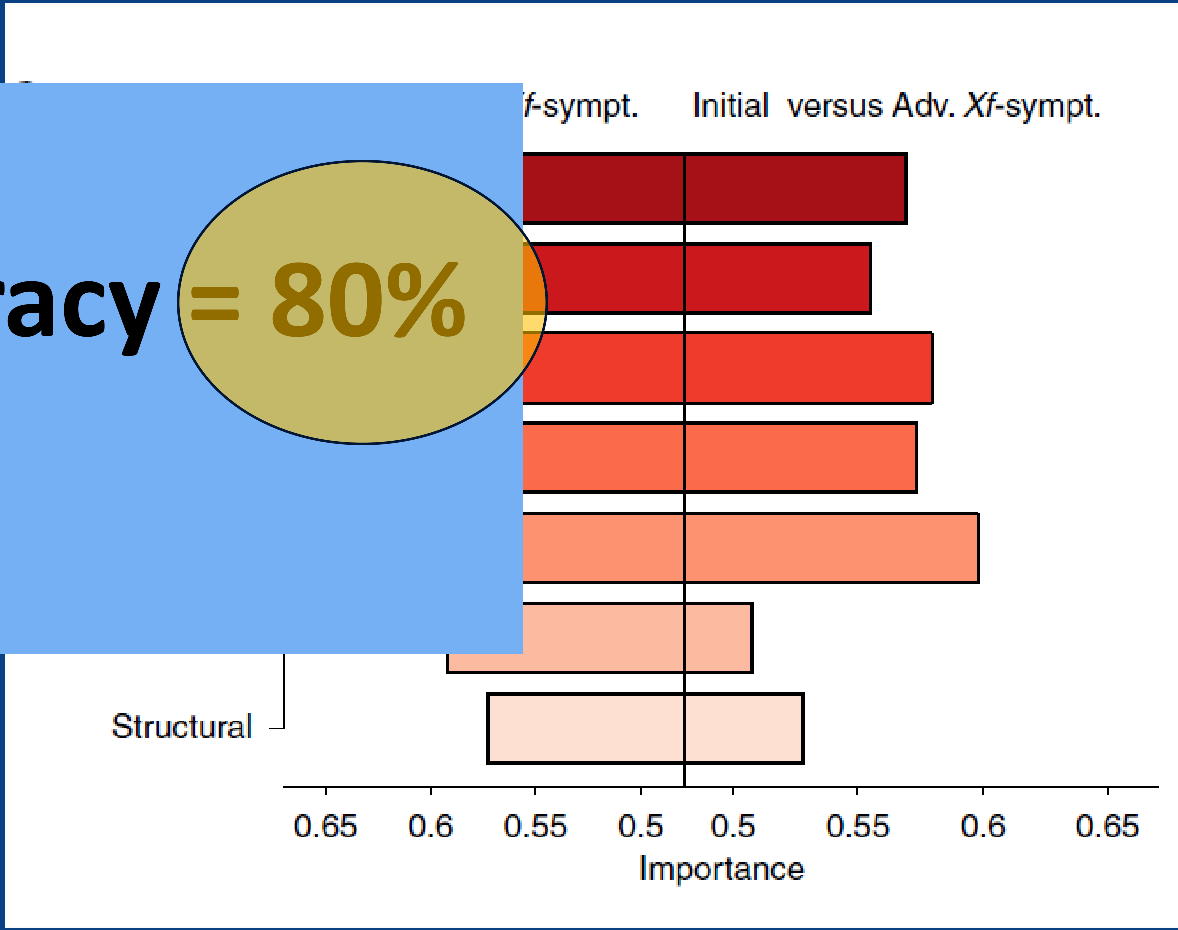
Kappa=0.65

Sensitivity of Plant Traits to *Xf* symptoms - olive

Spectral plant traits



Spectral functional groups

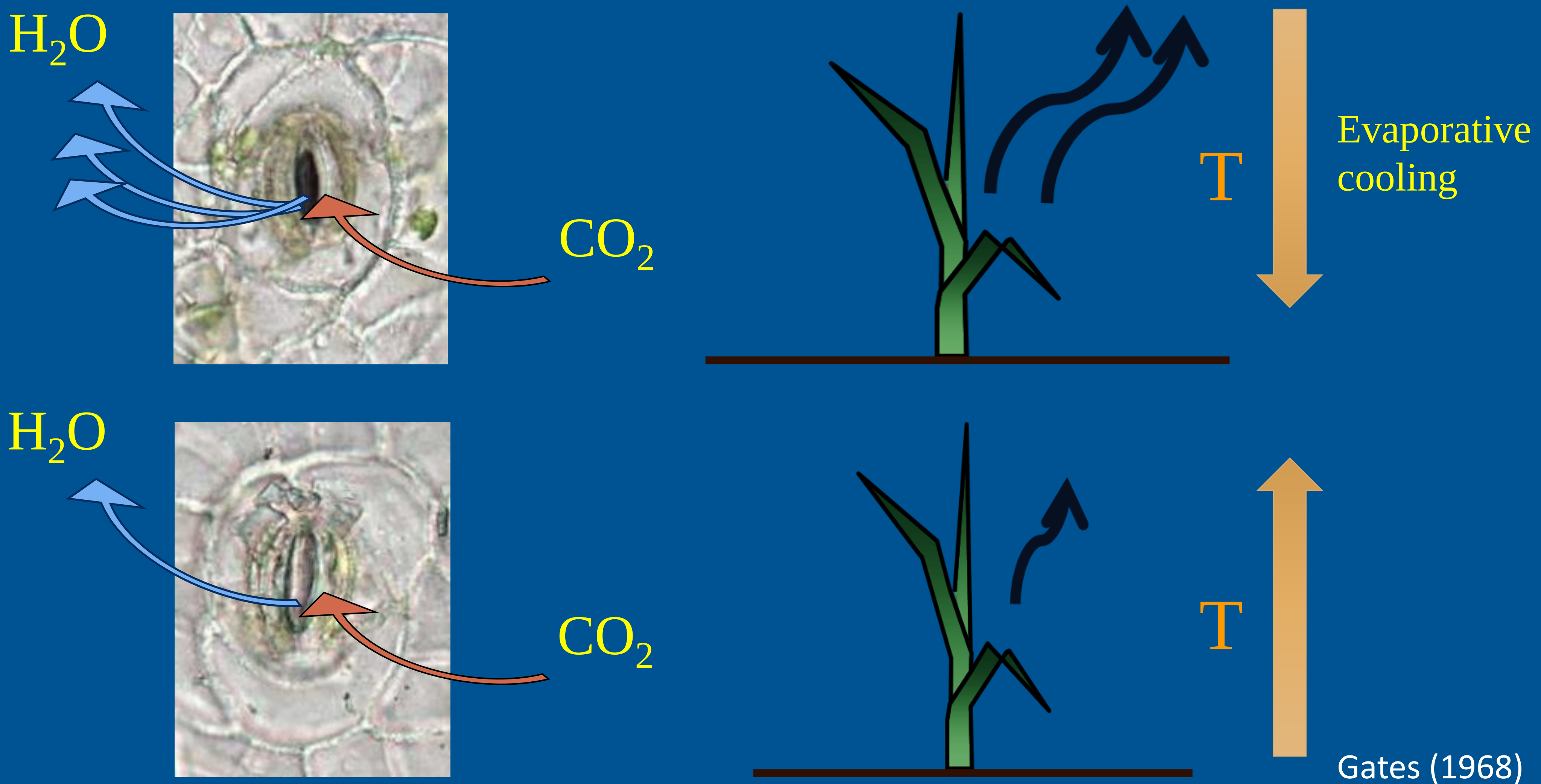


Overall accuracy = 80%

Kappa=0.65

Understanding abiotic stress to improve biotic stress detection

Transpiration - Temperature



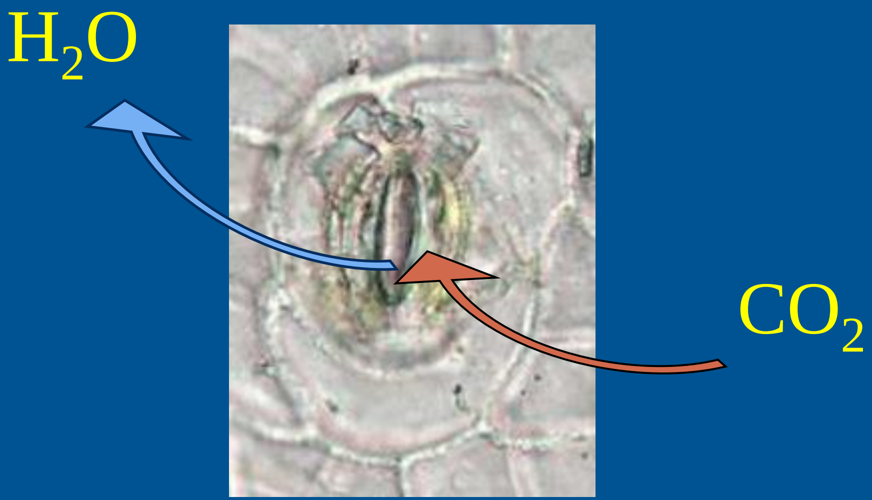
Gates (1968)
Jackson *et al.* (1977)

Transpiration - Temperature

Vascular plant pathogens:

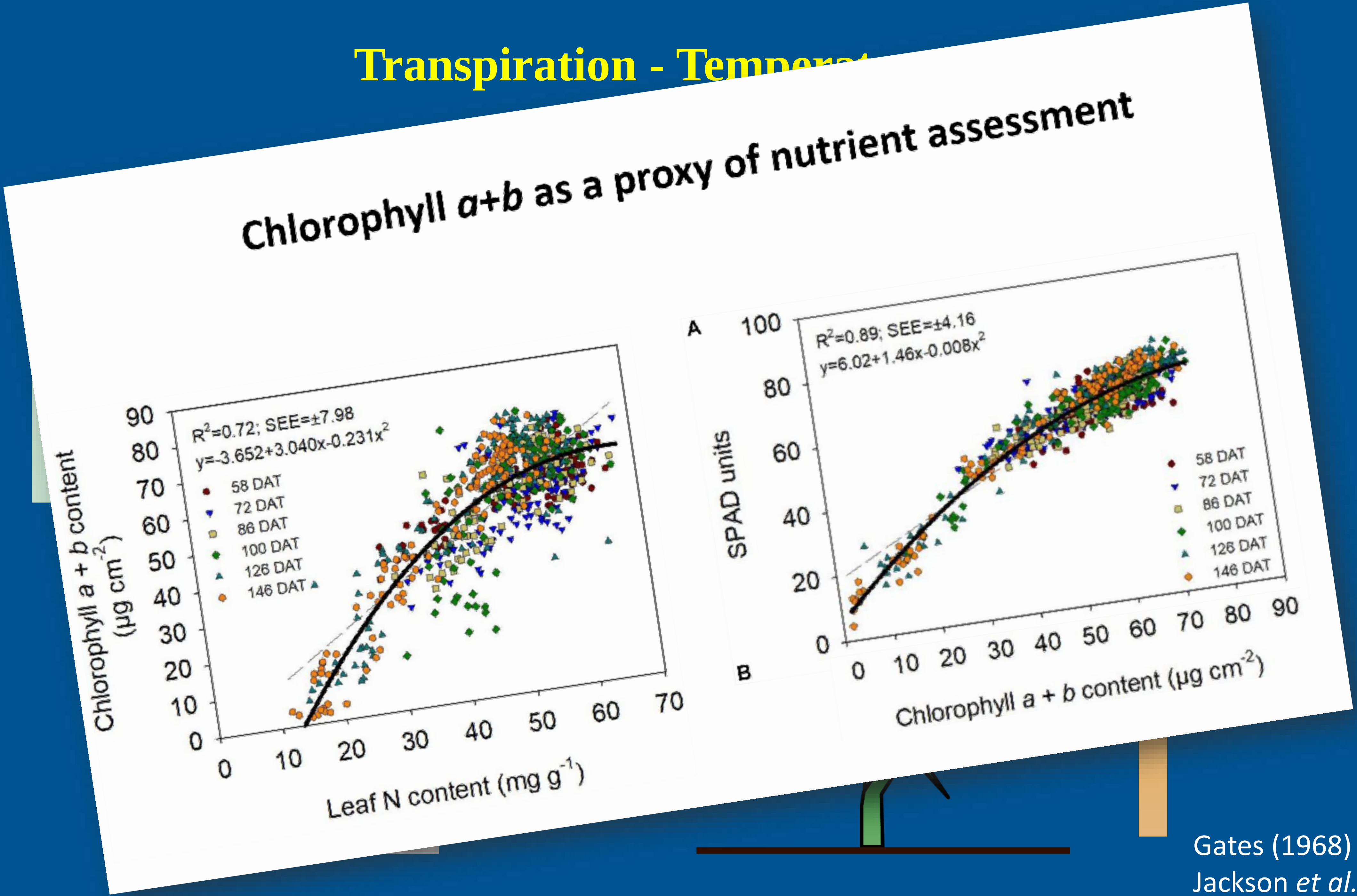
→ **Colonize and blocks the vascular system → interfere with water and nutrients flow**

→ **Confounding effects with water stress**



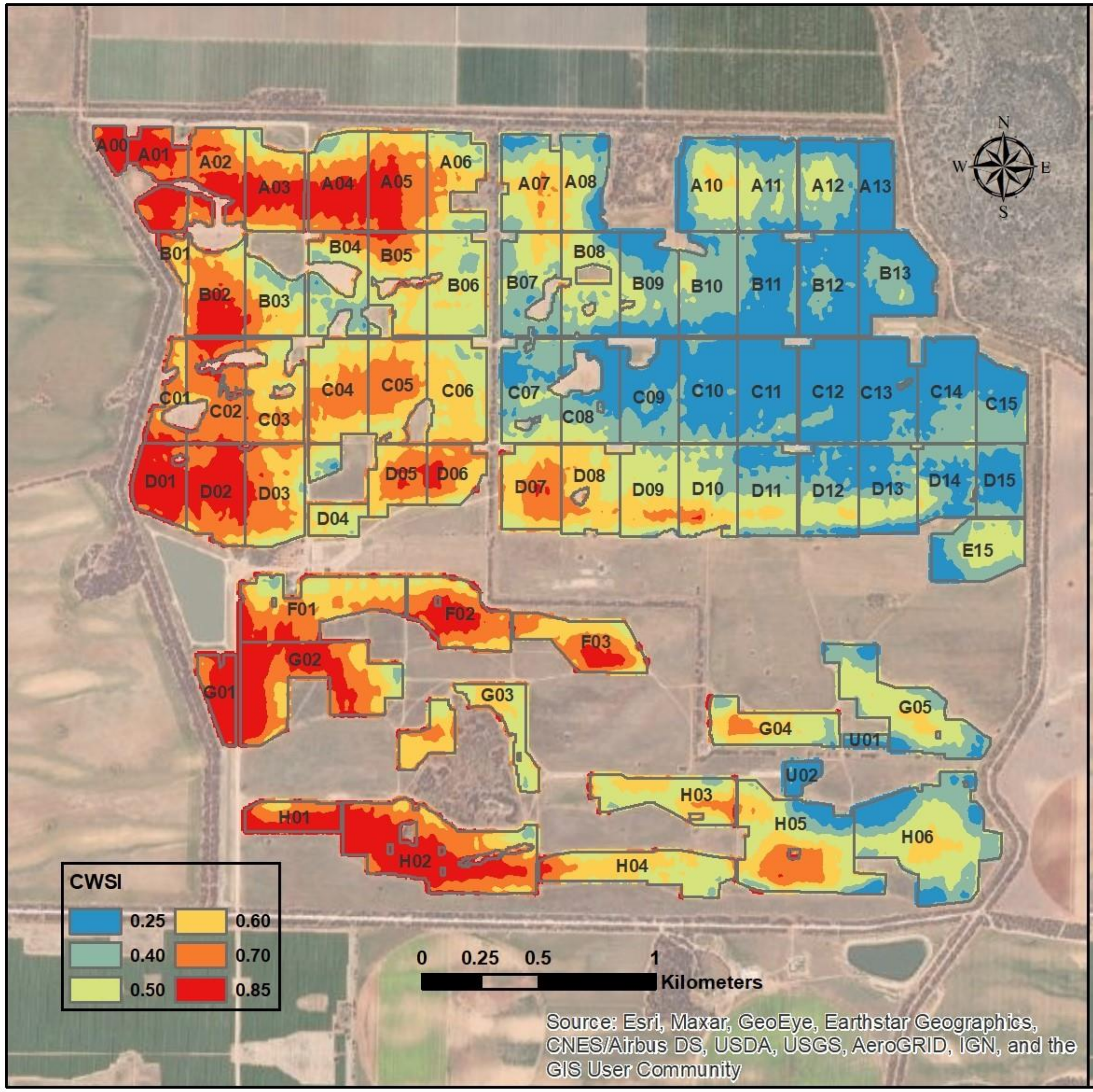
Gates (1968)
Jackson *et al.* (1977)

Transpiration - Temperat

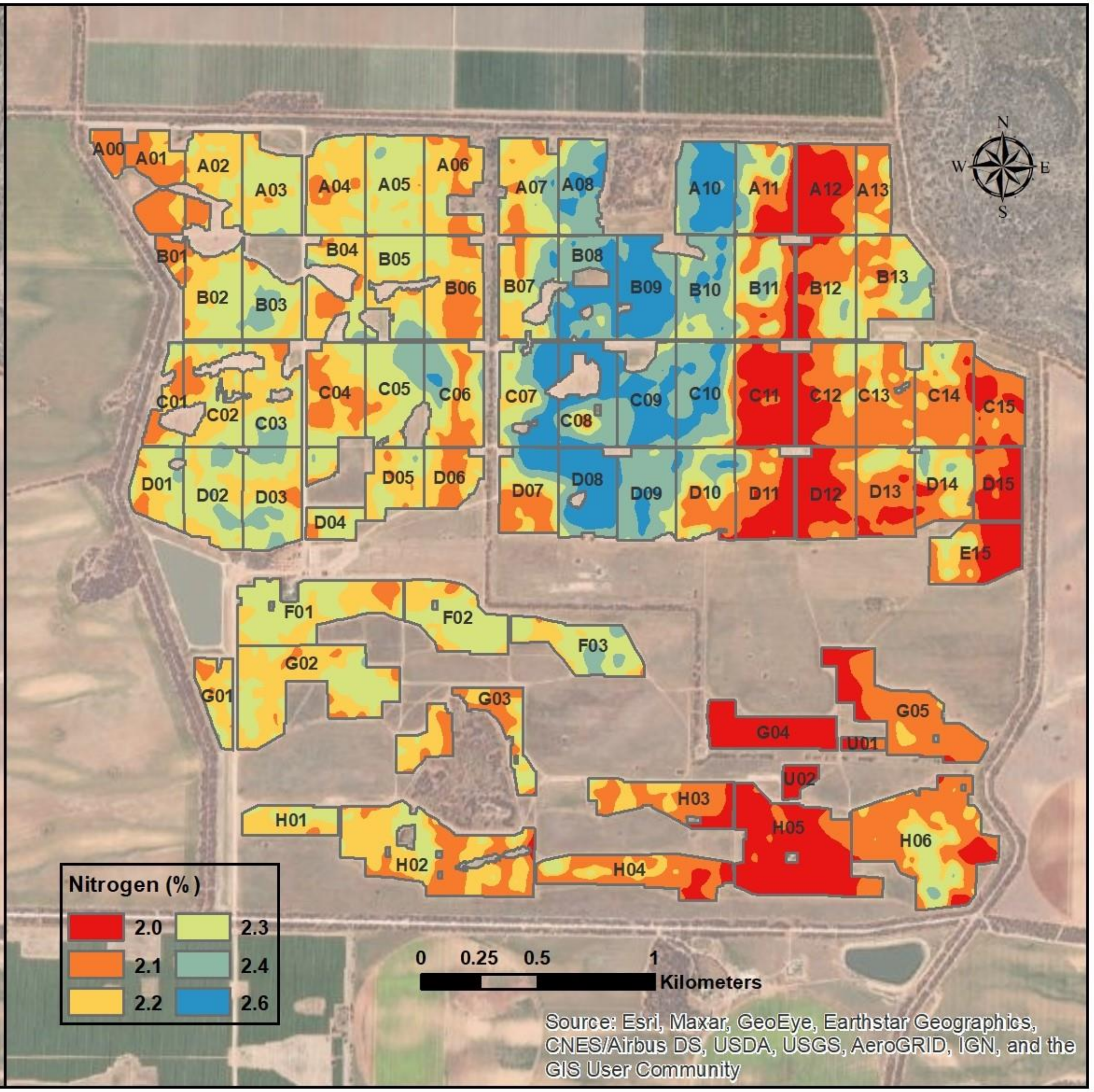


Gates (1968)
Jackson *et al.* (1977)

Water stress



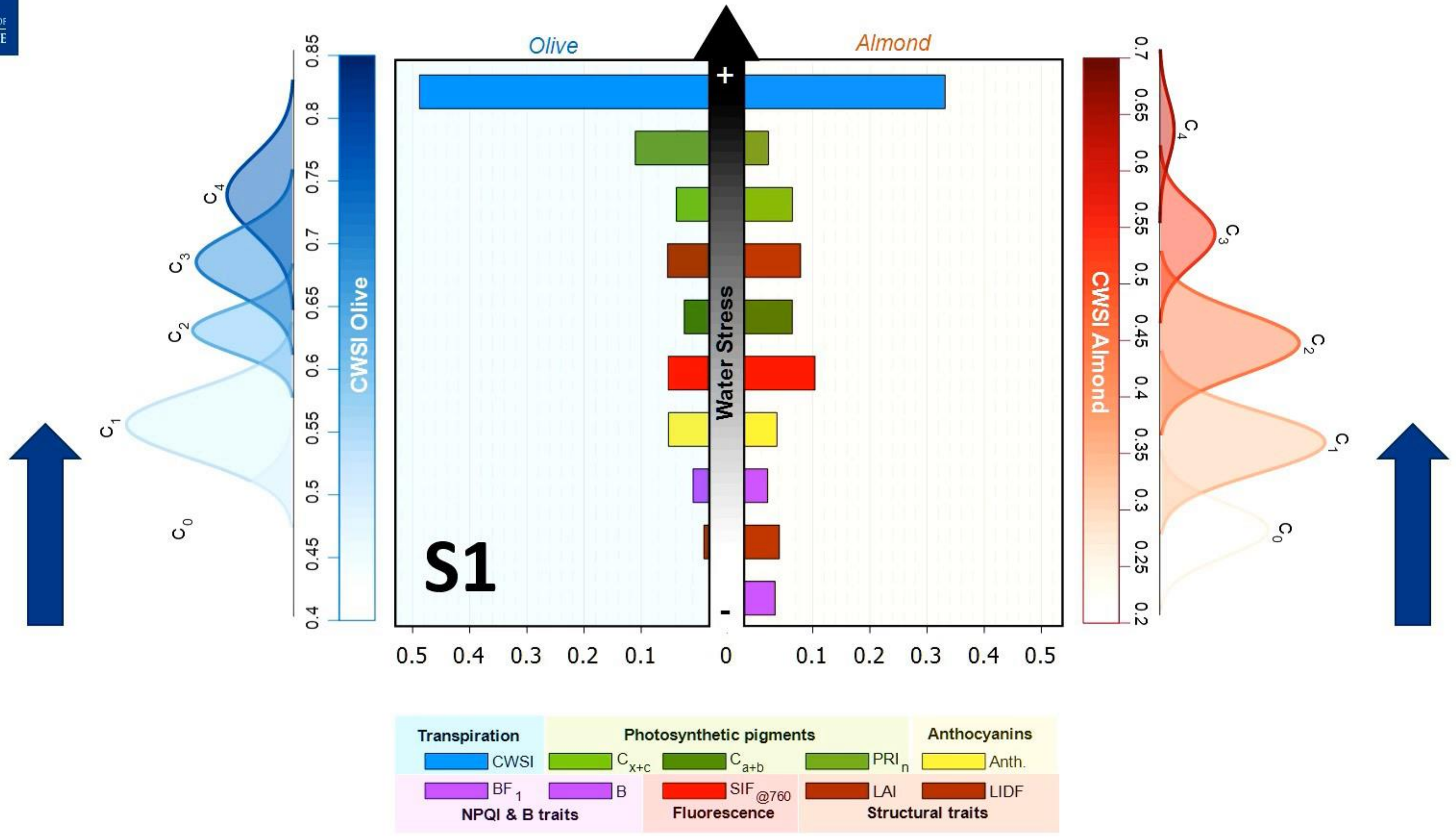
Nitrogen %



1200 ha almond orchard, VIC (AU)

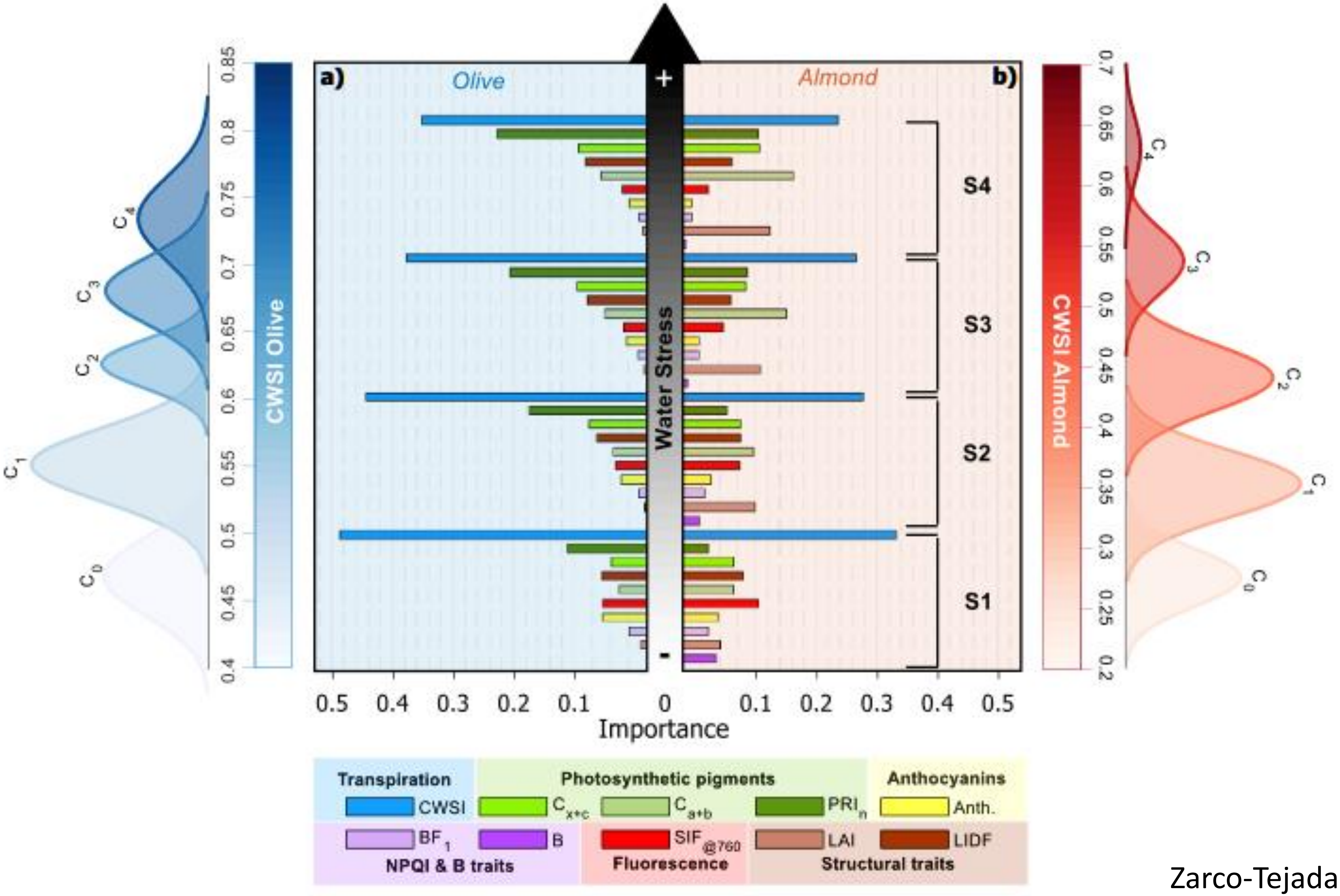
Wang *et al.* (2022)

Importance of plant traits to detect water stress as a function of stress levels



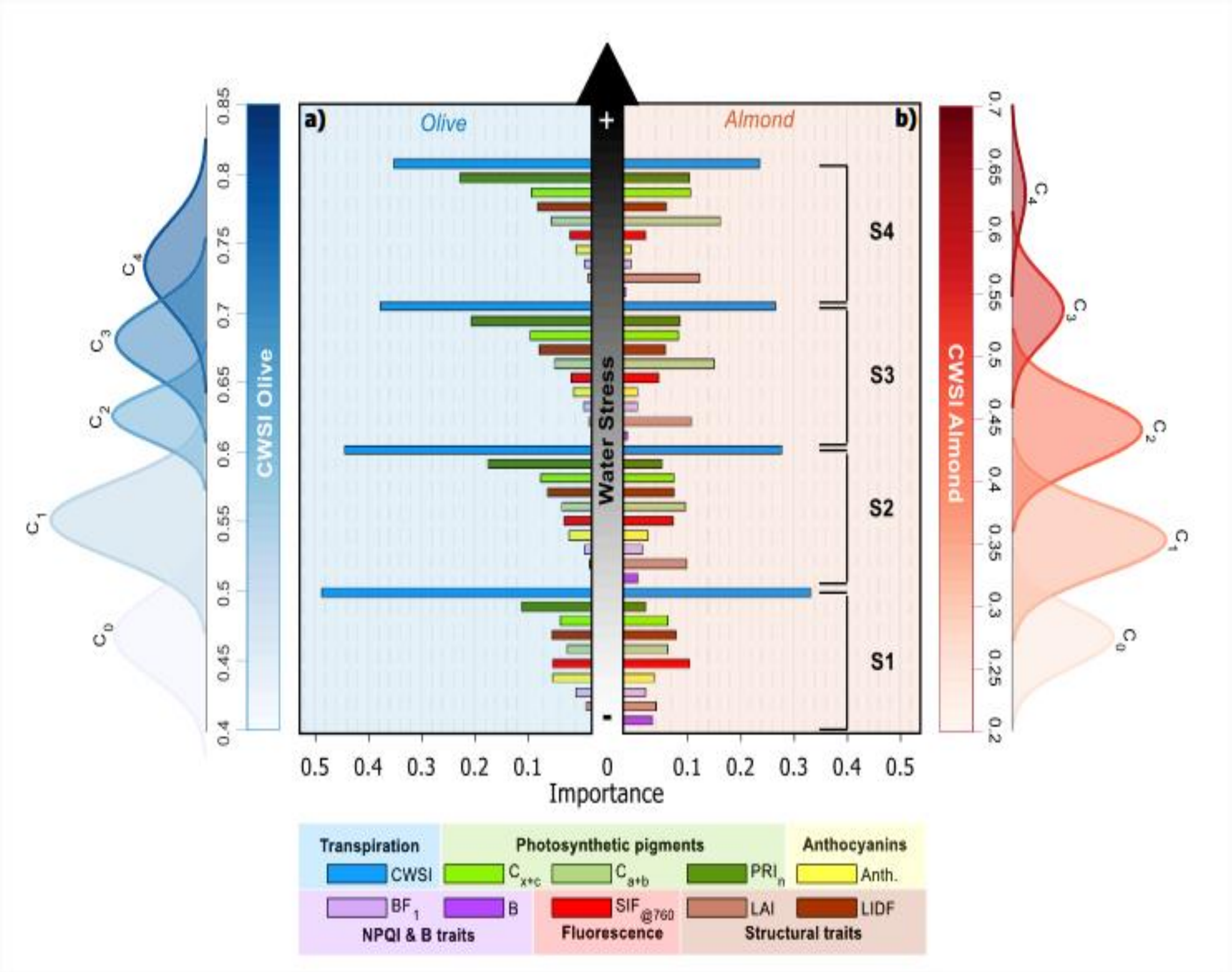
Zarco-Tejada *et al.* (2021)

Importance of plant traits to detect water stress as a function of stress levels



Zarco-Tejada *et al.* (2021)

Dynamics of thermal & hyperspectral with water stress

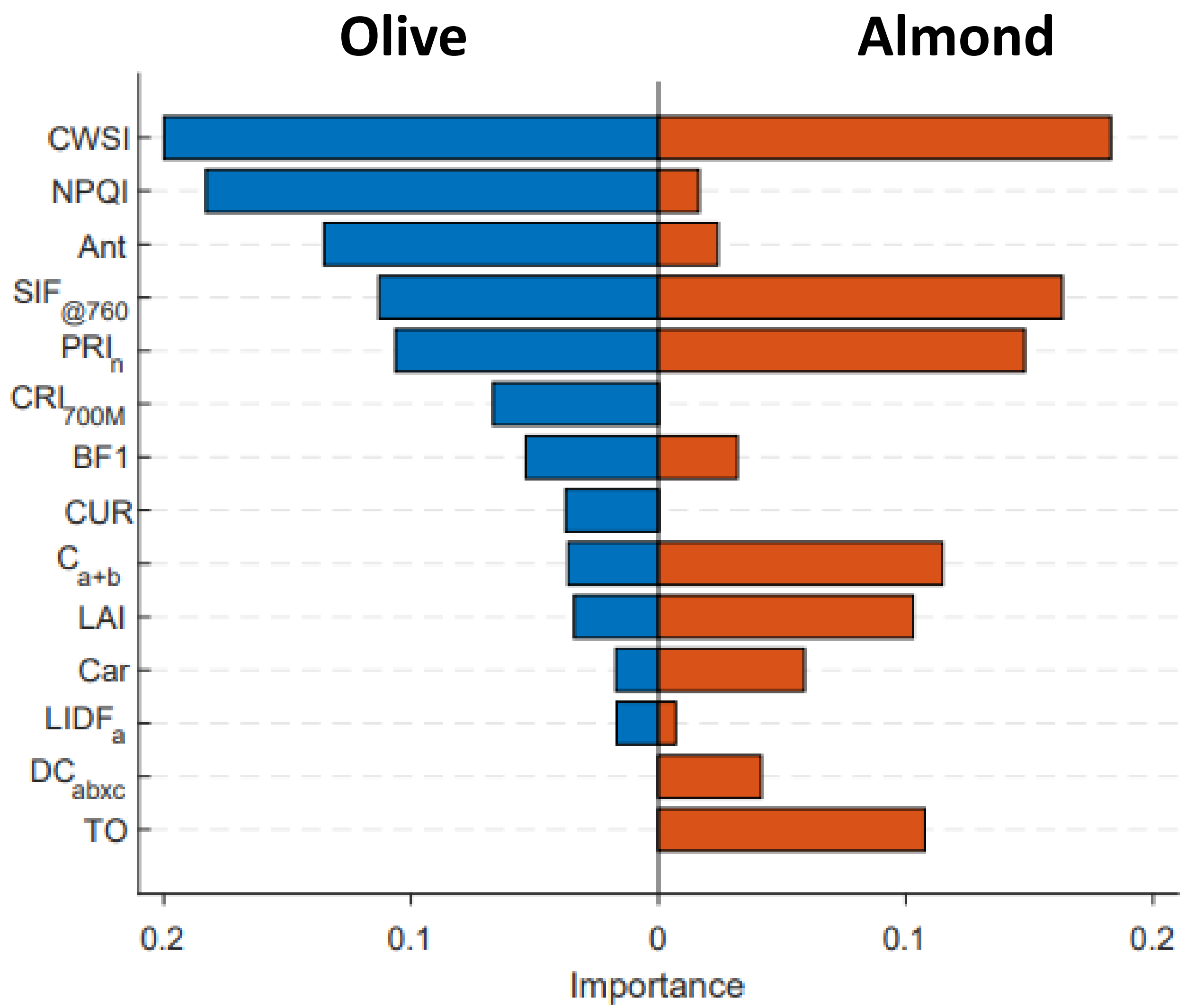


Zarco-Tejada *et al.* (2021)

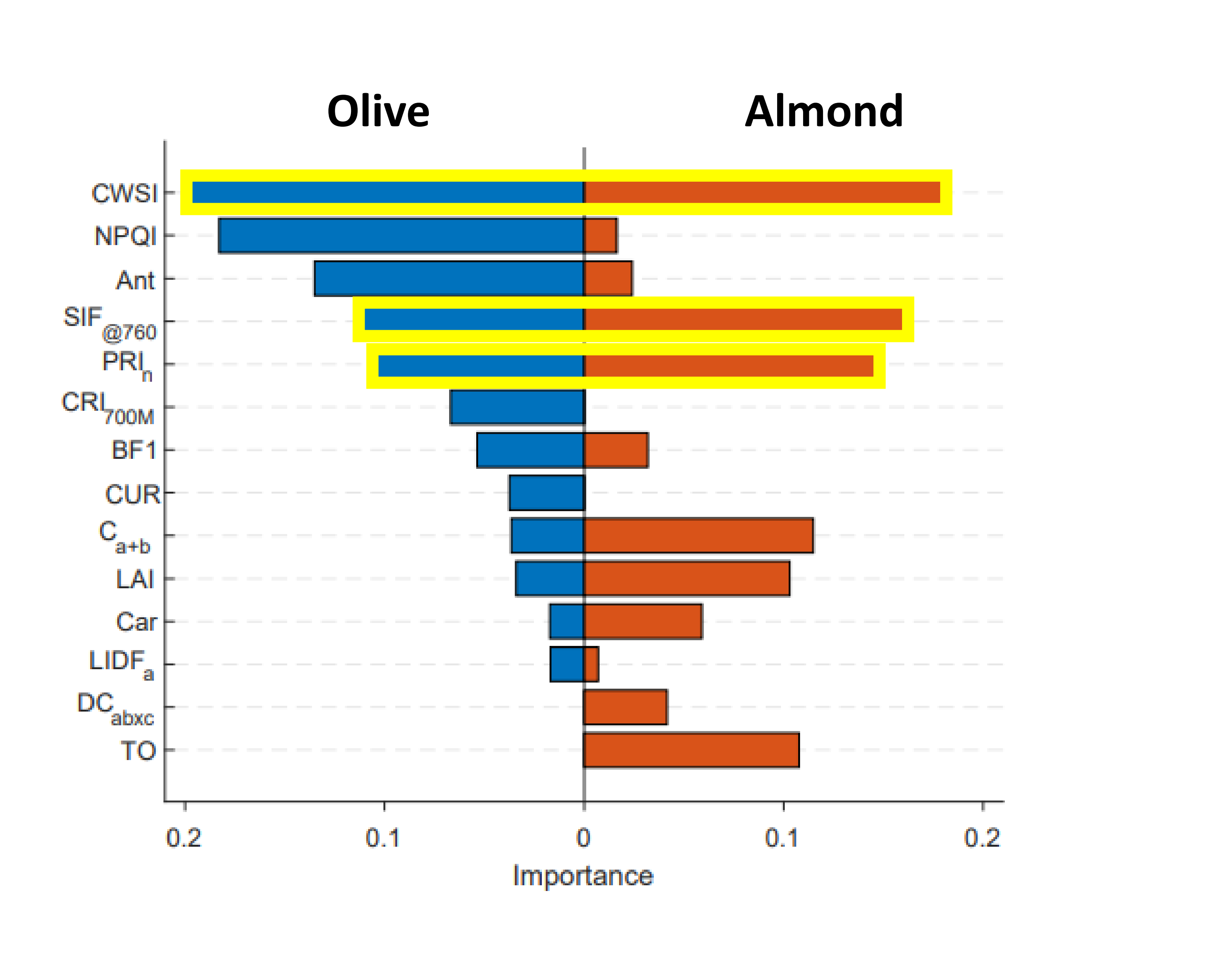
- At early stages, thermal is the most important water stress indicator
- As water stress ↑ the relative importance of thermal ↓
- After thermal, hyperspectral traits showed high sensitivity to water stress:
  - ➢ C_{a+b}, C_x ↑ importance with water stress
- Thermal and SIF → inverse trends with increasing water stress levels

RS traits are species- and pathogen-specific

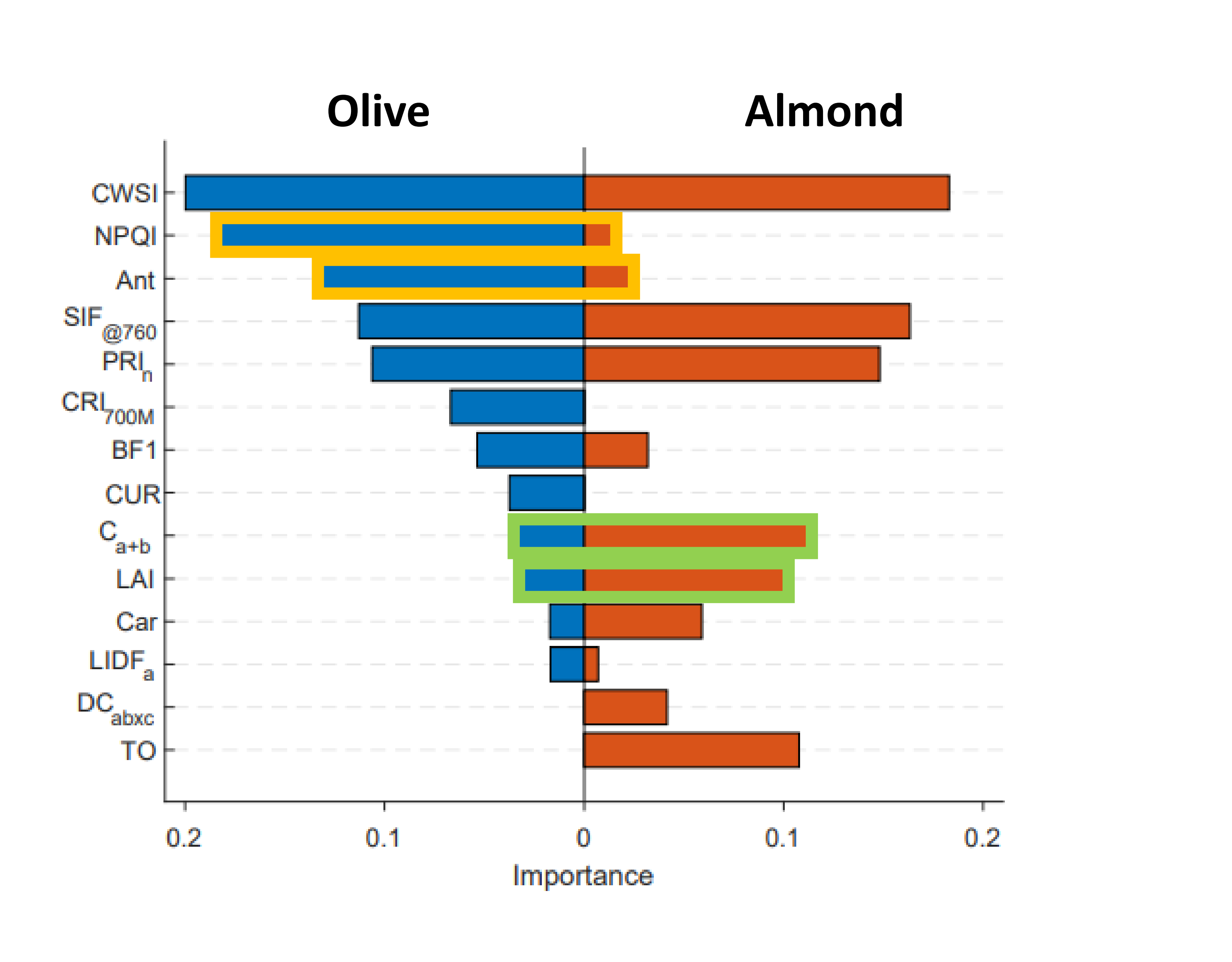
Importance of *Xf*-sensitive spectral traits in olive vs. almond



Importance of *Xf*-sensitive spectral traits in olive vs. almond

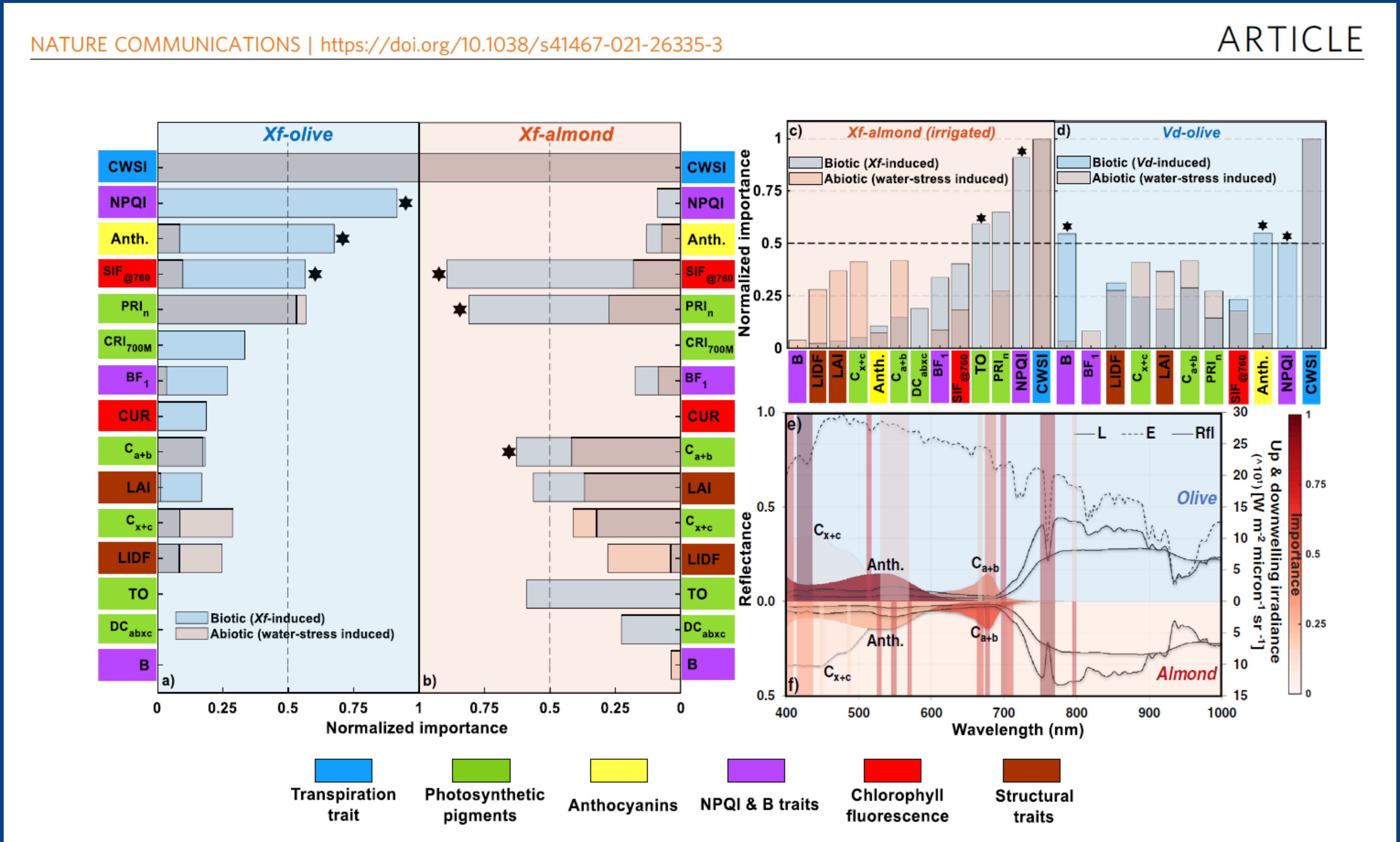


Importance of *Xf*-sensitive spectral traits in olive vs. almond



Hyperspectral indicators are species-specific *(almond vs olive)* and pathogen-specific *(Xf vs Vd)*

Accuracy > 92%

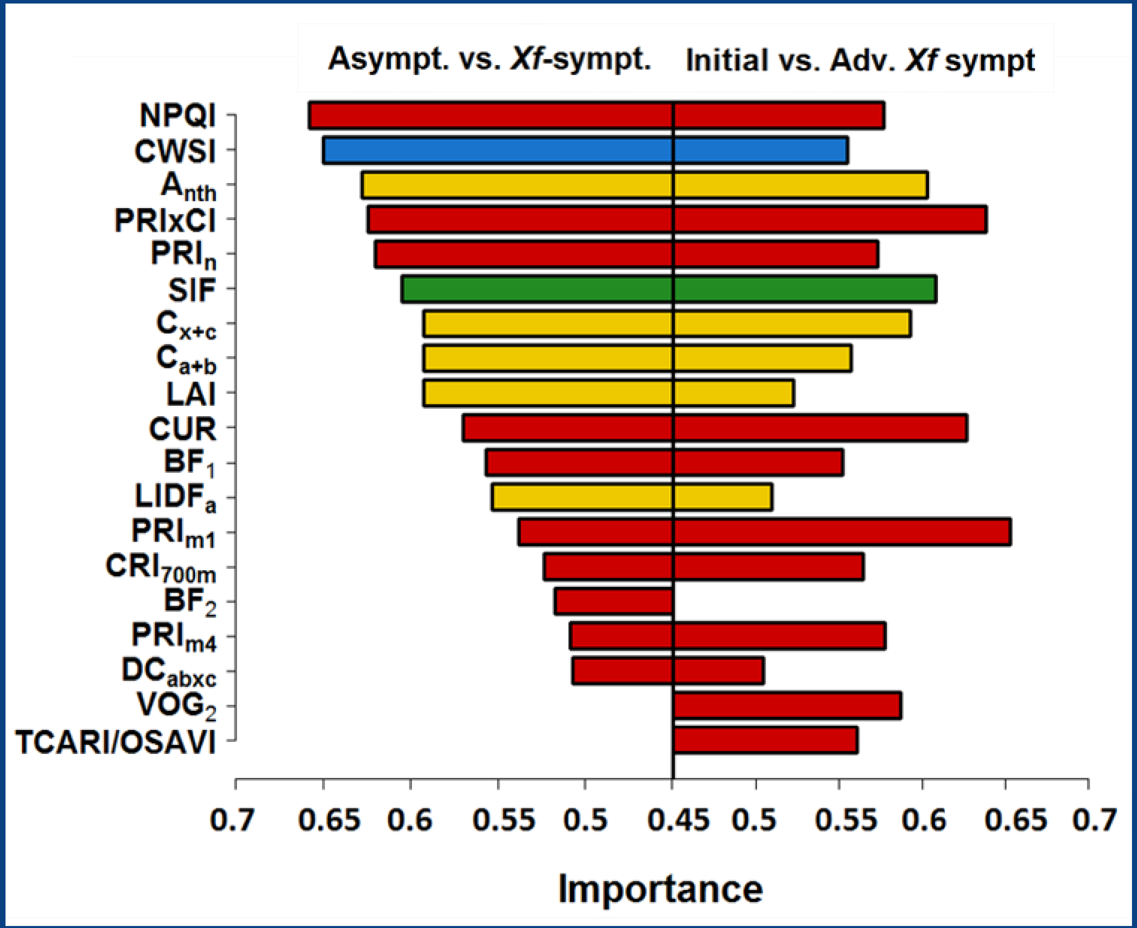


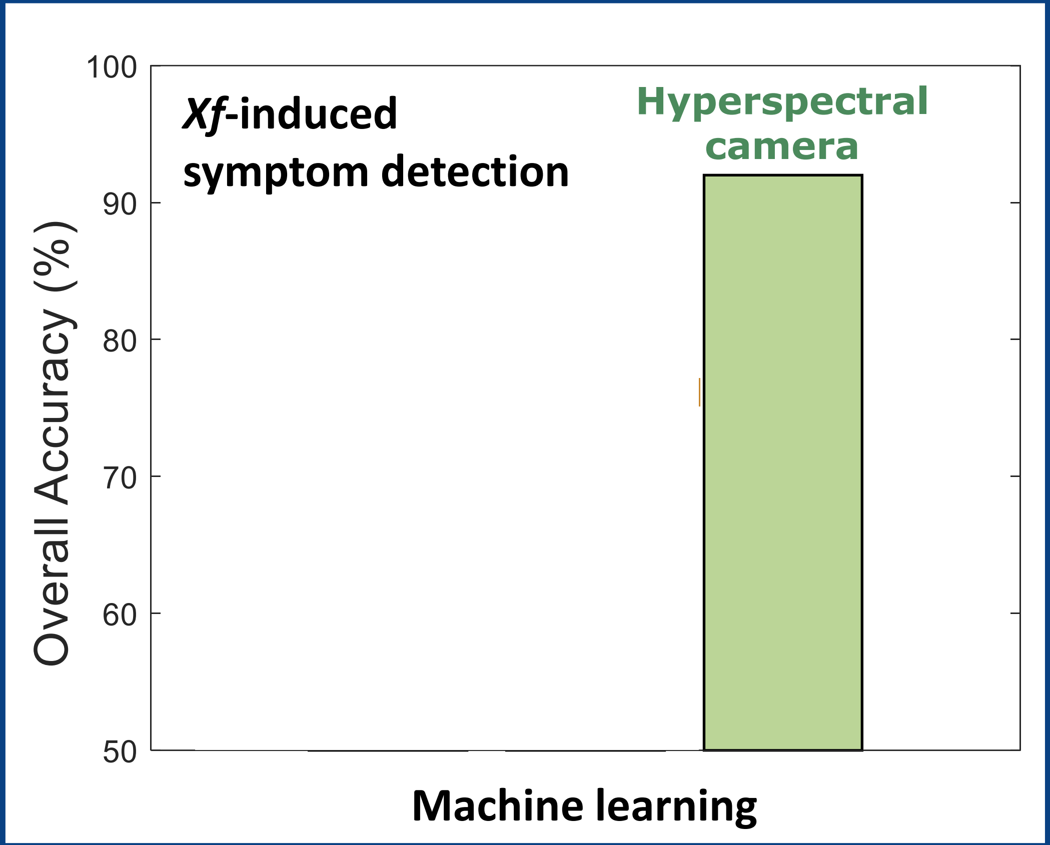
Zarco-Tejada *et al*. (2021)

Need for hyperspectral data ?

Sensitivity of Plant Traits to *Xf* symptoms

Hyperspectral traits

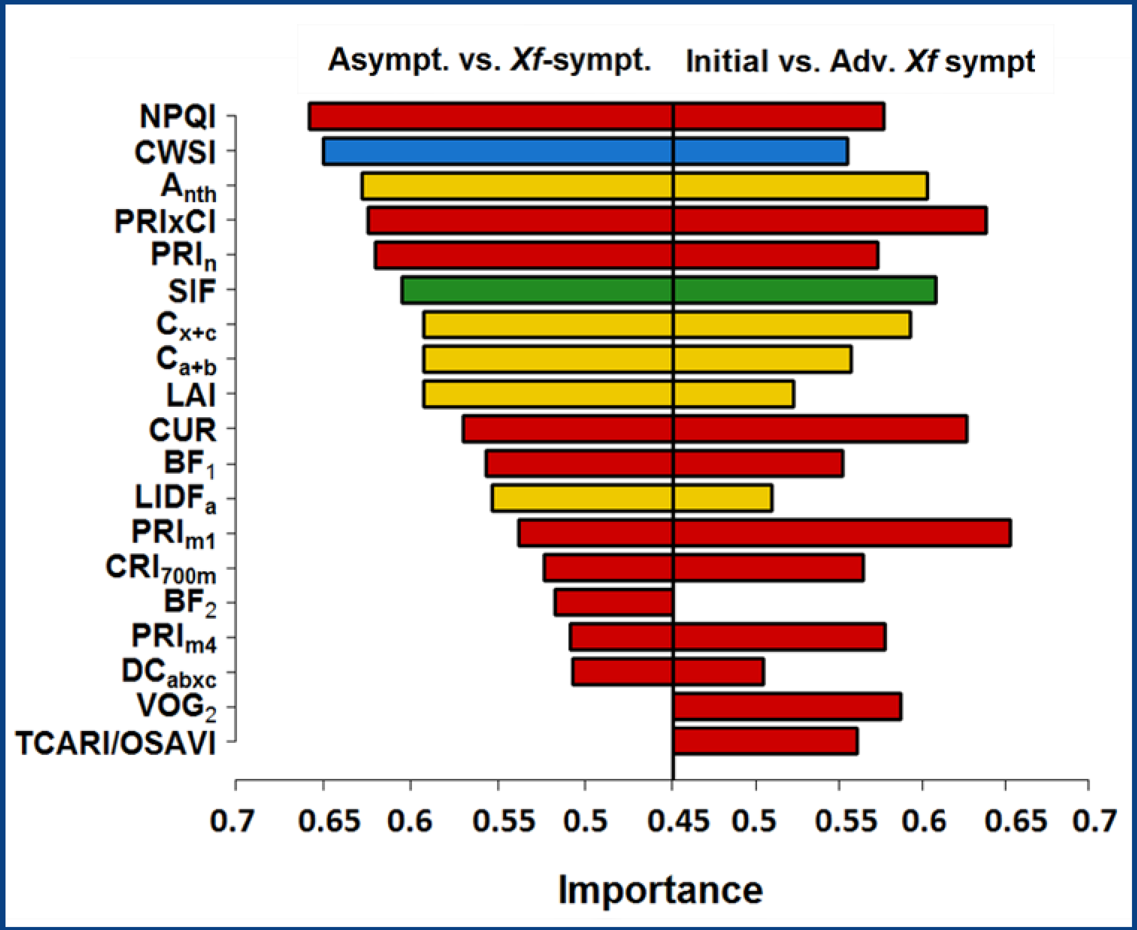


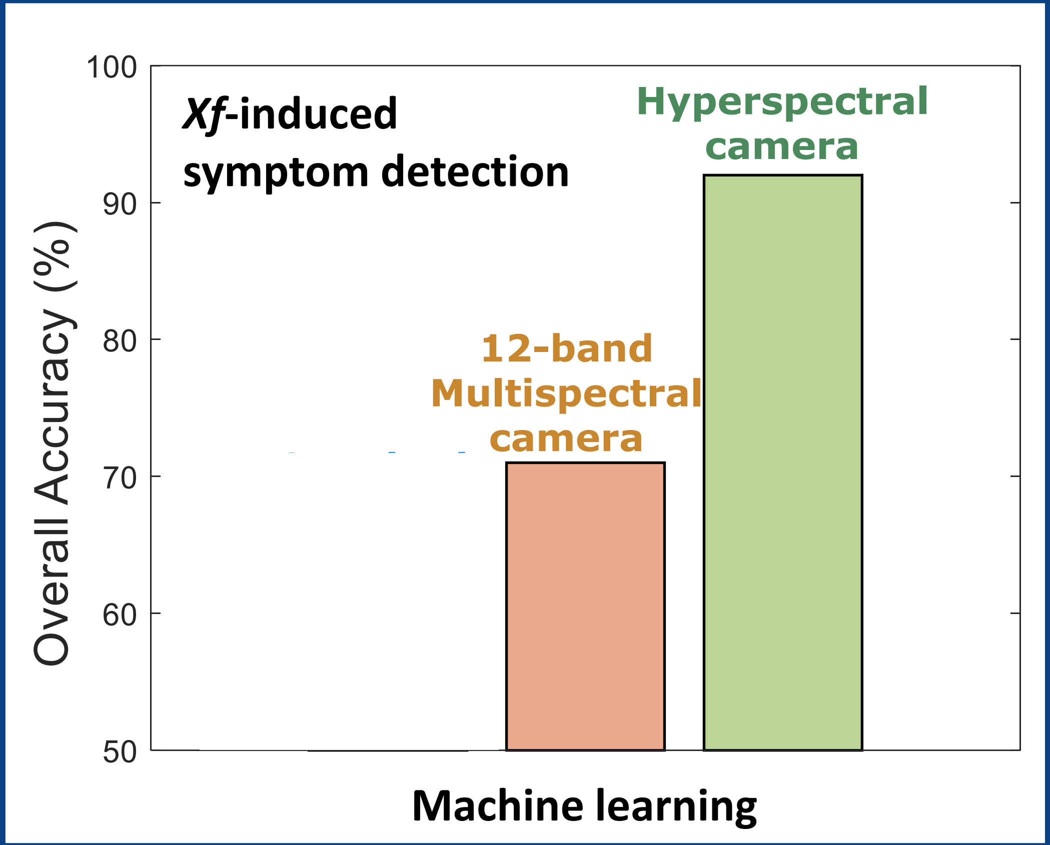


Poblete *et al.* (2020; 2021; 2023)
Zarco-Tejada *et al.* (2018)

Sensitivity of Plant Traits to *Xf* symptoms

Hyperspectral traits





Poblete *et al.* (2020; 2021; 2023)
Zarco-Tejada *et al.* (2018)

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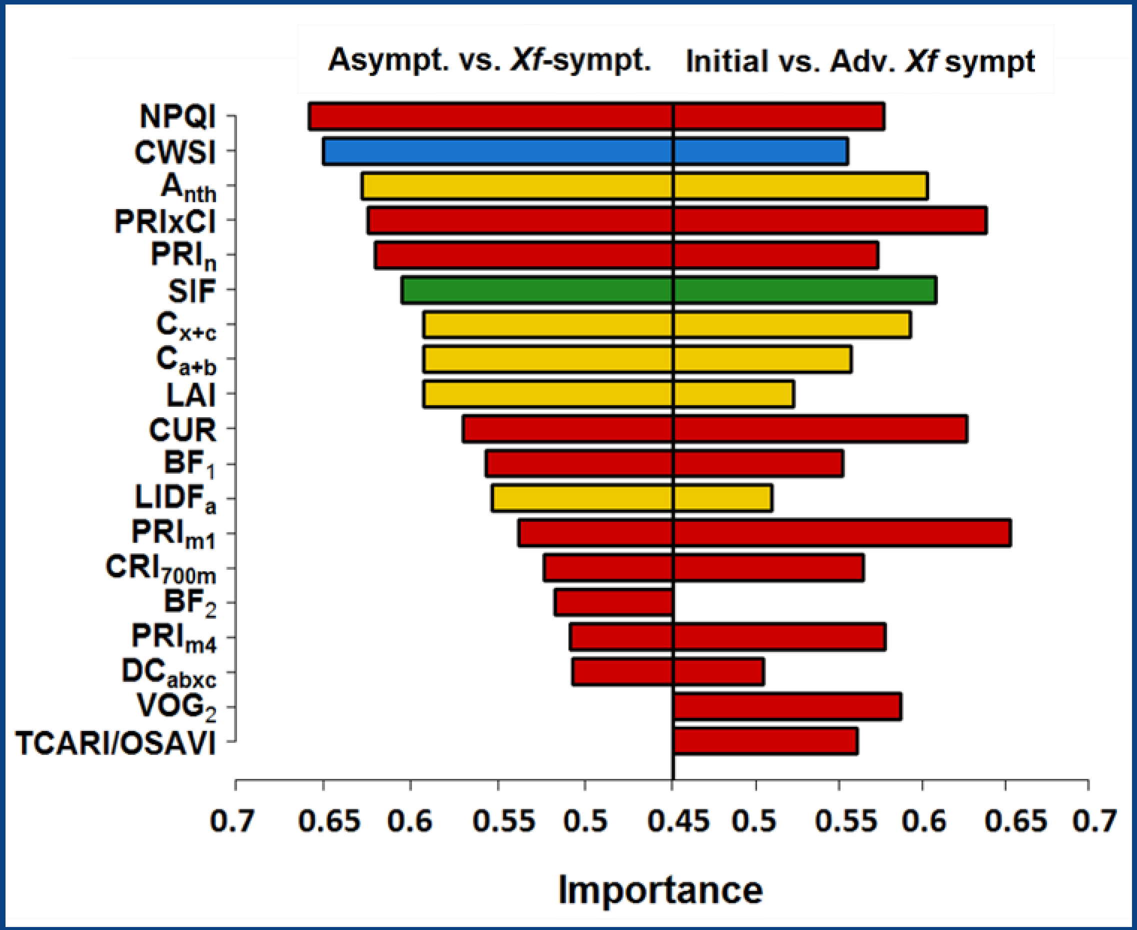
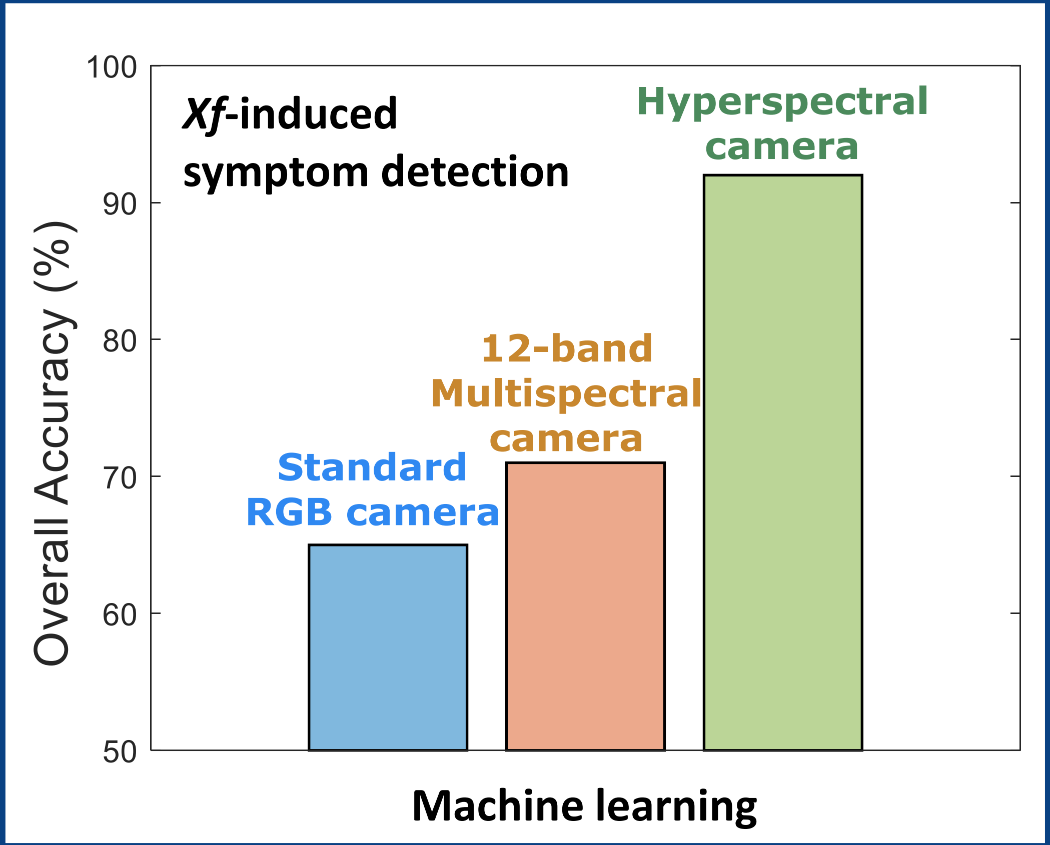
Sensitivity of Plant Traits to *Xf* symptoms

Hyperspectral traits





Poblete *et al.* (2020; 2021; 2023)
Zarco-Tejada *et al.* (2018)

Conclusions & Final Remarks

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1. Progress made is the last 20 years with hyperspectral & thermal data for biotic-induced stress detection across species **(OA>0.8-0.9; k>0.6)**

2. **Traits (RT) critical for robust detection** of stress (avoiding site-specific empirical models)

3. **Species-specific spectral indicators** & traits identified for *Xf*-, *Vd*- and *Ph*-induced symptoms (CWSI, NPQI, Anth, Xanth, SIF and PRI_n)

4. Quantifying the **abiotic status** is critical for improved detection of **biotic stress**:
   - Almond: OA: 83% (κ=0.65) → 94% (κ=0.87)
   - Olive: OA: 77% (κ=0.43) → 92% (κ=0.83)

5. Airborne (thousands of hectares) / drone (hundreds of hectares) hyperspectral and thermal imagery can be used for **early** disease detection and monitoring

6. Satellite data (commercial & Sentinel-2) can be used for disease monitoring at **medium / advanced** severity levels → **failing to detect biotic stress at early stages**

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Full list of authors cited in the presentation:

Zarco-Tejada, P.J., Poblete, T., Calderon, R., Hornero, A., Hernández-Clemente, R., Kattenborn, T., Montes-Borrego, M., Román-Écija, M., Velasco-Amo, M.P., Susca, L., Morelli, M., Gonzalez-Dugo, V., Landa, B.B., Beck, P.S.A., Boscia, D., Saponari, M., Navas-Cortes, J.A.

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High-resolution hyperspectral and thermal imaging for the early detection of plant diseases

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