

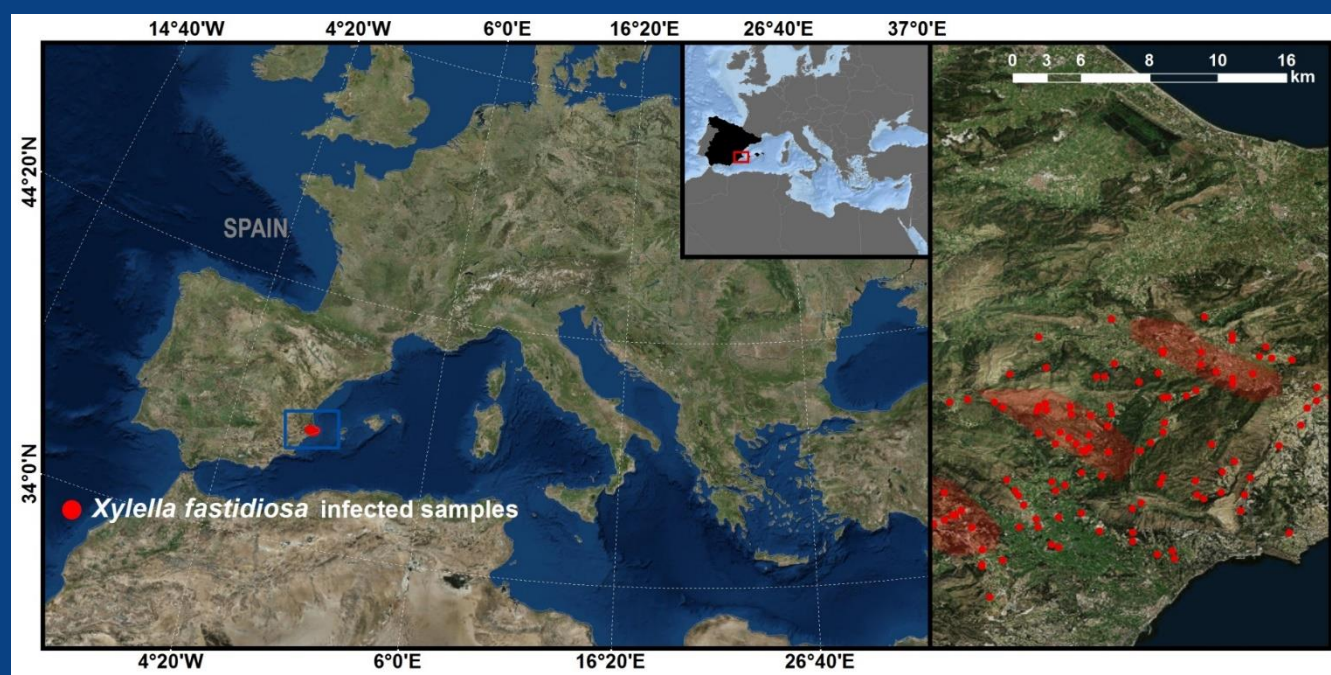
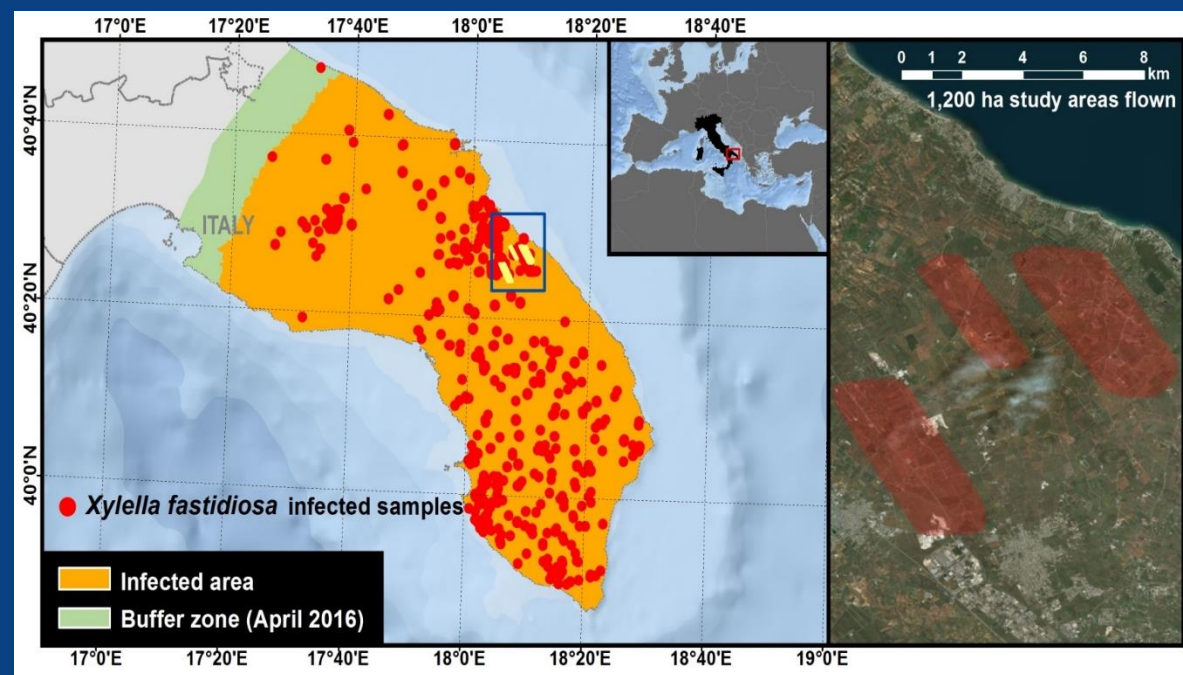


Detection of symptoms induced by *X. fastidiosa* with high-resolution multispectral satellite data: assessment with airborne hyperspectral imagery

Poblete¹ T., Navas-Cortes² J.A., Hornero^{2,1} A., Camino³ C., Calderon⁴ R., Hernandez-Clemente⁵ R., Landa² B.B., Zarco-Tejada^{1,2} P.J.

- (1) The University of Melbourne, Melbourne, AUSTRALIA
- (2) Instituto de Agricultura Sostenible (IAS), Consejo Superior de Investigaciones Científicas (CSIC), Córdoba, SPAIN
- (3) European Commission, Joint Research Centre (JRC)
- (4) Plant Pathology and Plant-Microbe Biology Section, School of Integrative Plant Science, Cornell AgriTech, Geneva, UNITED STATES
- (5) Department of Forestry Engineering, Universidad de Córdoba (UCO), Cordoba, SPAIN

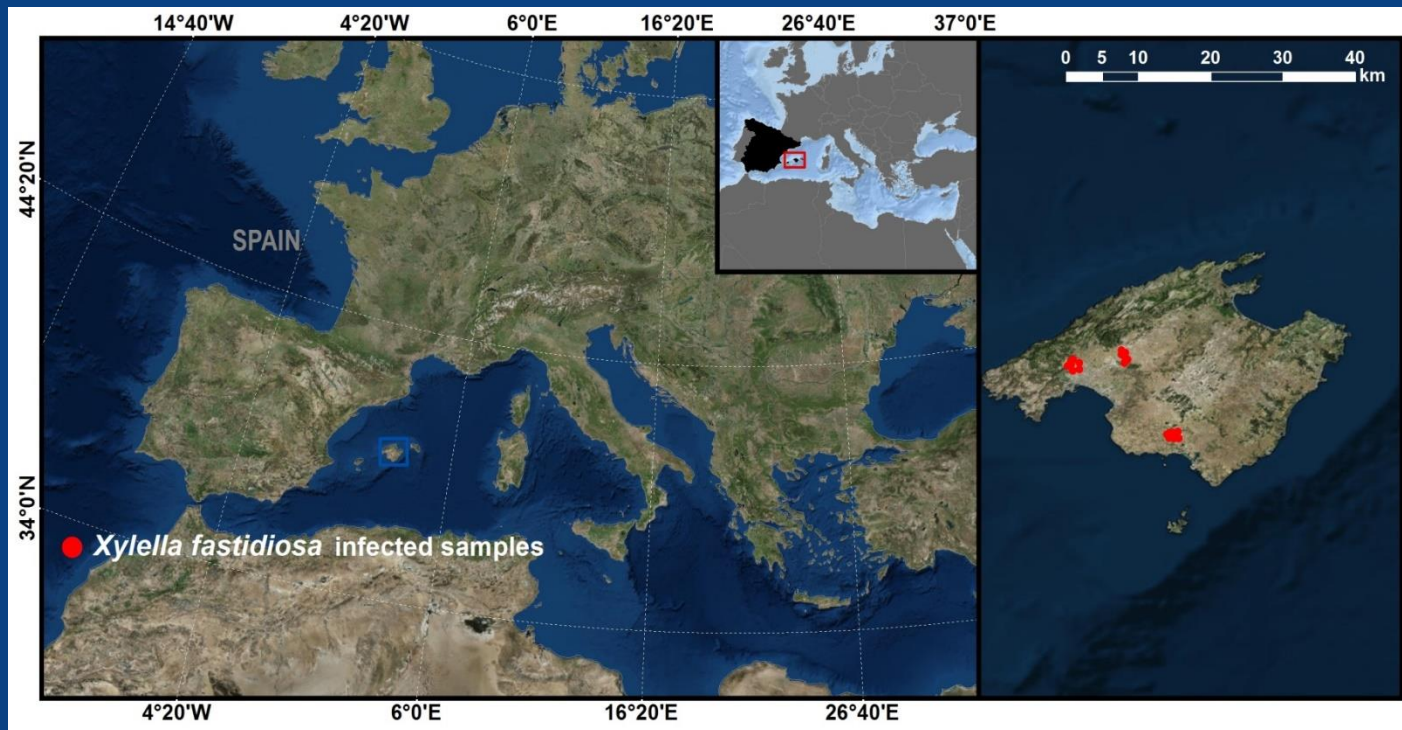




Airborne
campaigns in the
Puglia region, Italy

Airborne
campaigns in
Alicante region,
mainland Spain

***Xf* airborne
campaigns in
Europe –
2016 - 2023**



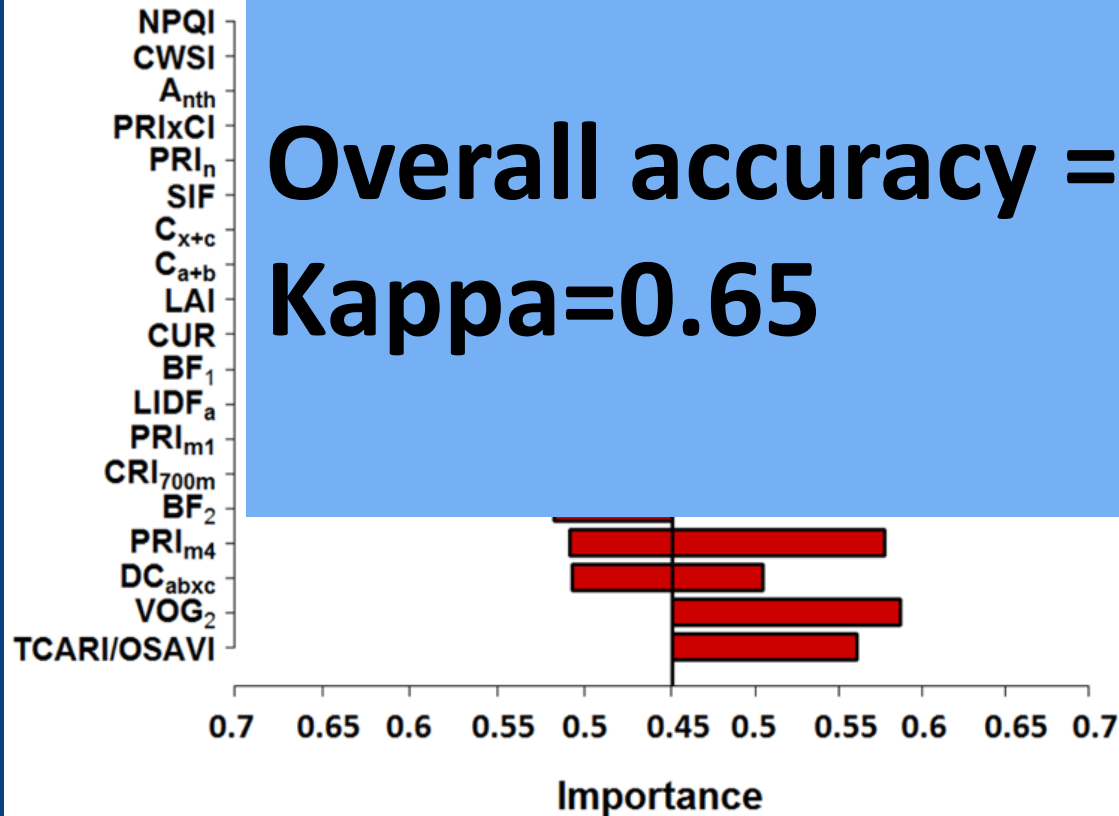
Airborne
campaigns in
the Balearic
Islands, Spain

2018

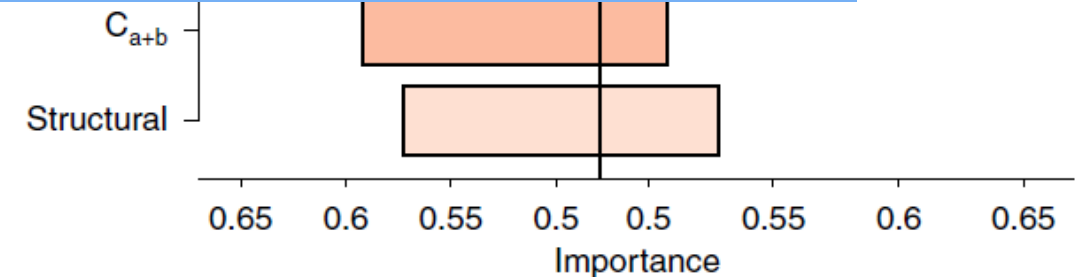
Sensitivity of hyperspectral traits to *Xf* symptoms - olive

Spectral plant traits

Overall accuracy = 80%
Kappa=0.65



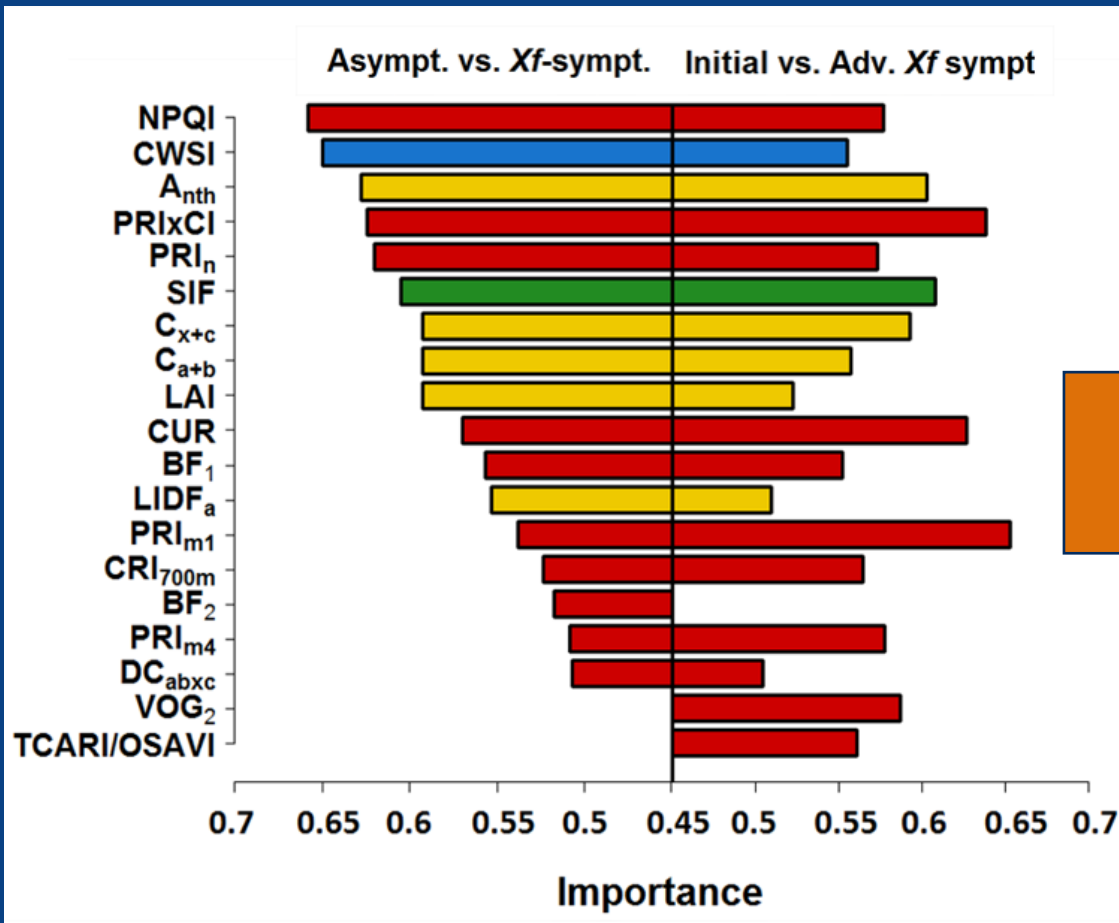
Spectral functional groups



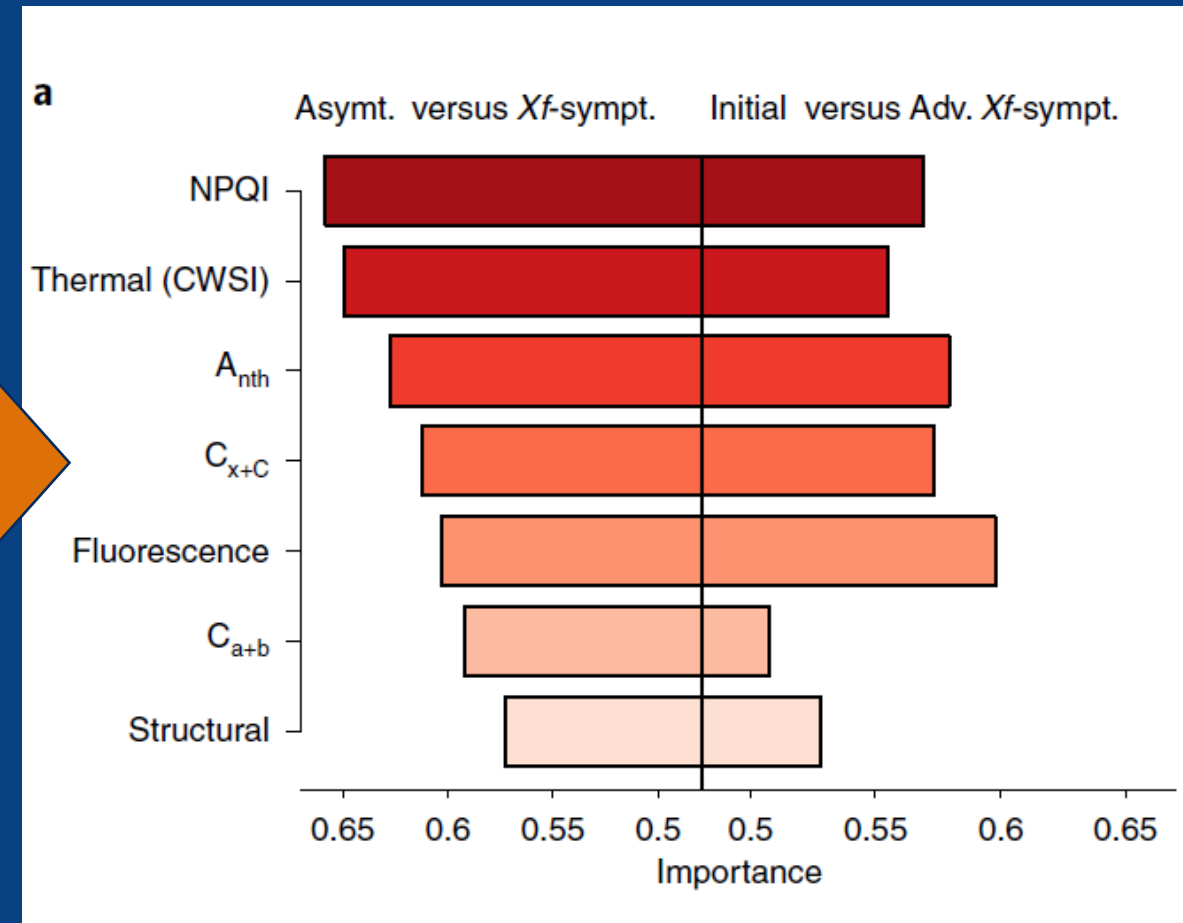
2018

Sensitivity of hyperspectral traits to *Xf* symptoms - olive

Spectral plant traits



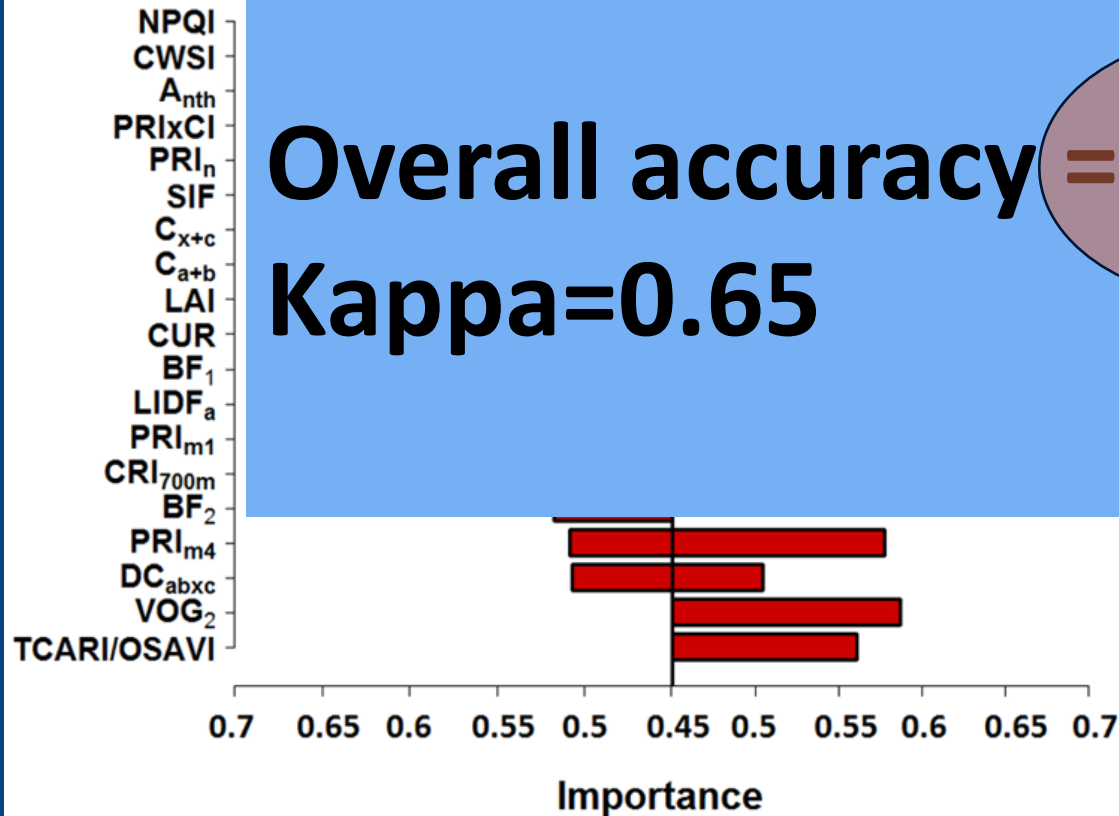
Spectral functional groups



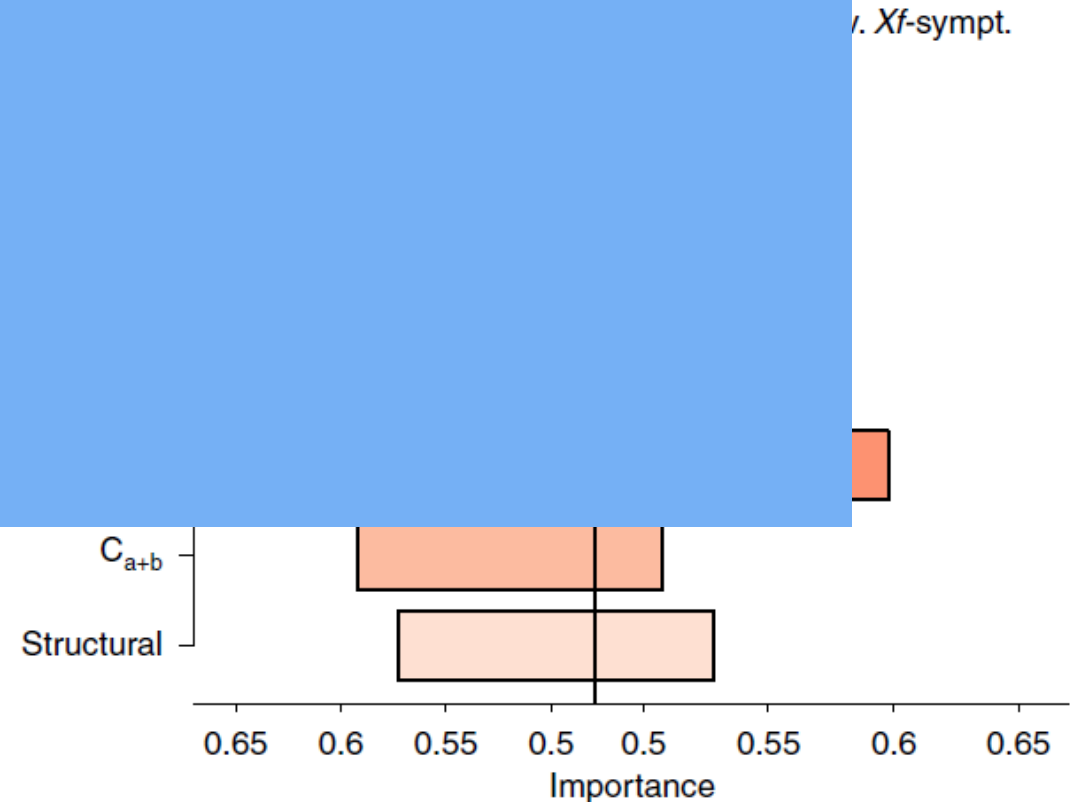
2018

Sensitivity of hyperspectral traits to *Xf* symptoms - olive

Spectral plant traits



Spectral functional groups



2018

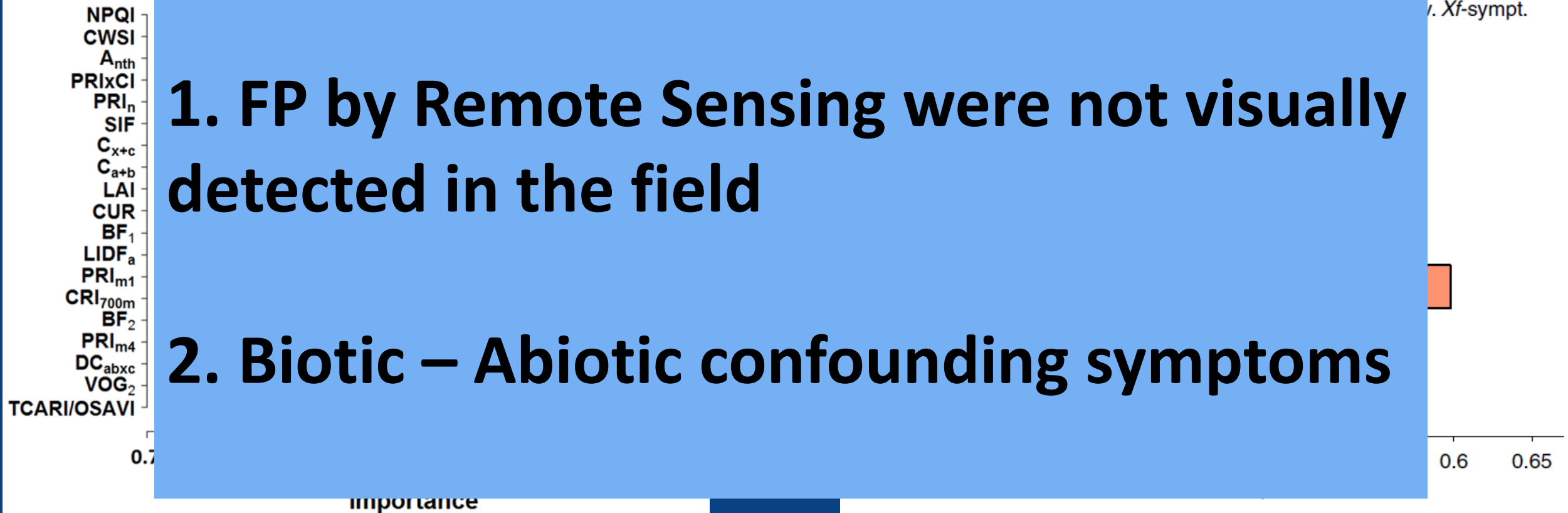
Sensitivity of hyperspectral traits to *Xf* symptoms - olive

Spectral plant traits

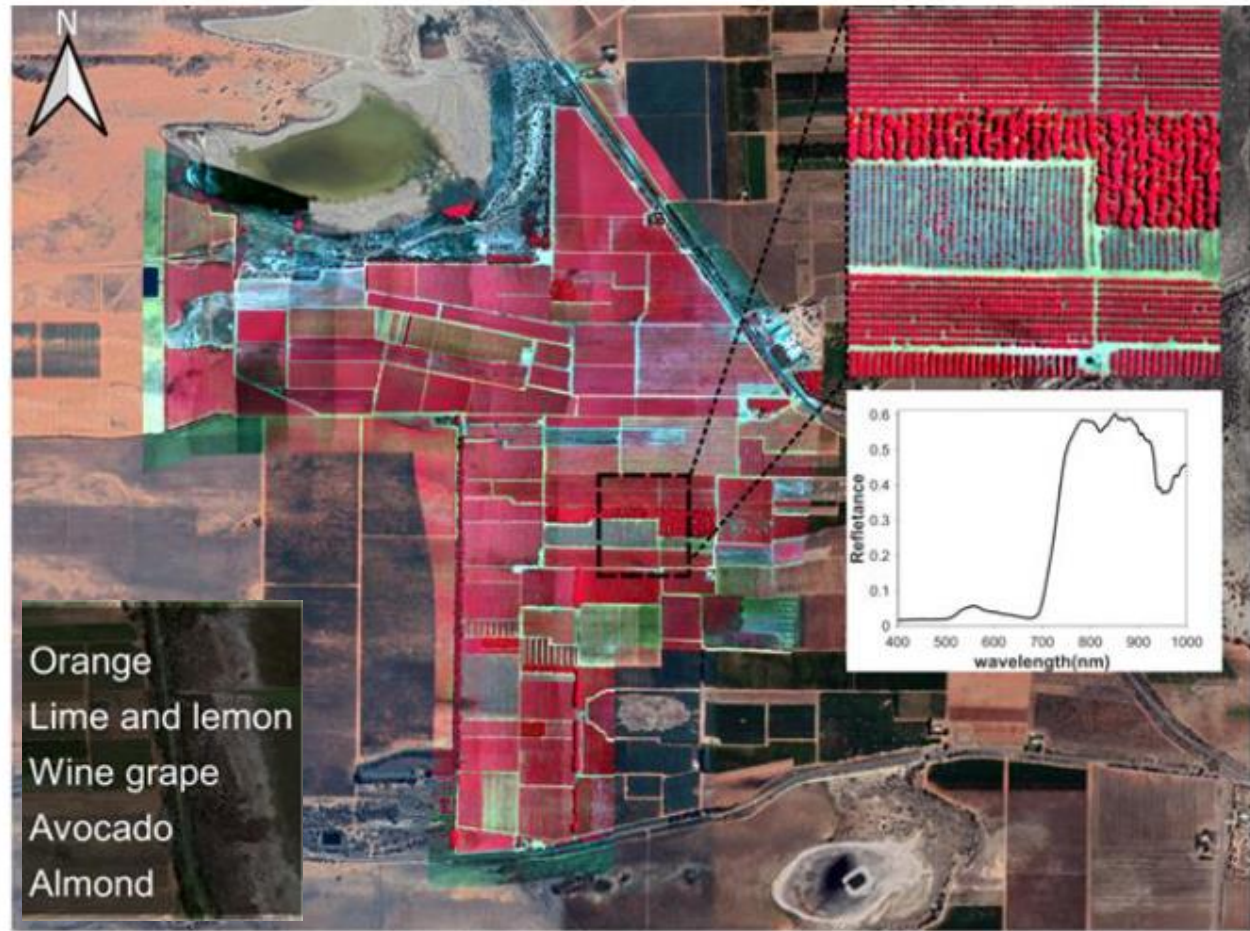
Spectral functional groups

1. FP by Remote Sensing were not visually detected in the field

2. Biotic – Abiotic confounding symptoms



Large natural variability of water and nutrient stress



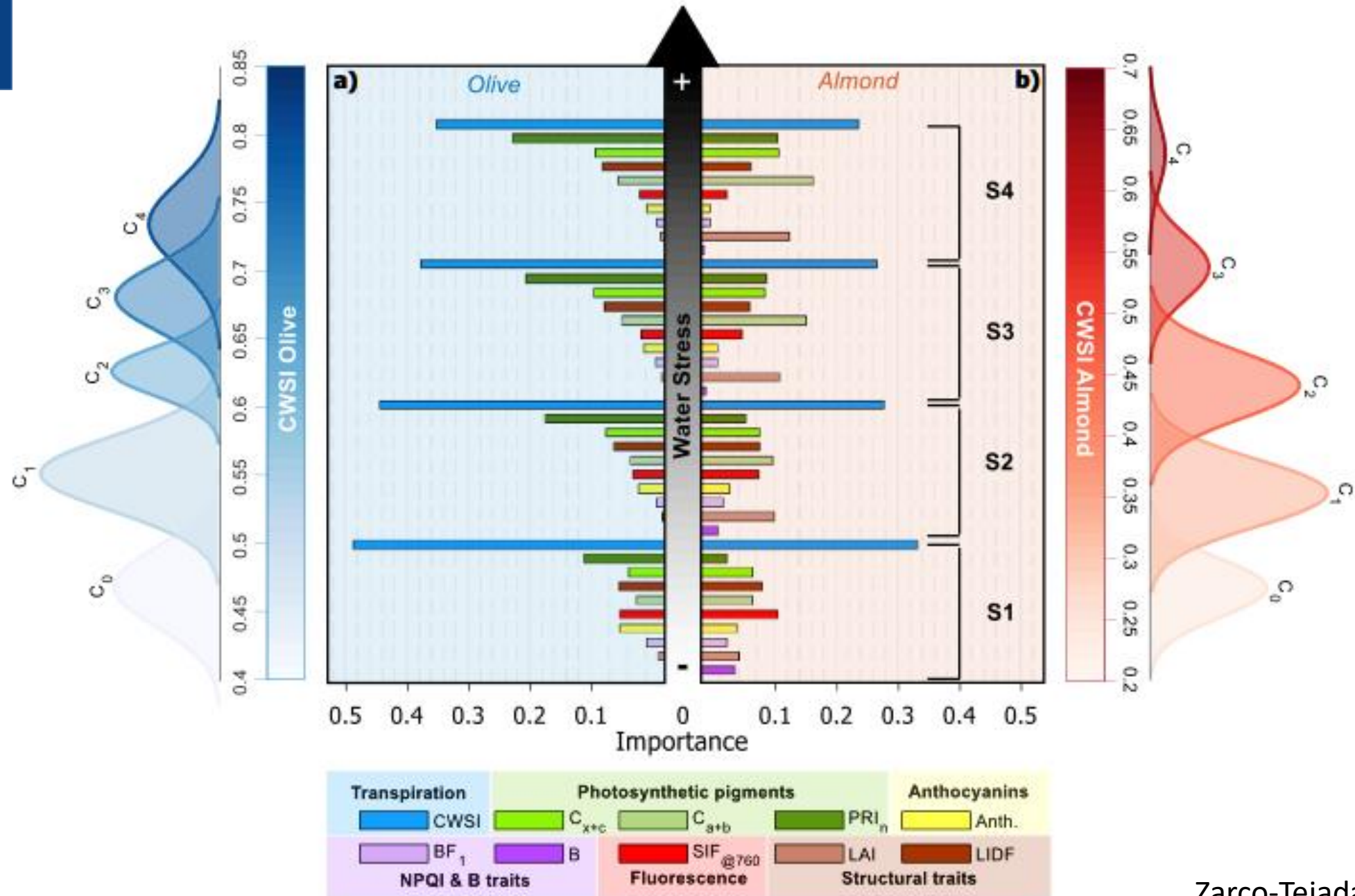
Hyperspectral image



Thermal image

2021

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

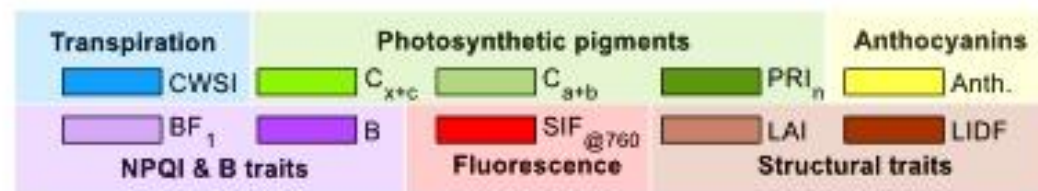


2021

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

Quantifying the **abiotic status** is critical for **improved detection of biotic-induced stress**:

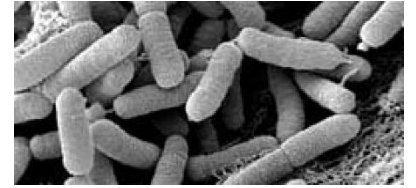
- Almond: OA: 83% ($\kappa=0.65$) \rightarrow 94% ($\kappa=0.87$)
- Olive: OA: 77% ($\kappa=0.43$) \rightarrow 92% ($\kappa=0.83$)



2021

Disentangling biotic and abiotic stress

Xf

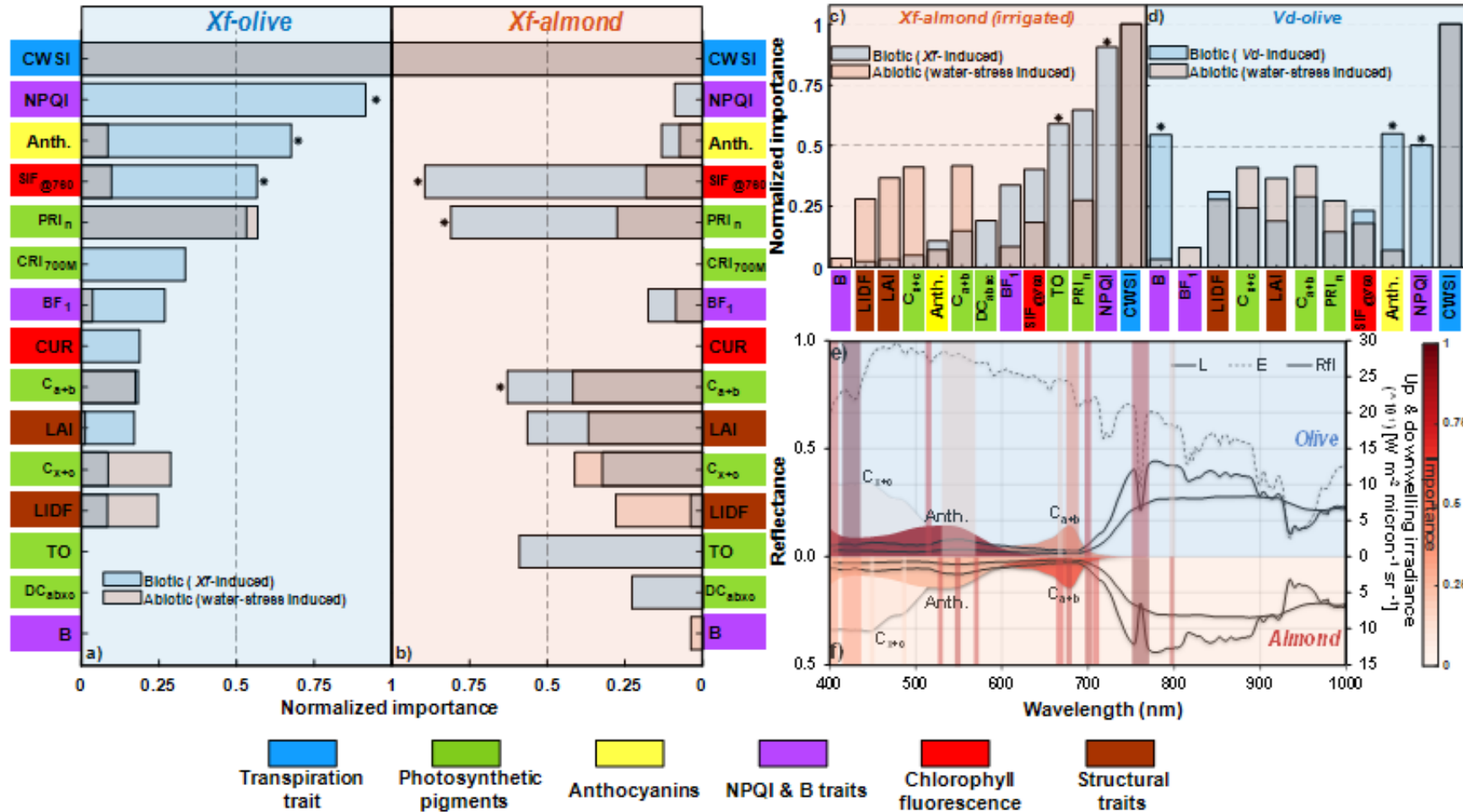


OA=92% ($\kappa=0.83$)
compared with qPCR

Vd



OA=93% ($\kappa=0.87$)
compared with qPCR





New questions

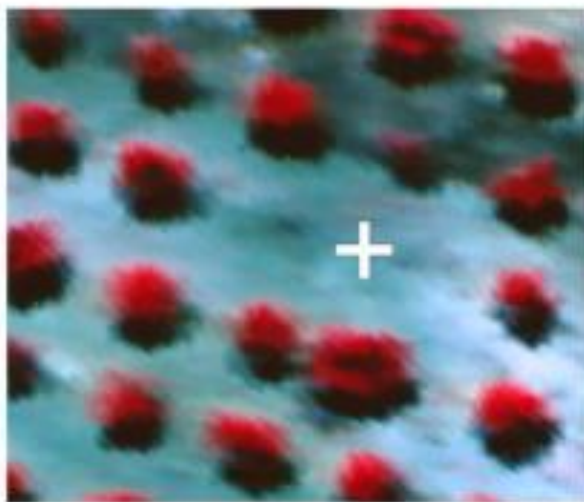
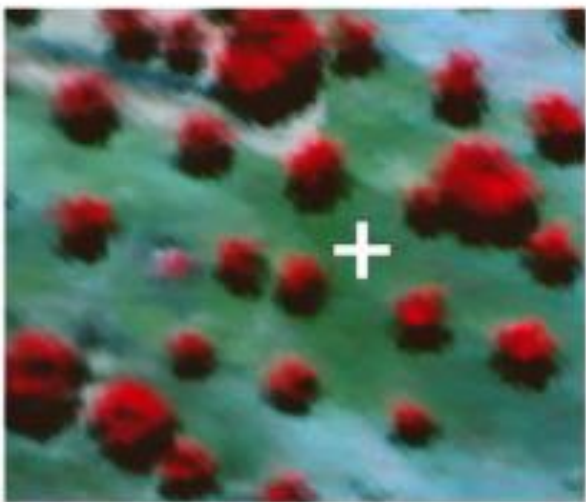
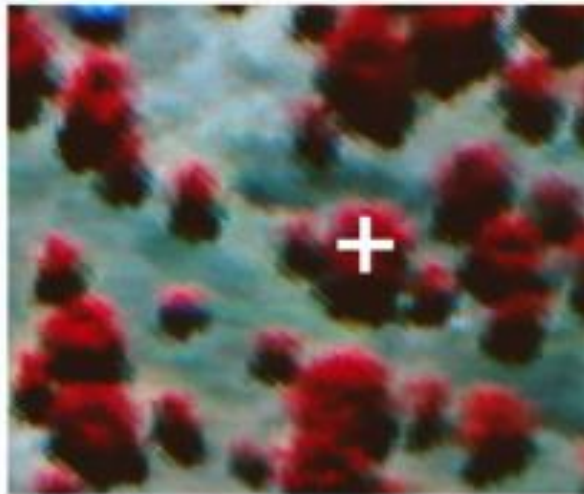
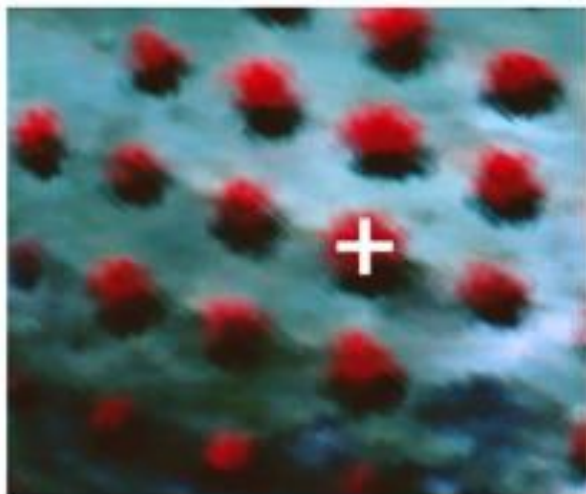
- Operational *Xf*-induced symptoms detection with **existing high-resolution multispectral satellites**
- Operational use of **hyperspectral satellites** for *Xf* detection



New questions

- Operational *Xf*-induced symptoms detection with **existing high-resolution multispectral satellites**
 - Sentinel-2, Worldview 2/3
- Operational use of **hyperspectral satellites** for *Xf* detection
 - BeXyl

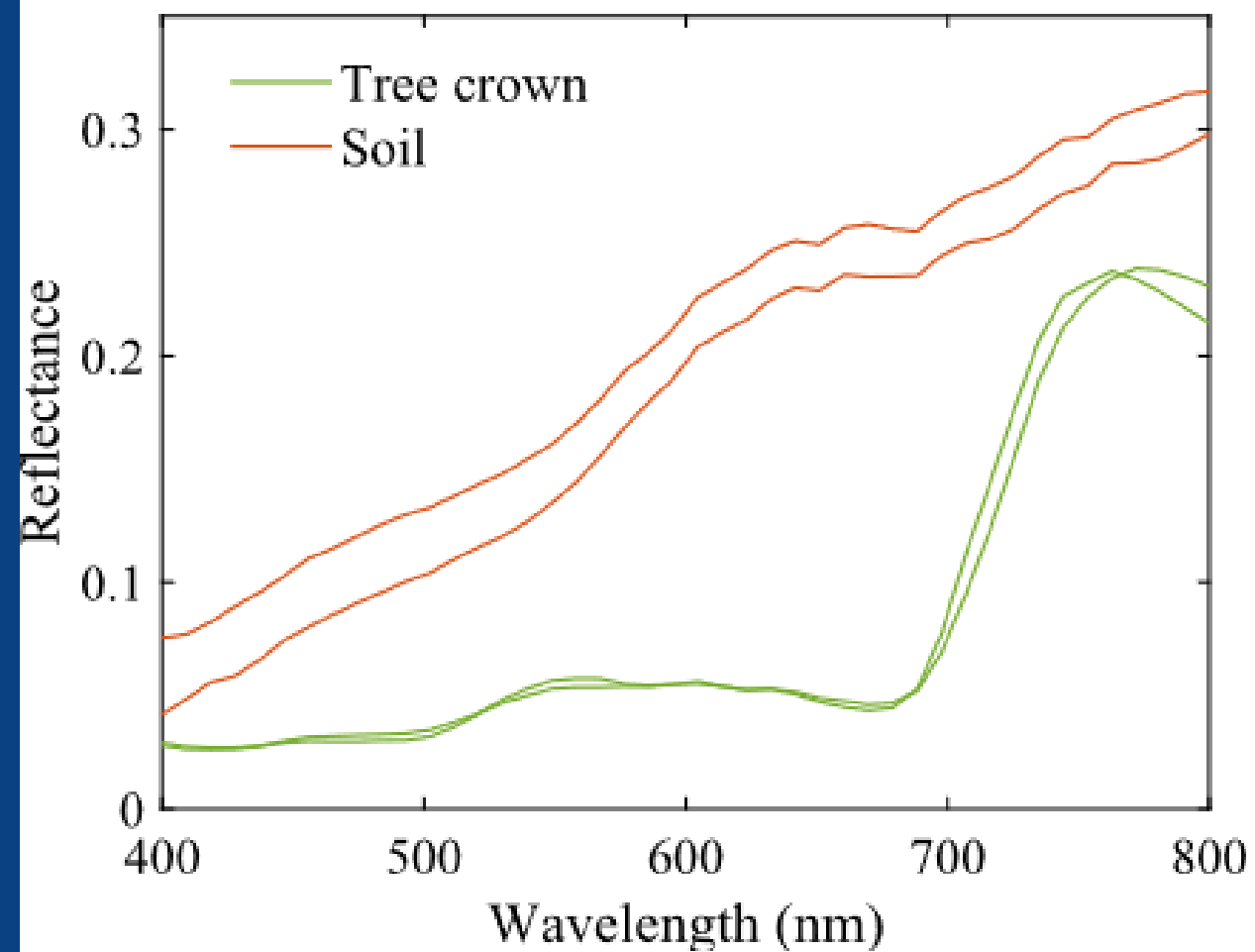
Airborne hyperspectral



Satellite Worldview-3 multispectral

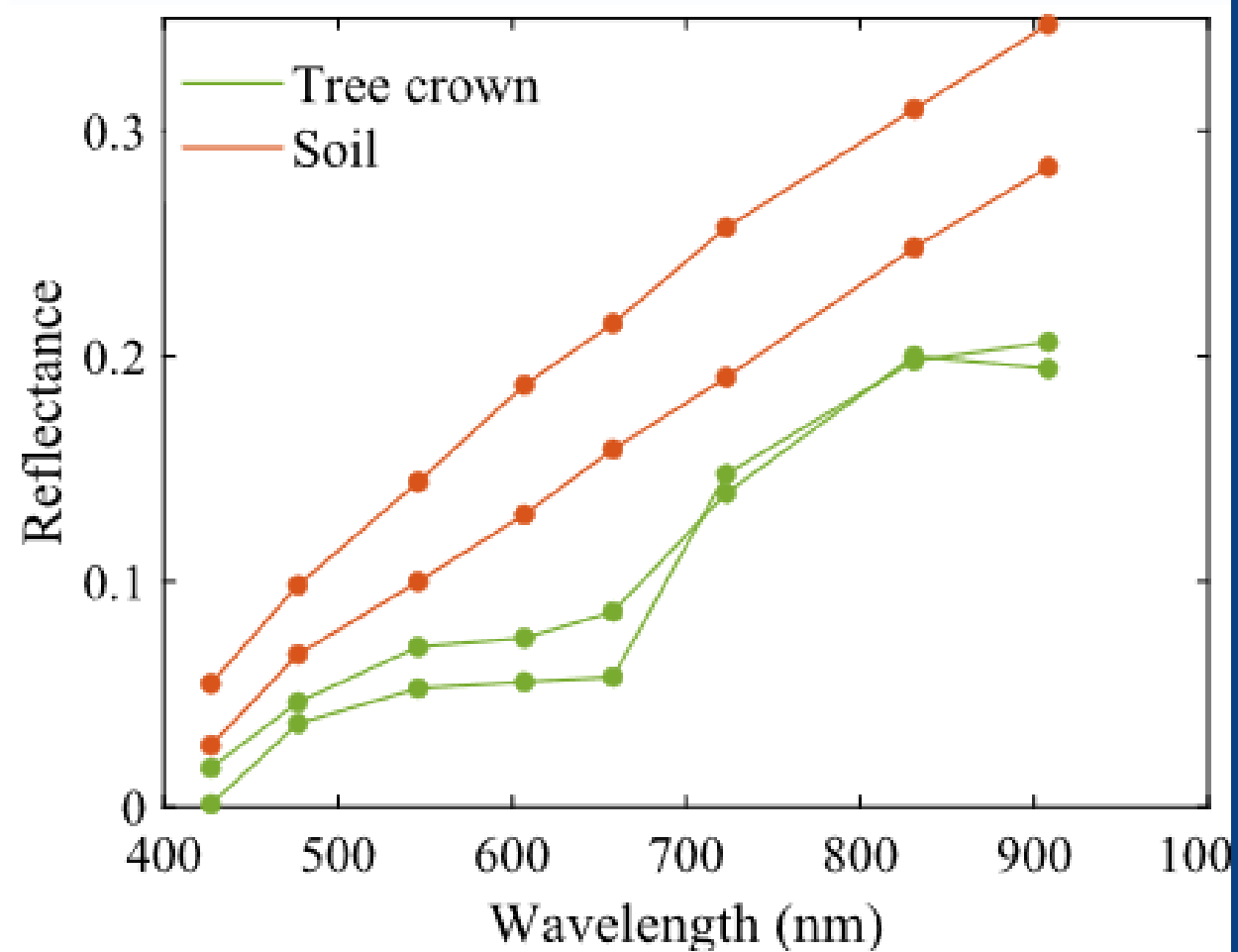


Airborne hyperspectral



(A)

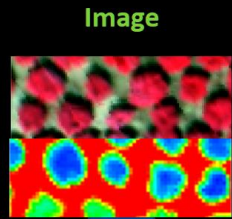
Satellite Worldview-3 multispectral



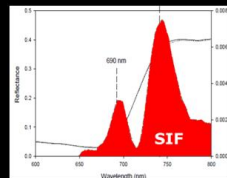
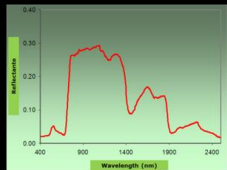
(B)

Disease detection framework from hyperspectral data

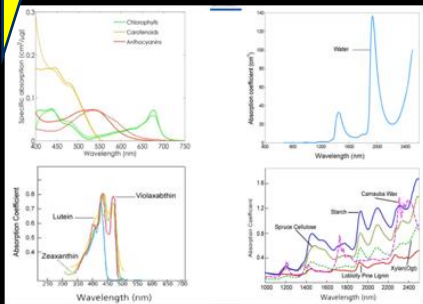
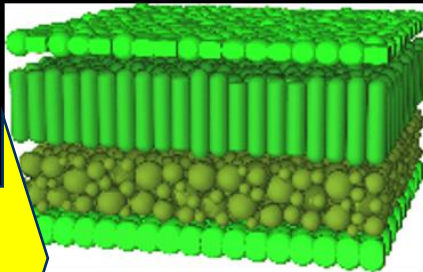
Mechanistic models



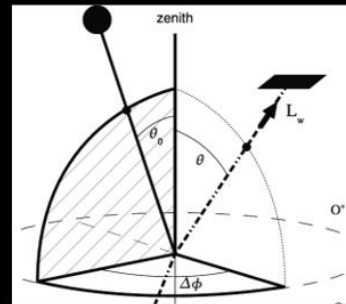
Spectra



Leaf Model



Canopy Model



Model-retrieved
Plant Traits

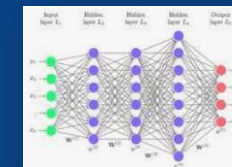
C_{a+b}
 C_{x+c}
 A_{nth}
 C_w
 C_m
 LAI
 $LIDF$

 SIF
 V_{cmax}
 A

Importance of each
RS-based indicator

Structural changes
Photosynthetic pigments
Fluorescence emission
Transpiration
Spectral indicators

Machine
Learning

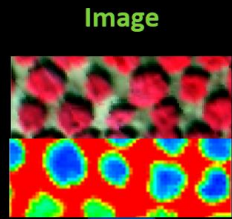


Disease
detection

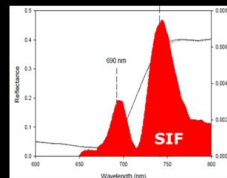
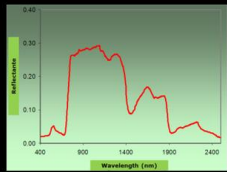
Zarco-Tejada *et al.* (2018; 2021)
Poblete *et al.* (2023)

Disease detection framework from hyperspectral data

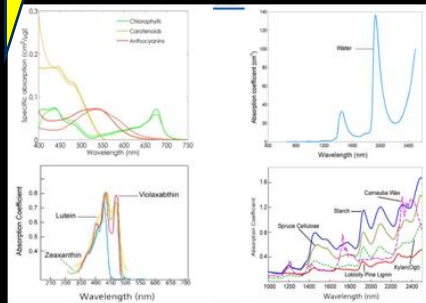
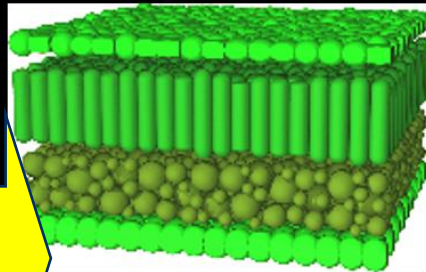
Mechanistic models



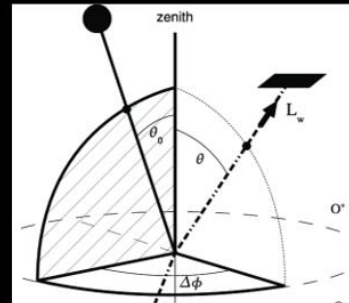
Spectra



Leaf Model



Canopy Model



Model-retrieved
Plant Traits

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

 SIF
 V_{cmax}
 A

Importance of each
RS-based indicator

Structural changes

Photosynthetic pigments

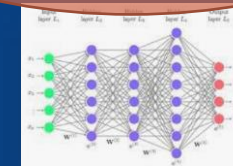
Fluorescence emission

Transpiration

Spectral indicators

Machine
Learning

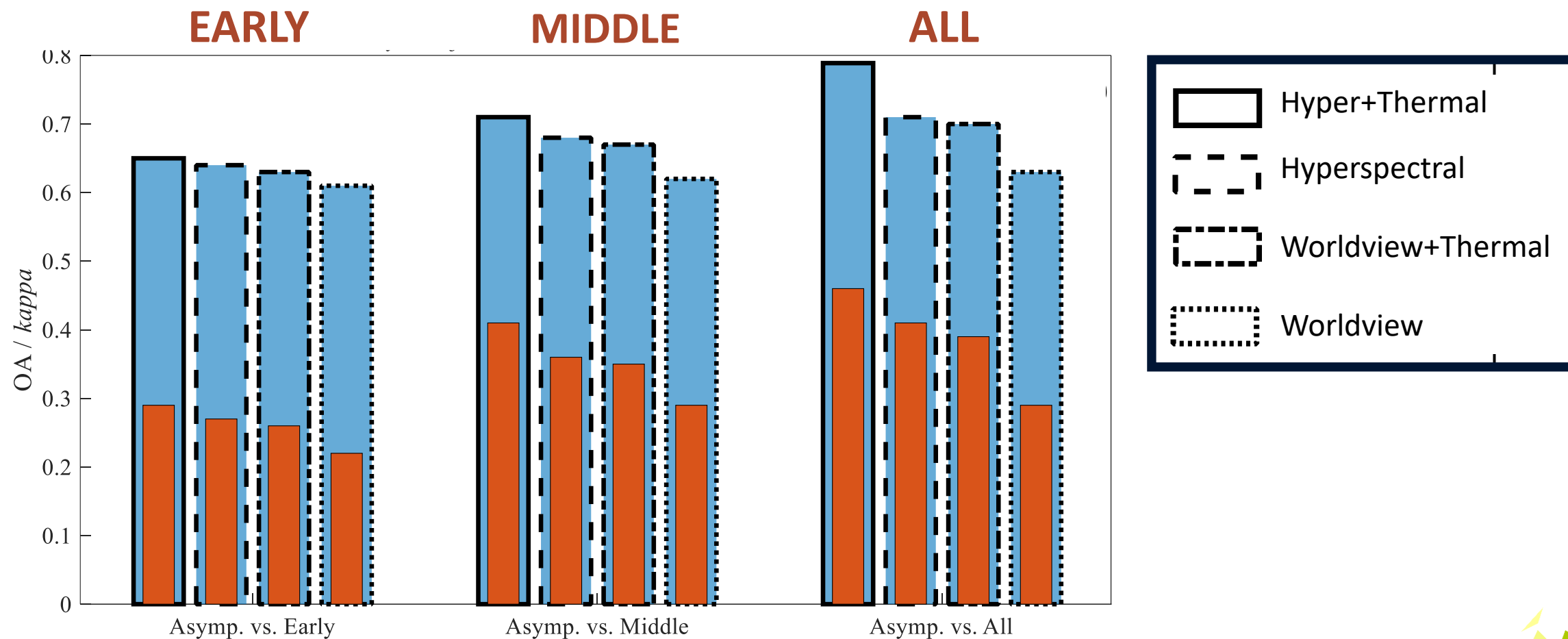
Disease
detection



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

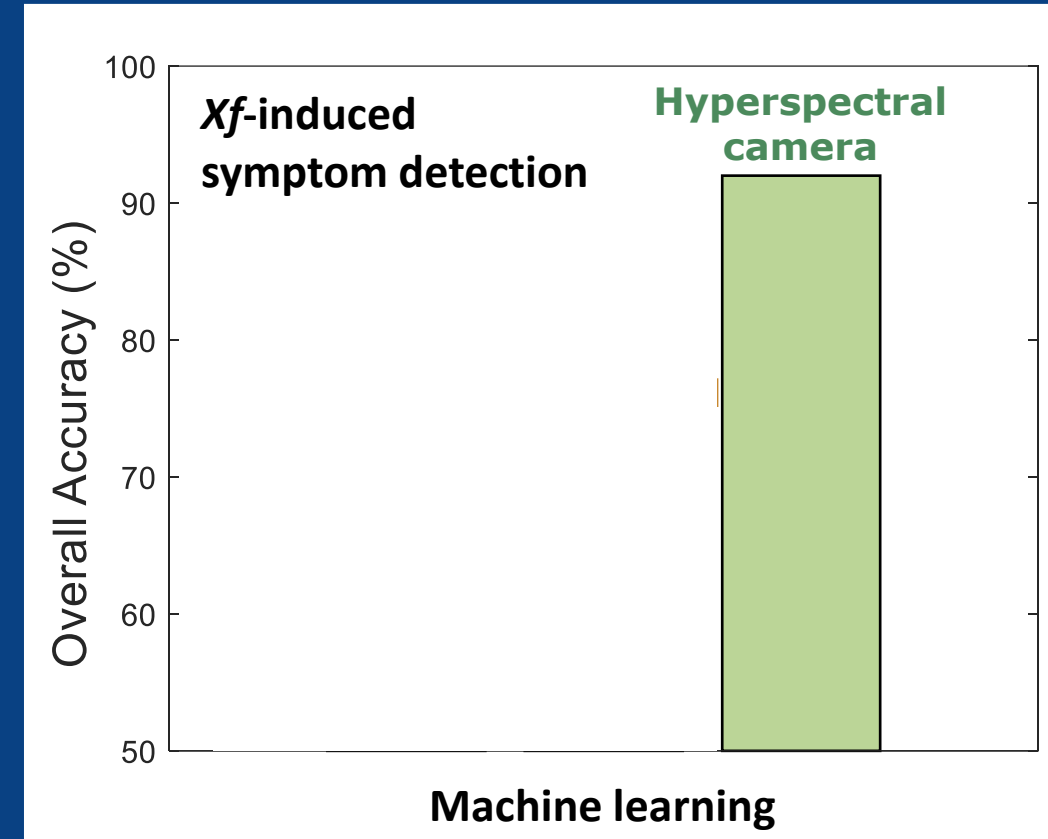
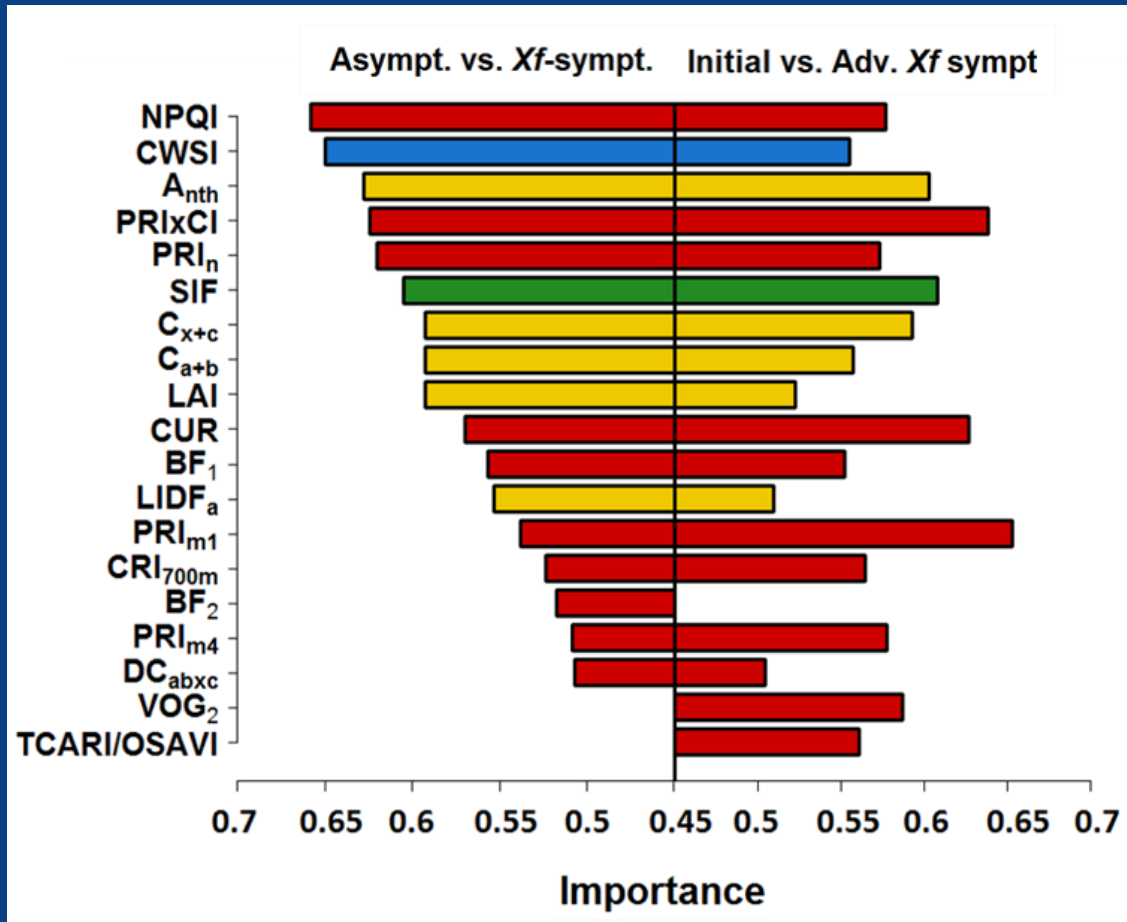
2023

XF DETECTION WITH HIGH-RESOLUTION COMMERCIAL SATELLITES



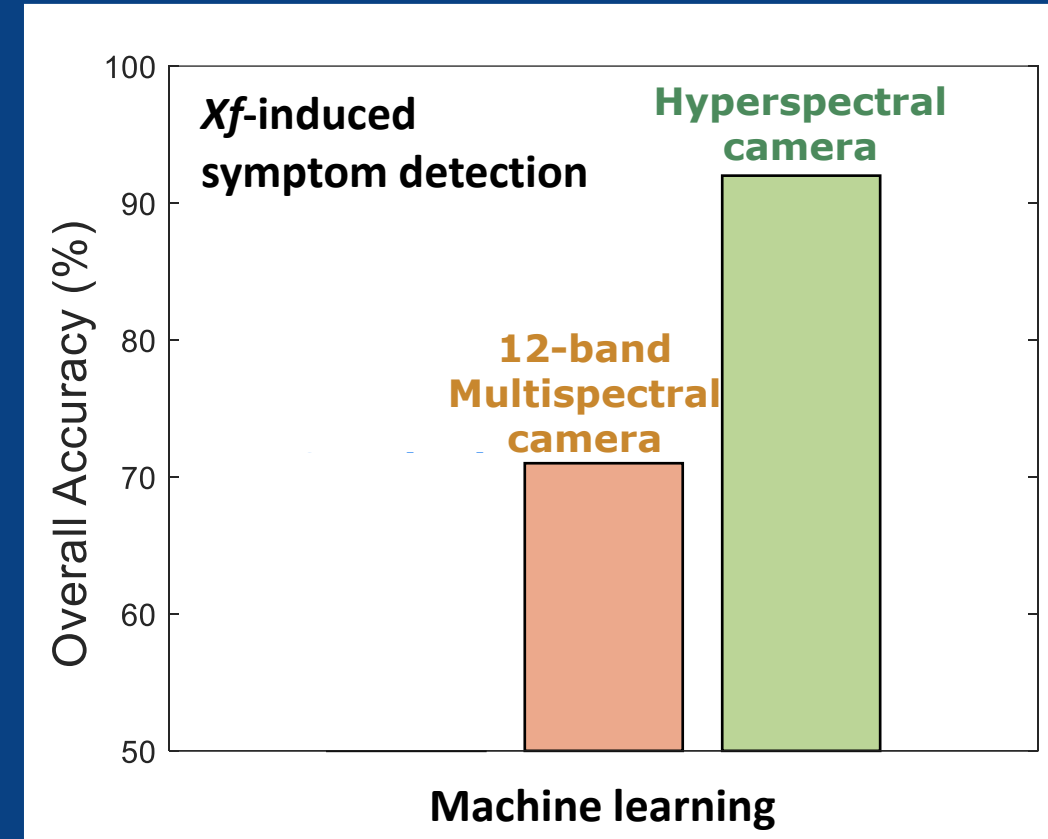
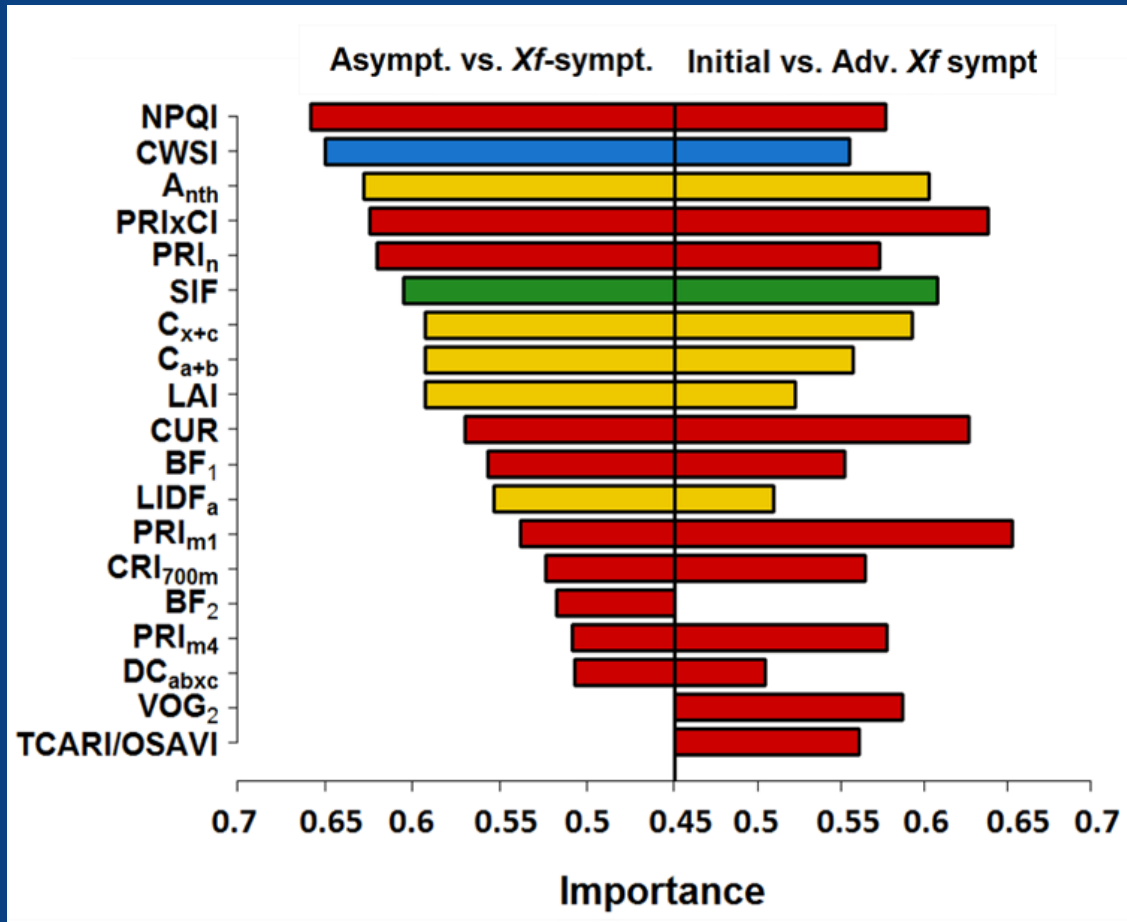
Sensitivity of Plant Traits to *Xf* symptoms

Hyperspectral traits



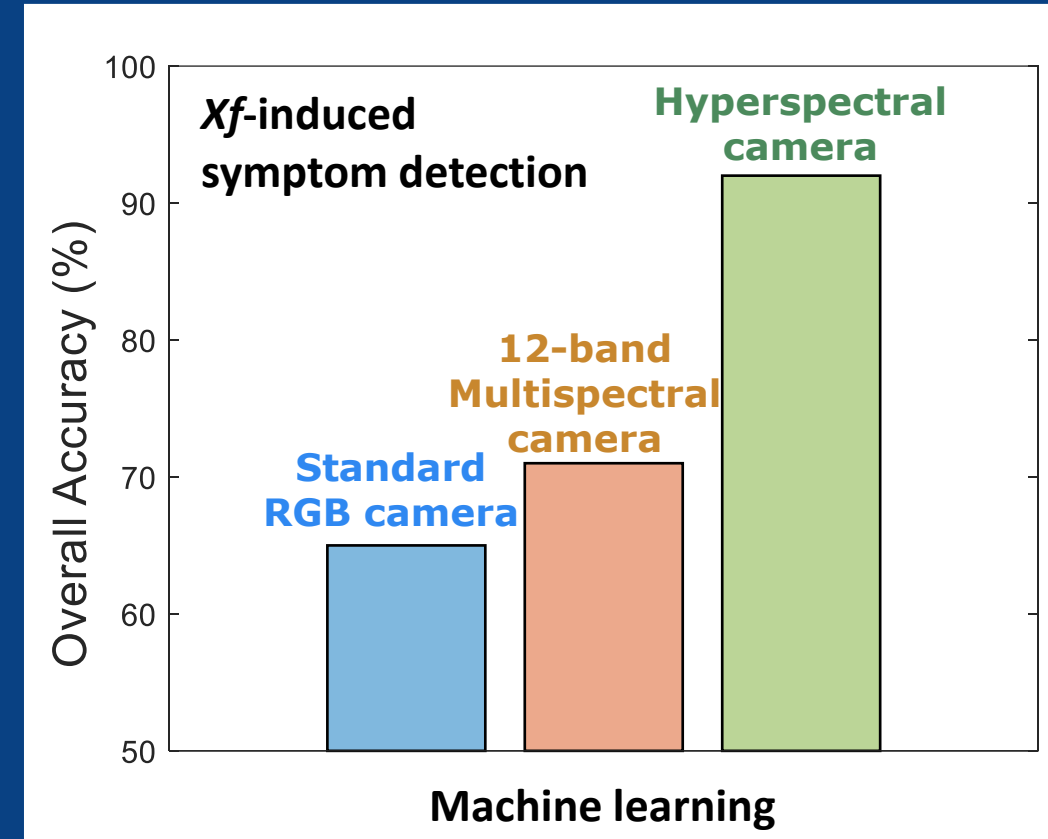
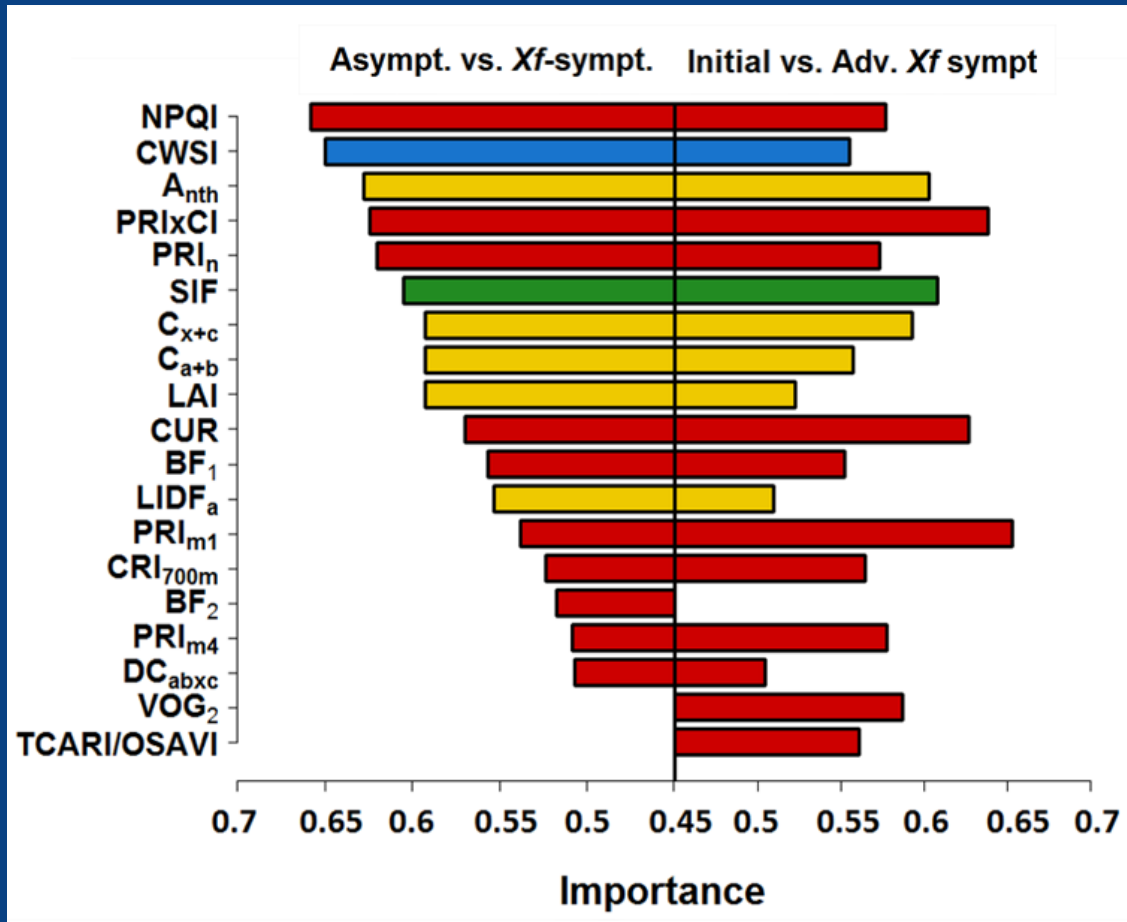
Sensitivity of Plant Traits to *Xf* symptoms

Hyperspectral traits



Sensitivity of Plant Traits to *Xf* symptoms

Hyperspectral traits



CONCLUSIONS

- **Middle** and **Advanced stages** of the disease **can be detected** with multispectral satellite imagery
- **Early** detection of *Xf*-induced symptoms **failed** with multispectral data: hyperspectral required
- Analyses of the disease progression show that **specific spectral bands are required** to detect *Xf* at early stages
 - Highest sensitivity: **SIF, blue NPQI, anthocyanins, and xanthophylls**
- Current work focuses on **new hyperspectral satellites** for mapping early stages of *Xf* infection



Detection of symptoms induced by *X. fastidiosa* with high-resolution multispectral satellite data: assessment with airborne hyperspectral imagery

Poblete¹ T., Navas-Cortes² J.A., Hornero^{2,1} A., Camino³ C., Calderon⁴ R., Hernandez-Clemente⁵ R., Landa² B.B., Zarco-Tejada^{1,2} P.J.

- (1) The University of Melbourne, Melbourne, AUSTRALIA
- (2) Instituto de Agricultura Sostenible (IAS), Consejo Superior de Investigaciones Científicas (CSIC), Córdoba, SPAIN
- (3) European Commission, Joint Research Centre (JRC)
- (4) Plant Pathology and Plant-Microbe Biology Section, School of Integrative Plant Science, Cornell AgriTech, Geneva, UNITED STATES
- (5) Department of Forestry Engineering, Universidad de Córdoba (UCO), Cordoba, SPAIN

