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# Determining the leaf biochemical and phytosanitary status of orchard trees using spectroscopy from visible to long-wave infrared range

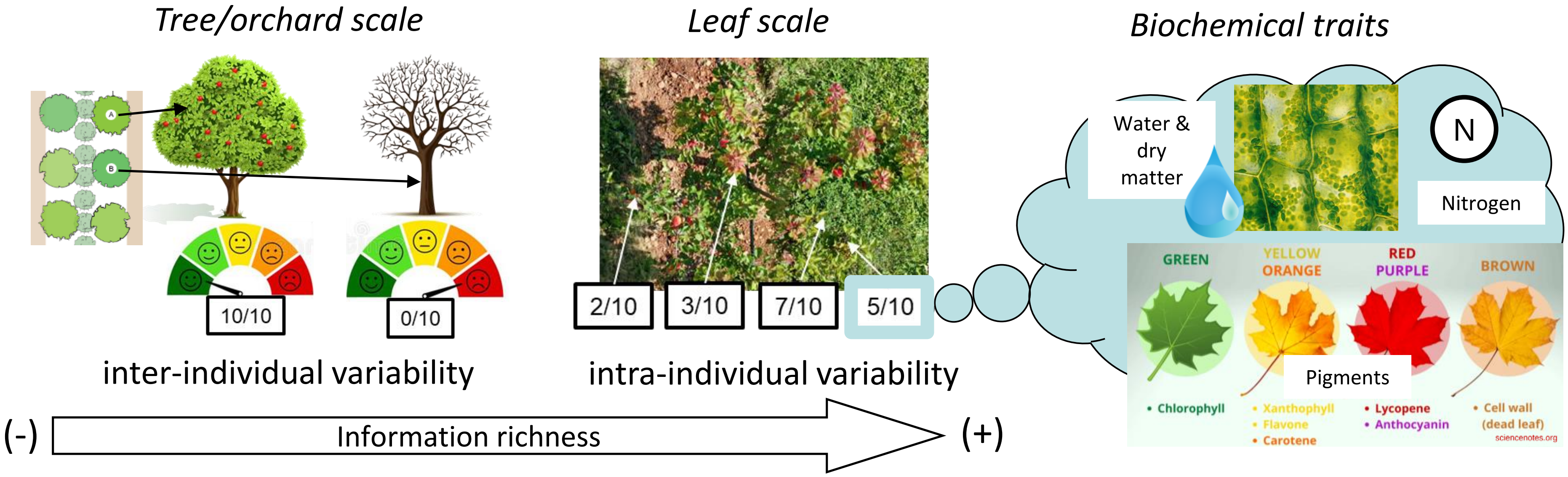
**K. Adeline**, N. Sikora, J.-P. Segaud, S. Jay, J.-B. Féret, S. Serino, D. Dumont, G. Vercambre, M.-N. Corre, M. Roth

20th HELIOSPIR meeting, Montpellier, 11th-12th June 2024

# Context

**Exploring the gain of remote sensing data collections at (sub)centimetric scale for a better determination of biotic and abiotic stress symptoms in contrasting agro-ecological practices**

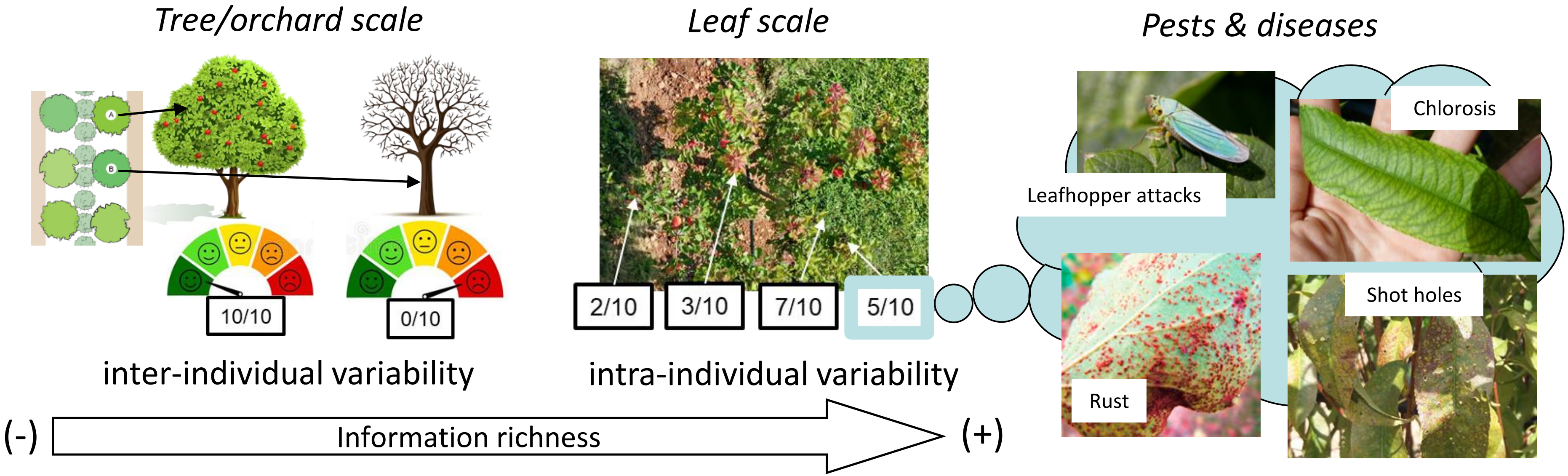
→ Use of non-destructive and high-throughput optical spectroscopic measurements giving access to biochemical traits highlighting photosynthetic status, water resources, nutrient and biomass allocation



# Context

**Exploring the gain of remote sensing data collections at (sub)centimetric scale for a better determination of biotic and abiotic stress symptoms in contrasting agro-ecological practices**

→ Goal to further determine the type and intensity of pests and diseases from leaf discoloration, water stress, nutrient loss and biomass change



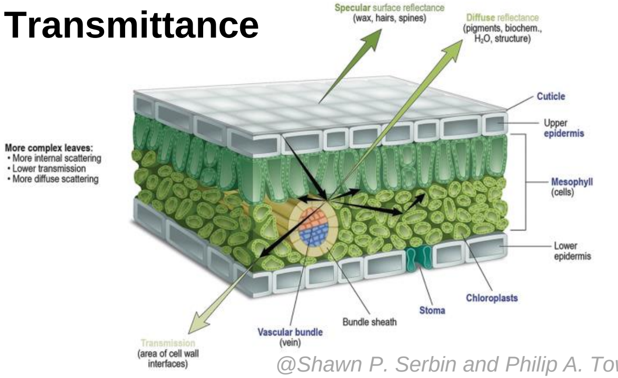
# Objectives

**Explore relationships between optical data, biochemical traits and pest/disease scores to derive the phytosanitary status at leaf scale**

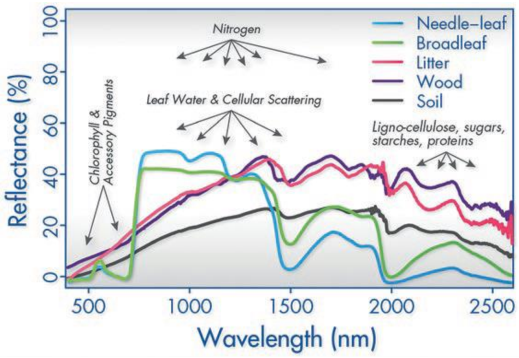
**Our study targets peach and apricot tree orchards for two agro-ecological applications: (1) inputs management and (2) variety breeding.**

*Spectrocopic data in the visible to short-wave infrared range (VSWIR: 0.4-2.5 µm) is efficient to quantify biochemical traits from statistical and physical methods for different vegetation physiological conditions (Wang et al., 2023 ; Gaubert et al., 2023).*

**Reflectance**
Absorbance
**Transmittance**

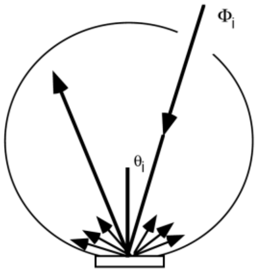



@Shawn P. Serbin and Philip A. Townsend




**Spectral absorptions of leaf biochemical traits**

**Directional-hemispherical** measurements with integrating spheres




@Labsphere

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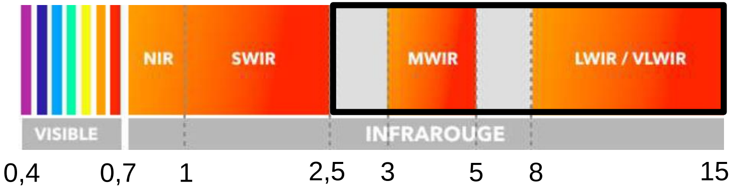
→ Interest for the mid- to long-wave infrared spectral domain (MWIR/LWIR: 2.5-15 µm) ?




**Little available data because tough requirements in the measurement protocol :**

- cooling the detector with liquid nitrogen
- purging the integrating sphere of water vapor and carbon dioxide with nitrogen gas

Choice of the substitution method to measure optical properties

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→ From statistical to physical methods, which are the most effective ?
→ Is it possible to estimate pest and disease scores ?

**Statistical (data-driven):**
- fast
- datasets

**Physical (model-driven):**
- generalizable
- parameterization

**Biotic and abiotic factors can be unmixed from the spectral features ?**

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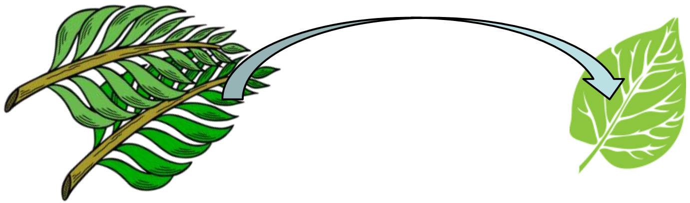
*For statistical methods, building relevant datasets is very demanding in terms of human and instrumental resources and is costly for laboratory analysis because a large number of samples is needed.*

→ Can we find a compromise by working at shoot scale instead of leaf scale ?



**The first work presented relies on raw spectra and a diversified set of leaf observations.**

# Sites

Two INRAE experimental stations:

**INRAE Domaine Saint Paul (Avignon)**
- Peach orchard, one variety (Nectarlove cv),
- Conventional treatment with fertilization trials since 3 years and irrigation trials (ECOPECHE network)

**INRAE Domaine Amarine (Bellegarde)**
- Apricot orchard, 150 varieties replicated in 5 blocks (CORE COLLECTION network),
- Low phytosanitary inputs




# Materials

Samplings:

- 5 dates (from June to October 2023), top and bottom tree crown part, 4 leaves from one shoot,
- For apricot: 5 varieties (including 1 monitored),
- For peach: 50%/100% irrigation (1 date) & 0N/180N fertilization trials (all dates)

Optical properties:

- **Leaf scale:** directional-hemispherical reflectance and transmittance of leaf adaxial side in the range 0.4-15µm (Perkin and Bruker spectroradiometers with integrating spheres)

Biochemical traits:

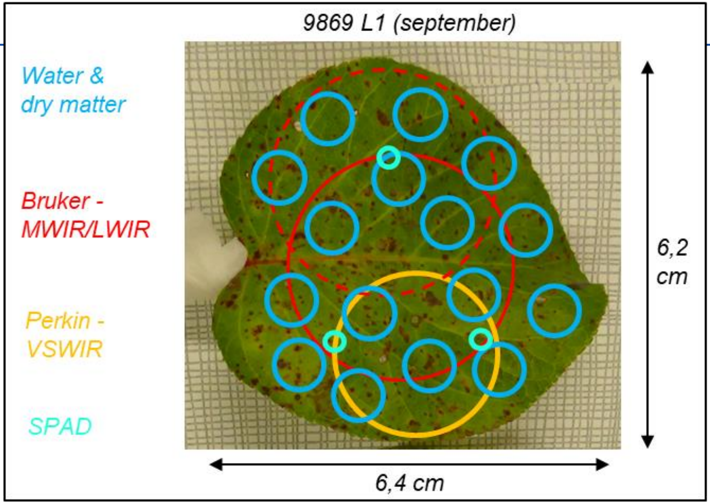
- **Leaf scale:** chlorophyll meter SPAD leaf-clip measurements, water and dry matter content,
- **Shoot scale:** pigments (phenolics compounds, chlorophylls and carotenoids) and total nitrogen contents

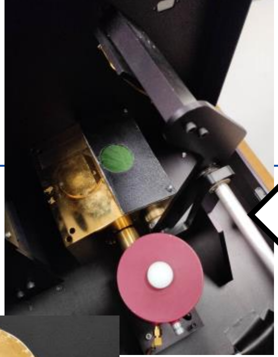
Pest/disease scores:

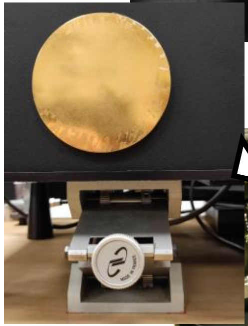
- **Leaf scale:** chlorosis, leafhopper attacks, shot hole and rust diseases

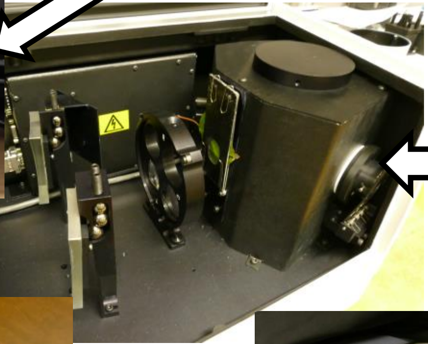
**155 samples at leaf scale and 31 samples at shoot scale**

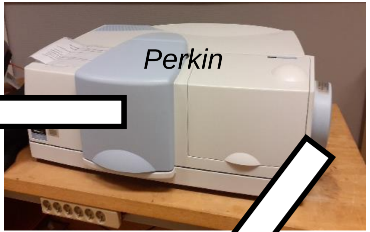
# Leaf observation scales

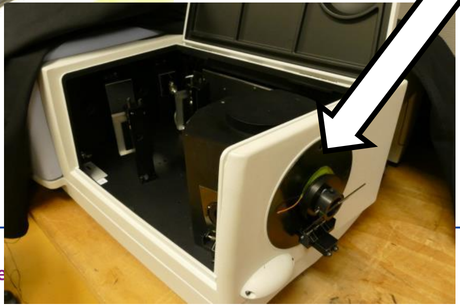


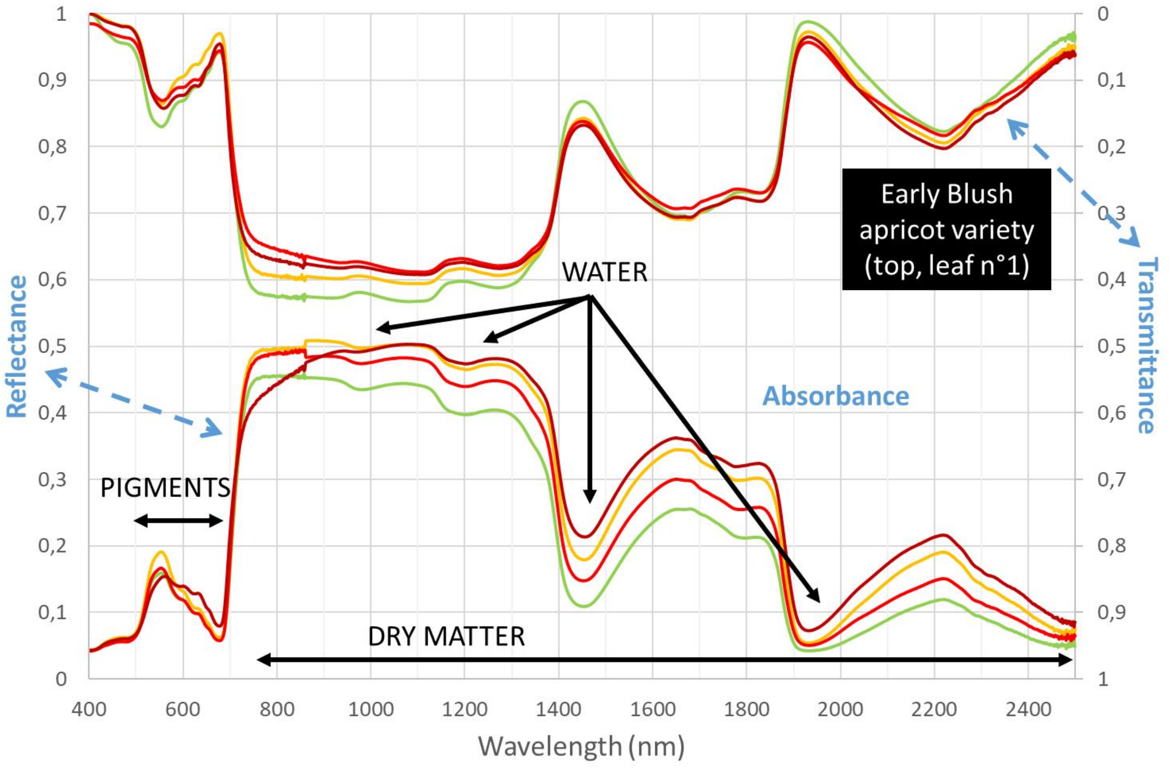



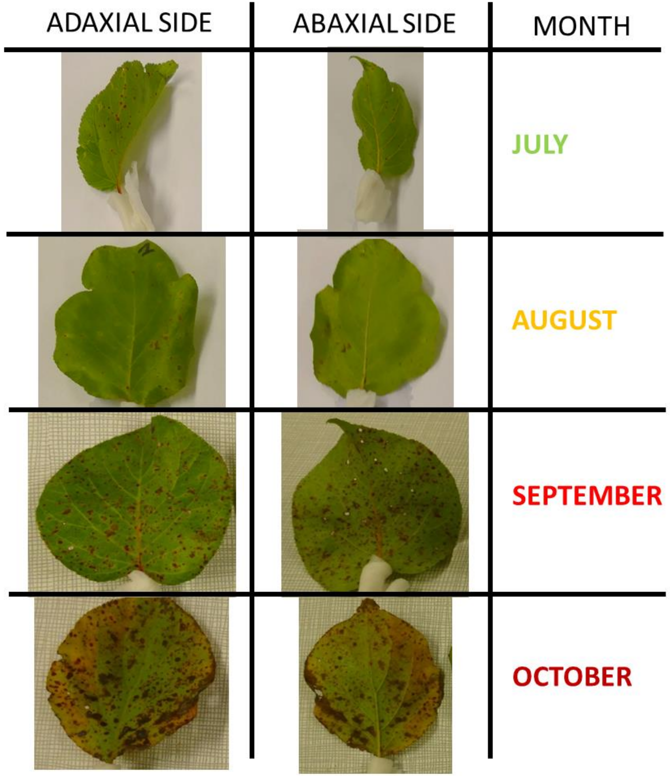





Raw data



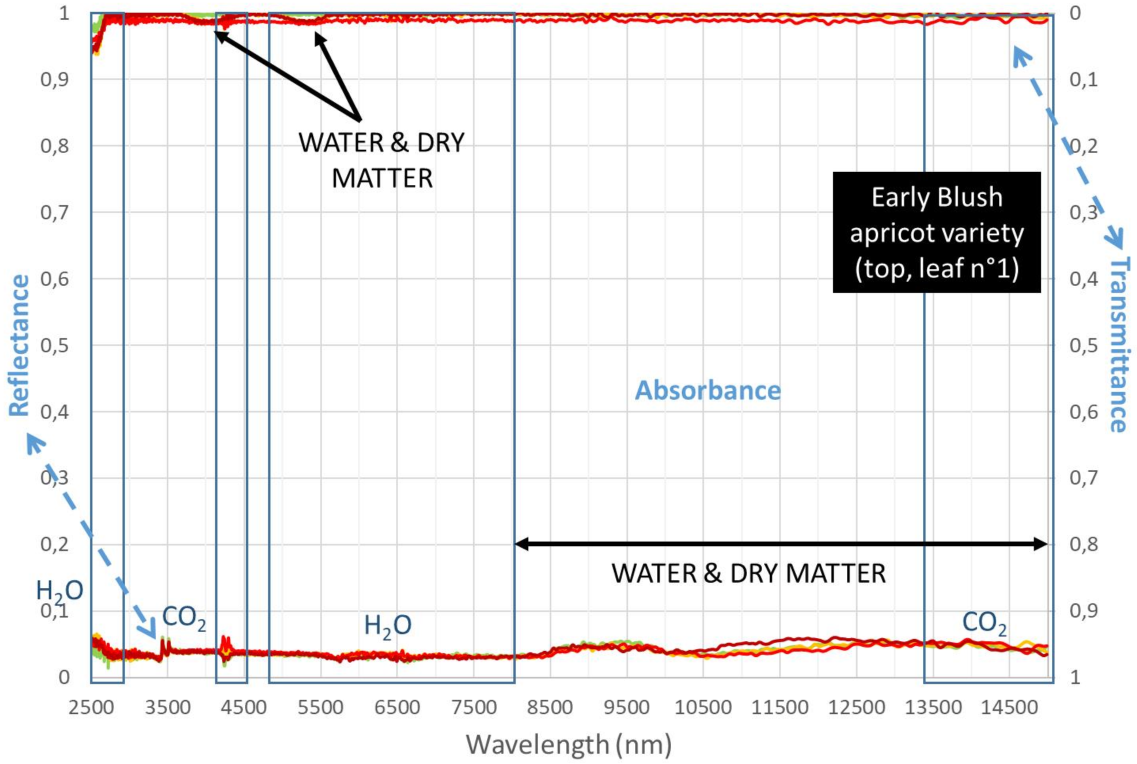

**BIOCHEMICAL TRAITS**

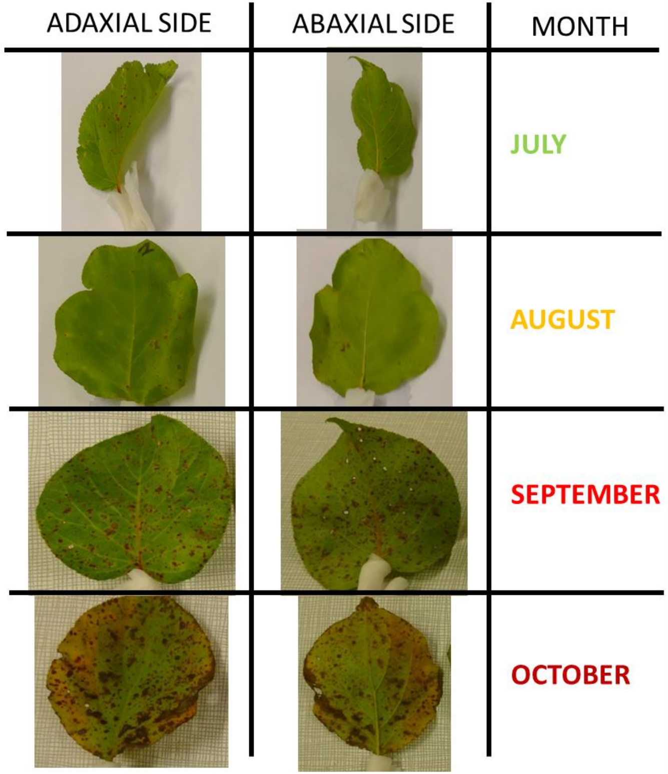
| Water content (g.cm-2) | Dry matter content (g.cm-2) | Total chlorophylls content (µg.cm-2) | Total nitrogen content (%) |
|---|---|---|---|
| 0.0165 | 0.0096 | 46.0 | 1.5 |
| 0.0088 | 0.0093 | 22.3 | 1.8 |
| 0.0825 | 0.0118 | 17.8 | 1.5 |
| 0.0076 | 0.0082 | 20.8 | 1.6 |

**PEST AND DISEASE SCORES**

| Frequency chlorosis (%) | Leafhopper attack | Shot hole intensity (%) | Rust intensity (%) |
|---|---|---|---|
| 0 | no | 40 | 0 |
| 0 | probable | 40 | 5 |
| 60 | probable | 90 | 20 |
| 70 | probable | 95 | 30 |

Raw data, sensibility to gas effects due to limited nitrogen purge time (priority given to number of samples, 32 measurements per day)

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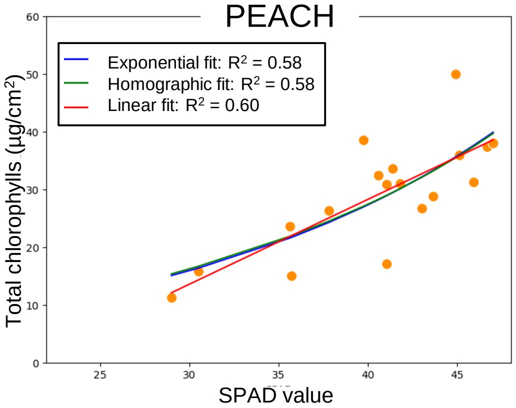
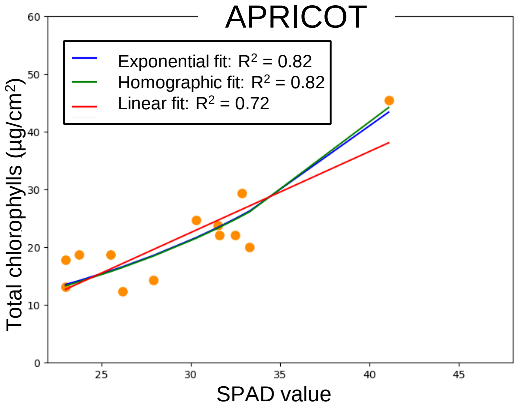
# SPAD calibration to upscale shoot scale data to leaf scale

→ Average of 12 SPAD measurements to get a value at shoot scale (4 leaves/shoot, 3 measurements/leaf)

**SPAD – total chlorophylls content**

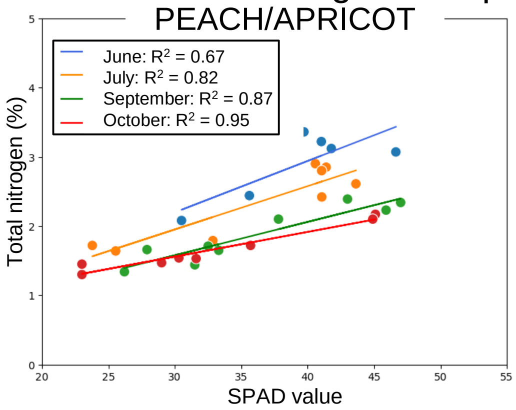
Choice of a homographic regression per species (in green)




**SPAD – total nitrogen content**

Choice of a linear regression per month




→ Application of the regression for each SPAD value to get total chlorophylls and nitrogen at leaf scale

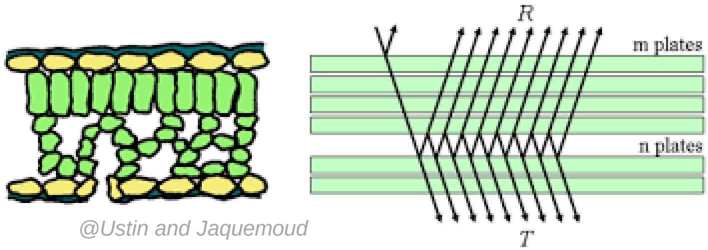
# Estimation methods

Use of both reflectance and transmittance

| Approach | Method and parameterization | Spectral range | Data |
|---|---|---|---|
| Statistical | PLSR (scikit-learn, train/test: 70/30%, 5 cross-validation, averaged metrics over 10 repetitions, relevant spectral bands from Variable Importance in the Projection or VIP) | 0.4 – 2.5 µm<br>2.5 – 15 µm<br>0.4 – 15 µm | All biochemical traits and pest/disease scores |
| Physical | Iterative inversion of the leaf radiative transfer PROSPECT-D (Powell optimization algorithm, optimized selection of spectral sub-ranges per trait) | 0.4 – 2.5 µm | Pigments, water and dry matter content |

**PROSPECT model**

Biochemical traits + one structural trait (N)




@Ustin and Jaquemoud

Directional-hemispherical optical properties

Direct modelling

Inverse modelling

# Results with the statistical approach

| | Spectral range | 0,4 - 2,5 µm (VSWIR) | | | | 2,5 - 15 µm (MWIR/LWIR) | | | | 0,4 - 15 µm (FULL RANGE) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Original scale | Data | R2 | RMSE | nRMSE (%) | LV | R2 | RMSE | nRMSE (%) | LV | R2 | RMSE | nRMSE (%) | LV |
| LEAF | Water (g/cm2) | 0.75 | 0.0012 | 11 | 6 | 0.6 | 0.0015 | 14 | 7 | 0.76 | 0.0011 | 11 | 7 |
| LEAF | Dry matter (g/cm2) | 0.78 | 0.0009 | 11 | 7 | 0.63 | 0.0012 | 14 | 3 | 0.72 | 0.001 | 11 | 3 |
| SHOOT | Chlorophylls (µg/cm2) | 0.59 | 5.6 | 16 | 11 | 0.2 | 7.9 | 22 | 5 | 0.54 | 6 | 17 | 7 |
| SHOOT | Nitrogen (%) | 0.75 | 0.22 | 13 | 13 | 0.4 | 0.32 | 20 | 6 | 0.65 | 0.26 | 15 | 10 |
| LEAF | Chlorosis frequency (%) | 0.53 | 16 | 24 | 5 | 0.22 | 17 | 26 | 4 | 0.38 | 15 | 24 | 6 |
| LEAF | Rust intensity (%) | 0.25 | 10 | 29 | 4 | 0.19 | 10 | 29 | 5 | 0.17 | 10 | 28 | 5 |
| LEAF | Shot hole intensity (%) | 0.36 | 18 | 23 | 8 | 0.34 | 18 | 23 | 2 | 0.3 | 19 | 24 | 2 |

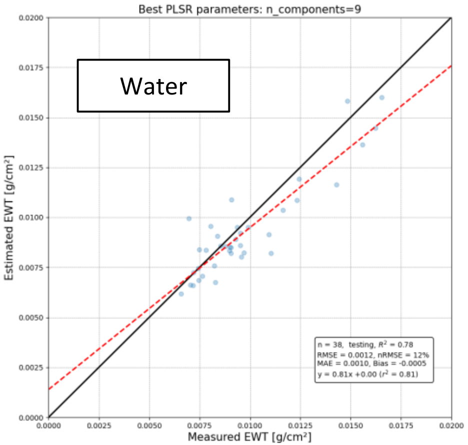
**Biochemical traits:** VSWIR > FULL RANGE > MWIR/LWIR (cf. all metrics, water: VSWIR ~ FULL RANGE), water/dry matter > nitrogen > chlorophylls (cf. nRMSE), excellent results in VSWIR for leaf scale traits and also nitrogen from shoot scale, slightly less better for chlorophylls from shoot scale but still acceptable

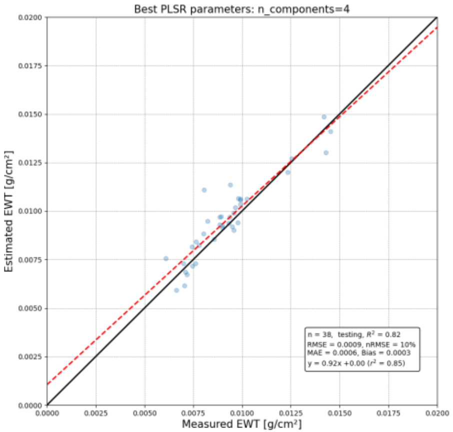
**Pest/disease scores:** no convincing results (RMSE > 10%, nRMSE values around twice those of biochemical traits), no particular spectral sensitivity, chlorosis & shot holes > rust (cf. nRMSE)

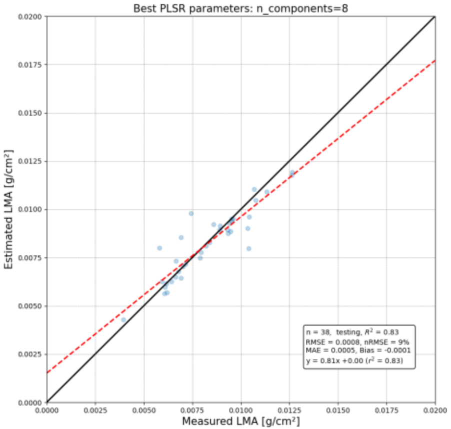


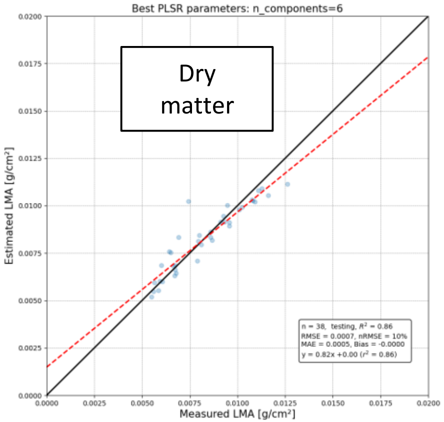
*R2: coefficient of determination, RMSE: Root Mean Square Error, NRMSE: normalized RMSE, LV: optimal number of latent variables*

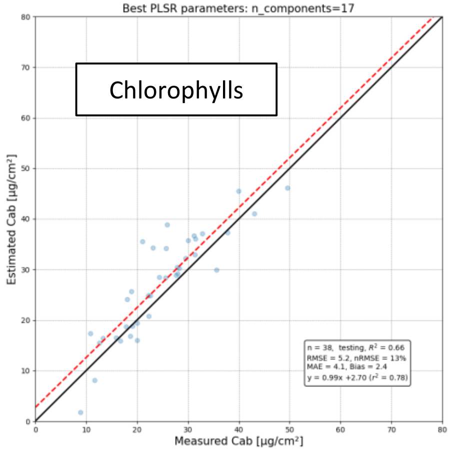
# VSWIR, results for 1rst/2nd iteration with test dataset

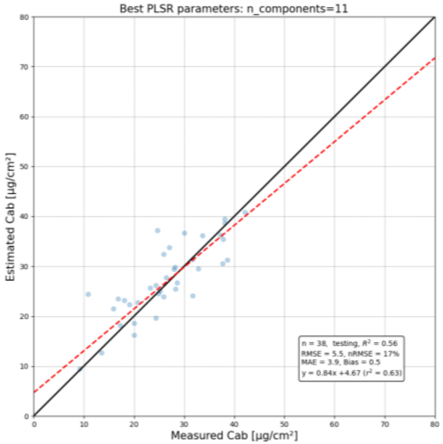


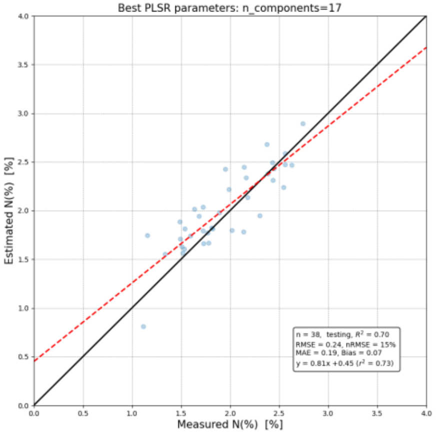



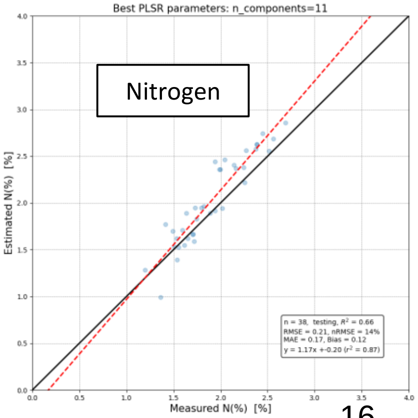



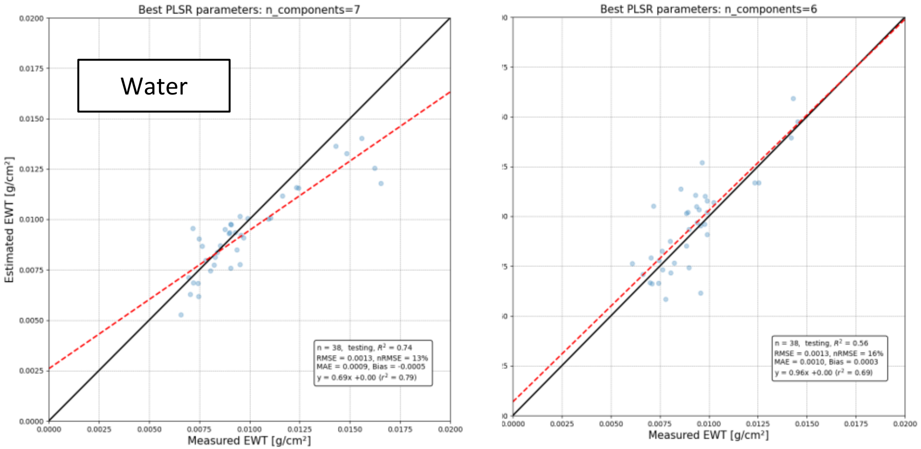



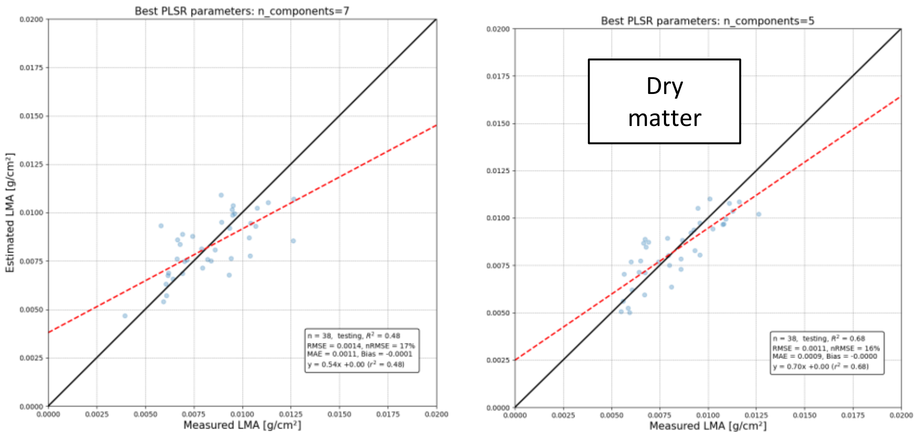



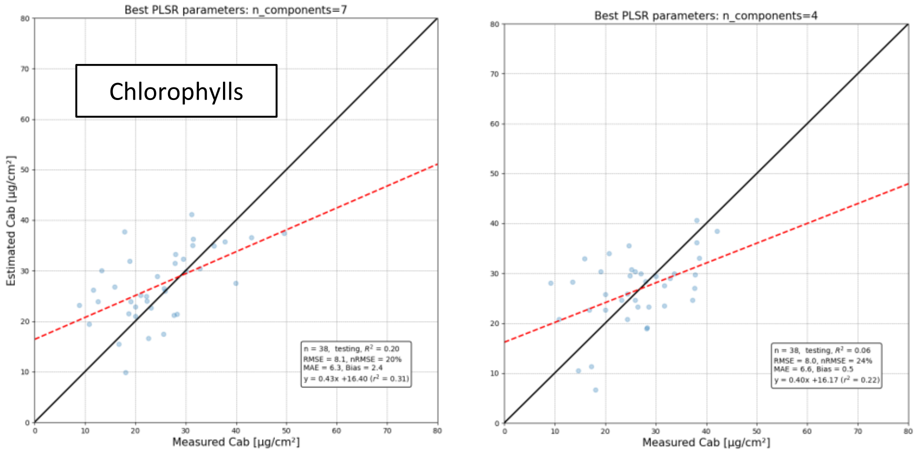



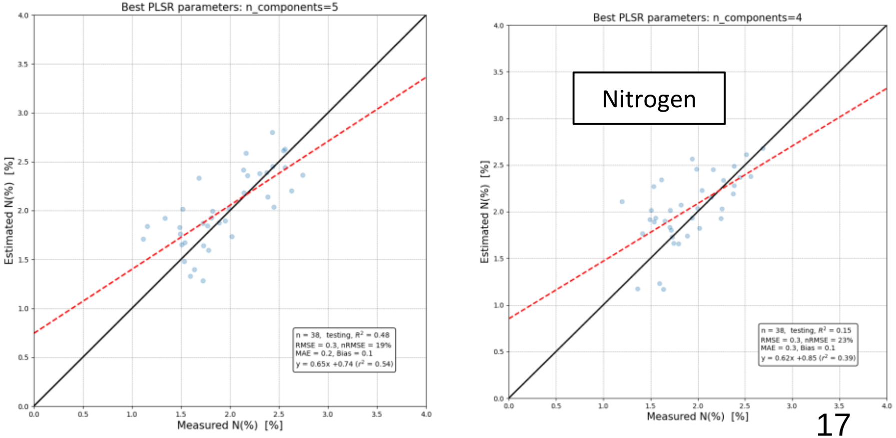



# MWIR/LWIR, results for 1rst/2nd iteration with test dataset

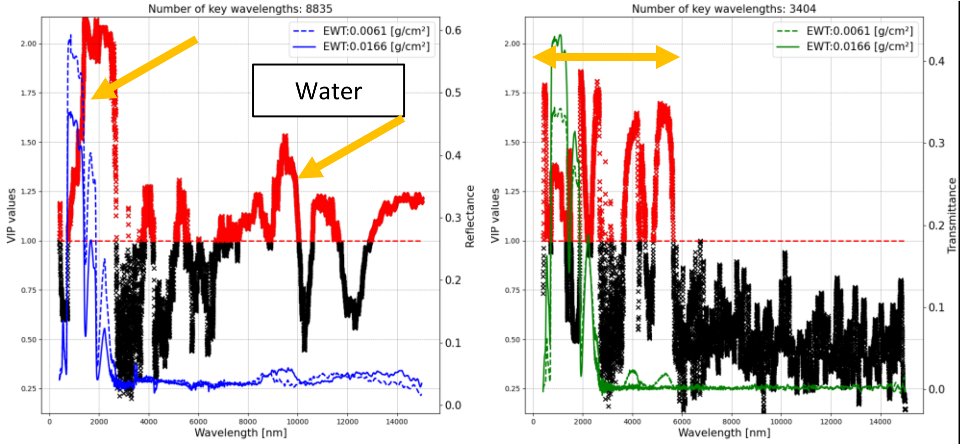


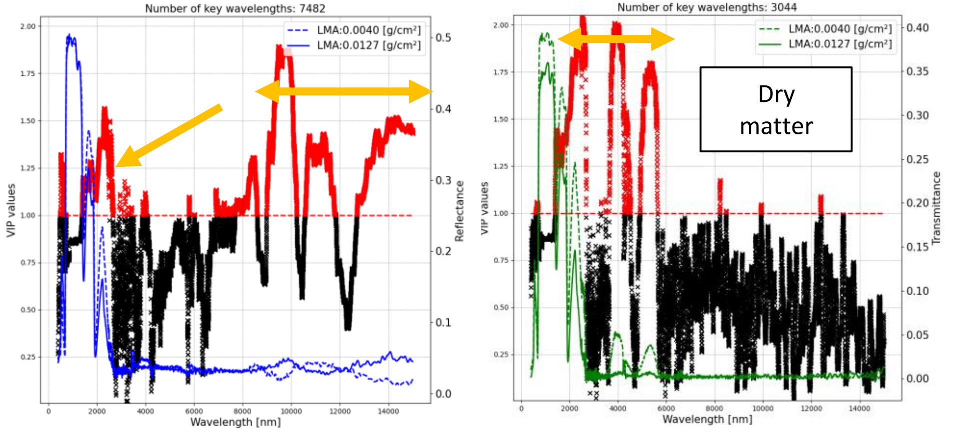



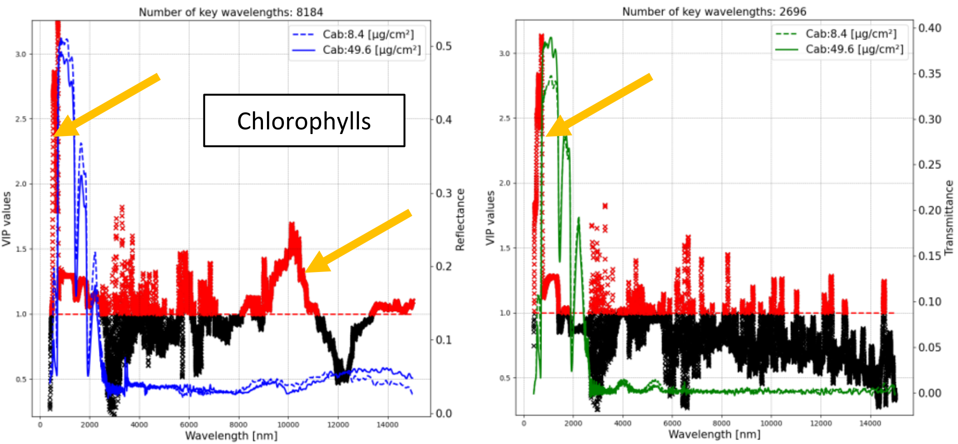



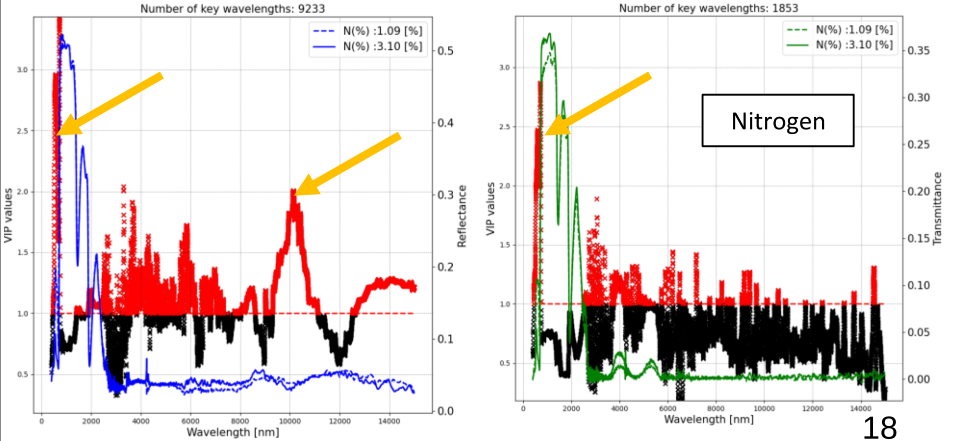



# Spectral bands are trait-sensitive if VIP > 1



# Results with the physical approach

| | | Spectral range: 0,4 - 2,5 µm (VSWIR) | | | |
|---|---|---|---|---|---|
| **Original scale** | **Data** | **R2** | **RMSE** | **nRMSE (%)** | **Spectral range in nm (R: reflectance, T: transmittance)** |
| LEAF | Water (g/cm2) | 0.85 | 0.001 | 10 | 1100 – 1800 (T) |
| LEAF | Dry matter (g/cm2) | 0.71 | 0.002 | 17 | 1800 – 2400 (R + T) |
| SHOOT | Chlorophylls (µg/cm2) | 0.75 | 6.29 | 15 | 580 – 720 (R) |

**Biochemical traits:** water > chlorophylls > dry matter (cf. nRMSE), excellent results at leaf scale, slightly less better for chlorophylls from shoot scale but still acceptable (cf. RMSE)

**Comparison with statistical approach in the VSWIR range:** physical > statistical for water and the opposite for dry matter, more or less equivalent for chlorophylls (cf. all metrics)



*R2: coefficient of determination, RMSE: Root Mean Square Error,*
*NRMSE: normalized RMSE, LV: optimal number of latent variables*

# Conclusions and perspectives

- → From raw leaf reflectance and transmittance spectra, good results are globally obtained to derive biochemical traits, but not for pest/disease scores.
- → Using the VSWIR domain leads to better performances than MWIR/LWIR domain alone, the later being mostly useful only for water and dry matter content estimations (as shown in literature for other species).
- → Results are mitigated in terms of performances between physical and statistical approach depending on the biochemical trait.
- → The use of SPAD measurements at shoot scale is promising to get estimations of chlorophylls and nitrogen at leaf scale relying on built-up regressions.

**Prospects:**

- → Use spectral preprocessings (SNV, CR, CWT, derivatives, etc.), select more specific spectral intervals,
- → Study variable correlations (PCA) and estimate pest/disease scores from biochemical traits,
- → Test variable joint estimations with multi-output PLSR,
- → Test hybrid approaches relying on the training of machine learning algorithms on simulated datasets from physical models,
- → Building of a new dataset in 2024 in agreement with future UAV-borne acquisitions over the orchards.

# Thank you

- Projet ANR CANOP “Remotely sensed leaf biochemistry intra-individual variability in orchard tree CANOPies for agroecology” (2023-2026, grant: ANR-22-CE04-0002)
- Website of the project and future data access: https://remotetree.sedoo.fr/canop



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