Caractérisation de maladies du blé tendre d'hiver par spectroscopie proche-infrarouge sur essais en champ

Characterization of soft winter wheat diseases using near-infrared spectroscopy in field trials

25e Rencontres HelioSPIR, Montpellier, 11-12 Juin 2024

[1]* François STEVENS, [2]Louise LECLÉRE, [2]Yannick CURNEL, [2]Viviane PLANCHON, [3]Maxime TROIANI, [3]Pierre DEFOURNY, [1]Vincent BAETEN et [1]Philippe VERMEULEN.

[1] Unité qualité et authentification des produits,
Centre wallon de Recherches agronomiques, 5030 Gembloux – Belgique

[2] Unité agriculture, territoire et intégration technologique,
Centre wallon de Recherches agronomiques, 5030 Gembloux – Belgique

[3] Earth and Life Institute, Université catholique de Louvain,
1348 Louvain-la-Neuve – Belgique

Our project aims at developing applications for a future constellation of satellites

SPAGHYTI

SPace for AGriculture with HYperspectral Teledetection & Innovation

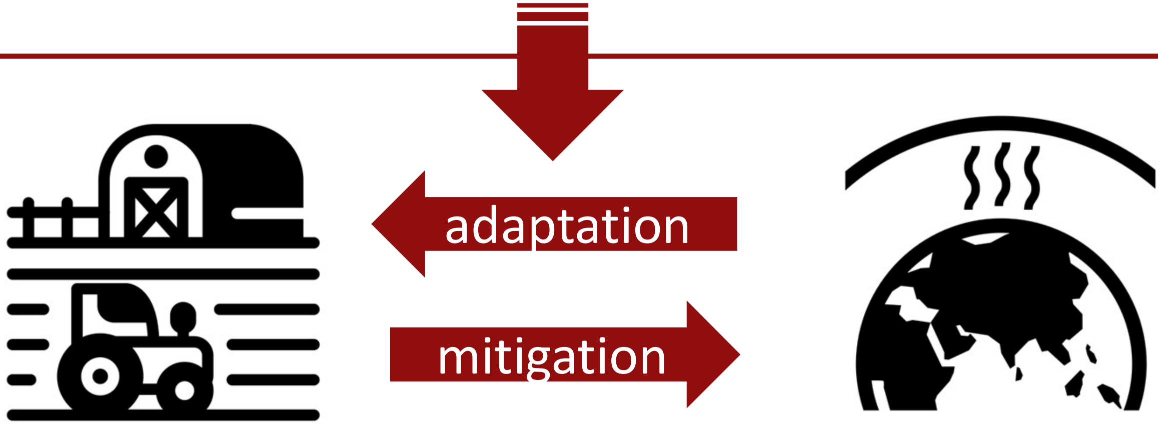
Future constellation of hyperspectral micro-satellites dedicated to agricultural monitoring	⟷	Development of agricultural applications based on field trials and a portable spectrometer

constellr AMOS ADVANCED MECHANICAL AND OPTICAL SYSTEMS DELTATEC LET'S DESIGN THE FUTURE Wallonie recherche CRA-W EARTH & LIFE INSTITUTE wagralim Skywin Wallonie

Agricultural monitoring allows combining economical prosperity with environmental sustainaibility in the context of climate change

Agricultural monitoring – Smart farming – Precision agriculture

- Rational use of inputs
- Adapted varieties
- Early detection and remediation
- Yield optimization



Agricultural systems

Climate & biodiversity crisis

Icon credit: Turkkub, OneShoot, Athok ,Lihum Studio, Arlyanto Deni, Laymik from The Noun Project

One of the selected applications focuses on the detection of biotic stress, in particular yellow rust, on soft winter wheat

Wheat yellow rust
Pucciniastriiformis f.sp. tritici

- Early in the growth season
- Fresh and humid conditions

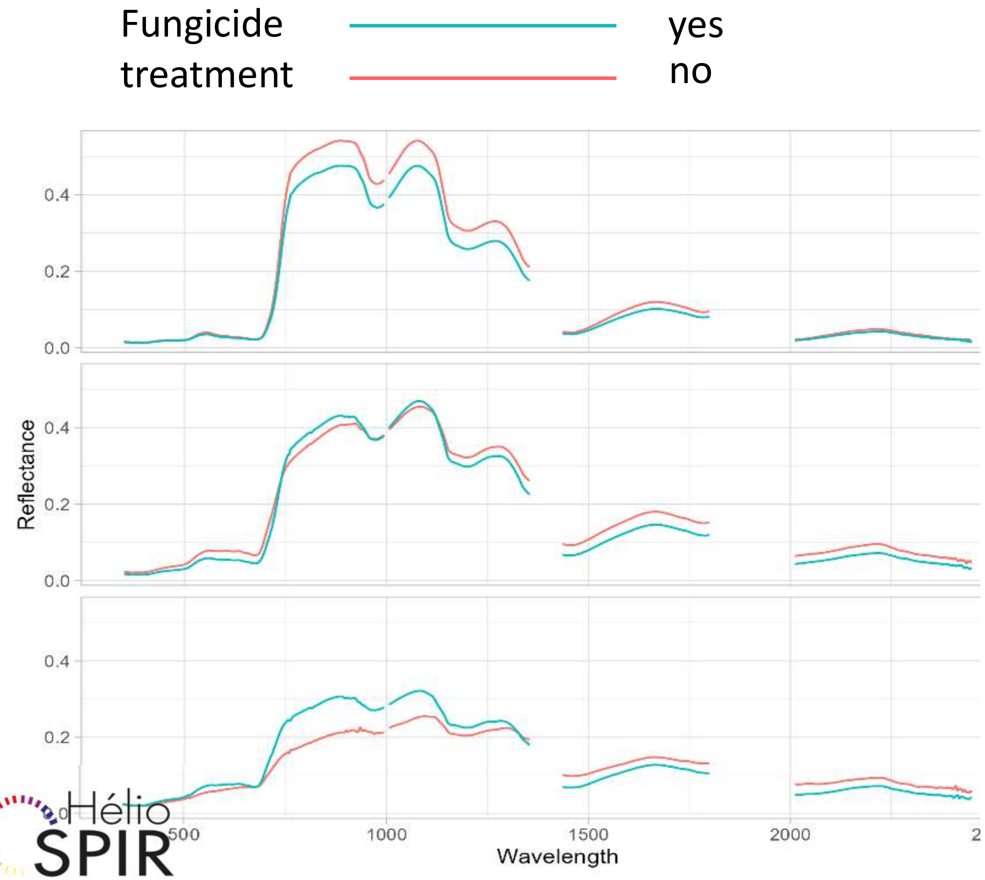
Symptoms

- Yellow stripes on leaves
- Early disease-induced senescence
- Decreased yield (up to 50 %)
- Reduced grain quality

Hélio SPIR

Wallonie recherche CRA-W

The spectrum of wheat evolves differently during the growing season if contaminated by yellow rust



Date	BBCH code	YR (1-9)	Senescence (%)
2023-06-06	60 Start flowering	1/5	
2023-06-27	75 Medium milk	-	20/70
2023-07-03	80 Start ripening	-	40/80


Fungicide treated vs. no treatment at end of flowering

Different methods have been used to detect or quantify YR on wheat in the field

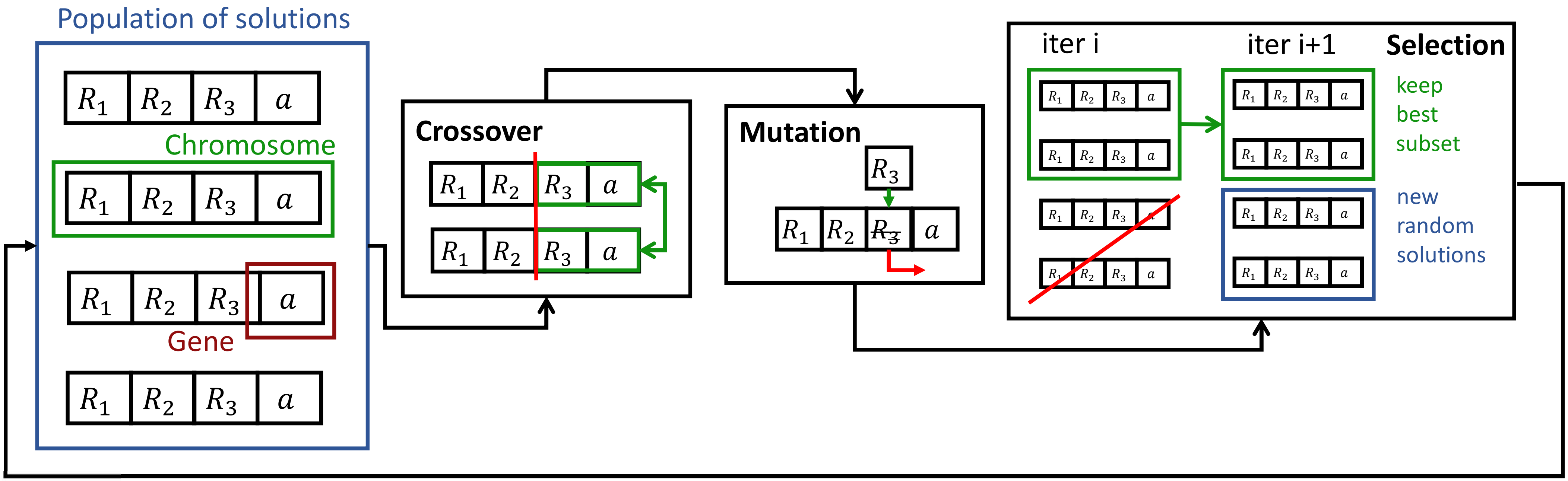
Method	Acquisition	Result	Reference
Physiological Reflectance Index PhRI = $(R_{550} - R_{531}) / (R_{550} + R_{531})$	Canopy spectral reflectance	Significant correlation at all growth stages ($p < 0.05$)	Zhang et al. 2012
Yellow Rust Index YRI = $(R_{550} - R_{531}) / (R_{550} + R_{531}) + 0.5\ R_{736}$	Leaf spectral reflectance	$R^2 = 0.86$, accuracy against other diseases = 0.92	Huang et al., 2014
PLSR	Canopy ground-based hyperspectral imaging	Regression of YR pixel ratio $R^2 = 0.72$, RPD = 1.6	Whetton et al., 2018
Feature selection + SVMR	Canopy ground-based hyperspectral imaging	Regression of YR pixel ratio $R^2 = 0.63$	Bohnenkamp et al. 2019

We have tested multivariate modelling and spectral index (SI) approaches

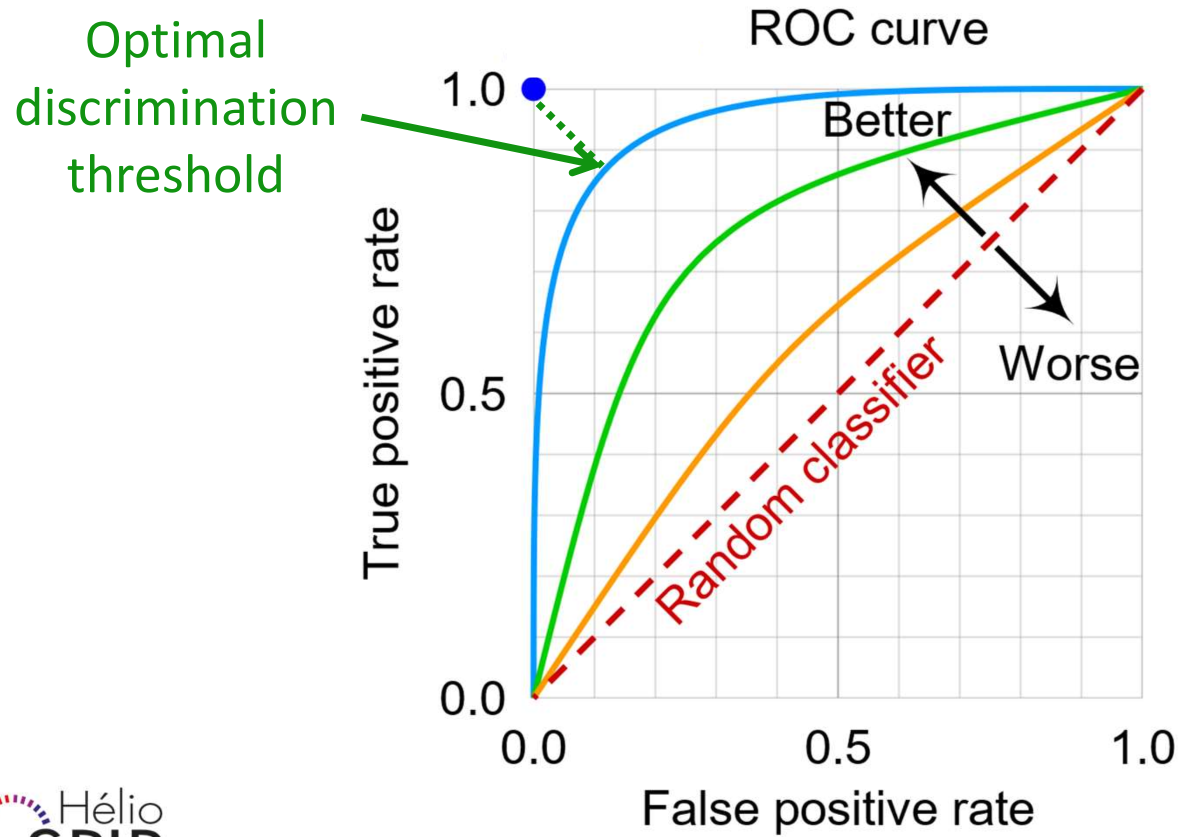
1. Calculate (non-linear) *correlation* between YR and *existing SIs*
2. Discriminate YR infection class by *PLS-DA:* class 1 (no visible symptoms) vs classes 2-9 (sparse to generalized symptoms)
3. Develop an optimal SI by *genetic algorithm* (GA)

Genetic algorithm mimics the process of natural evolution to select a set of variables

Optimal index: $\boldsymbol{I(R_1, R_2, R_3, a) = \frac{R_1 - R_2}{R_1 + R_2} + a.R_3}$ with $-1 < a < 1$, R_i: reflectance at wavelength i



The ROC curve is used to evaluate discrimination performance and find the discrimination threshold



AUC: Area Under the ROC Curve

GA maximizes the fitness function:

$$f\big(I(R_1, R_2, R_3, a)\big) = \mathrm{AUC}(I)$$

AUC	Accuracy
90-100	Excellent
80-90	Good
70-80	Fair
60-70	Poor
50-60	Very poor

Two trials have been used for calibration and two other ones for validation

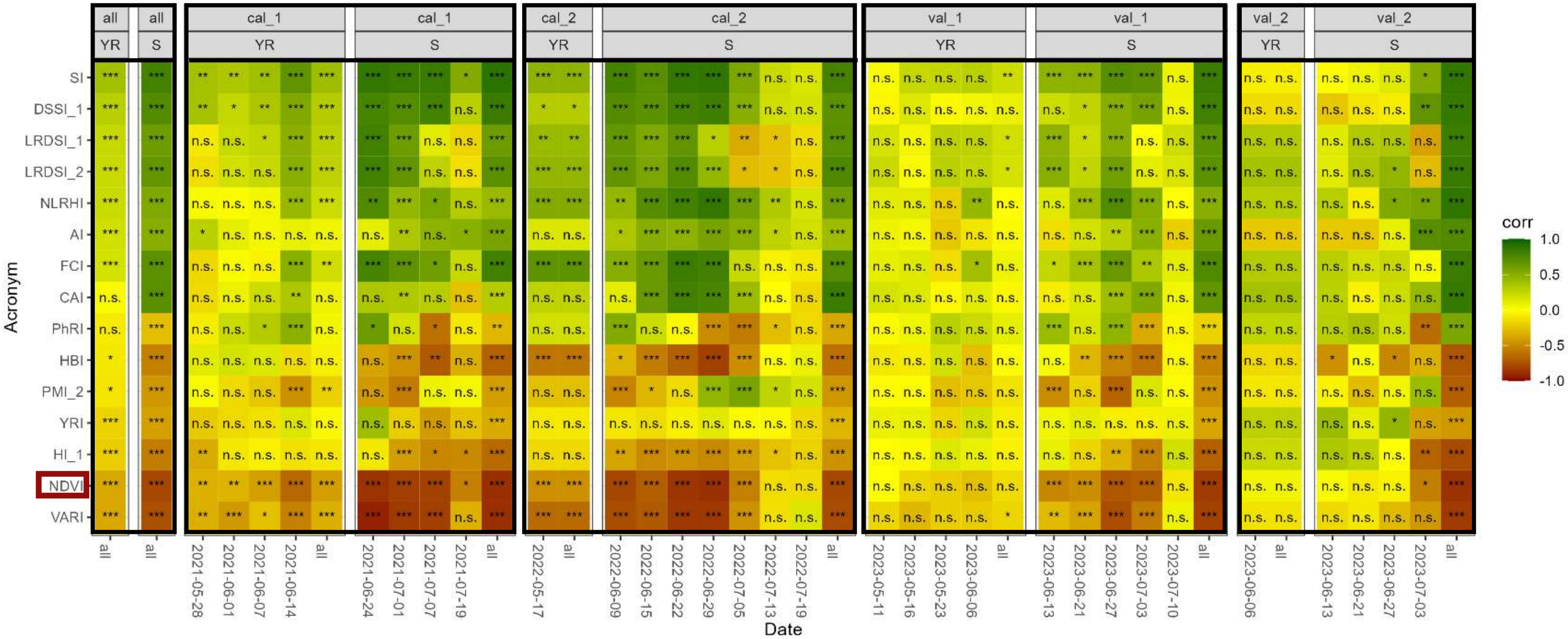
Name	Year	Varieties	Fungicide	#Dates	#Plot / Var, Date	#Obs (YR)	Stress (#Dates)
cal_1	2021	16	No	8	4	512 (256)	Senesc (4), YR (4)
cal_2	2022	16	No	9	4	544 (64)	Senesc (8), YR (1)
val_1	2023	41	Yes/No	10	2	820 (164)	Senesc (5), BR, PM, Septo, TakeA, YR (4)
val_2	2023	1	Variable	5	20	100 (20)	Senesc (4), YR (1)

- In total 3 variety trials and 1 fungicide trial
- Different years for calibration and validation

Field plots were measured from top using an ASD FieldSpec spectrometer and a pistol grip

Wavelength range	350 nm – 2500 nm
Resolution VNIR @ 700 nm	3 nm
Resolution SWIR @ 1400 & 2100 nm	8 nm
Spectral Sampling (Bandwidth) VNIR @ 700 nm	1.4 nm
Spectral Sampling (Bandwidth) SWIR @ 1400 & 2100 nm	1.1 nm
Scanning time	100 milliseconds
NEdL (Noise Equivalent Radiance) - VNIR @ 700 nm	1.0×10^{-9} W/cm²/nm/sr

Many existing SIs show significant correlation with YR and senescence (S) on different dates and trials

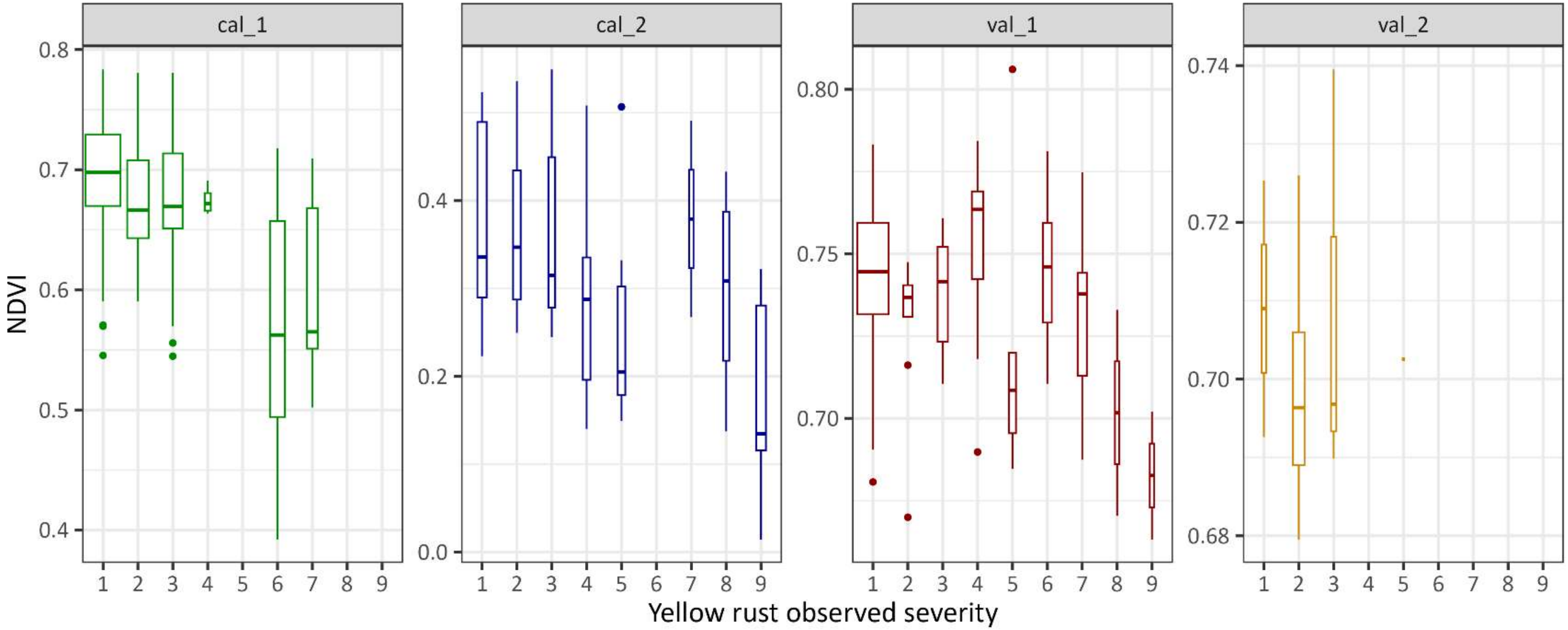


p-value: *** < 0.001 < ** < 0.01 < * <0.05 < n. s

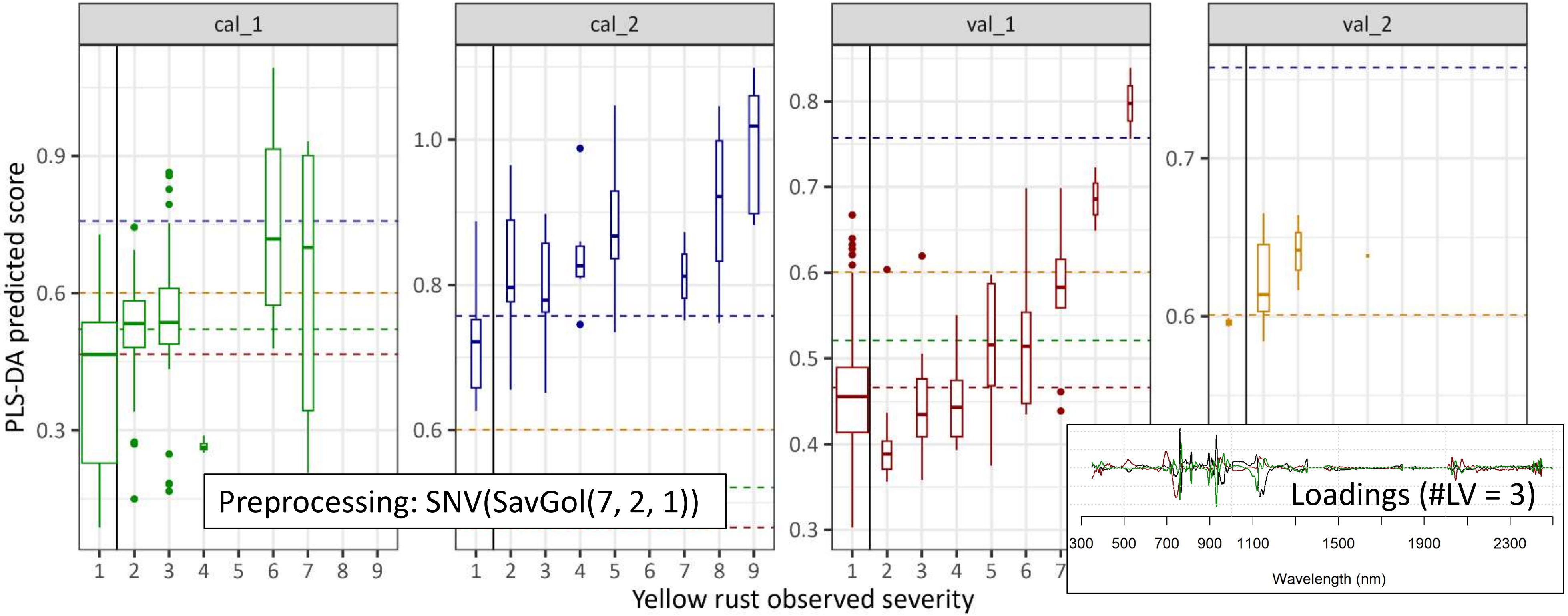
Hélio SPIR

Wallonie recherche CRA-W

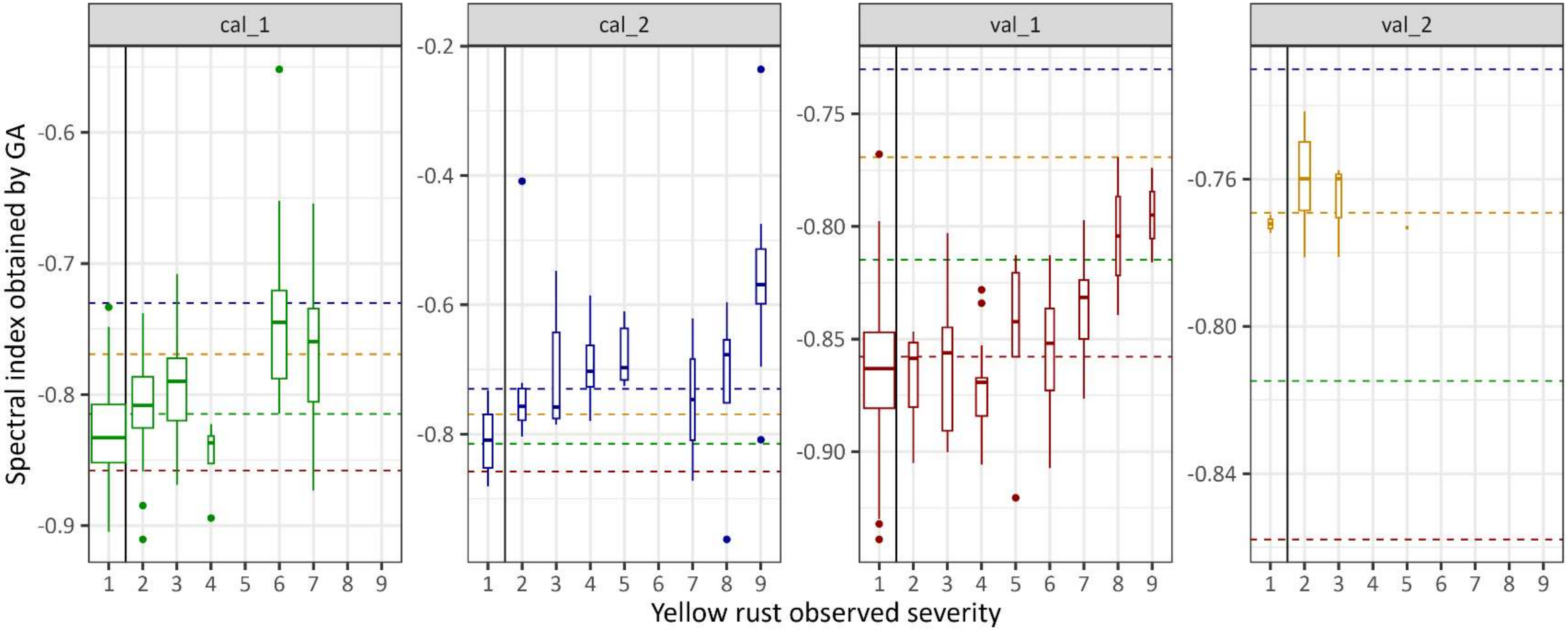
The NDVI shows a globally negative trend with observed YR severity for all trials



PLS-DA predicted score shows a strong relationship with YR severity on calibration and validation trials



The GA-obtained index shows a globally positive trend with observed YR severity



Optimal index = $(R_{734} - R_{696}) / (R_{734} + R_{696}) - 0.893\ R_{1927}$

Hélio SPIR

Wallonie recherche CRA-W

The AUC is better for calibrated models than for indices, but performance is always limited on val_1

Source	AI	CAI	DSSI_1	FCI	HBI	HI_1	LRDSI_1	LRDSI_2	NDVI	NLRHI	PMI_2	PhRI	SI	VARI	YRI
cal_1	0.53	0.52	0.65	0.60	0.45	0.55	0.64	0.64	0.71	0.62	0.41	0.48	0.71	0.69	0.49
cal_2	0.62	0.57	0.64	**0.75**	0.26	0.60	0.57	0.59	0.68	**0.81**	0.51	0.51	0.68	0.72	0.46
val_1	0.52	0.50	0.56	0.52	0.50	0.54	0.57	0.56	0.58	0.52	0.46	0.55	0.61	0.56	0.47
val_2	0.36	**0.78**	0.58	0.64	0.44	0.42	**0.94**	**0.97**	0.58	0.53	0.19	**0.86**	0.64	**0.89**	0.56

Source	GA index	GA index
cal_1	**0.76**	**0.73**
cal_2	**0.88**	**0.86**
val_1	0.58	0.56
val_2	**0.75**	**0.86**

Conclusions

- Most existing SIs show a relationship with YR
- Both PLS-DA and GA optimized indice can predict YR but, in the case of val_1, only for stronger infection levels
- There is a need for more data both for calibration and for validation to assess more thorougly the predictive ability.

Perspectives

- Need for more data. Will be available soon data from:
  - New measurement campaign on field trials
  - Drone flight on trial
  - EnMap satellite image on farm plot
- Test more complex index formula with GA (up to 5 wavelengths)
- When more data will be available, test prediction by growth stage
- Add uncertainty to predictions
  - For PLS-DA, use resampling methods (bootstrap, jacknife, …)
  - For GA, also consider that different runs could give slightly different models du to random initialization.

Do not miss it !!

Vibrational Spectroscopy and Chemometrics course

14-18 OCTOBER 2024
GEMBLOUX BELGIUM

Wallonie recherche
CRA-W

REGISTRATION
https://tinyurl.com/chemometrics2024

Contact :
François STEVENS
f.o.stevens@gmail.com