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

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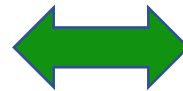
[3] Earth and Life Institute, Université catholique de Louvain, 1348 Louvain-la-Neuve – Belgique

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

SPAGHYTI

SPace for AGriculture with HYperspectral Teledetection & Innovation
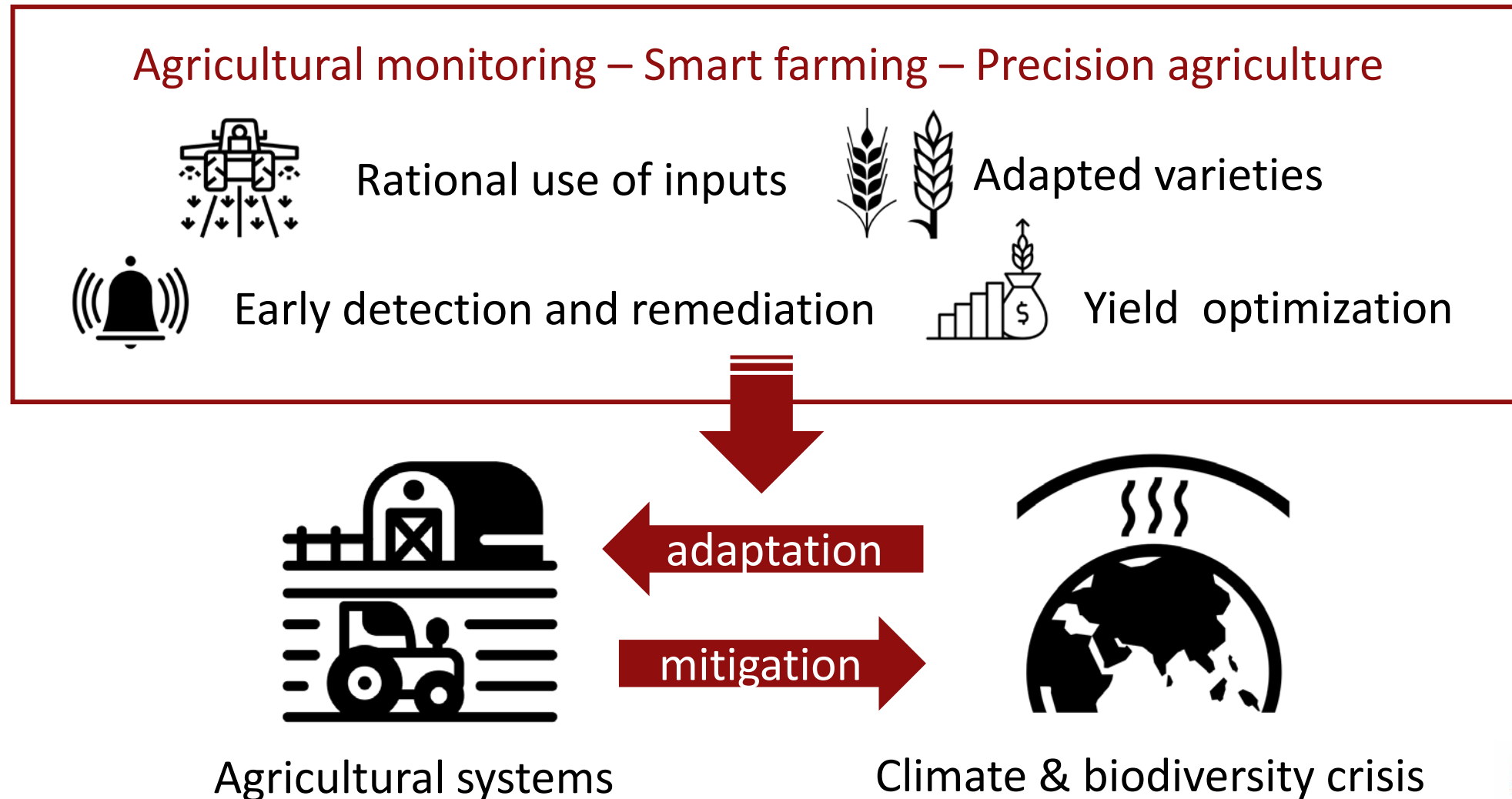
| Future constellation of hyperspectral micro-satellites dedicated to agricultural monitoring | ⟷ | Development of agricultural applications based on field trials and a portable spectrometer |

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

adaptation

mitigation

Agricultural systems

Climate & biodiversity crisis

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

Wheat yellow rust
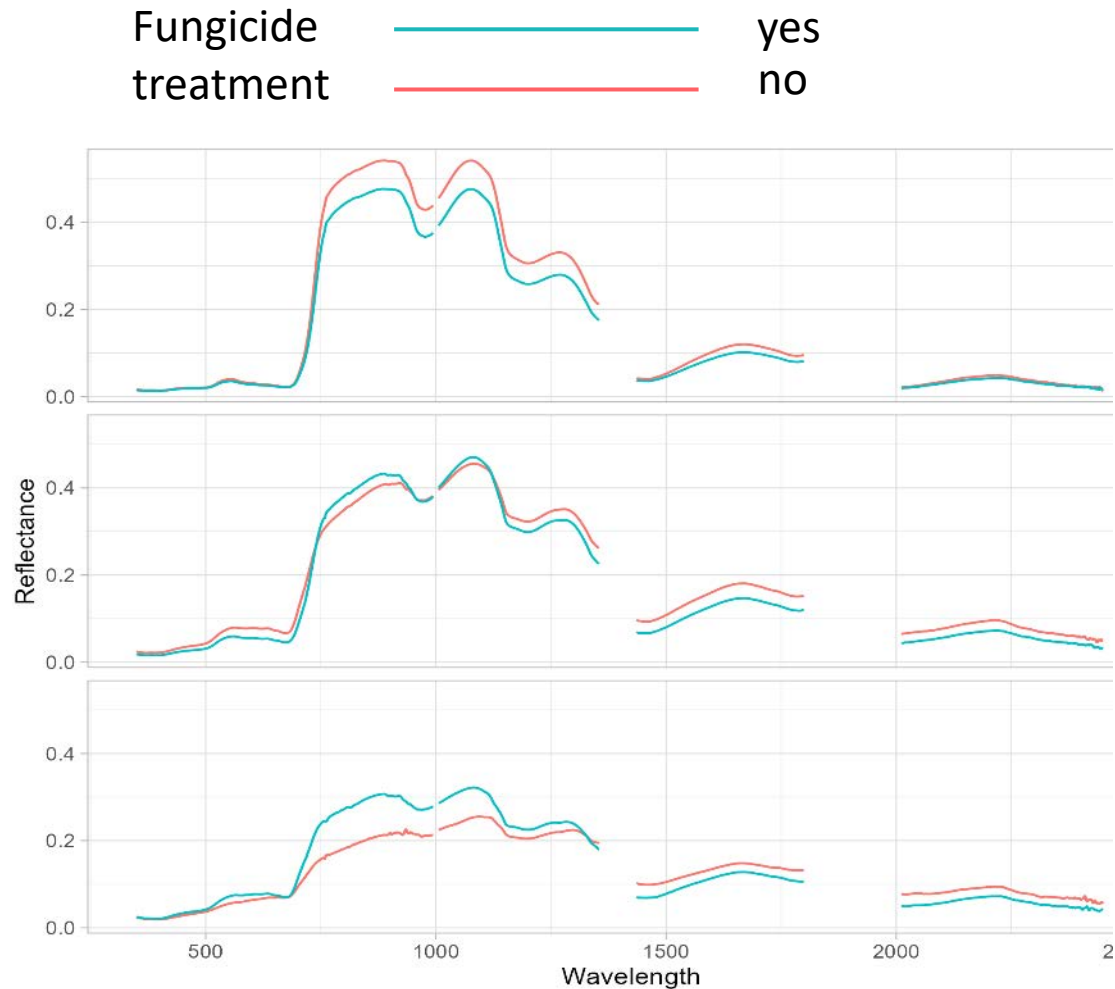*Pucciniastriiformis f.sp. tritici*

- 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

Yellow rust

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

Fungicide treatment — yes (teal), no (red)

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

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# 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)

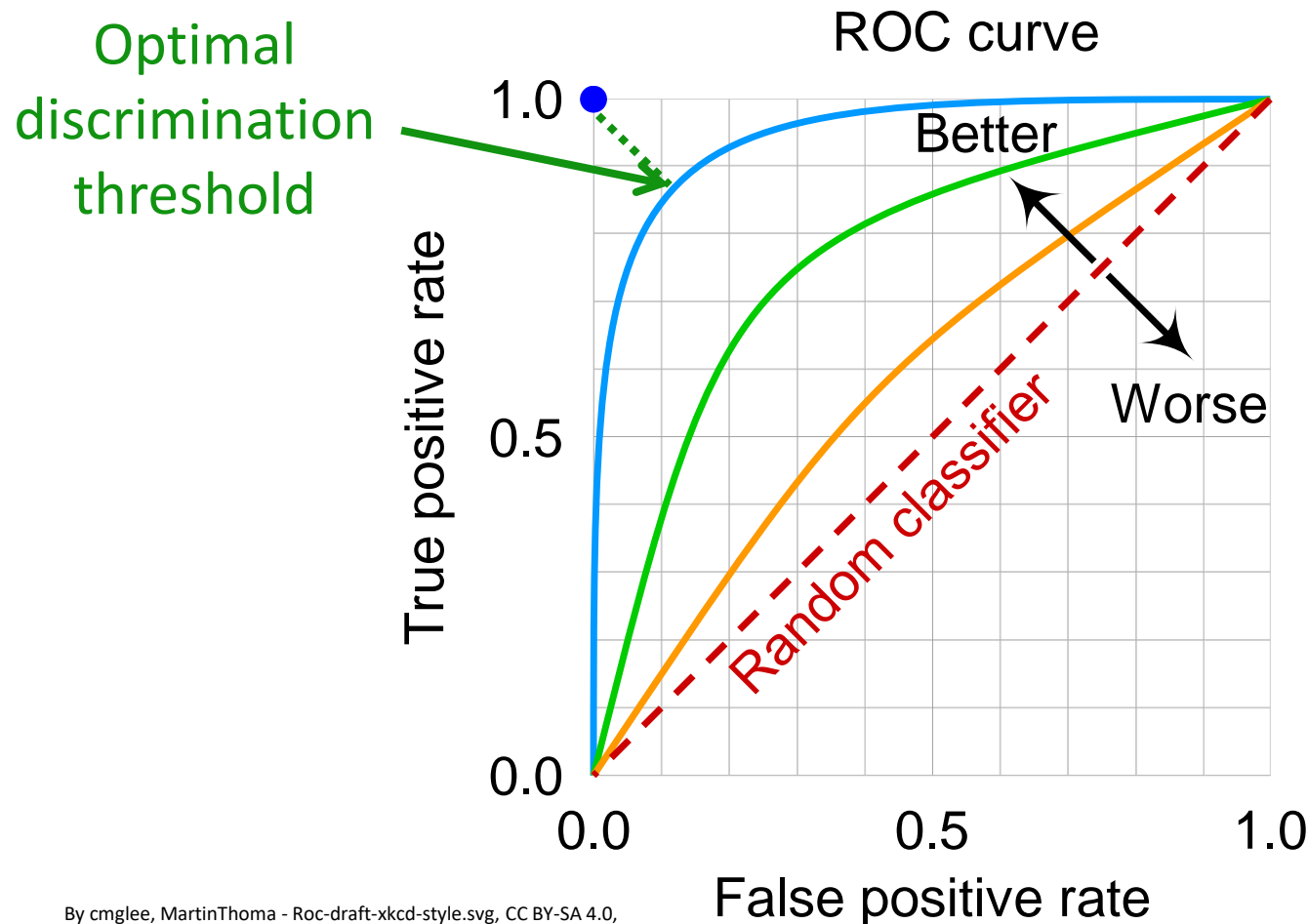3. Develop an optimal SI by *genetic algorithm* (GA)

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

Optimal index: $I(R_1, R_2, R_3, a) = \frac{R_1 - R_2}{R_1 + R_2} + a.R_3$ with $-1 < a < 1$, R_i: reflectance at wavelength i
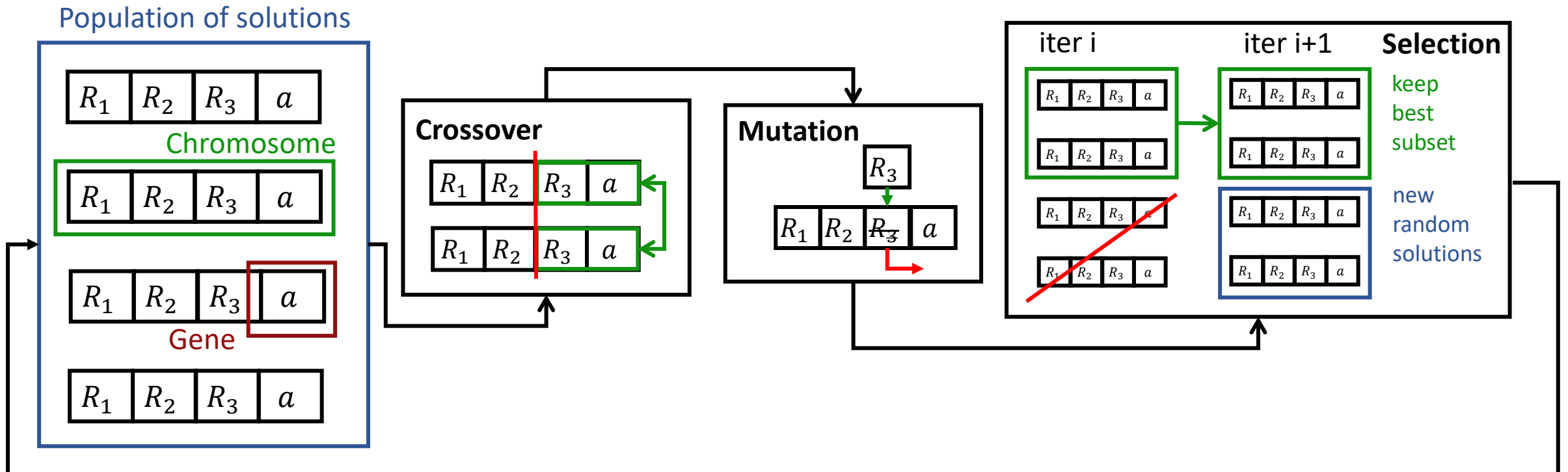
The ROC curve is used to evaluate discrimination performance and find the discrimination threshold

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/cm^2/nm/sr

Many existing SIs show significant correlation with YR and senescence (S) on different dates and trials
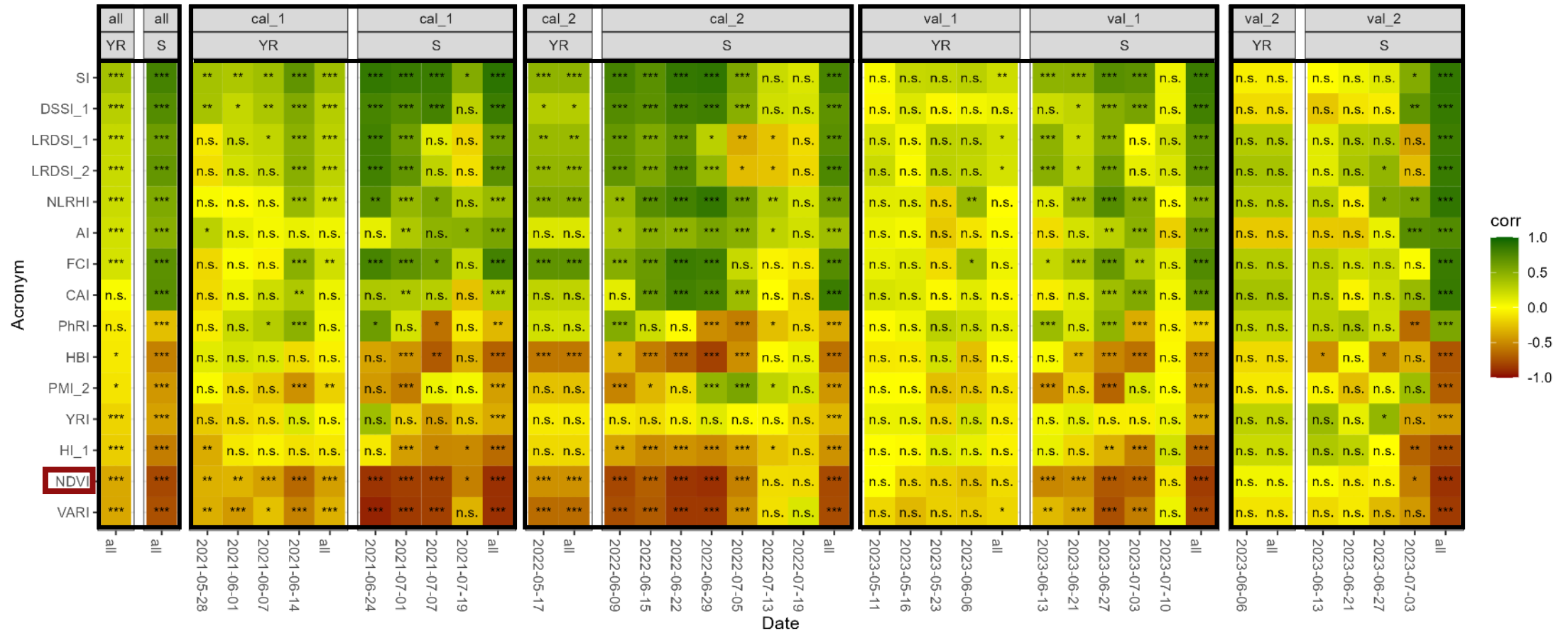
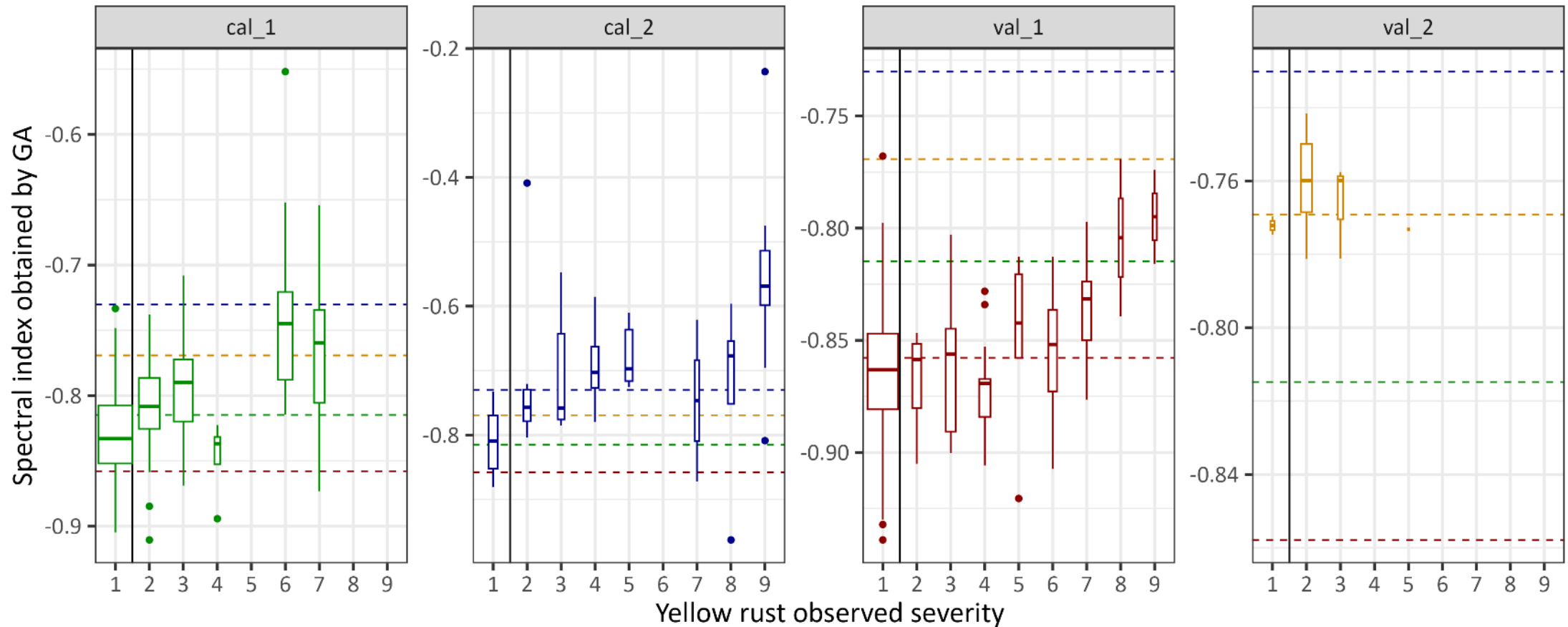
p-value: *** < 0.001 < ** < 0.01 < * <0.05 < n. s

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

Preprocessing: SNV(SavGol(7, 2, 1))

Loadings (#LV = 3)
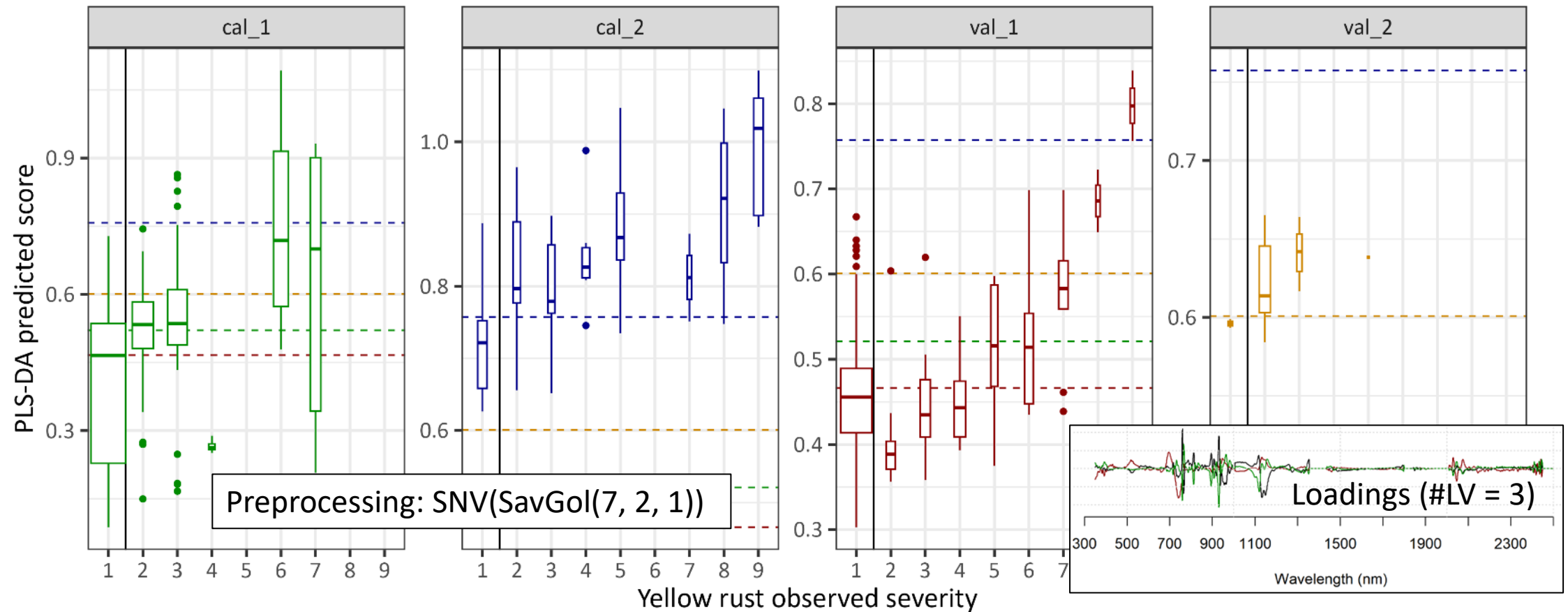
The GA-obtained index shows a globally positive trend with observed YR severity

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

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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**

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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

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REGISTRATION

https://tinyurl.com/chemometrics2024

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