Estimation of sugar beet resistance to Cercospora Leaf Spot disease using UAV multispectral imagery

S Jay, A Comar, R Benicio, N Henry, Marie Weiss, F Baret

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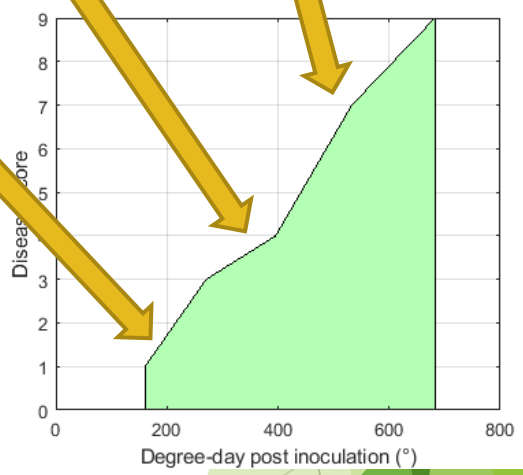
Context

- Plant diseases, a major issue affecting crop yield,
- Several challenges related to plant diseases, including:
  - (Early) detection of plant disease (precision agriculture),
  - Asssessment of cultivar resistance to disease (cultivar selection or phenotyping).
- The Cercospora Leaf Spot (CLS) disease, a major threat for sugar beet plants.
- Selection of CLS-resistant cultivars is one of the solutions (with crop rotation and use of fungicides).

Context

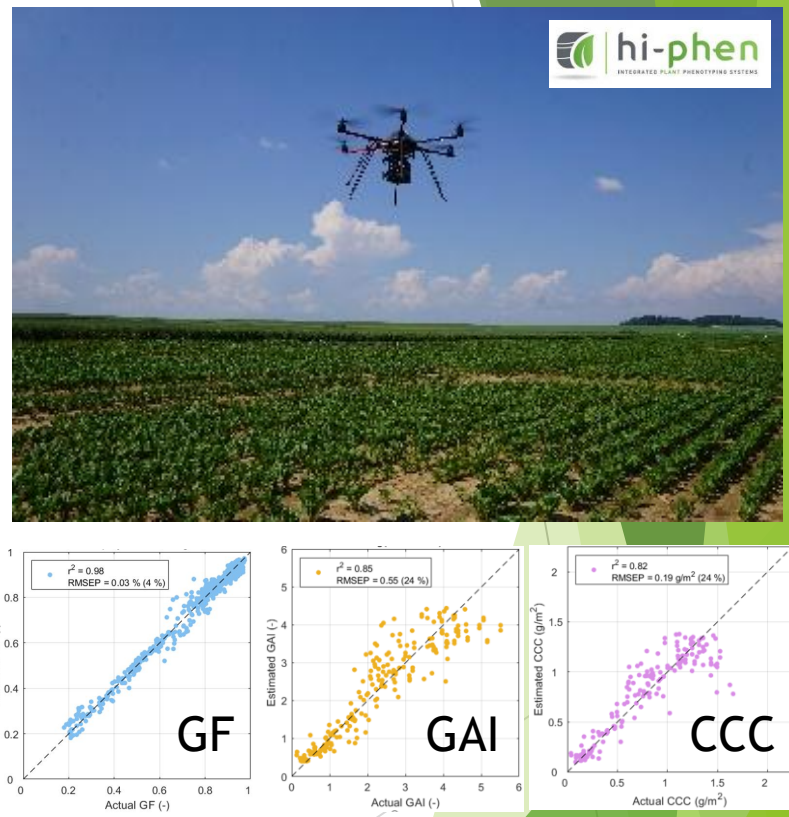
- The reference method to assess CLS resistance:
  - Visual assessment of disease severity by experts at several dates: score ranging from 1 (healthy plants) to 9 (plants destroyed),
  - Integration of the disease evolution curve (ADPC = Area under Disease Progression Curve, *Shaner & Finney, 1977*)
- About the ADPC method:
  - (Generally) Accurate,
  - Subjective (e.g., inter-expert variability), time-consuming,
  - Application for phenotyping is difficult due to the high number of microplots.
- Need for an automatic method to study CLS development.



* G. Shaner, R. Finney (1977). The Effect of Nitrogen Fertilization on the Expression of Slow-Mildewing Resistance in Knox Wheat. *Phytopathology*, 1051-1056.

Context

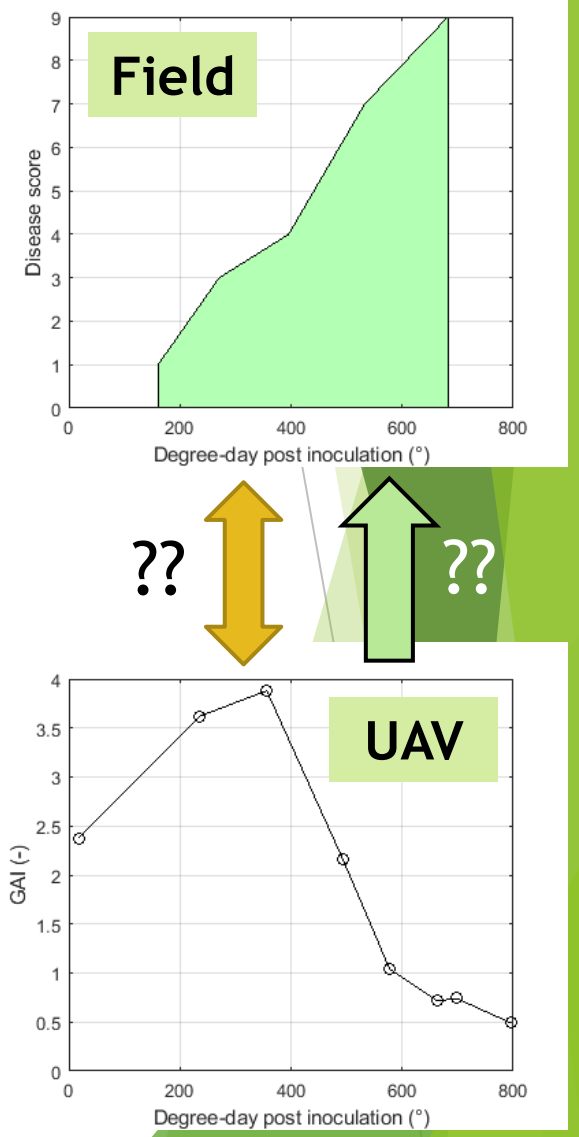
- UAV (Unmanned Aerial Vehicle) multispectral remote sensing, a promising approach for assessing sugar beet resistance to CLS,
  - Provides <u>accurate</u> estimates of canopy structure and biochemistry (*Jay et al., 2018*), e.g.,
    - Green Fraction (GF),
    - Green Area Index (GAI),
    - Canopy Chlorophyll Content (CCC).
  - <u>Efficient</u> (in terms of microplots / unit time).



* S. Jay, F. Baret, D. Dutartre, G. Malatesta, S. Héno, A. Comar, M. Weiss, F. Maupas (2018). Exploiting the centimeter resolution of UAV multispectral imagery to improve remote-sensing estimates of canopy structure and biochemistry in sugar beet crops. *Remote Sensing of Environment*, in press.

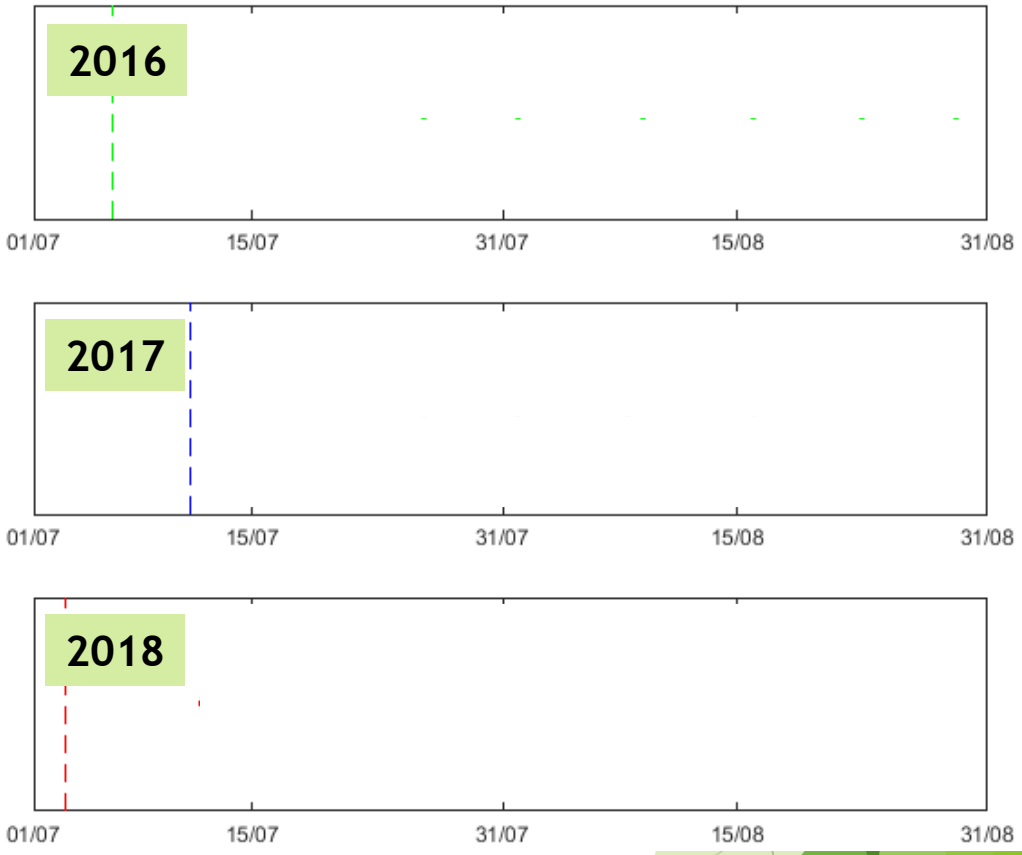
Context

- Objectives:
  - Relating the dynamics of CLS severity as evaluated from field measurements, with the dynamics of remote-sensing variables,
  - Estimating instantaneous disease scores and sugar beet resistance based on time series of remote-sensing variables.
- Hypothesis:
  - The observed decrease in GF/GAI is primarily due to CLS, not to natural senescence (the latter would occur later if no CLS).

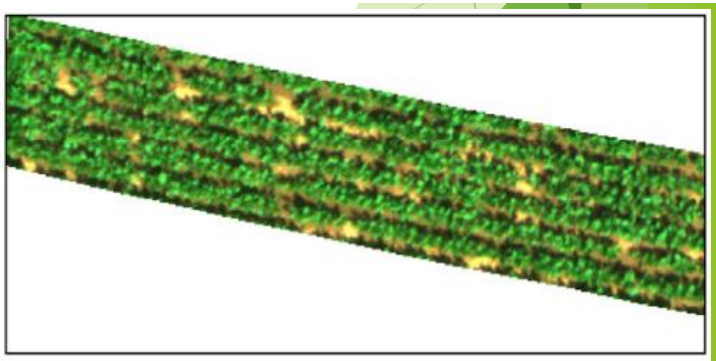


Data

		2016	2017	2018
Number of microplots		80	1374	1522
Number of dates	Field			
	UAV			



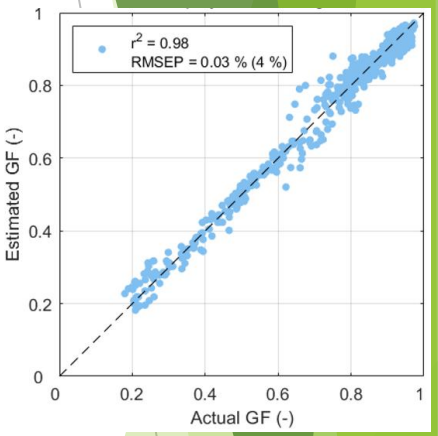
- Acquisitions in Casteljaloux (47),
- Plants inoculated, not treated (except in 2016)
- Disease scores evaluated by experts (4-6 times),
- UAV images
  - 20 m < Flight altitude < 50 m
  - AIRPHEN multispectral camera,
  - Six bands: 450, 530, 570, 675, 730, 850 nm,
  - Spatial resolution ≈ cm.



Methodology: dynamics of remote-sensing variables

- Two remote-sensing variables estimated for each UAV multispectral image of microplot
  - Mean NDVI over all pixels: $NDVI = \frac{R_{850}-R_{675}}{R_{850}+R_{675}}$ (*Rouse et al., 1973*)
  - GF (Green Fraction) estimated by thresholding the VARI (*Gitelson et al., 2002*) image, as described in *Jay et al., (2018)*
- For both NDVI and GF variables, three dynamics are compared:
  - Dynamics #1: Raw values,
  - Dynamics #2: Values normalized by the maximum value,
  - Dynamics #3: Values normalized by the maximum value and set to 1 before this maximum.
- The six dynamics were resampled to the dates of visual scoring.

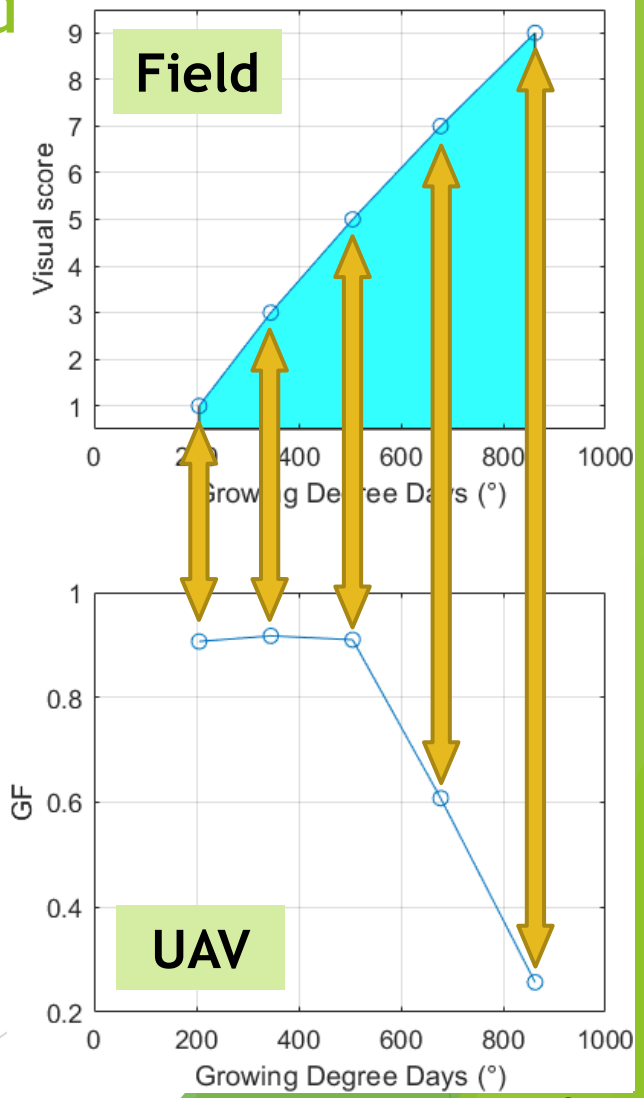
Jay et al., (2018)



* J.W. Rouse *et al*. Monitoring vegetation systems in the great plains with ERTS. Third Earth Resour. Technol. Satell. Symp., 1:309:317, 1973.
* A.A. Gitelson *et al*. Novel algorithms for remote estimation of vegetation fraction. Remote Sens. Environ, 80: 76-87, 2002.
* S. Jay, F. Baret, D. Dutartre, G. Malatesta, S. Héno, A. Comar, M. Weiss, F. Maupas (2018). Exploiting the centimeter resolution of UAV multispectral imagery to improve remote-sensing estimates of canopy structure and biochemistry in sugar beet crops. *Remote Sensing of Environment*, in press.

Methodology: estimation of instantaneous disease scores and cultivar resistance

- Gaussian Process Regression used to relate instantaneous disease scores and NDVI- and GF-based variables.
- Estimated instantaneous disease scores integrated to estimate ADPC, as for visual scores.
- Estimation performance evaluated using 3-fold cross-validation, e.g., calibration with 2016/2017 and test with 2018, etc (randomly selecting the same number of samples for both years used for calibration x 10)

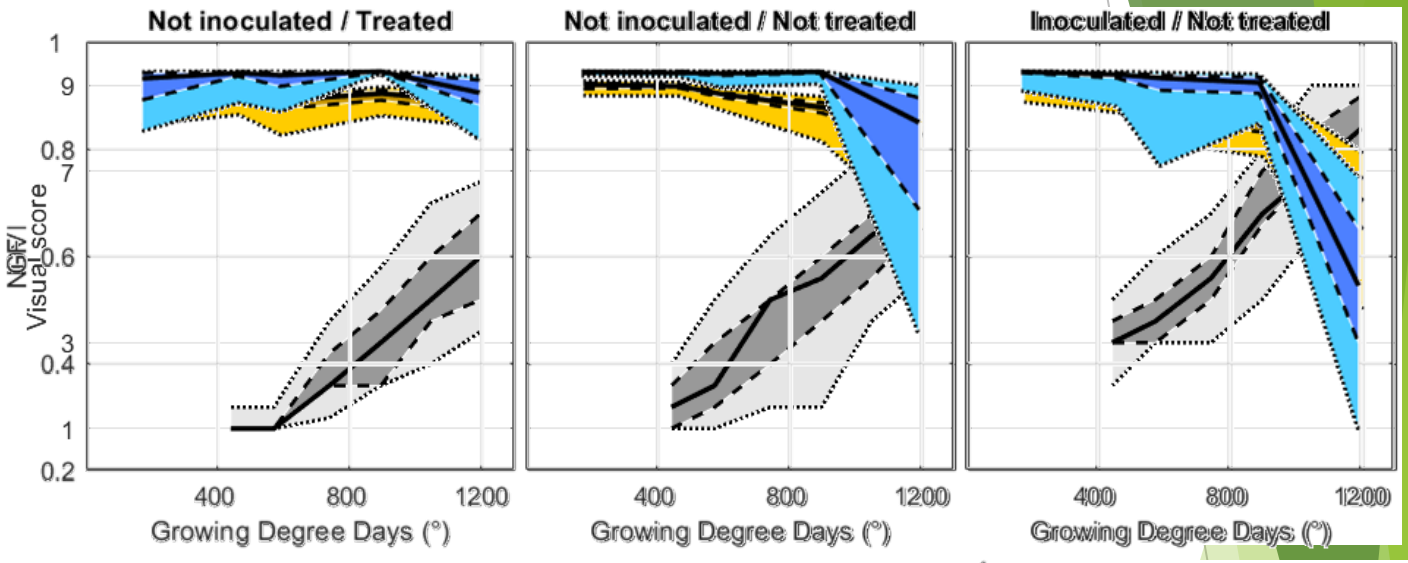


Results: comparing the dynamics

2016 VISUAL SCORES

2016 NDVI

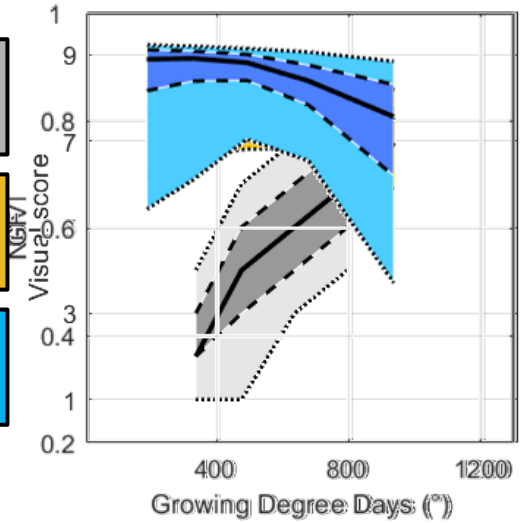
2016 GF



2017 VISUAL SCORES

2017 NDVI

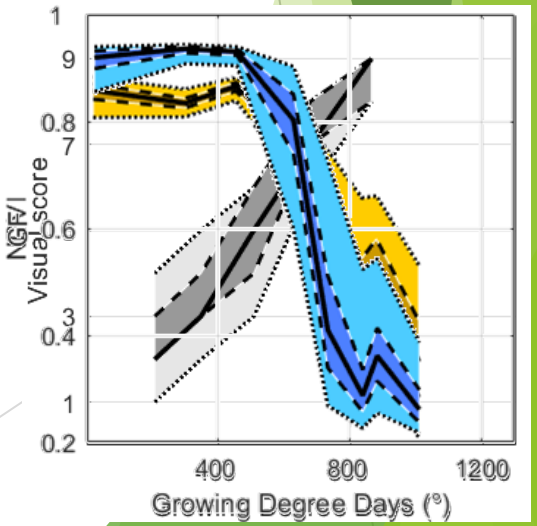
2017 GF



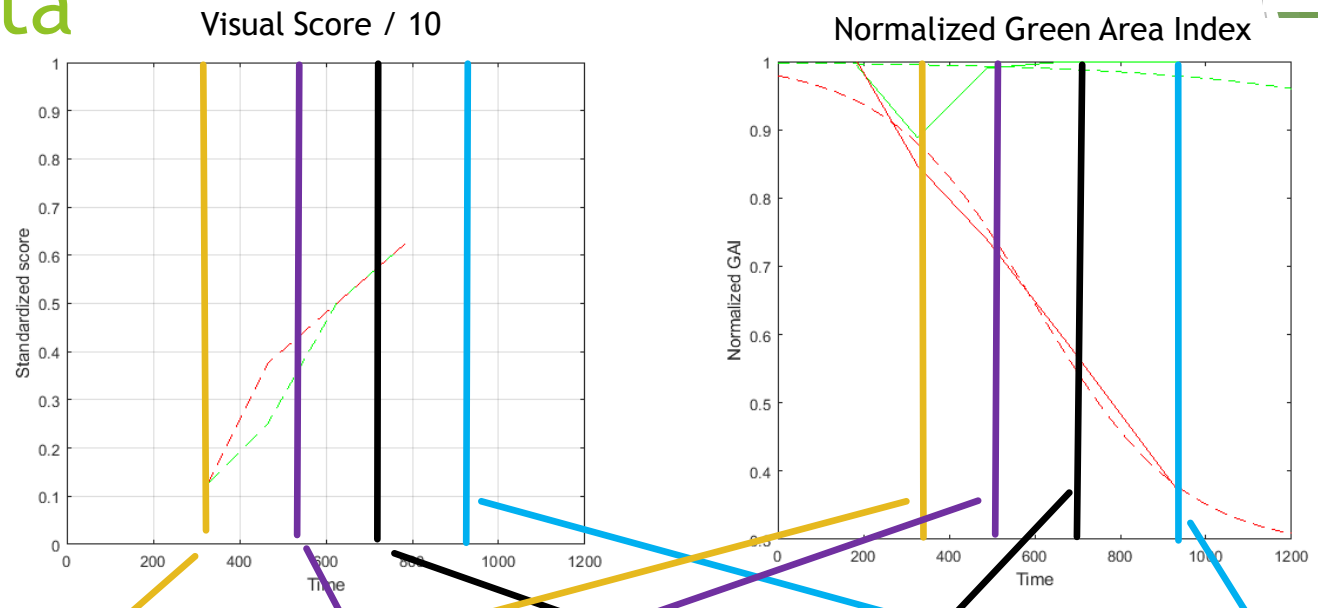
2018 VISUAL SCORES

2018 NDVI

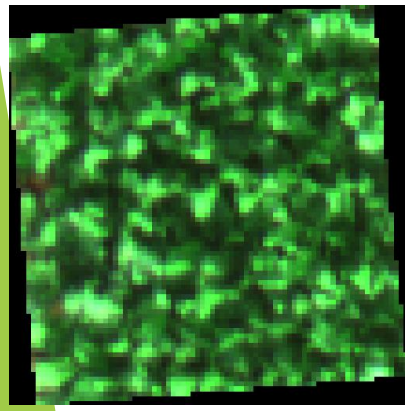
2018 GF



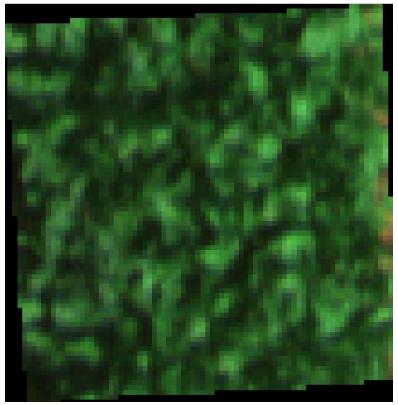
Data



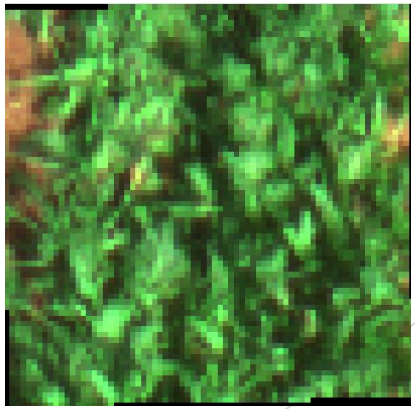
GAI = 2,95



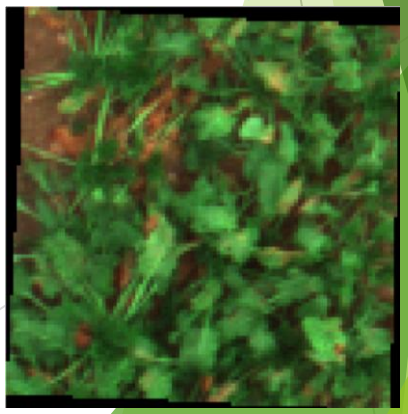
GAI = 2,56



GAI =2,04

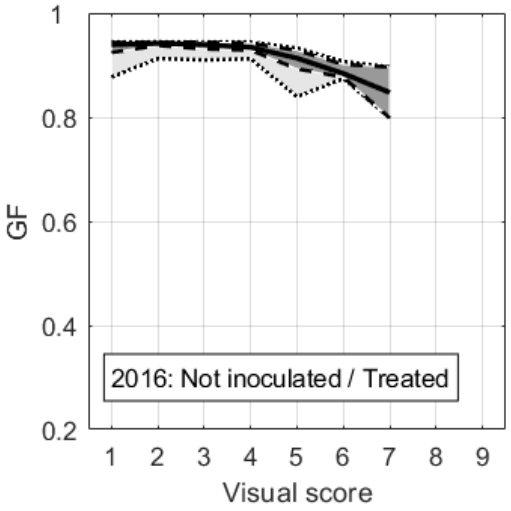


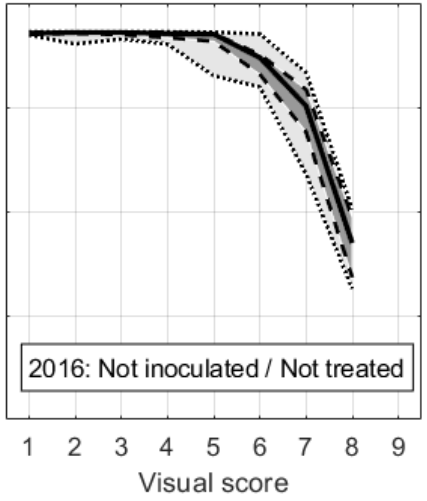
GAI = 1,29

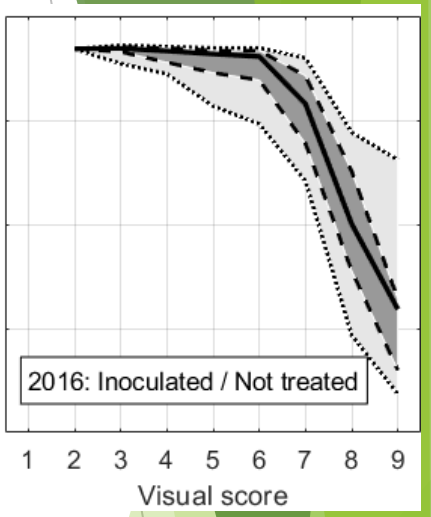


Results: remotely-sensed GF vs visual scores (#1: raw)

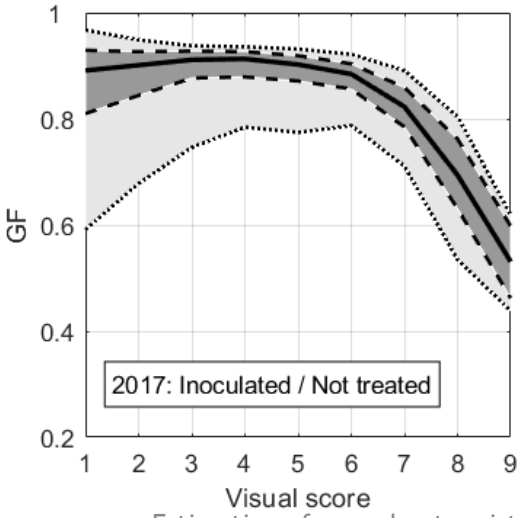
2016
(80 µ-plots)



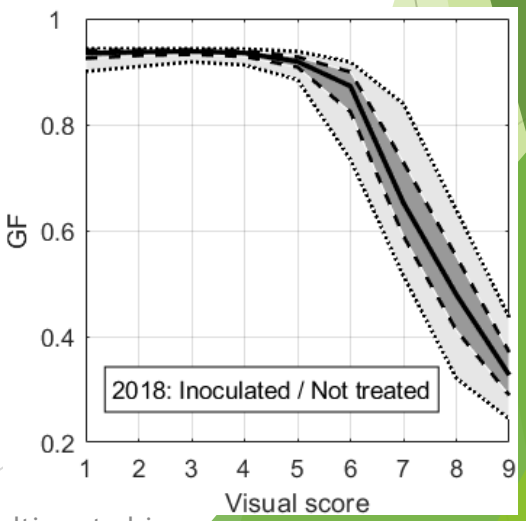




2017
(1374 µ-plots)

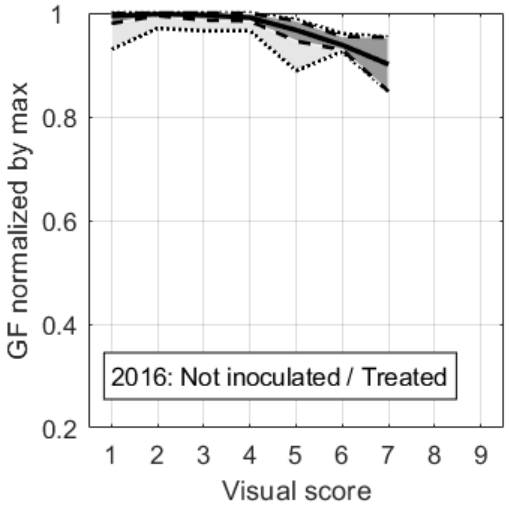


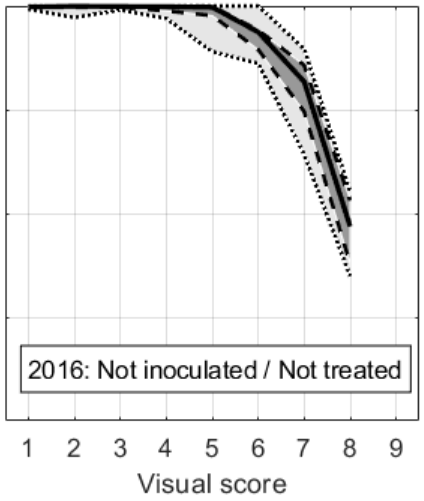
2018
(1522 µ-plots)

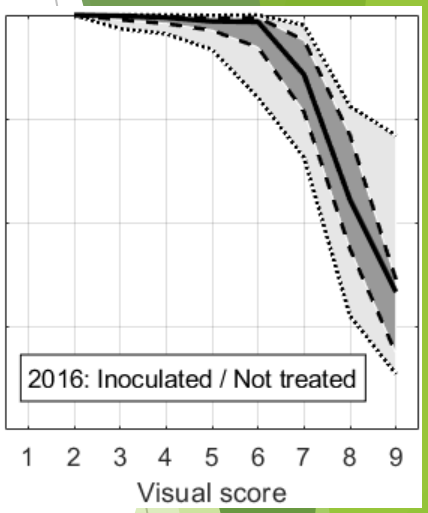


Results: remotely-sensed GF vs visual scores (#2: normalized)

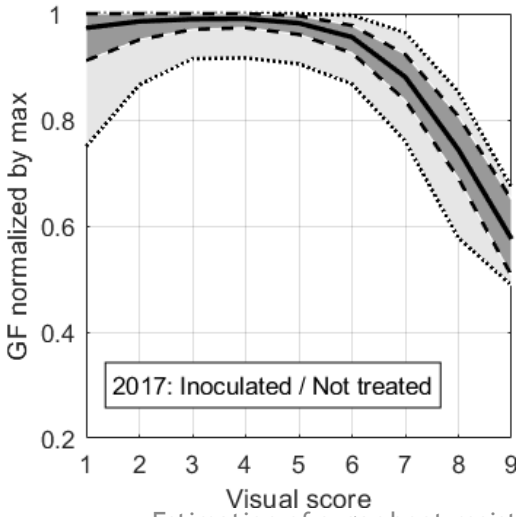
2016
(80 µ-plots)



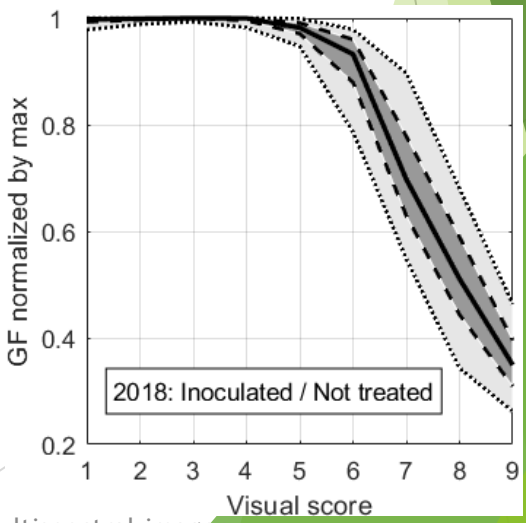




2017
(1374 µ-plots)

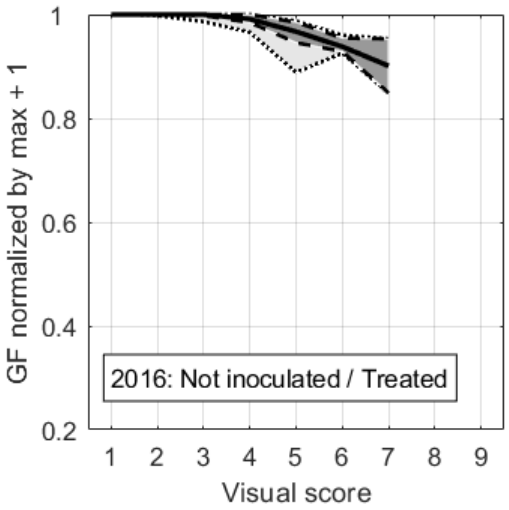


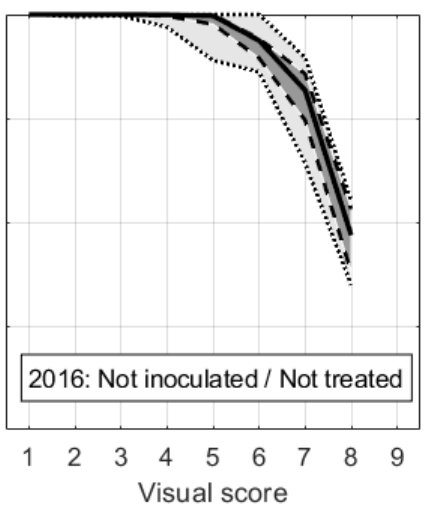
2018
(1522 µ-plots)

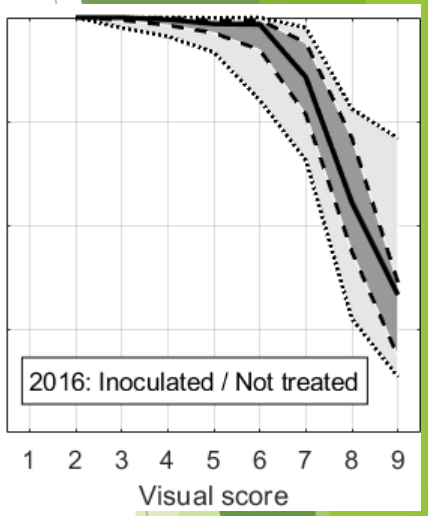


Results: remotely-sensed GF vs visual scores (#3: normalized + 1)

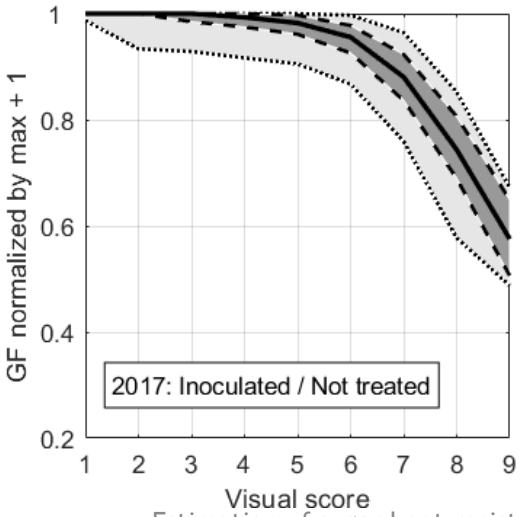
2016
(80 µ-plots)



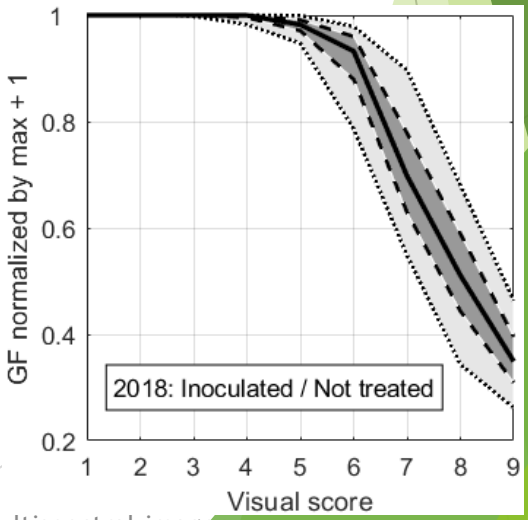




2017
(1374 µ-plots)



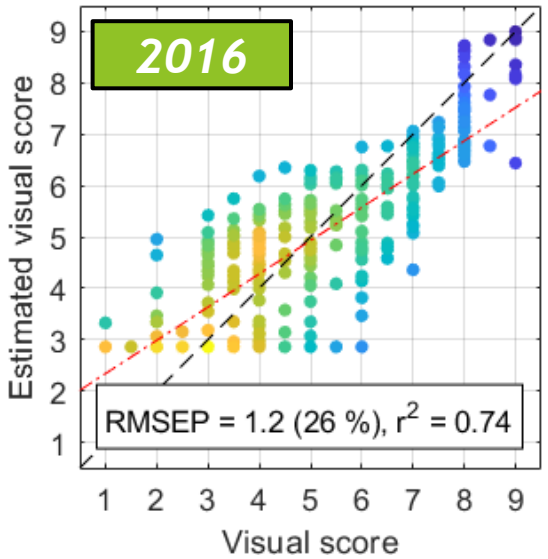
2018
(1522 µ-plots)

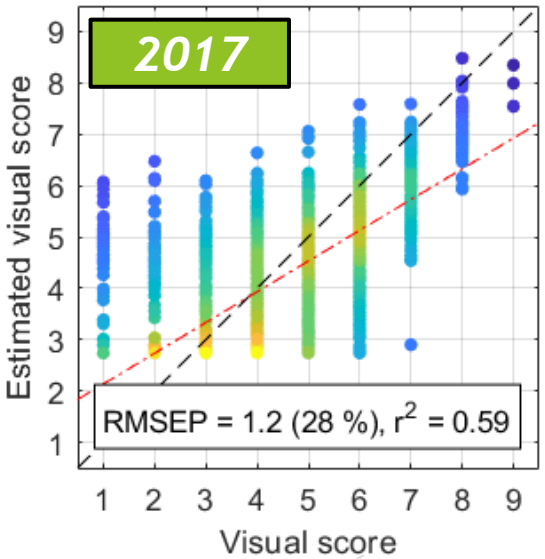


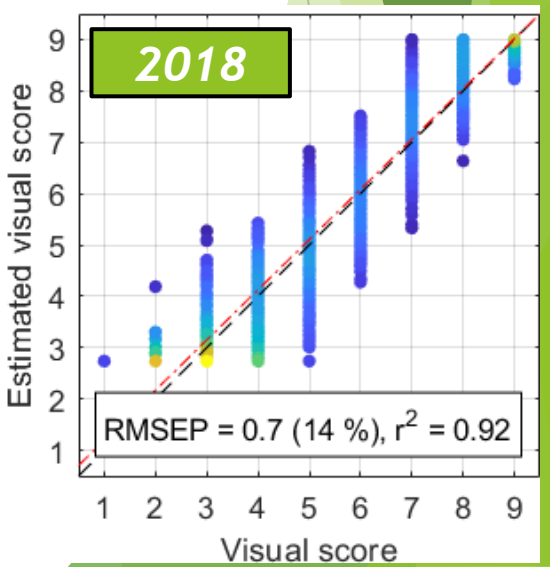
Results: estimating instantaneous disease scores

RMSEP (%)

Remote-sensing variable	Dynamics type	2016	2017	2018	All
NDVI	#1: Raw	36	48	33	39
GF	#1: Raw	35	50	20	35



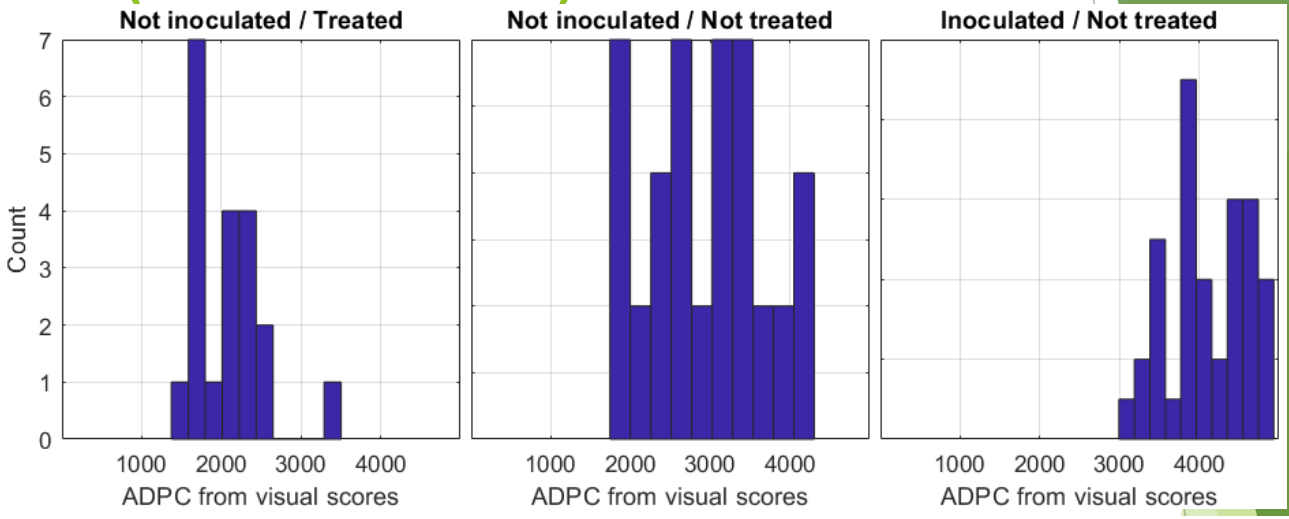




Results: estimating sugar beet resistance (field ADPC)

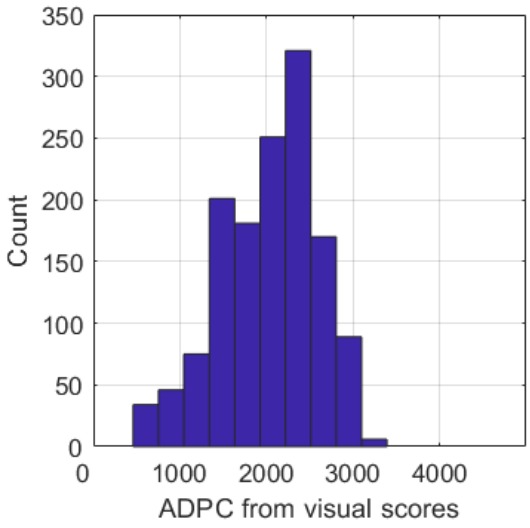
2016 VISUAL SCORES

2016 ADPC



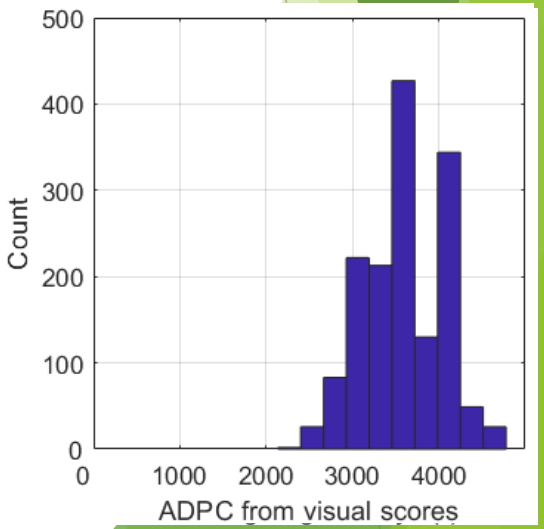
2017 VISUAL SCORES

2017 ADPC



2018 VISUAL SCORES

2018 ADPC

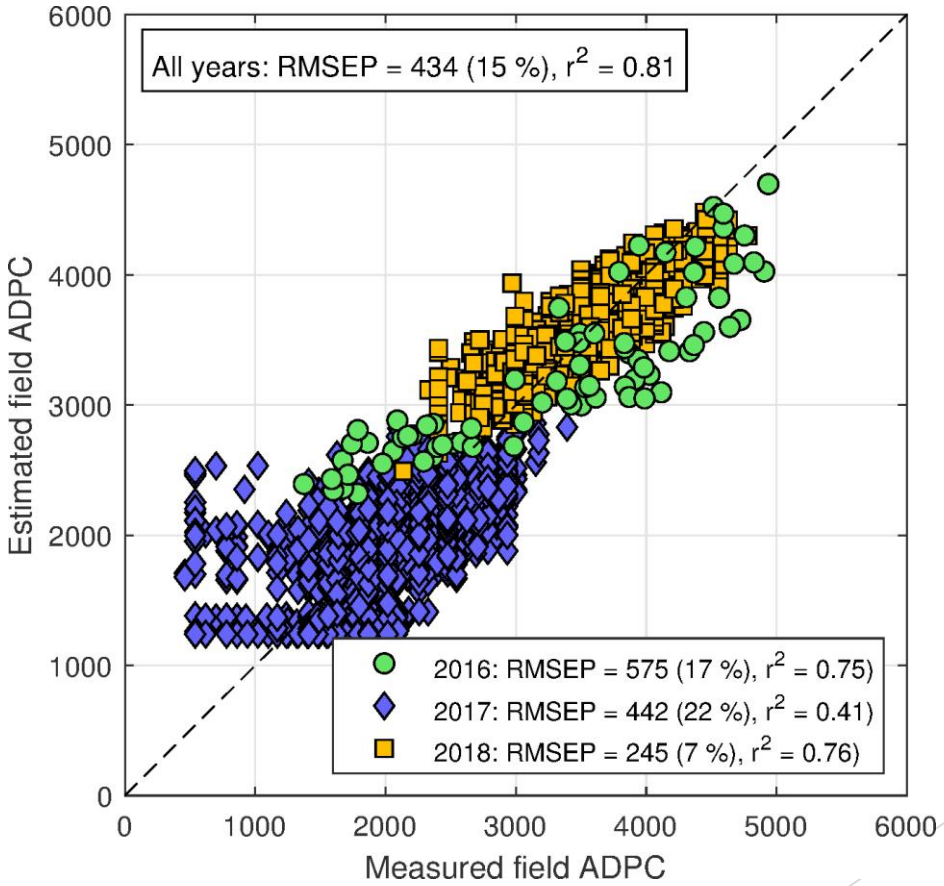


Results: estimating sugar beet resistance (field ADPC)

RMSEP (%)

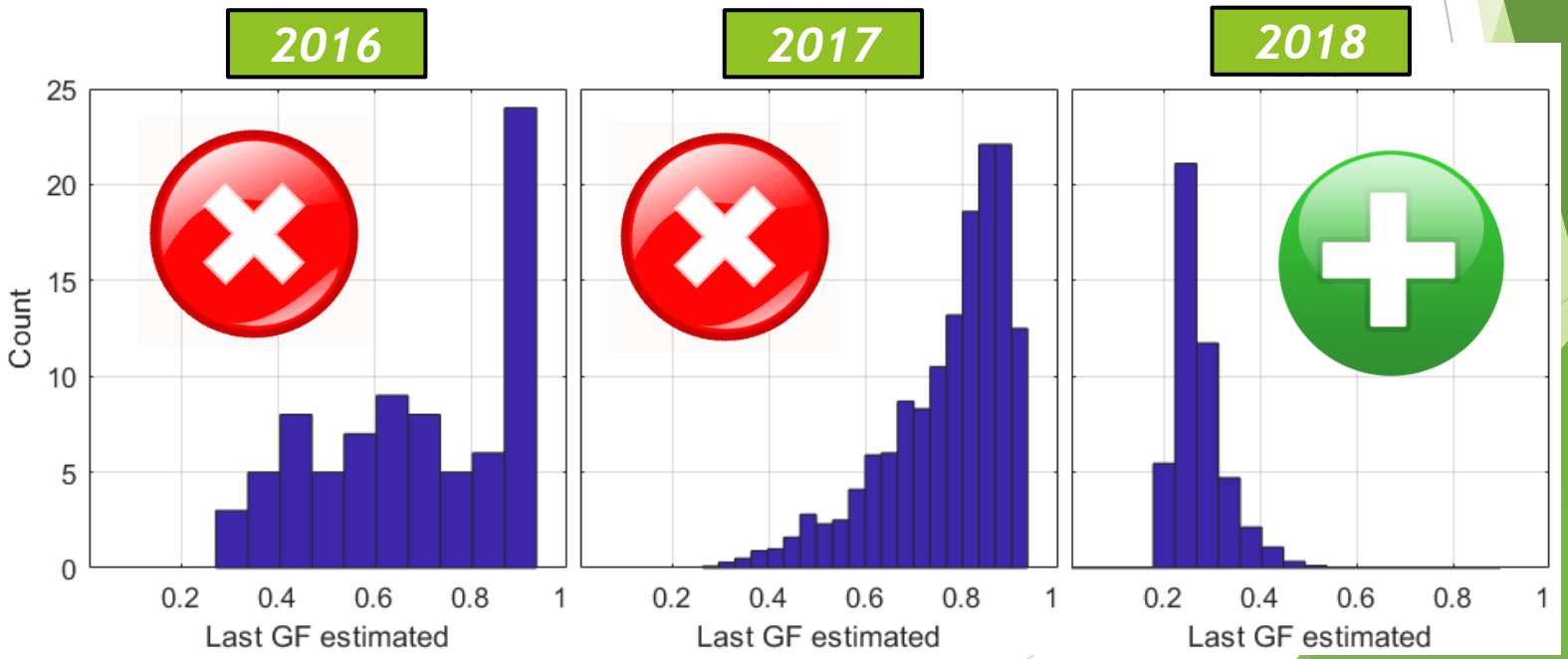
Remote-sensing variable	Dynamics type	2016	2017	2018	All
NDVI	#1: Raw	24	37	11	21
GF	#1: Raw	24	39	10	24

Results: estimating sugar beet resistance (field ADPC)

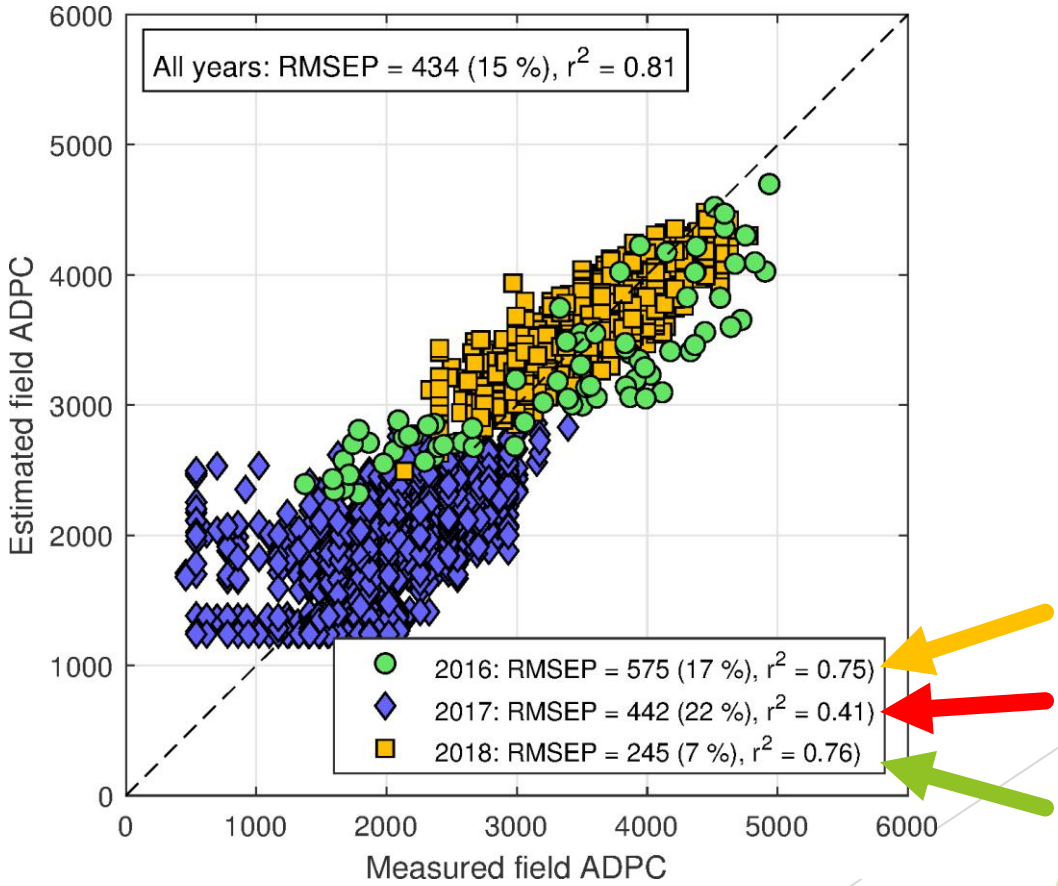


Guidelines for future experiments

- Poor estimation of low scores with UAV multispectral imagery,
- Unlike visual scoring, UAV estimation of ADPC requires sufficiently late measurements with scores of 8-9 for all microplots.



Results: estimating sugar beet resistance (field ADPC)

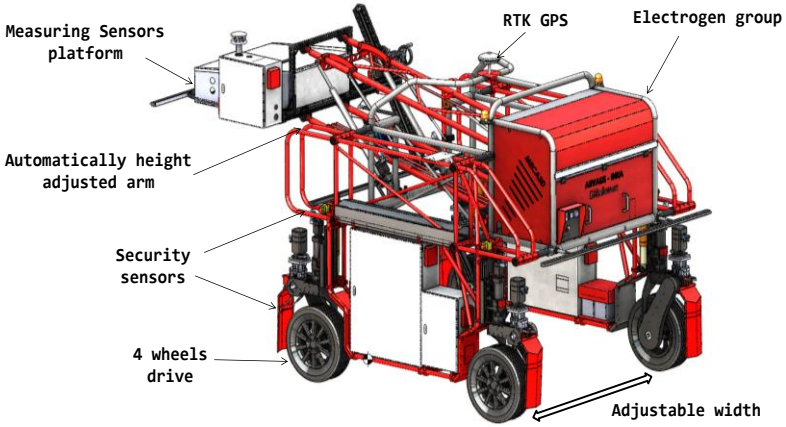


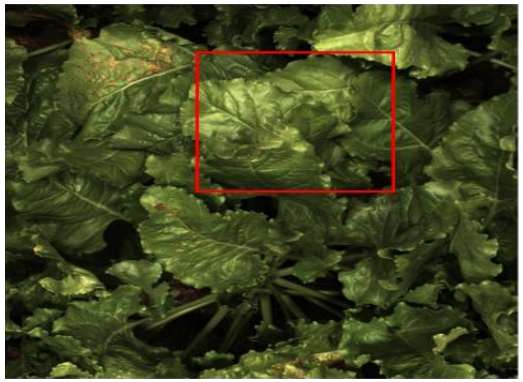
Some conclusions

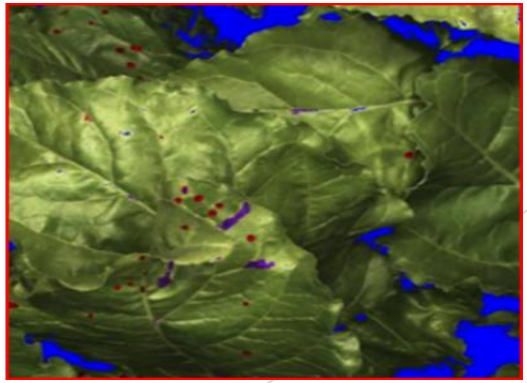
- Possible to estimate instantaneous disease scores from UAV multispectral imagery,
  - High scores > low scores
- Estimated scores used to estimate cultivar resistance to CLS,
- Importance of a proper time coverage for UAV measurements,
  - Problem is not about finding the inflection point, but about finding the dates of scores = 8-9
- Limitation for precision agriculture:
  - Poorly sensitive to low scores (< 5) => needs spatial resolution !
  - How to distinguish between CLS, powdery mildew, natural senescence…?

Some perspectives

- Comparing UAV and UGV; does spatial resolution help ? (paper to come).

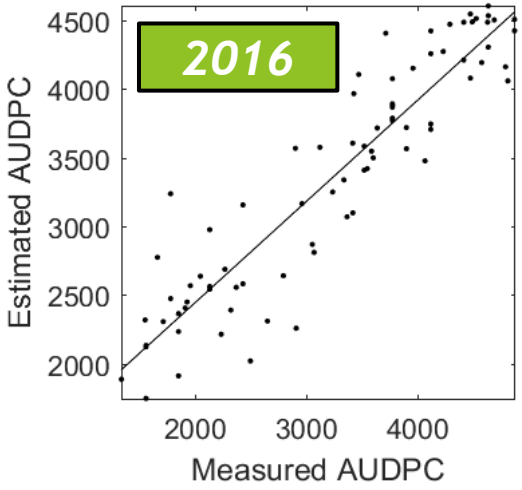


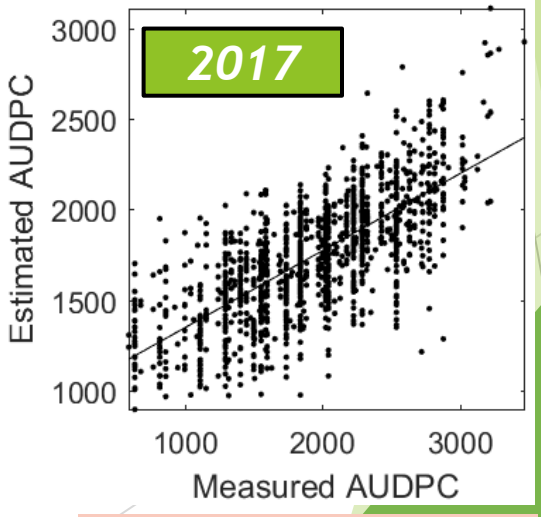




Some perspectives

- Submillimeter-scale UGV RGB images allow the extraction of additionnal useful features, e.g.,
  - Spot density,
  - Spot size.
- Combining both features with GF leads to more accurate estimation of instantaneous scores (especially scores < 5) and ADPC.





UAV: RMSEP = 575
UGV: RMSEP = 300

-48 %

UAV: RMSEP = 442
UGV: RMSEP = 360

-19 %

Thanks for your attention !!