



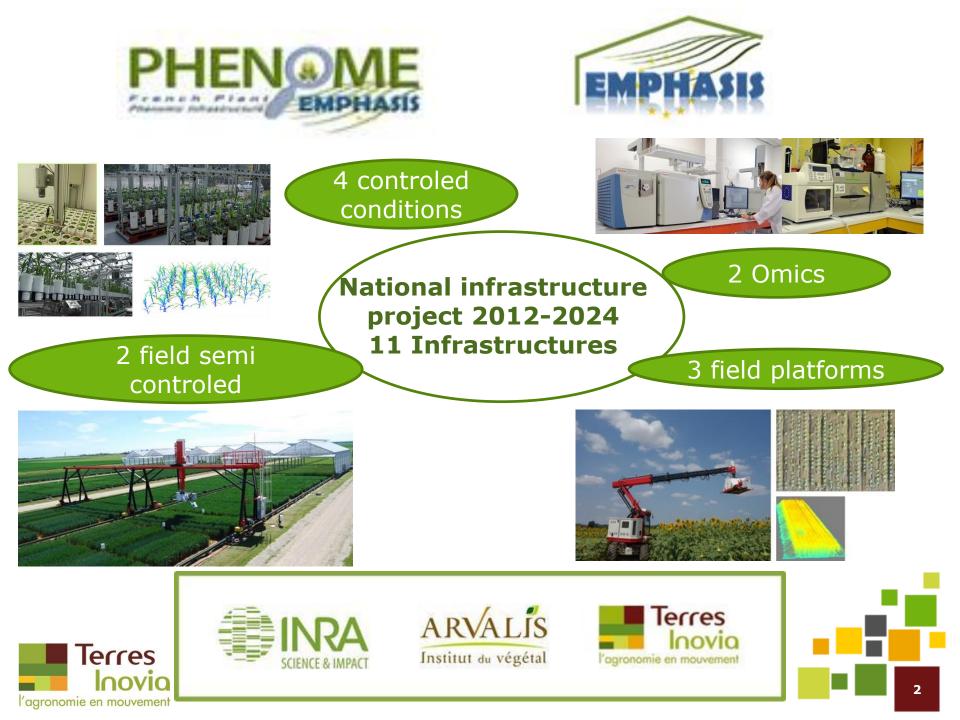
PHENOVIA a field experimental platform in Burgundy for WOSR phenotyping under low chemical inputs.

X.Pinochet, F.Kazemipour-Ricci, P. Marget, V.Deytieux, F.Salvi, L.Thiery, JL.Lucas



French Technical Institut for Oil Crops, pulses, and Hemp





PHENOVIA : one of the field platform near Dijon (Burgundy)

• Located on INRA Farm of Bretenière :



- 120 ha
- 12 ha
- 4 fields
- 1000 µplots/ year







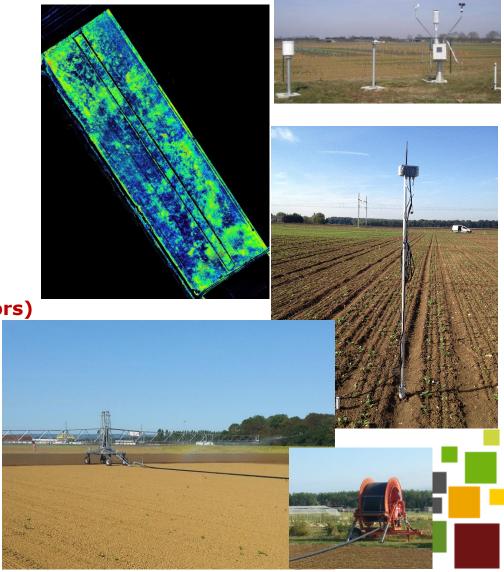


Investments for a performing environment characterization and high throughput phenotyping tools

- A top level Weather station
- Soil heterogeneity maps
 - Resistivity,
 - Soil water content capacities
 - NDVI on non watered spring crop
 - Yield on non watered spring crop
- T°, wetness captors
 - Soil (permanent or movable captors)
 - Canopy
 - Wireless data transmission
- Irrigation facilities available



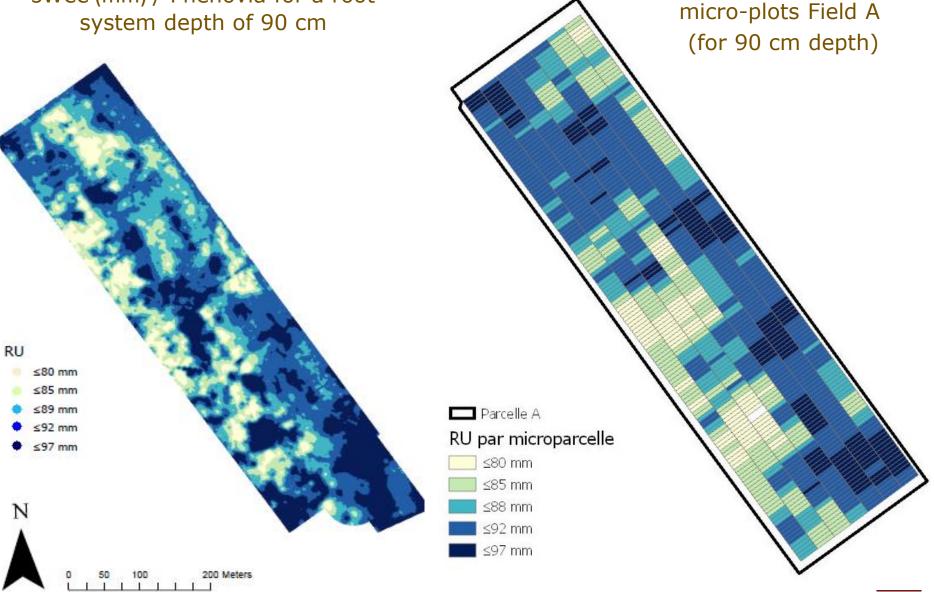




Precise Description of soil water content

capacities - Marc Janin (2018)

SWCC (mm) / Phénovia for a root system depth of 90 cm



SWCC (mm) per



Phénotyping tools tested





SunScan



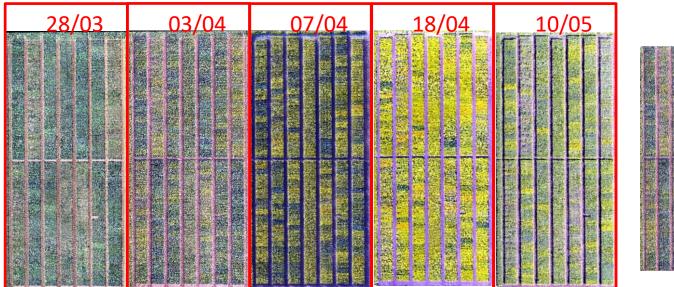


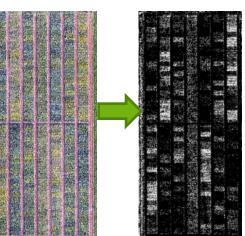


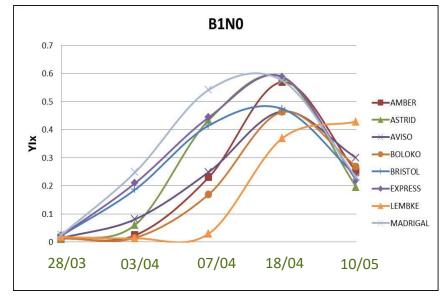


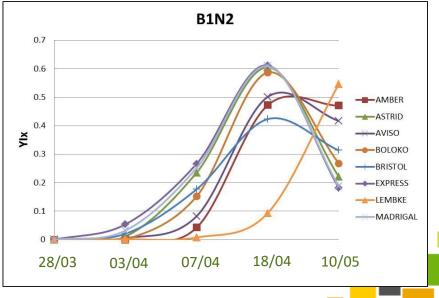
Investments for a performing environment characterization and high throughput phenotyping tools

Crop establishment	Vegetative phase	Phenology
 ✓ Vigour ✓ Speed of Soil covering ✓ Plant density 	 ✓ growth ✓ Biomasse/LAI 	✓ Flowering dynamic
Terres Inovio l'agronomie en mouvement		







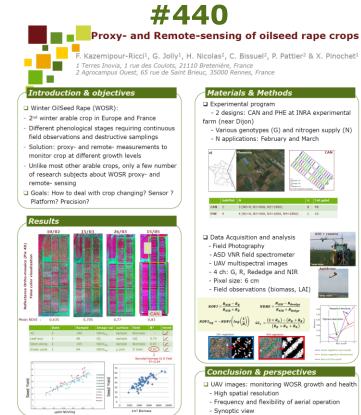






Actually the main challenge is on data storage and processing

Data processing in the framework of RAPSODYN project :



This work has been partly founded by ANR (French Nationa Agency for research) through PHENOME and RAPSODYN projects. This experiment was carried out in Experimental farm of French Agricultural Research Institute (INRA). We would like to thank the experimental teams of INRA and Terres Inovia for field works and also Airinov/Agridrone for UAV images services

- 2 designs: CAN and PHE at INRA experimental
- Various genotypes (G) and nitrogen supply (N) - N applications: February and March



- Field observations (biomass, LAI)

- UAV images: monitoring WOSR growth and health
- Frequency and flexibility of aerial operation
- → Better consideration of field heterogeneity Next step: estimation of agronomic variables
- Multi-vear and multi-site data
- Data from other Rapsodyn partners Statistical modeling and evaluation



Phenotyping and remote sensing: applying machine learning



INRA

MALIK J. 19, TA. PHAN 19, P. PATTIER 19, F. KAZEMIPOUR-RICCI (9, H. NICOLAS (9), F. HUSSON 19, P. PICHELIN (2), A. LAPERCHE⁽⁴⁾, X. PINOCHET⁽³⁾, and BISSUEL-BÉLAYGUE C. ⁽⁴⁾. Christine.Bissuel@agrocampus-ouest.fr

ROUND: High through put phenotyping of plant growth and health indicators using non-destructive tools has great interest to characterize crop canopies for agronomic and breeding applications. Green Leaf Area Index (GLAI) and biomass quantifications with non-destructive remote sensing methods are increasingly preferred, with satellite or drone-based multispectral images for their rapidity and inexpensiveness, but still difficult to calibrate for winter oil seed rape. Other methods, e.g. semi-empirical methods based on vegetation indices and radiative method transfer model inversion method, have shown the value of remote sensing for estimating biophysical variables [1] and have been calibrated on rapeseed [2].

ES: With the rise of computer power, apply machine learning (ML) algorithms [3,4] to provide a robust and ready-to-deploy model to predict green leaf area index (GLAI) of winter oil seed rape (WOSR) canopies using UAV images performed in multi-year context. Take into account more predictors, e.g. quantiles to preserve across

- pixel variability of all spectral bands instead of vegetation indices values. Train and compare well known ML algorithms,
- · Evaluate the performances of the best model on a set of new UAV images to discriminate the GLAI kinetics of several genotypes (G), under contrasting nitrogen conditions (N), in a field contex

Herve, Nicolas@agrocampus-ouest.fr



N1 (0) & N2 (80) N1 (0) & N2 (80)

We used 10 data sets of observed GLAI values, collected during vegetative period and assessed by planimeter LICOR (1m2 /sampling plot) vs drone multispectral images (10m² /UAVplot) (Fig. 1 & 2).

ML, variables, train & validation: : 8 ML algorithms are tested (support vector machine (SVM). Gaussian process (GP), generalized additive model (Gam), random forest (RF), ...). A double cross-validation is performed. First of all, the calibration of each model is done by cross-validation to determine the parameters to be used. The comparison of the best models of each method is carried out on a second independent data set containing genotypes different from those used to calibrate the model

SULTS: . Performance of 8 ML algorithms: the best model obtained to predict GLAI presented a RMSE=0.23 (Fig.3), being more accurate than the best vegetation-indexbased regression model (RMSE=0.28). Reflectances are more explanatory than vegetation indices, and the NIR band is the most contributor to the GLAI estimate.

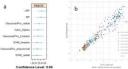


Fig. 3. a) RMSE of the different ML models. b) Measured vs predicted GLAI value (SVM, radial model, median & QS, Q25, Q75, Q75) for 3 dates x 2 years, during 3 period of vegetative growth for represend (automus, spring before or after fertilisation. H) or N2and vs predicted GLAI values

SIONS & PERSPECTIVES: • UAV images provide suitable data & application of Machine Learning, coupled with more statistical measures, improves GLAI modeling accuracy and would enable frequent, exhaustive and non-destructive predictions of the overall growth dynamics on both small (m²) and large (ha) areas. • Furthermore, deep learning algorithms would be interesting for other high trough put phenotyping: as fractional vegetation cover, crop biomass. Also, its ability of pattern recognition could distinguish organ types, plant health status, discriminate canopy architectures or screen genotypi variability for various traits. Further studies will focus on the validation of prediction model for new datasets for new genotypes.





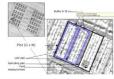
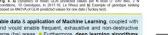


Fig 2 Sectors for a ata from UAV images: reflectance NDVIlog, MCARI, MCARI2, ation indices (NDVI, NI edge, NDRE) Each UAV plo

 Agronomic applications: GLAI models allow to establish a dynamic of crop growth and discriminate N and G effects and to investigate G×N interaction more precisely and by providing additional information to that obtained by field observations

••••





9



loovia

lerres

Terres

l'aaronomie en mouvement





> Phenovia :

Since 2012...

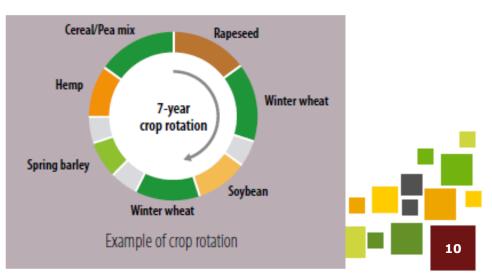


more than 7000 µplots already done mainly for quantitative genetics Oilseed rape, Soybean, Pea

2018 : The farm became the CA-SYS platform : Long term experimental platform on agro-ecology at various scales CA-SYS : *C*o-disigned *A*groecological-*SYS*tem Experiment

- Multi-performant Agro- Systems
- Maximizing biological processes;
- Strong reduction of pesticides
- Longer rotations .





PHENOVIA takes the opportunity to focus on low chemical inputs plant/canopy phenotyping

- > Plant nutrition / fertilization / Biostimulant expérimentations
- > IPM strategies / Biocontrol of bioagressors tests
- > Variety testing under low chemical inputs
- The platform is open to collaboration
 - We would be pleased to welcome your expérimentations
 - Open to collaborative projects
 - Ready to discuss your protocols

contact us x.pinochet@terresinovia.fr f.kazemipour@terresinovia.fr pascal.marget@inra.fr





Many thanks for your attention









- D. DeFornel G. Jolly F.Kazemipour J-L. Lucas J. Pacquetet X. Pinochet F. Salvi
- L. Thiery



C. Bissuel A.Laperche H. Nicolas P. Pattier P. Pichelin



