Derivation of global vegetation products from European sensors

Marie Weiss, EMMAH, UMT CAPTE

March 2019

Outline

- Introduction
  - The Institute : INRA
  - The lab: EMMAH
  - The Team: CAPTE
- Developping Medium Resolution Products
  - Requirements
  - Evolution of algorithms based on machine learning
  - Lessons Learned
- Developping High Resolution Products
  - 1D vs 3D RTM inversion
  - Ground-based machine learning vs RTM inversion
  - Mixing ground based and satellite information

French National Institute of Agronomic Research - INRA

Objectives : meet the challenges of agricultural research

Ensure global food and nutritional security in a context of transitions: climatic, energetic, demographic

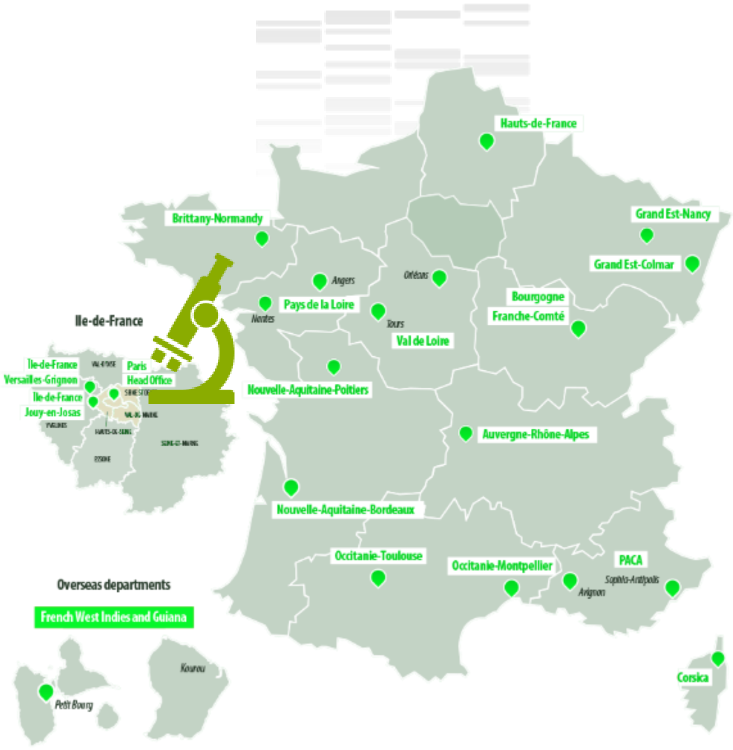
Food & nutrition

Agriculture

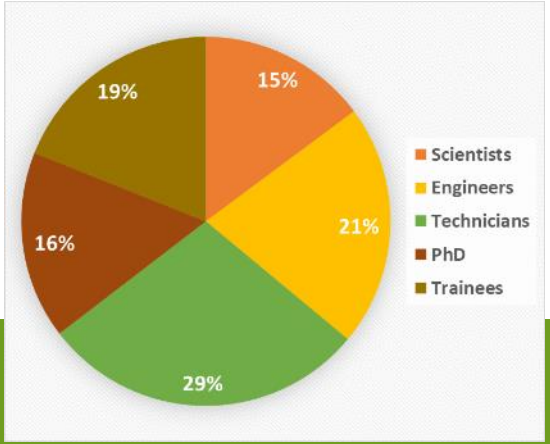
Environment

- **Develop agricultural systems that are:**
  - Competitive and respectful of the environment, regional differences and natural resources;
  - Adapted to human dietary needs and to new uses of agricultural products.
- **Through international and multidisciplinary scientific research of excellence and by disseminating results to all stakeholders (open science)**

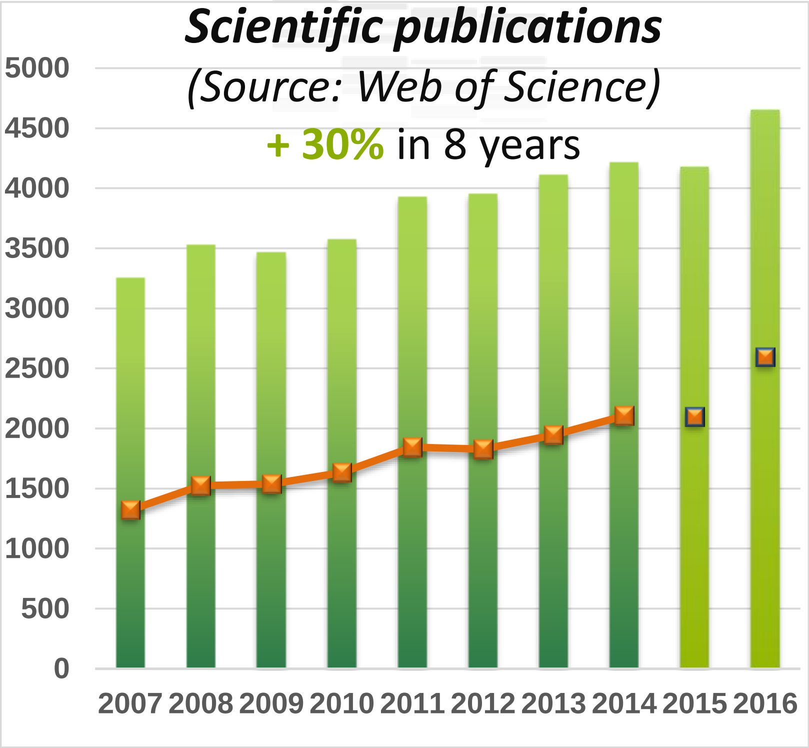
INRA Today



- **17 centres, 13 research departments**
  http://www.inra.fr/en/
- **184 research units, 45 Experimental units**
- **≈13 500 staff (60% permanent)**



INRA: producing, knowledge & innovation



38 companies created based on INRA results (1999-2016)

318 new research contracts (2015)

1291 licences on patents, know-how, software & databases, plant variety rights (2015)

EMMAH: UNIT AT INRA

Mediterranean Environment and Modelling of Agroecosystems

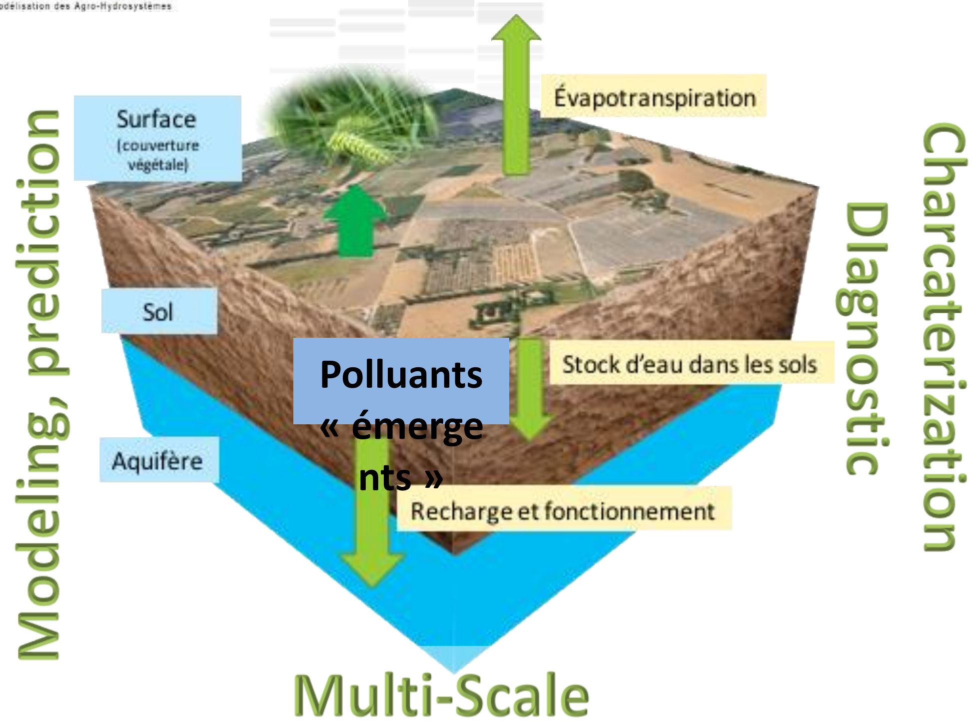
EmmaH
UMR 1114 INRA-UAPV
Environnement Méditerranéen et Modélisation des Agro-Hydrosystèmes

- **Joint Lab (INRA+University of Avignon)**

INRA SCIENCE & IMPACT — AVIGNON UNIVERSITÉ

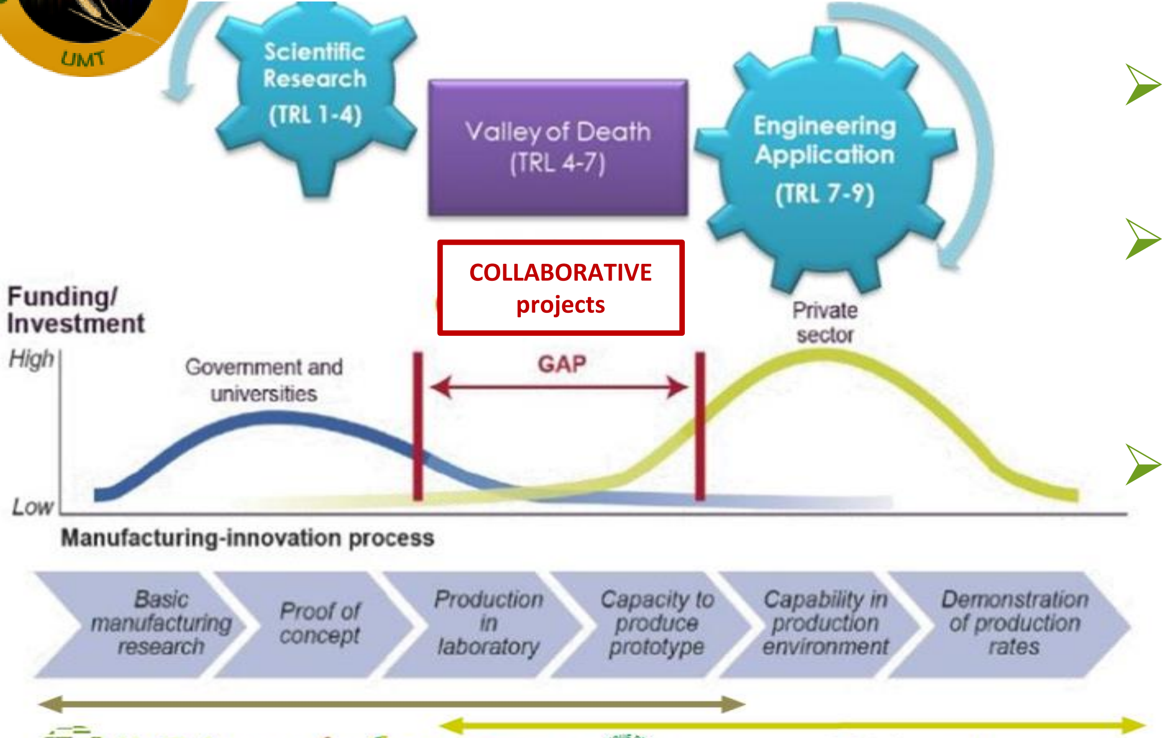
- **58 permanent staff (60%), 5 teams**

EMMAH: context & objectives



- Aquifers – Vulnerability
- Landscape spatial representation of (water budget, production)
- Coupling & Modeling (biology & physics, human & social sciences), multiscale integrative approach
- Sensors, Image analyses, Decision Support Tools

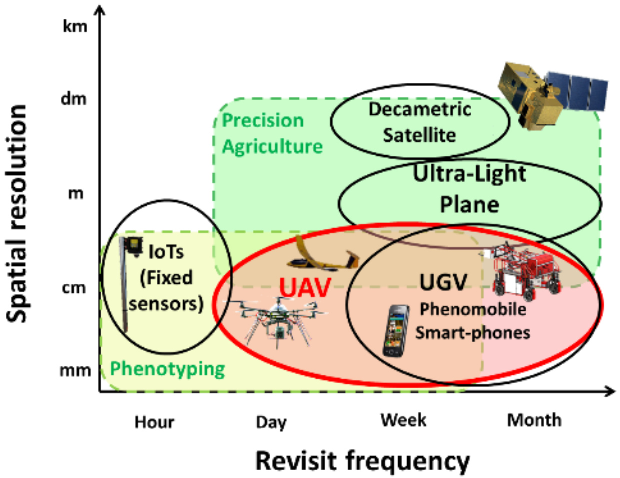
CAPTE (CAPteurs et Teledetection) Since 2012



- Research Institute
  - INRA
- Technical institutes
  - ARVALIS
  - ITB, Terres Innovia, Acta
- Startup company
  - HIPHEN (2014)

CAPTE (CAPteurs et Teledetection

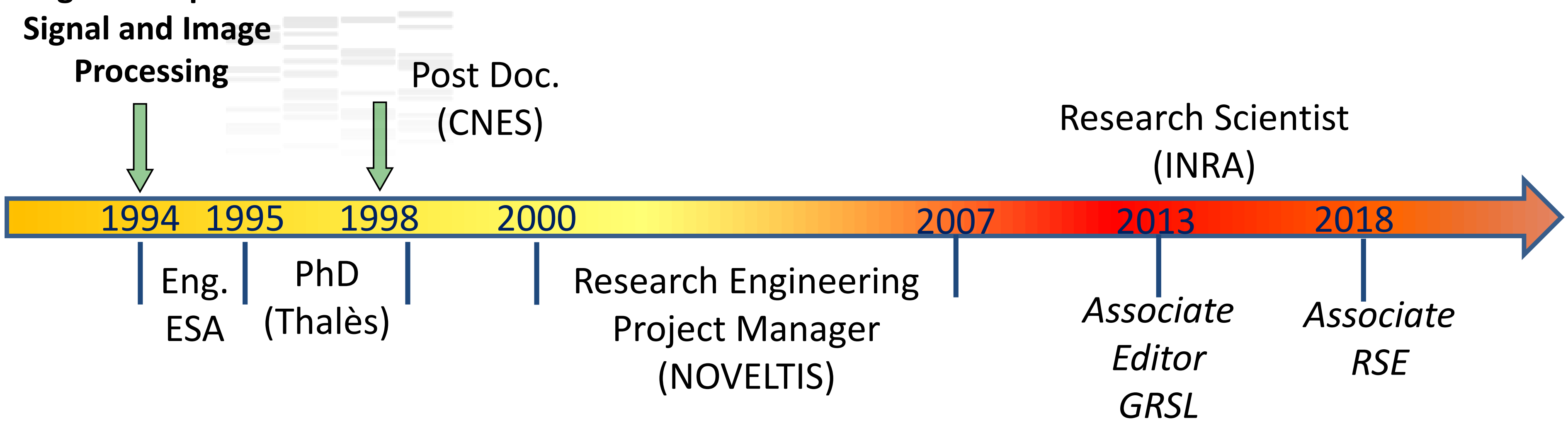
Development of crop characterization methods



- Phenotyping
- Support for decision making
- Resource management at the territory scale

Sensors/Vectors → Operating Mode → Analysis → Services

Who Am I?



Canopy biophysical variable estimation from multi-scale remote sensing

- Radiative Transfer Modelling, Coupling with Crop functioning models
- Model Inversion (Machine learning)
- Validation
- Software development

Outline

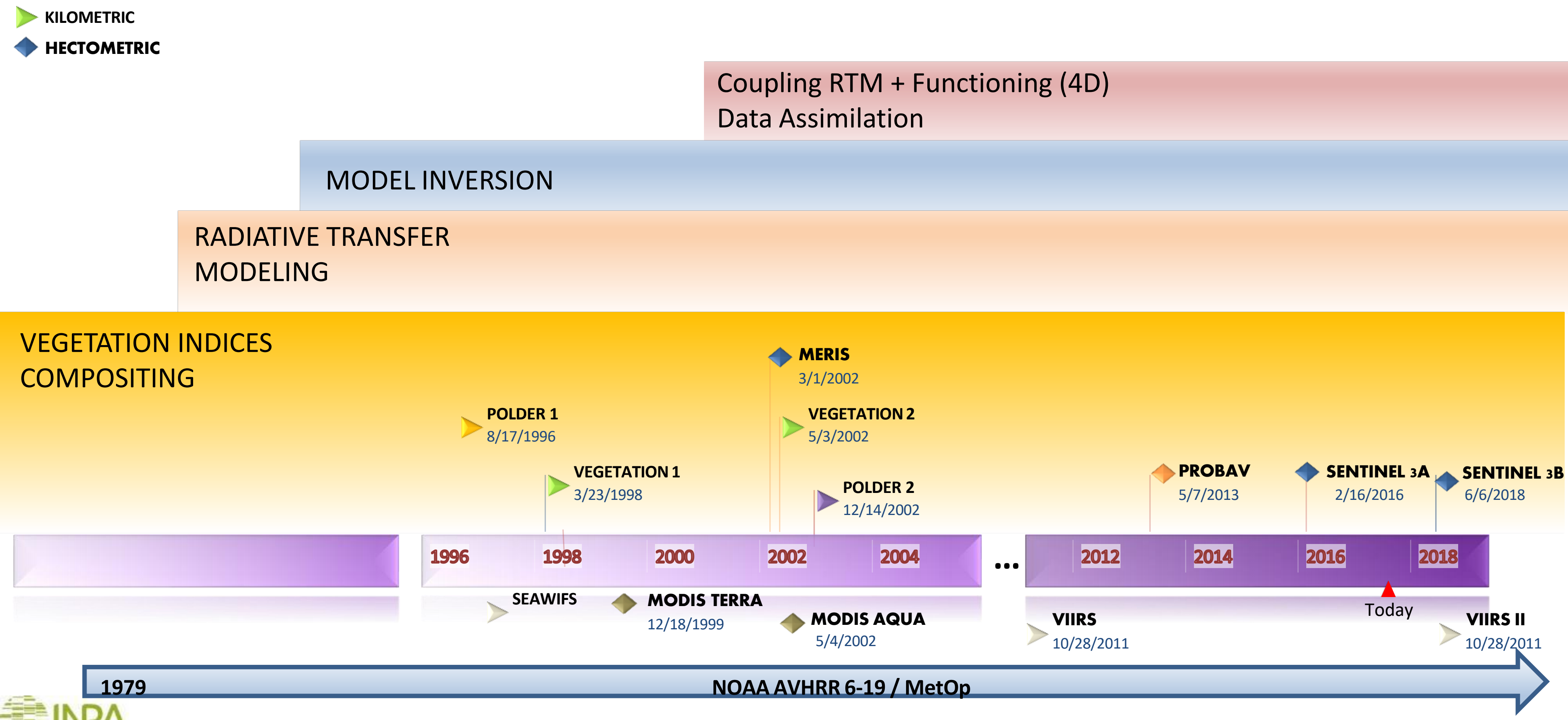
- Introduction
  - The Institute : INRA
  - The lab: EMMAH
  - The Team: CAPTE
- Developping Medium Resolution Products
  - Requirements
  - Evolution of algorithms based on machine learning
  - Lessons Learned
- Developping High Resolution Products
  - 1D vs 3D RTM inversion
  - Ground-based machine learning vs RTM inversion
  - Mixing ground based and satellite information

Derivation of global vegetation products from European medium resolution sensors

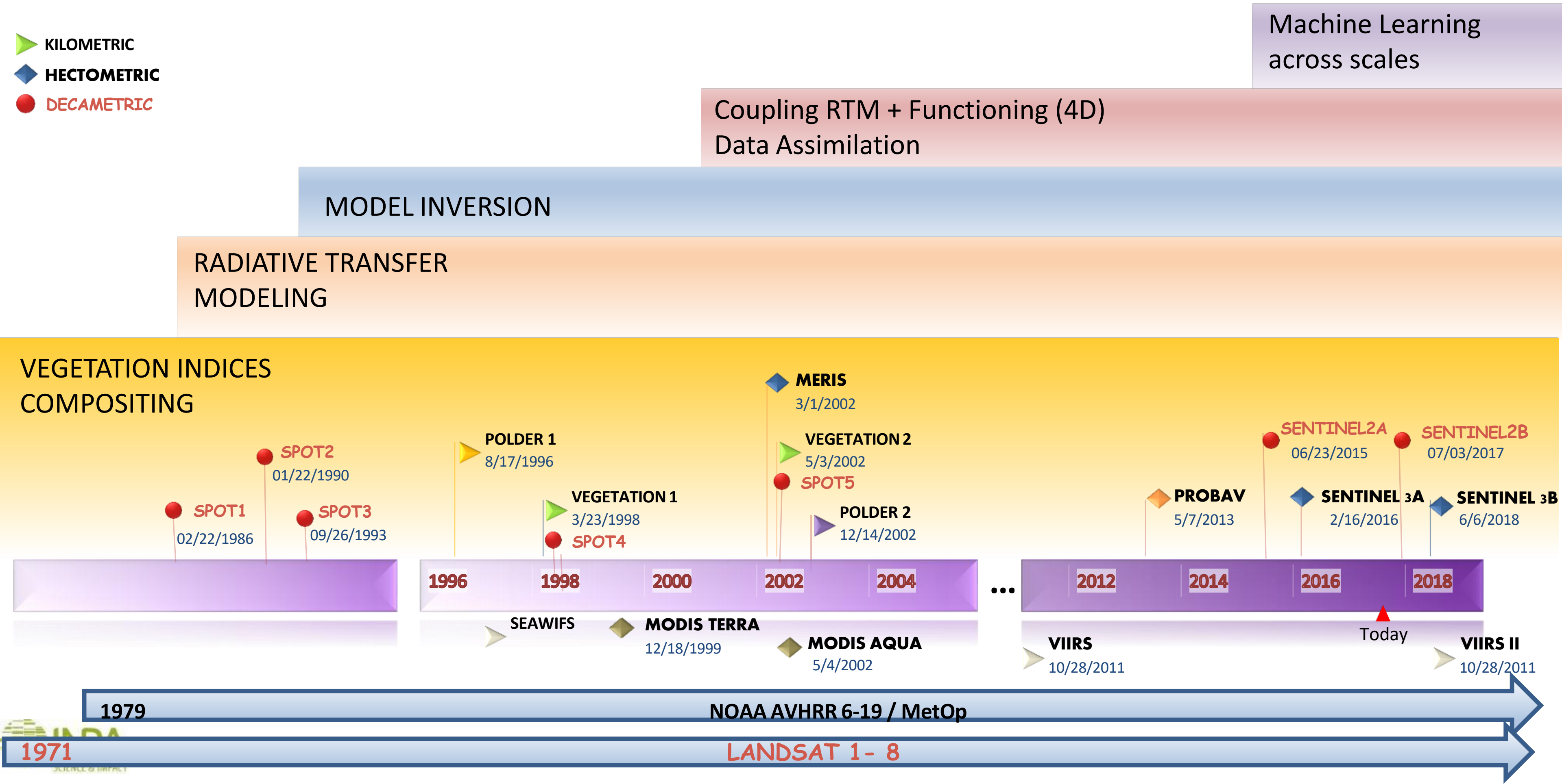
Marie Weiss, UMT CAPTE, EMMAH

March, 2019

MEDIUM RESOLUTION: GLOBAL COVERAGE – HIGH TEMPORAL FREQUENCY



MEDIUM RESOLUTION: GLOBAL COVERAGE – HIGH TEMPORAL FREQUENCY



REQUIREMENTS FOR GLOBAL MEDIUM RESOLUTION PRODUCTS

COPERNICUS Initiative (ex: GMES):

- Provide reliable information to European users in charge of public missions, relying primarily on space and in-situ observations
- Establish a European observation capacity

Key characteristic

- Long term and operational: not a one-off scientific demonstration, but a reliable, sustainable & trustworthy operational set of services


Land


Marine


Atmosphere


Emergency


Security


Climate Change

Meet the user needs

- Accuracy : Quality Flags / Confidence Intervals / Validation
- Continuity & Consistency : through time & between sensors
- No Gap / Back-up Algorithms

USERS ALWAYS ASSOCIATED TO THE PRODUCT DEVELOPMENT

Meet technical requirements

- Operational context + Near Real Time
- Easy access to the community (ESA does not deliver Level2 & 3 data)

TECHNICAL CENTERS (VITO/CNES) INVOLVED IN PROJECTS

COPERNICUS PORT FOLIO

https://land.copernicus.eu/global/products/lai

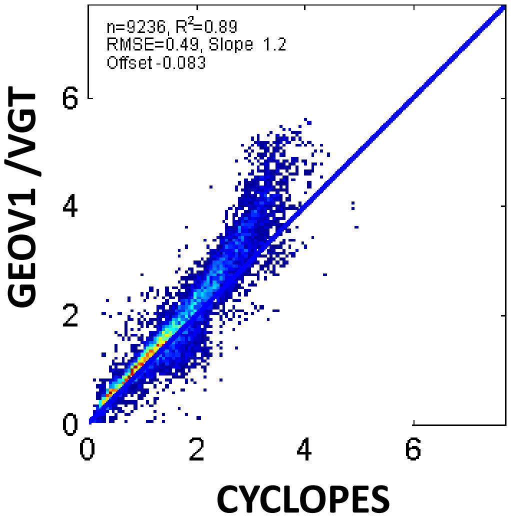
BIOPHYSICAL ALGORITHMS: MACHINE LEARNING

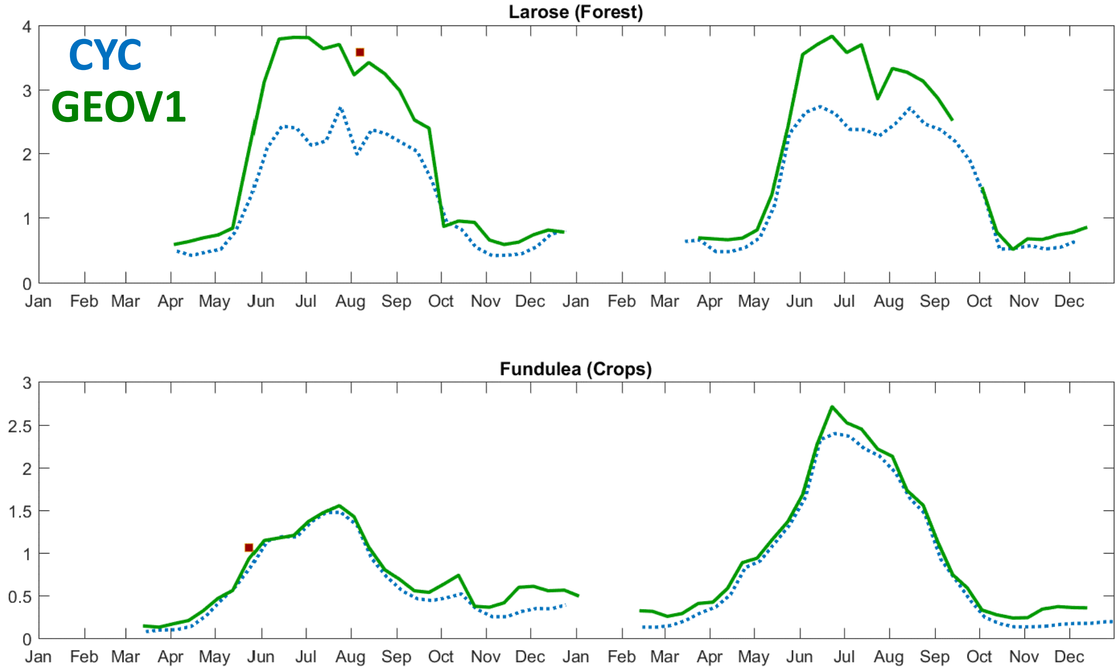
- Principle:
  - calibrate non linear relationships between inputs (reflectance) and outputs (biophysical variable)
- Machine learning:
  - currently neural networks
  - Generic algorithm
- Setting up of the learning dataset is crucial: representativeness
  - Vegetation types, development stages & environmental conditions
  - Radiometric Noise
  - Observational configuration

COPERNICUS LAI/FAPAR/FCOVER PRODUCTS

	Name	Sensors	Resol.	Learning	Input	Temporal compositing			Improvement
						Smoothing	Gap Fil.	NRT	
	CYCLOPES	VGT1	1km	Sim. Generic	TOC Red/NIR/ SWIR	Ref. Weighted 30 days	✗	✗	
	GEOV1	VGT1/VGT2 /PROBAV	1km	Meas. Generic	TOC Red/NIR/ SWIR	Ref. Weighted 30 days	✗	✗	Accuracy (High LAI)
	GEOV2	VGT1/VGT2	1km	Meas. Generic	TOA Red/NIR/ SWIR	Product 30 days	✗	✗ 1-2 day lag	Temporal consistency
	GEOV3 1km	VGT1/VGT2 /PROBAV	1km	Meas. EBF/Non EBF	TOC RED/NIR Red/NIR/ SWIR	Product Variable temp window	Climato	✓	NRT, temporal consistency, completeness
	GEOV3 300m	PROBAV	300m	Meas. EBF/Non EBF	TOC Red/NIR	Product Variable temp window	Data	✓	NRT, spatial resolution

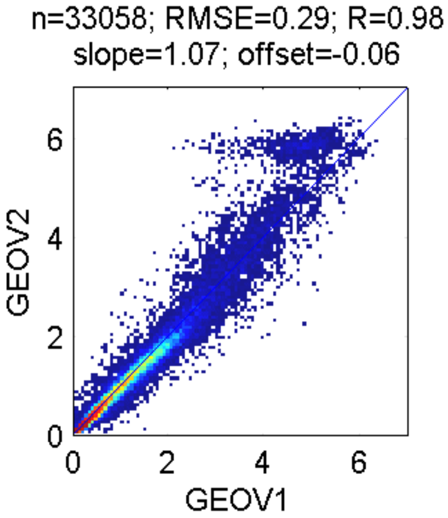
RESULTS : PRODUCT COMPARISON CYCLOPES vs GEOV1 ACCURACY

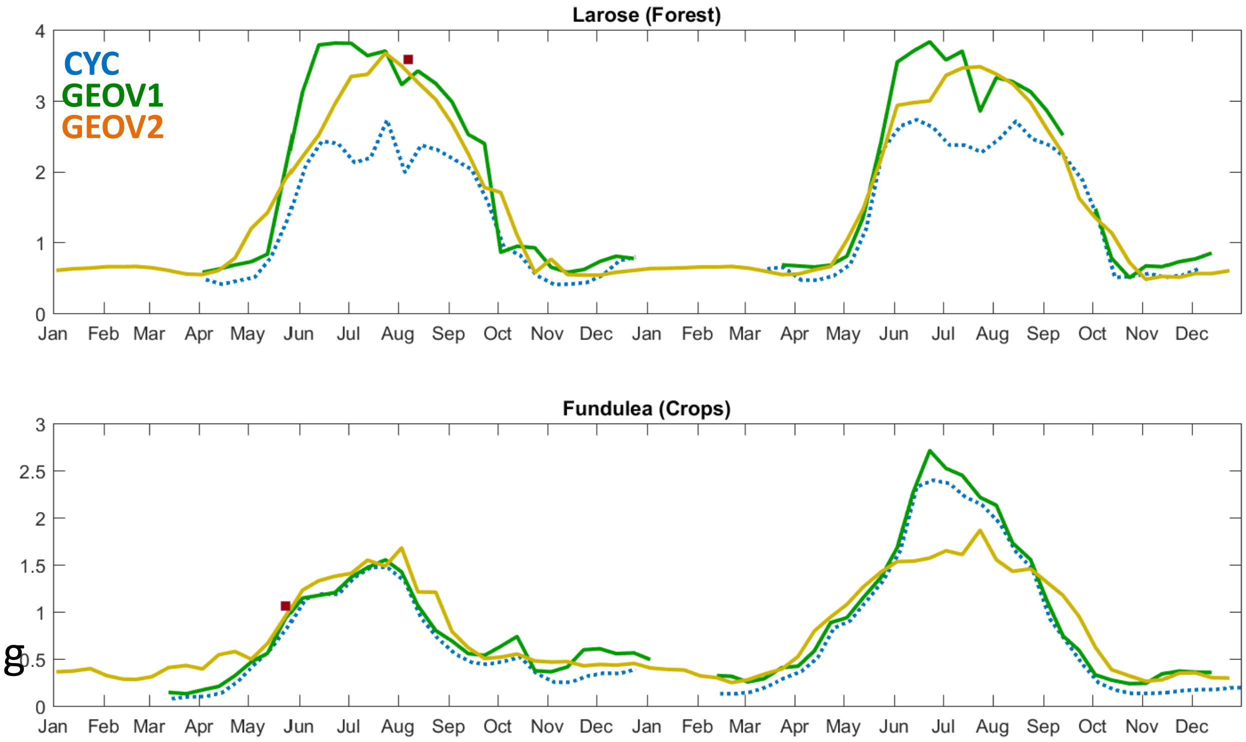




- GEOV1/CYC =>Learning:
  - GEOV1= FUSE MOD+CYC
  - CYCLOPES = PROSAIL

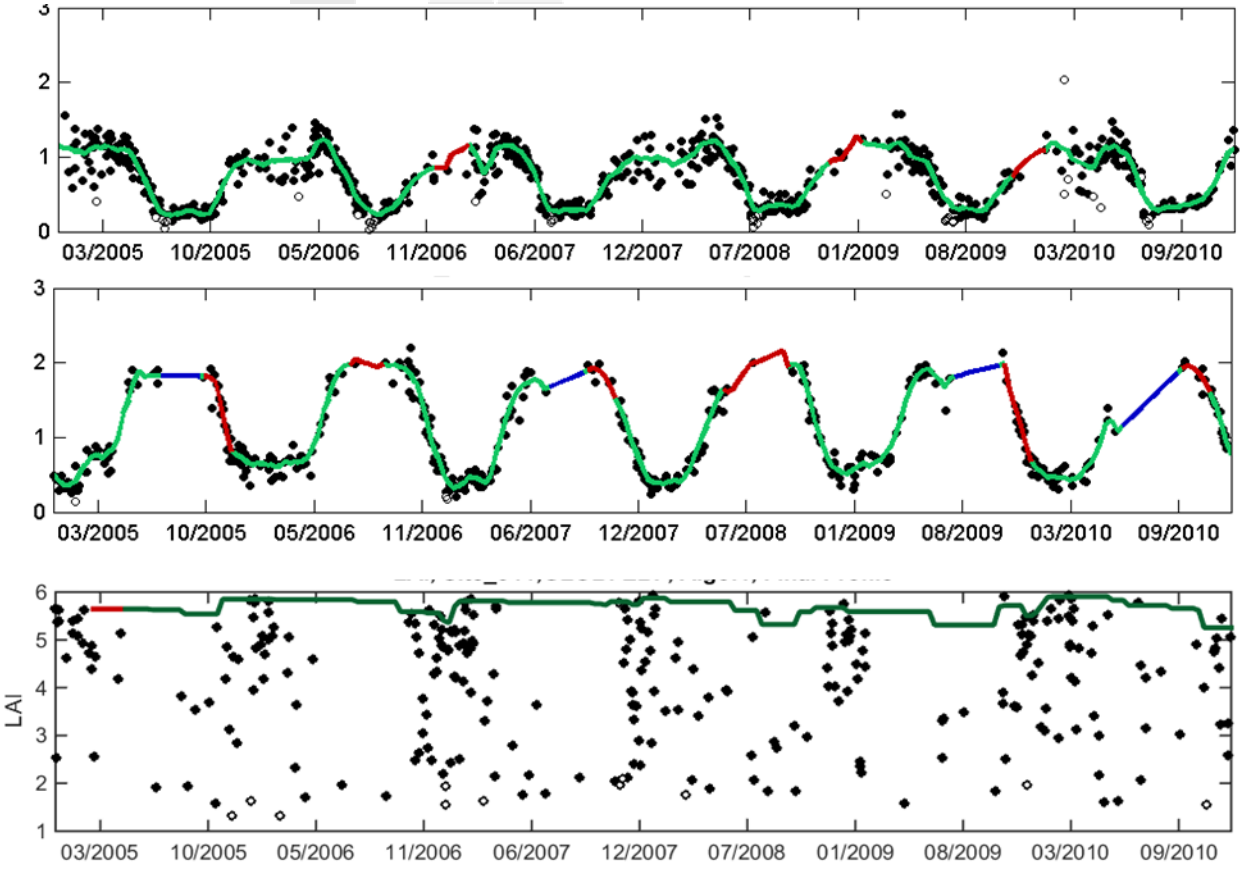
RESULTS : PRODUCT COMPARISON GEOV2 vs GEOV1





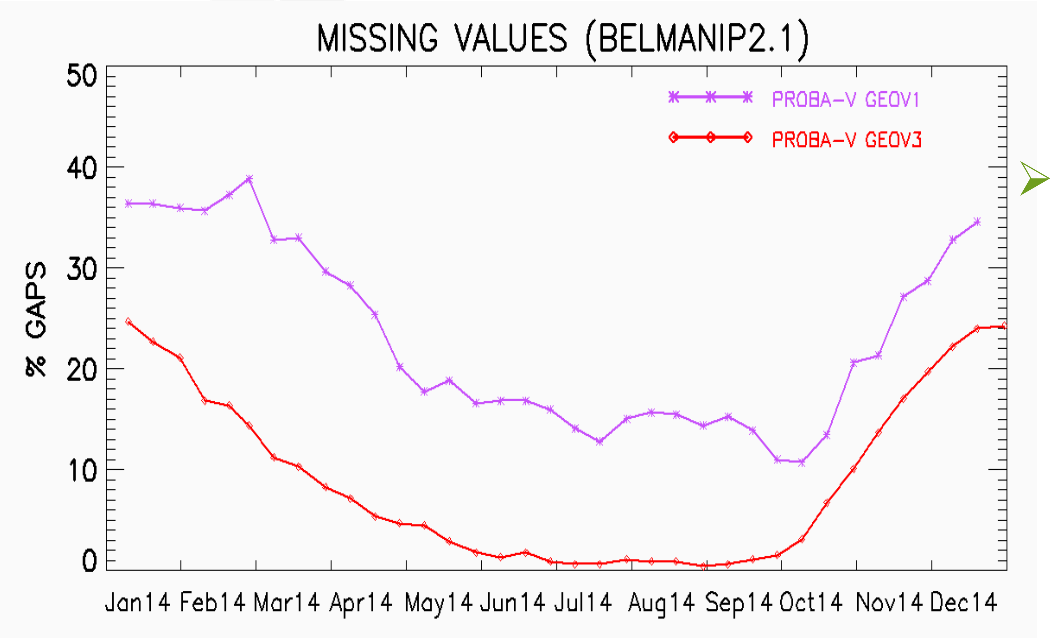
- GEOV2/GEOV1:
  - Temporal compositing at product level
  - TOA vs TOC

RESULTS : GEOV3 – 1km



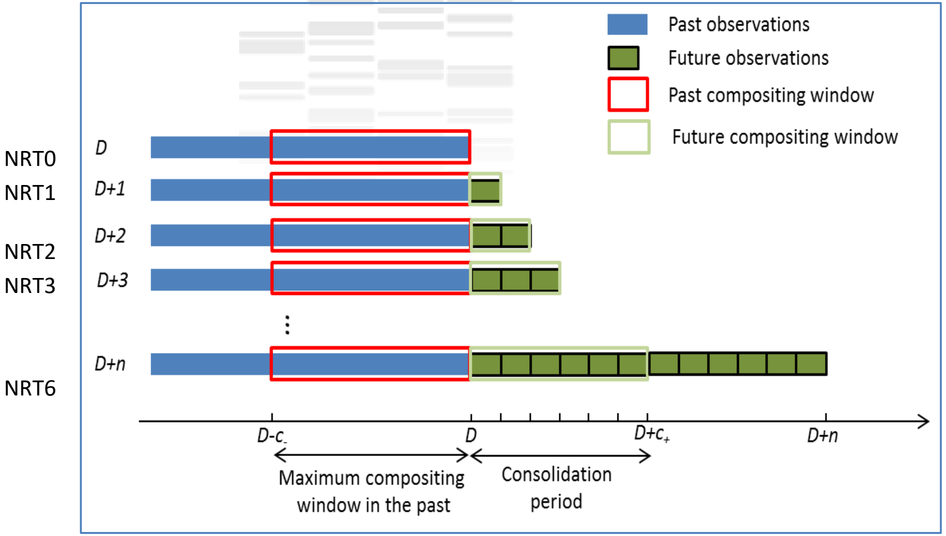
- GEOV3-1km/GEOV2:
  - Gap filling
  - Climatology based

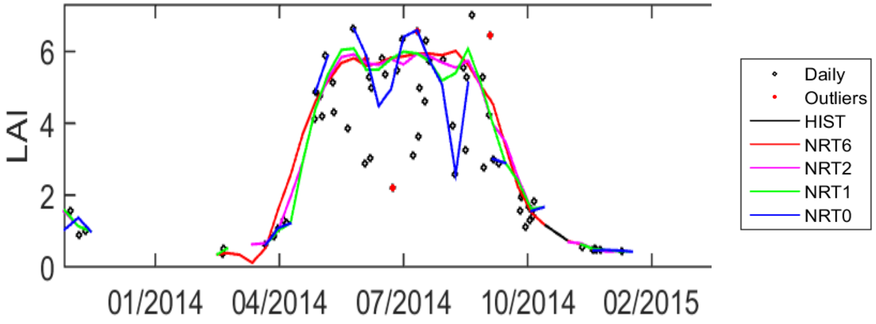
RESULTS – GEOV3 – 300m

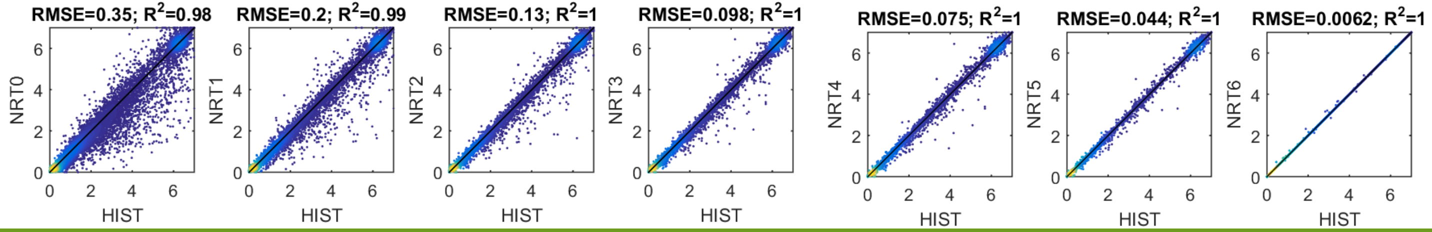


- GEOV3-300m/GEOV3-1km
  - No climatology
  - Polynomial fitting in GEOV3 reduce the %gaps
  - Winter period: gaps are too large because of snow & bad weather

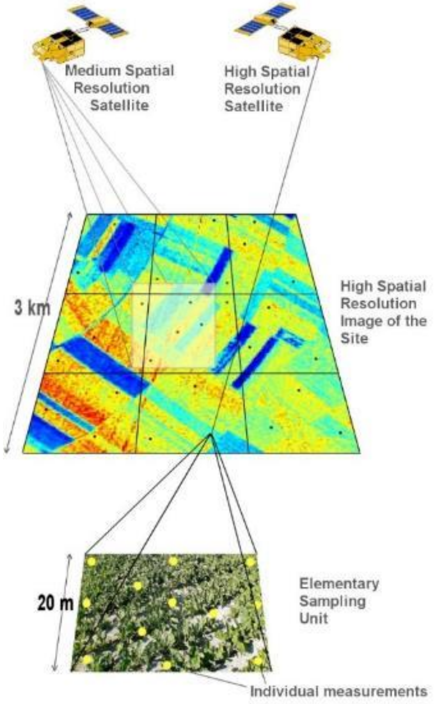
RESULTS – GEOV3 - NEAR REAL TIME







…. AND VALIDATION



- 2000-2005:
  - 73 campaigns
  - Similar to BigFoot/MODLAND
  - Main limitations: spatial sampling vs man power
  - Use of HR data to spatially interpolate local measurements
- 2006:
  - Ground measurements: not enough
  - Product inter-comparison database + machine learning
- 2011:
  - Web platform for product intercomparison
  - BELMANIP2
- 2013-2015:
  - 20 ground campaigns

WHAT DID WE LEARN: biophysical algorithm

- Cloud mask accuracy
- TOC/TOA reflectance as inputs
  - Very good performances achieved with TOA as inputs but requires a larger training dataset
- Class - Specific processing
  - EBF: can be identified easily and should be processed separately
    - Cloud occurrence
    - Temporal course
  - Other vegetation classes?
    - Dependence on map classification (update frequency? Mis-classification?)
- Machine learning
  - Use of actual satellite data is better but limited by the availability of ground data (currently MODIS+CYCLOPES fused products)
- Effective/True LAI
- Ground truth at medium resolution
  - Limited by man power
  - PSF of medium resolution instruments can not be neglected in heterogeneous conditions

WHAT DID WE LEARN : temporal aspect is fundamental

- Temporal consistency
  - Compositing at the product level : better compromise between the temporal smoothness and the data fit
  - Adaptive temporal window (function of amount of available data)
- Gap filling
  - a priori information provides better results than mathematical fitting
  - Use of climatology
    - Too long period masks possible recent evolution
    - Too short period more sensitive to atypical previous years
  - Polynomial fit
    - Sensitive to noise
- Near Real Time :
  - Not adequate at the very beginning of growing or senescent phase
  - Projection is highly dependent on the amount of available data in the previous temporal window

Many thanks to all my collaborators & partners

F. Baret

A.Verger
F. Camacho
R. Lacaze
B. Smets
K. Pavageau
C. Bacour
S. Garrigues

M. Leroy
P. Bicheron
B. Berthelot
P. Rossello
H. Eerens
T. Block
B. Scholze

R. Myneni
Y. Knyazikhin
B. Tan
W. Yang
A. Pragnère
B. Combal
O. Hautecoeur

V. Bruniquel
O. Hagolle
C. Di Bella
M.E.Beget
D. Raymaekers
H. Fang
J. Demarty
E. Fillol

F. Jacob
P. Pacholcyzk
H. Makhmara
G. Duveiller
P. Defourny
M. Claverie
V.Demarez

S. Buis
R. Lercerf
S. Kandasamy
E. Vermote
W. Li
D. Allard
C. Lattore …
…

Outline

- Introduction
  - The Institute : INRA
  - The lab: EMMAH
  - The Team: CAPTE
- Developping Medium Resolution Products
  - Requirements
  - Evolution of algorithms based on machine learning
  - Lessons Learned
- Developping High Resolution Products
  - 1D vs 3D RTM inversion
  - Ground-based machine learning vs RTM inversion
  - Mixing ground based and satellite information

HIGH RESOLUTION PRODUCTS

- Since june 2015, launch of SENTINEL-2A (=>10 days), 2017, launch of SENTINEL-2B (=>5 days)

Spatial Resolution	Wavelengths
10m	Blue, green, Red, NIR (large)
20m	Red-Edge (3 bands), NIR (narrow)
60m	Blue, Middle Infrared (2 bands)

- Monitoring the Earth at decametric resolution is now possible
  - Focus on agriculture: crop specific algorithms => assimilation for decision support
  - Easier to validate (!)
  - Spatializing ground-based in situ measurements

Operational Products: generic vs crop specific algorithms

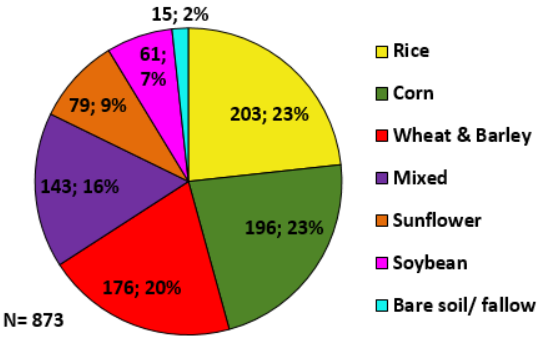
- Collection 1: generic
  - Similar to CYCLOPES algorithm, applicable to any crop type
  - NN trained on PROSAIL
  - Available to the scientific community (SNAP toolbox)
  - Comparison with ground-based algorithm

- Collection 2: crop specific
  - Ground-based Machine learning
  - 4D-RTM inversion with Machine Learning

- Ground validation campaigns

Generic vs specific - ground based

- IMAGINES database
  - LANDSAT8 + Ground: DHP,LAI2200, ACCUPAR (CEOS protocol): GAI, fAPAR, 20 sites
  - PROSAIL Simulations



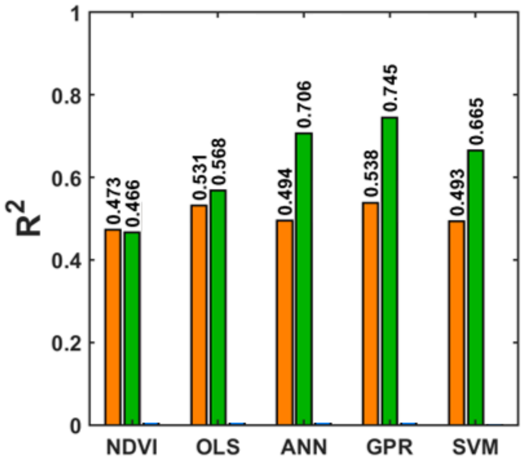
- Several algorithms
  - NDVI
  - Ordinary Least Square
  - Machine Learning: Gaussian Process Regression (GPR)/ Support Vector Machine (SVM)/Neural Networks (NN)
  - Training 2/3, Validation 1/3: statistics computed

PROSAIL: size of the learning database optimized for each method

Camacho et al, 2019. Submitted

Ground Based Generic algorithm: results

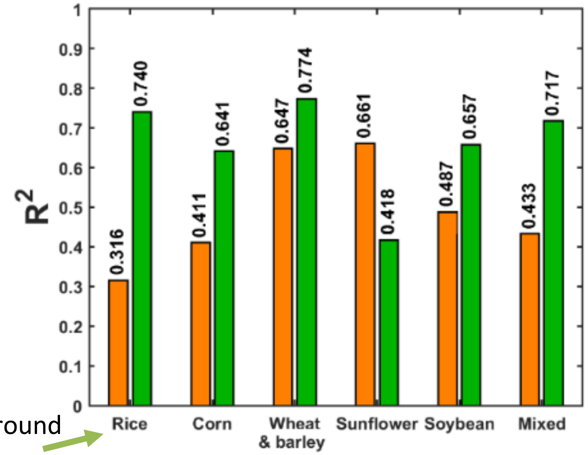
GAI crops



Learning on ground data

Learning on PROSAIL

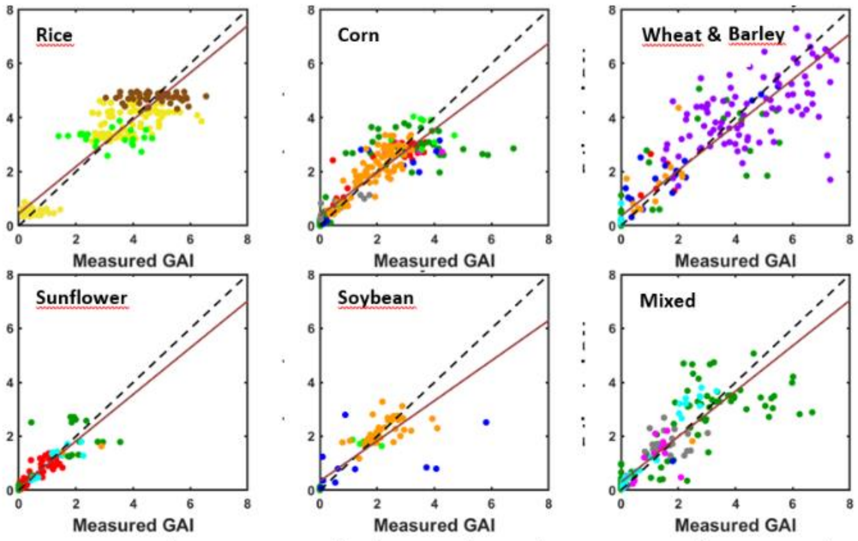
GAI per crop (GPR)



No water background In PROSAIL

- Generic algorithms perform better when trained on ground data
- Larger scattering for high GAI values when trained on simulations
- GPR outperforms the other methods

Crop specific algorithm – Ground based: results



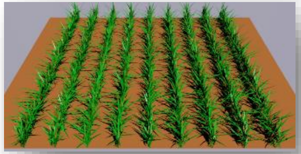
Training	Validation						
	Rice	Corn	Wheat & Barley	Sunflower	Soybean	Mixed	Generic
Rice	**0.79**	1.82	2.46	2.44	2.00	2.14	1.81
Corn	1.56	**0.77**	1.82	0.95	0.78	0.98	1.34
Wheat & Barley	1.53	1.59	1.19	1.06	1.73	1.45	1.50
Sunflower	2.08	1.15	2.38	**0.45**	0.85	1.34	1.74
Soybean	2.53	1.35	2.06	1.17	0.80	1.53	1.88
Mixed	1.82	0.87	2.18	0.89	0.77	0.89	1.52
Generic	0.82	0.83	**1.16**	0.61	**0.71**	**0.83**	**0.91**

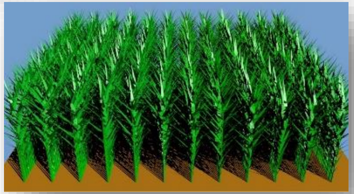
- Learning on one crop, applying to another significantly degrades the results
- Importance of having a good land cover map!

- Ground specific approaches slightly better
- Almost no bias
- Rice: intra-site variability not well captured

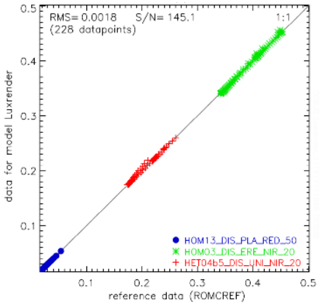
Specific – RTM simulations: Models

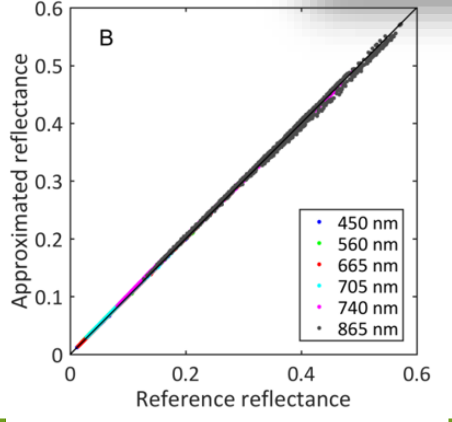
- 4D Mock-ups (3D architecture growth)
  - ADEL-WHEAT
  - Maize (Lopez-Lozano et al, 2007)



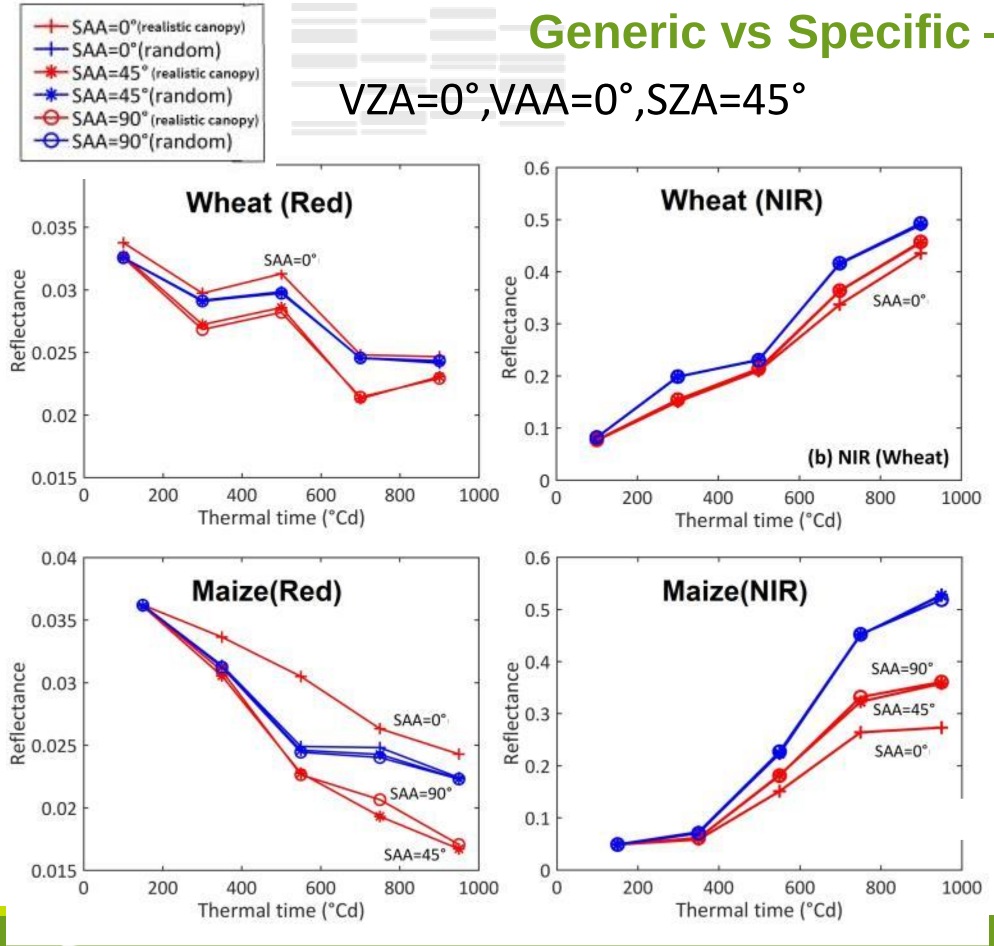


- RTM simulations
  - PROSPECT: optical properties
  - LuxCoreRender: ray tracing
  - Validation with ROMC
  - Fasten computation:
    - Decoupling soil/vegetation layers
    - Use the total absorption coefficient





Generic vs Specific – 1D vs 3D assumption

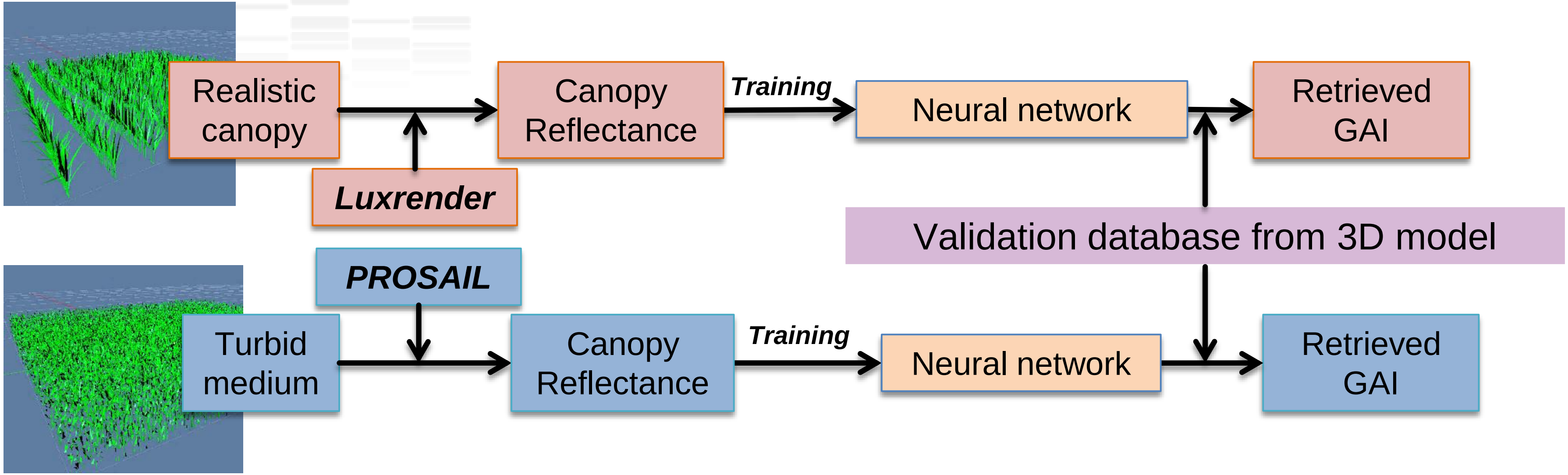


- 3D: leaves only
- 1D: same as 3D but leaves randomly oriented

- 1D: independent azimuth
  3D: high effects in row direction
- Red: influence of soil higher 3D
  NIR: 1D>3D (multiple scattering)
- Wheat is more turbid than maize for late stage

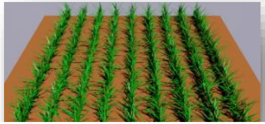
Generic vs Specific – Inverse, 1D and 3D RTM simulations

- 3DRTM and 1DRTM simulations

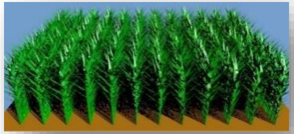


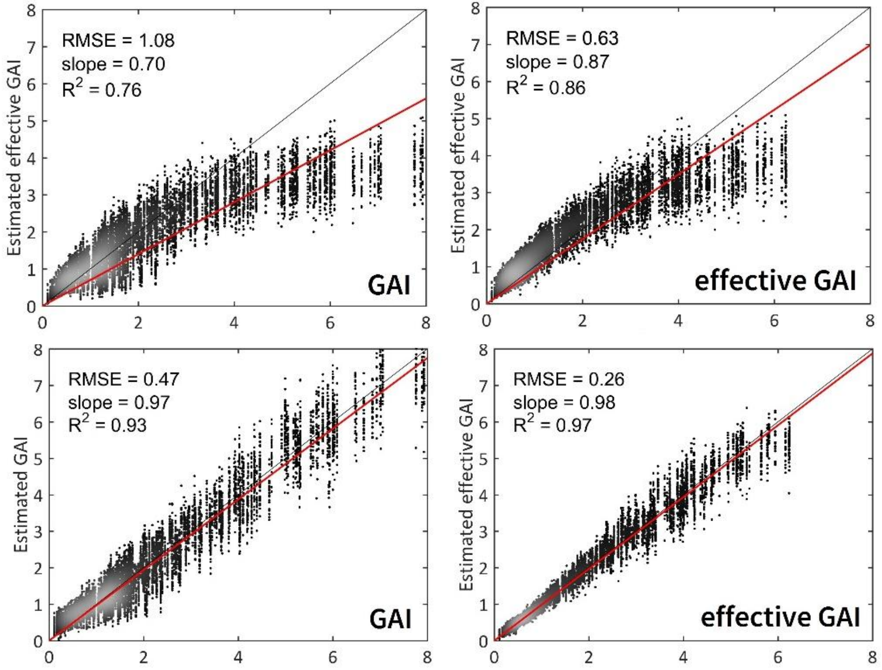
- 33750 cases for each species/observation geometry
- 70% learning, 30% validation, Neural Networks

Generic vs Specific – GAI: comparison on simulations



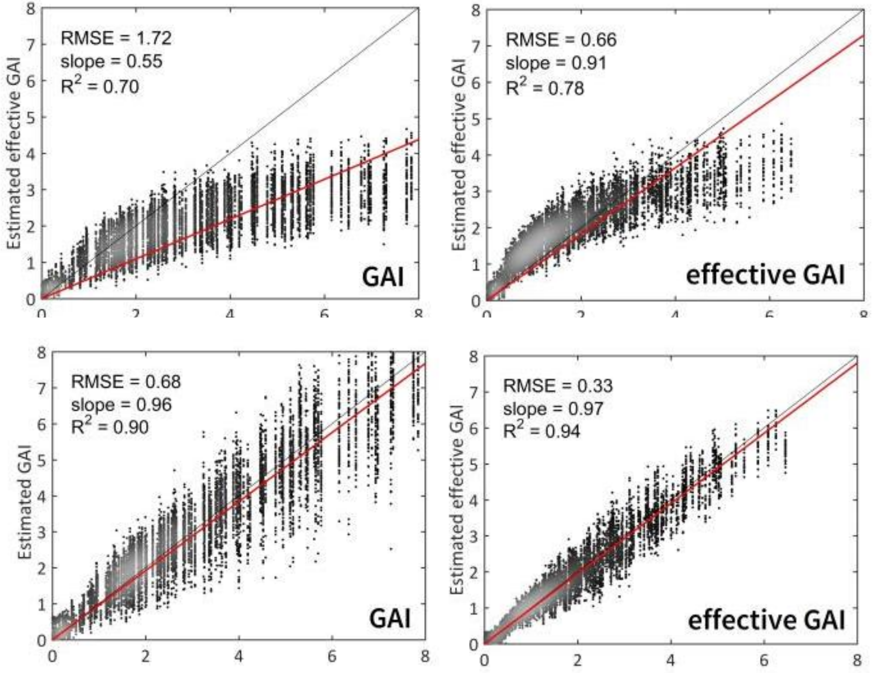
- Effective GAI better retrieved
- No saturation, no bias when using 3D



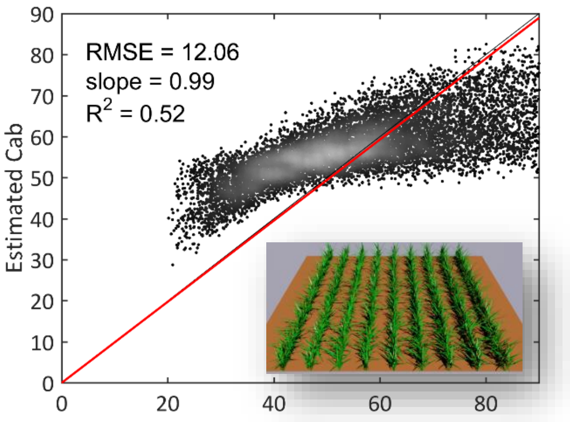


1D

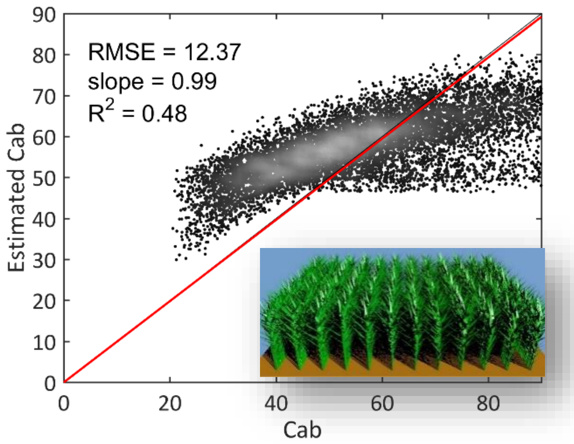
3D

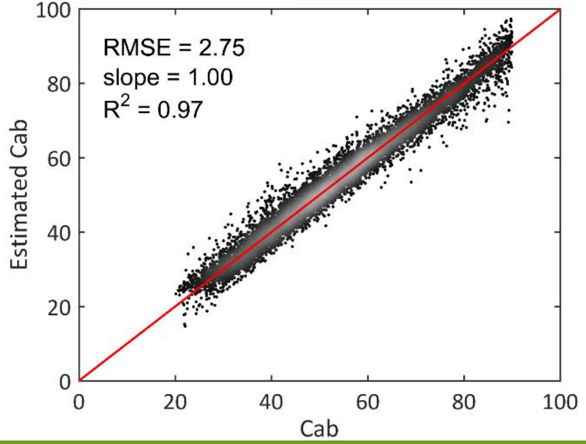


Generic vs Specific – Cab: comparison on simulations

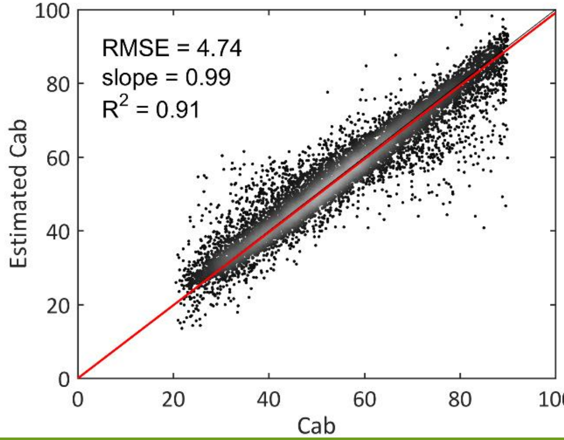


PROSAIL Training



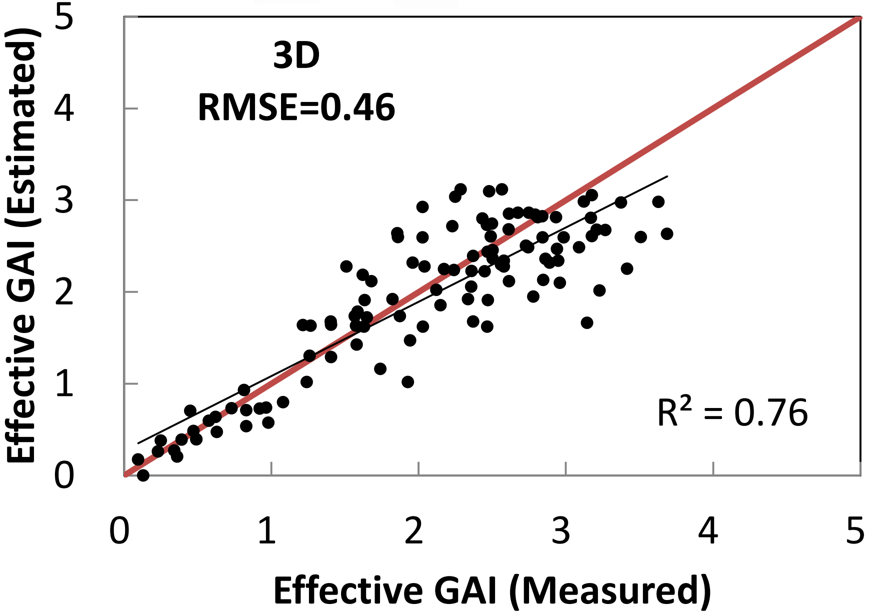


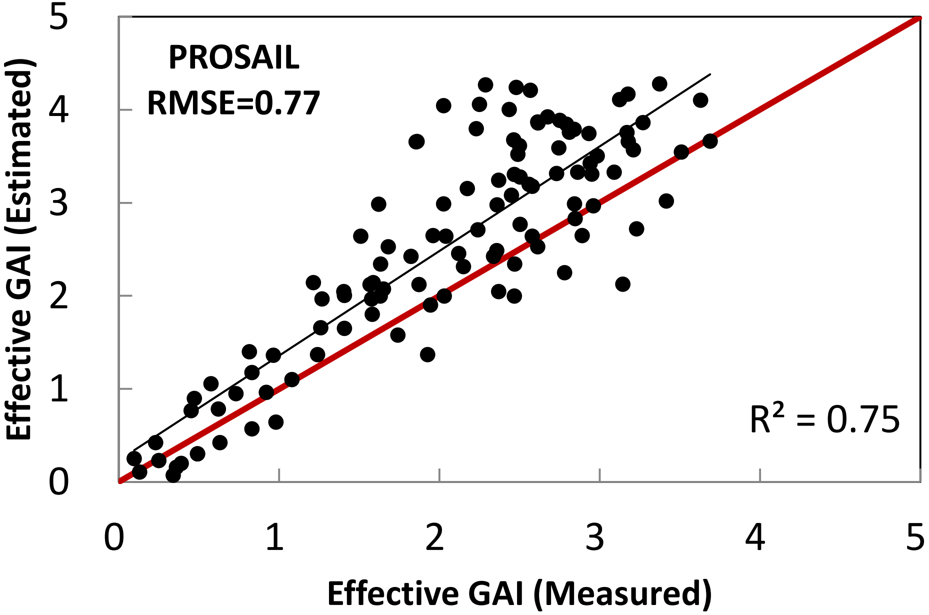
PROSPECT + 3D Training



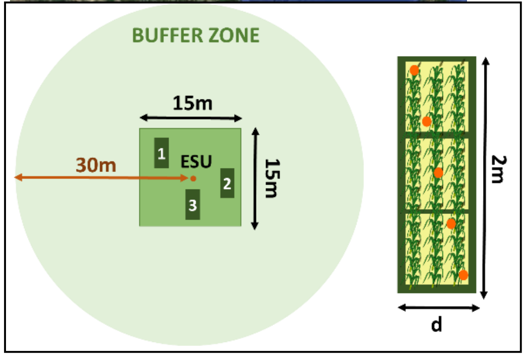
Generic vs Specific – Inverse, 1D and 3D RTM simulations

➢ Validation on IMAGINES dataset (LANDSAT 8)

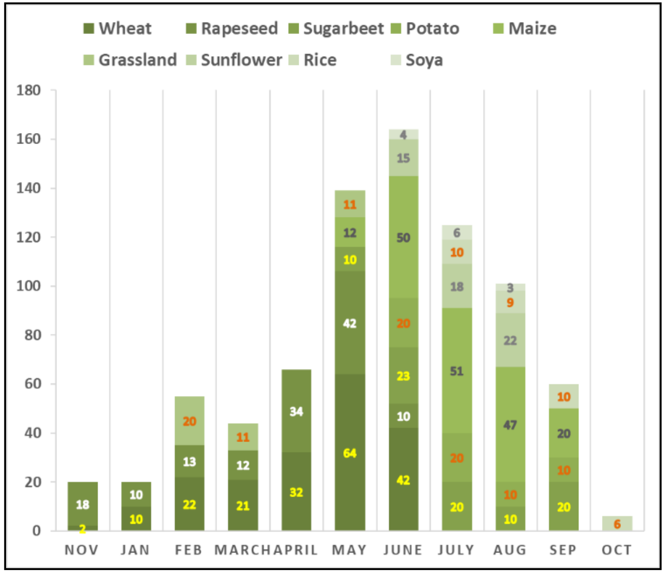




Extending the results: P2S2 database



- Measurements: GAI, Chlorophyll
  - DHP
  - SPAD
  - GPS



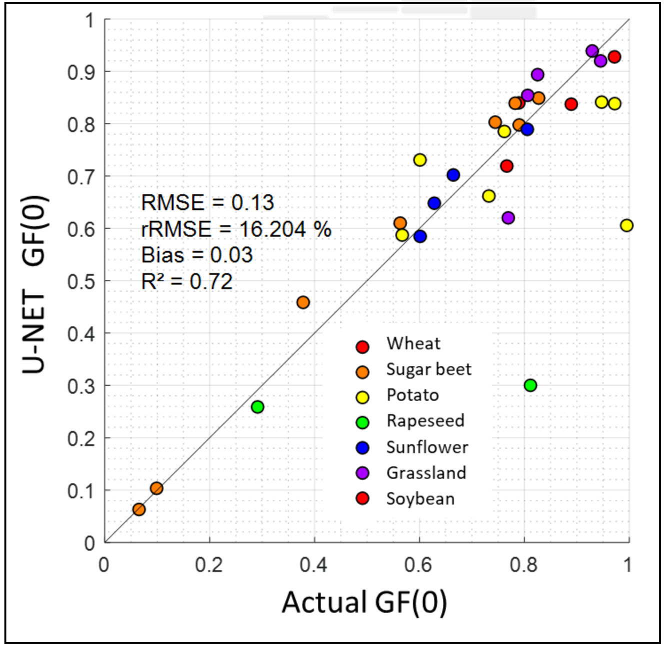
Site	Wheat	Rapeseed	Maize	Sunflower	Sugar beet	Rice	Potato	Soybean	Grassland
Camargue	✓		✓	✓		✓			✓
Toulouse	✓	✓	✓	✓				✓	
Boigneville	✓	✓	✓		✓				
Gembloux	✓	✓	✓		✓		✓		

P2S2 DHP : towards an DHP automatic processing

- Complex images (Downward)
  - Shadows
  - Green/yellow
  - Acquisition conditions (clouds/no cloud)

- Simple methods do not perform well when compared to manual classification (CAN-EYE)
  - Deep Learning: CNN
  - U-NET architecture, RESNET as backbone, pre-trained wit ImageNET
  - Training dataset: 5 existing datasets fully independent from P2S2 database

P2S2 DHP : towards an DHP automatic processing



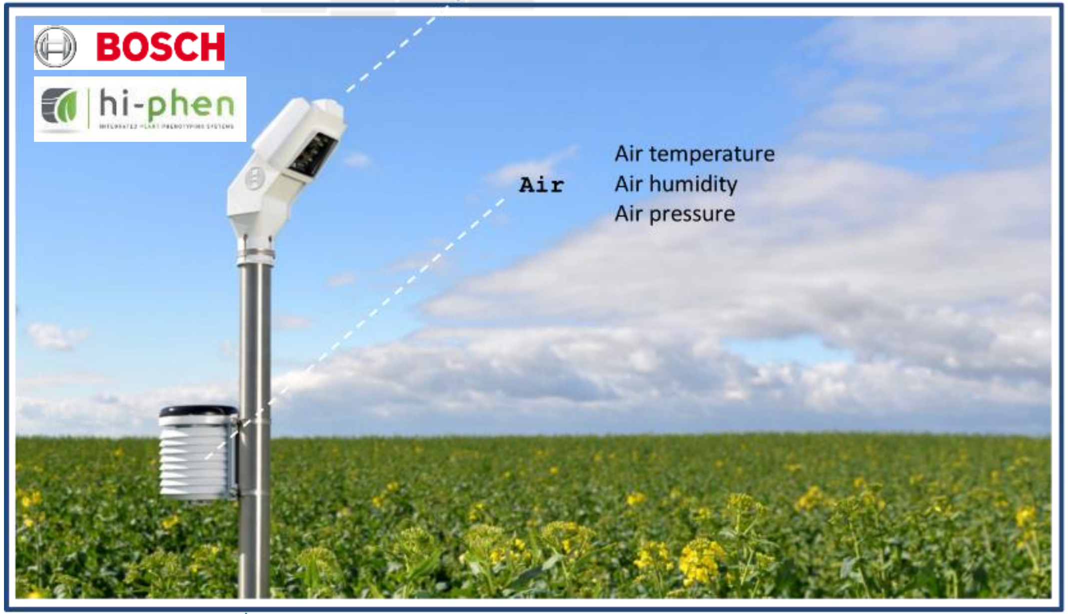
- Very good consistency
- CAN-EYE processing by two independent experts
- 180 Nadir images (+average over ESUs)
- Problems for some rapeseed images and potatoes: not represented by the training

Refinement scheduled with around 15 images from P2S2 dataset.

P2S2 DHP : example of problematic images

Mixing ground based satellite information

Light
- PAR sensor
- Multispectral canopy reflectance
- RGB camera

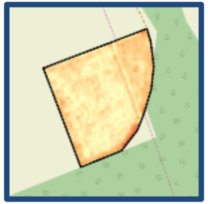


Air
- Air temperature
- Air humidity
- Air pressure

Soil
- Soil water potential
- Soil temperature
- PAR transmitted by the canopy

- IoT field sensors
  - Close range - Accurate
  - Photo Everyday
  - Data every 15 mns

- SENTINEL-2
  - Field scale
  - 5 days (no cloud)



OBJECTIVE:

Get Daily SENTINEL2 GAI

Mixing ground based satellite information

- Select fields to set up IOT Field Sensors
  - Based on farmer a priori knowledge
  - Based on historical data archive (including S2)
  - Set up IOTs to represent the heterogeneity of the area of interest

- IOT = temporal profile

  S2   = GAI level

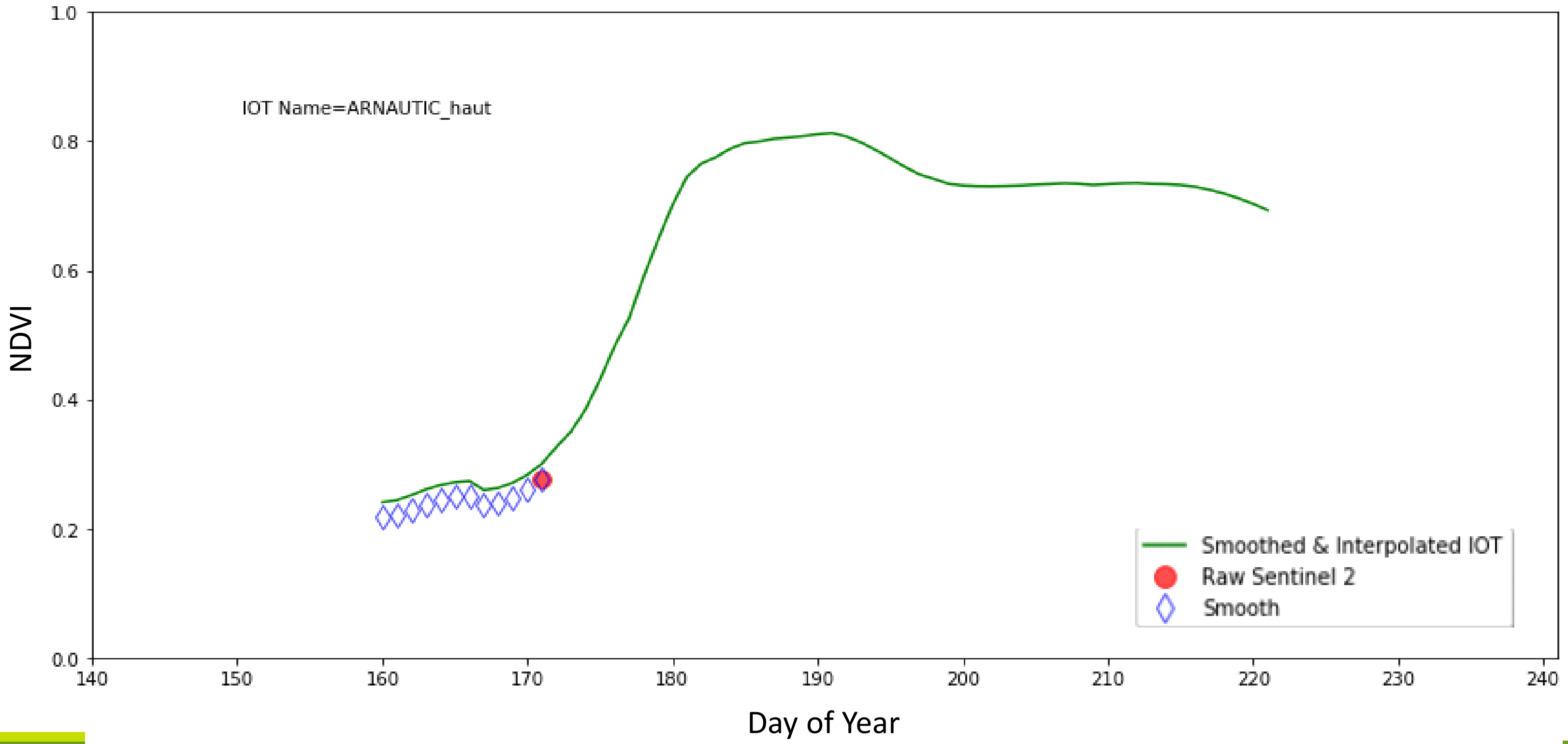
Each S2 pixel is asusmed to follow the temporal trend of 1IOT

KALMAN FILTER: RT, sequential update

KALMAN SMOOTH: Post Processing, all observations together

- NRT prediction

Mixing ground based satellite information



Conclusions & Perspectives

- **Crop specific Algorithm**
  - RTM: 3D-4D modelling : need more crop architecture model
  - Require a very accurate land cover map => improvements are expected from S2
  - Taking benefit form phenotyping: Deep learning combining accurate measurements & modelling
  - Transfer to hecto/kilometric products
    - Learning based on decametric products
    - Going backwards in time (reprocessing archive)
- **Validation**
  - Focus on the validation of decametric products (CEOS)
    - Measurements at this scale easy to complete and more and more available
    - Need to provide a consistent and robust database
  - Temporal monitoring of the vegetation cycle is mandatory
    - New sensors are becoming available (IOT)
  - Indirect validation of hecto/kilometric resolution through the validation of decametric products (estimate sensor PSF is mandatory)

Few more words on the phenotyping activities & Developments in CAPTE team

Norman Borlaug

Selection intensity
Increase population

Selection repeatability
repeatable measurements with limited environment effects

Genetic gain per year →

$$G = f \cdot i \cdot \varepsilon \cdot \sigma_g$$

← **Genetic variability**
Diversity of population

Cycles per Year

High-throughput phenotyping:

- Characterizing thousands of microplots
- Along the growing cycle
- With a suite of traits related to yield
- With high repeatability (and accuracy)

- **Yield has low heritability**
  - it depends on many factors linked in a complex way
- **Better phenotype for single traits impacting yield**
  - and combine them for yield estimates

Organ

Leaf: Size / orientation
Sanitary state
Biochemical composition

Stem: Diameter
height

Fruits/ears/panicles/flower

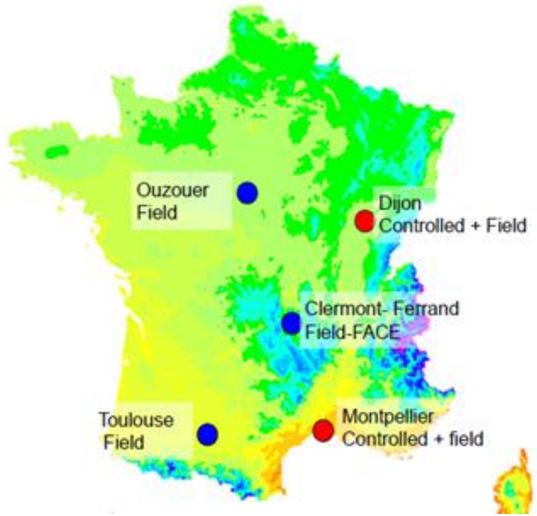
Plant

When not too much overlap between plants:
Early stages
Low plant density

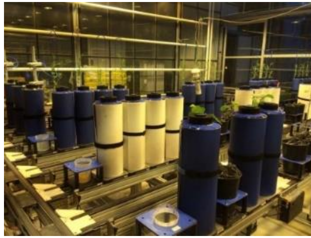
Canopy

Plant/stem density
height
Green fraction
GAI
FIPAR
3D structure

The experiment



2 Metabolomic



2 Controlled conditions

2 Semi-controlled

3 field platforms

Field Phenotyping

Drone

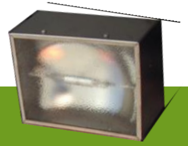
- Throughput: 1000 plot/h

  Almost simultaneous aquisition over the platform
- Sensible to wind
- Passive measurements

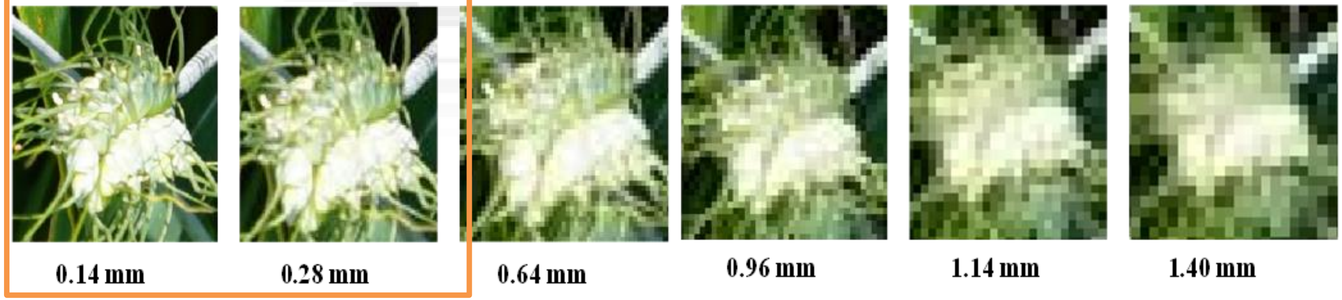
Phenomobile

- 150 plot/h

  Several hours between first and last plot sample
- Little sensitive to wind
- Active measurements

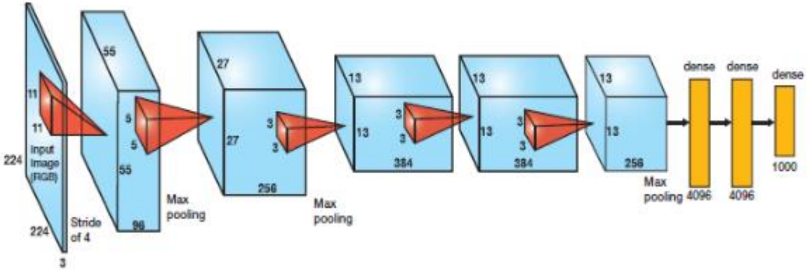


Ear Density



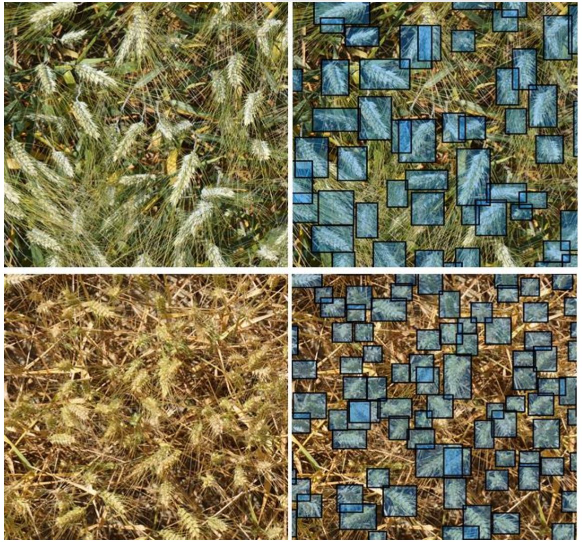
Need a spatial resolution better than 0.5mm

Faster-RCNN
Pretrained on the
COCO dataset

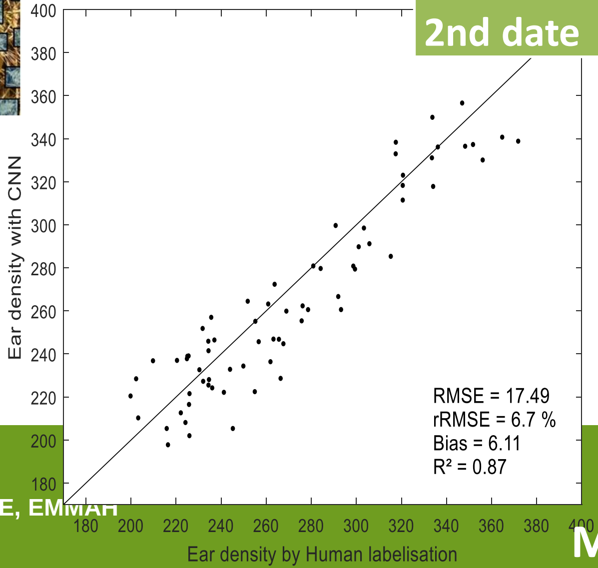


1st date only
240 labelled images, 80-170 ears
≈ 30000 ears

Ear Density: results



H² (%)	Date	WW	WS
Ground (Human)	June 7th	79.8	91.4
RCNN 1st date	June 2nd	86.9	88.5
RCNN 2nd date	June 16th	82.2	82.8



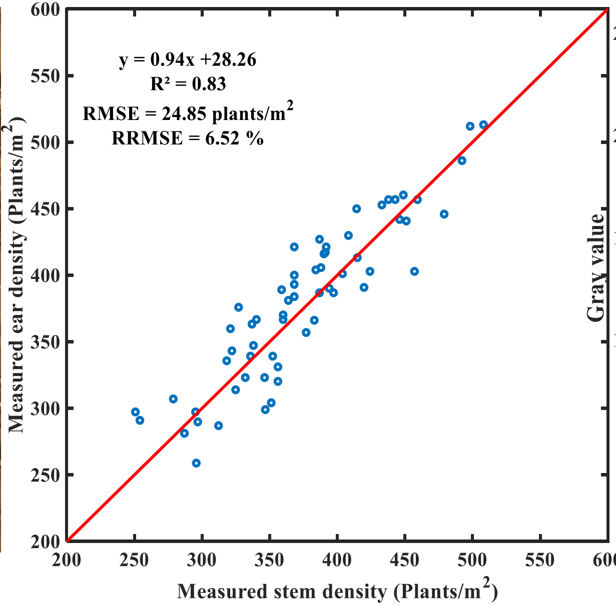
Very accurate and repeatable estimates of ear density

Madec et al, 2019

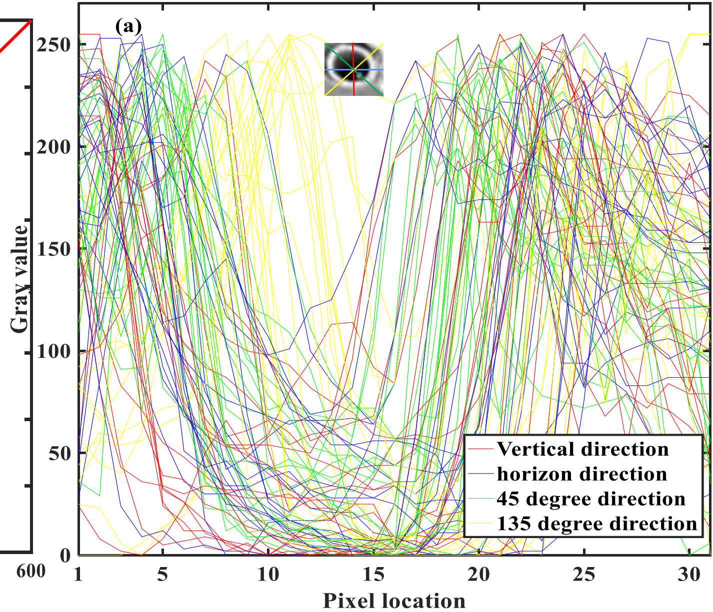
Tillering coefficient

$$\text{Tillering coefficient} = [\text{Nb. ear/plant}] = [\text{Nb. Stem/m}^2] \underbrace{* [\text{Nb. Ear/stem}] / [\text{Nb. Plant/m}^2]}_{[\text{Nb. ear/m}^2]}$$

Identifying stems



Comparing stems and ears



stem diameters

Thank you for your attention