

GLOBAM – outcomes to bridge the gap between agriculture monitoring and crop modeling at regional scale

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GLOBALAM – a Globally Distributed Agricultural Monitoring Experiment based on EO

***4,5-y research project supported by
Belgian Science Policy Office (2007-2011)***



***based on an international partnerships combining research
labs, EO production entities and operational systems (currently
AGRI4CAST, FOODSEC)***

***to bridge the gap between the operational crop monitoring
systems and the state of art in agriculture remote sensing***



Université
de Liège





The Foreign Agricultural Service (FAS) of the USDA



The Foreign Agricultural Service (FAS) of the U.S. Department of Agriculture (USDA) works to improve foreign market access for U.S. products, build new markets, improve the competitive position of U.S. agriculture in the global market place, and provide food aid and technical assistance to foreign countries. The FAS has the primary responsibility for USDA's international activities - market development, trade agreements and negotiations, and the collection and analysis of statistics and market information. The FAS also has food aid programs and helps to increase food aid availability in developing nations by mobilizing expertise for promoting agricultural economic growth.

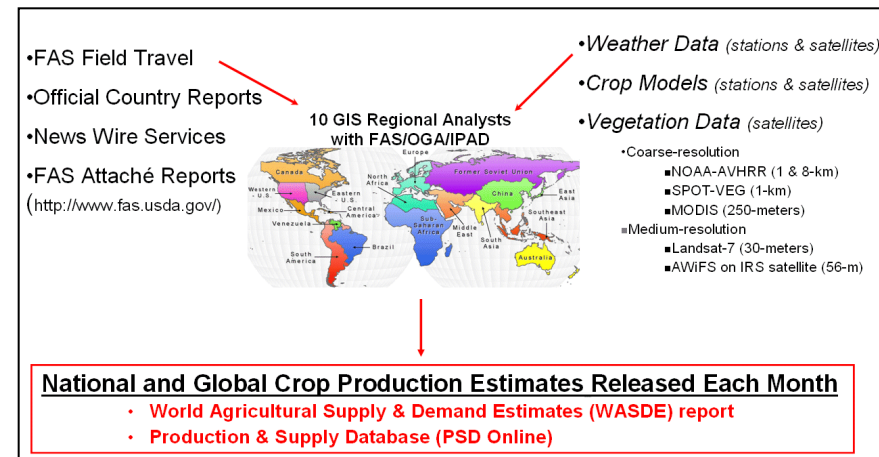
Objectives: The primary mission of the International Production Assessment Division (IPAD) of the FAS Office of Global Analysis (OGA) is to collect, analyze, and disseminate global crop condition and agricultural production information.



Data Used: IPAD relies on an “all data sources” and “convergence of evidence” approaches by incorporating information from:

- Daily weather data (i.e., precipitation and minimum/maximum temperature) from the World Meteorological Organization station network and the US Air Force Weather Agency (AFWA) satellite-derived products.
- Vegetation Indices (VI) from low resolution satellite imagery (MODIS, SPOT-VGT, and AVHRR)
- Crop models for soil moisture, crop growth calendars, winterkill and relative yield reduction.
- Crop travel by FAS attachés and IPAD crop analysts.
- Economic data from official government reports, trade and news sources, and econometric analyses

Procedures: Official crop statistics from other nations are critical in forming current crop estimates for the **World Agricultural Supply and Demand Estimates (WASDE)** report, but in practice, not all countries have crop-estimating agencies capable of making reliable, timely, or objective production forecasts. Also, many major producing and trading countries do not publish crop reports until well after the crop has been harvested. In the interim, USDA must monitor global precipitation, temperature, NDVI (Normalized Difference Vegetation Index) and other parameters over major crop producing regions that are economically important to the United States trade.





The CropWatch System of the CAS, China



With about 20 years of research experience, the Institute of Remote Sensing Application (IRSA) of the Chinese Academy of Science (CAS) developed the CropWatch System in 1998 and has operated it ever since.

CropWatch covers China and 26 major grain-growing countries of the world. The system monitors crop conditions and production, drought, crop planting structure and cropping index. CropWatch currently publishes 7 monthly bulletins and 20 newsletters annually. The provision of timely and accurate information helps Chinese governmental departments and organizations to make sound decisions.

Data used::

- **Remote sensing data:** MODIS, 250 m for China and 1 km at global scale, Resourcesat-1 AWiFS, 56 m, B-J CCD, 32 m, Landsat TM 30 m, ENVISat ASAR 30m, Radarsat-1 ScanSAR, CBERS-01/02 20 m.

In the early period of CropWatch NOAA AVHRR and SPOT vegetation data were used.

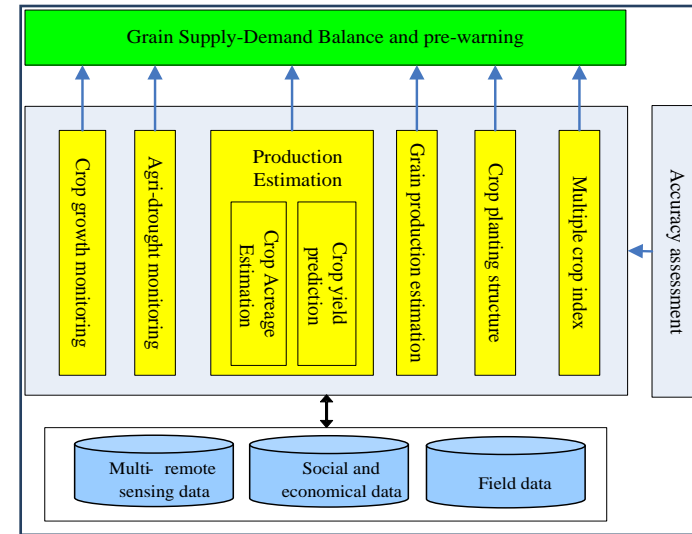
Currently data from Chinese Satellite HJ-1 are also ingested into the system.

- **Geo-spatial data:** landuse / landcover data of China, 1:100,000., GLC 2000 landcover data, 1 km, global crop phenology data.

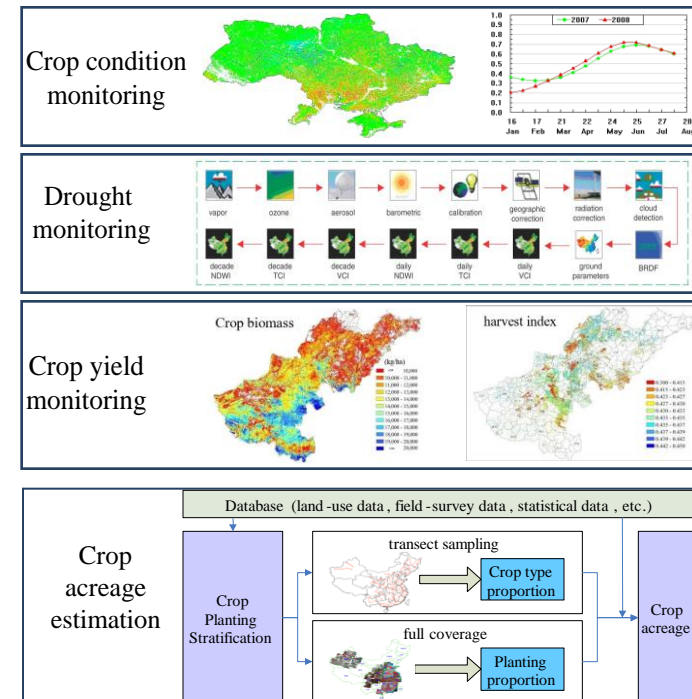
- **Other data:** global meteorological data for agro-meteorological; condition assessment; field observation data in experimental plot for validation.

Methodology:

- For crop condition monitoring, CropWatch uses two models based on snapshot and crop growing process;
- For drought monitoring, RS based vegetation indices are computed and used in a crop drought model;
- For crop yield estimation, four models are run, namely: the agro-meteorological model, the remote sensing index model, a combination of both, and the biomass model;
- For crop acreage estimation, a new method is used, integrating remote sensing technology with ground sampling.
- For grain production estimation, changes relative to average grain yields and planted area are evaluated.



CropWatch structure



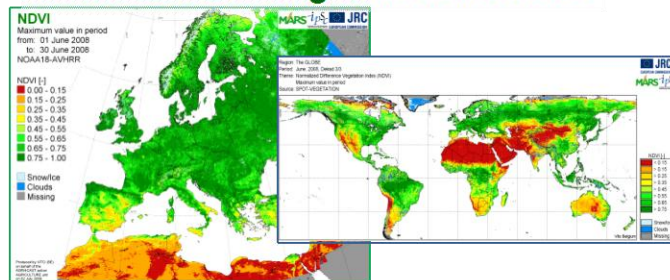


The MARS Project of the European Joint Research Centre



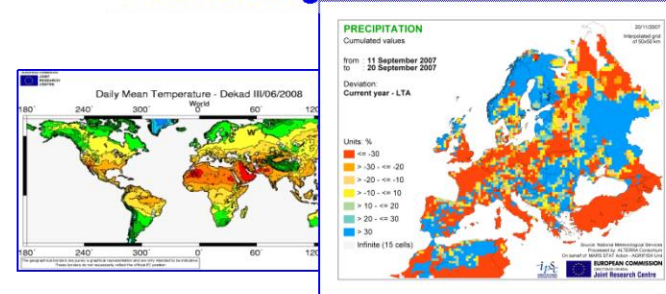
The MARS Project of the Joint Research Centre of the European Commission started in 1988. Since 1993, the MARS Project is running a crop yield forecasting system for the quantitative assessment of the major crops in European Member States. Since 2000, this expertise has been applied outside the European Union to cover the EU neighboring countries, and services have been developed to support Europe Aid and Food Security policies.

Remote Sensing infrastructure



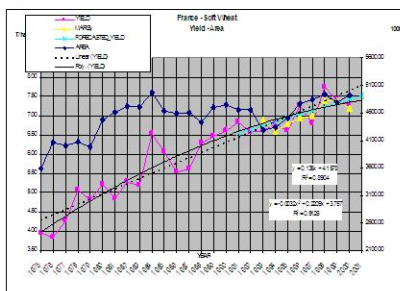
Vegetation state & meteo indicator
since 1981 Europe, 1998 worldwide

Meteorological infrastructure



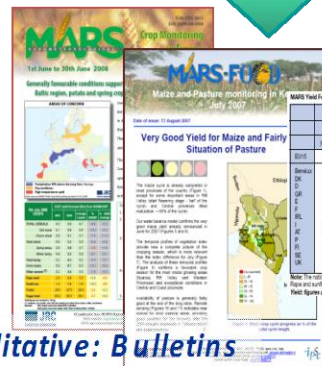
Worldwide ECMWF data + archive
Observed ground data since 1975 Europe
under construction for Africa

Statistical infrastructure



Time series
regression, similarity
analyses, etc

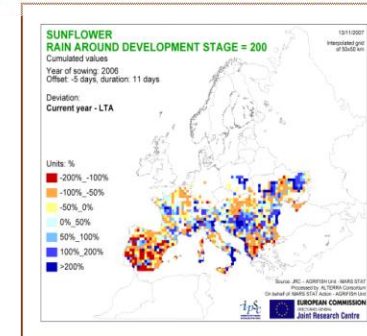
Crop assessment Yield forecasts



Qualitative: Bulletins
and Early Warning

Quantitative:
Yield
forecasts

Crop Model infrastructure



Agromet indicators derived
from crop-growth models:
WOFOST / LINGRA / WARM
or GWSI **Source : GEOSS Ag., 2010**

Satellite observation contribution

Spatial resolution

Use

Food security	Ag prod trade
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5km - 1km

1km - 250m

250m - 60m

60m - 10m

10m - 1m

hourly images

daily images

1 to 3 images per 15 days

1 to 2 images per month

1 to 2 images per season

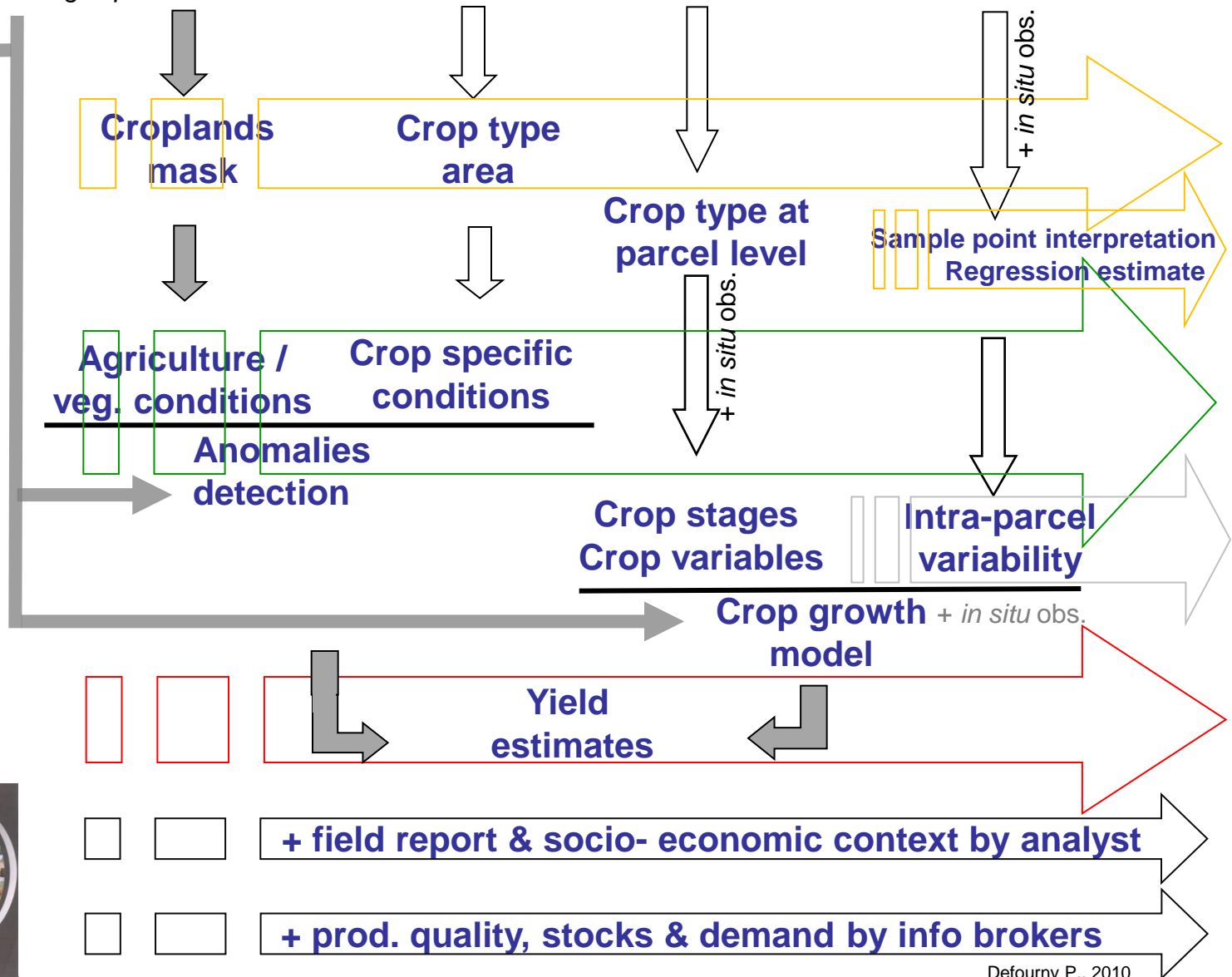
Revisiting capabilities

**Meteo
cond.**

Area

Crop Growth

Yield



Area outlook

**Agric.
map**

Area estimate

Monthly bulletin

Early warning

Precision farming

Yield forecast

**Prod
estimate**

Vulnerab. report

Int market report

Defourny P., 2010

LOBAM objectives

to develop and test methods potentially operational over large areas and in different agro-ecological contexts



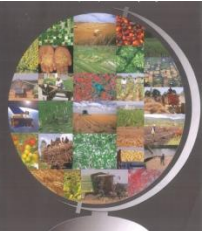
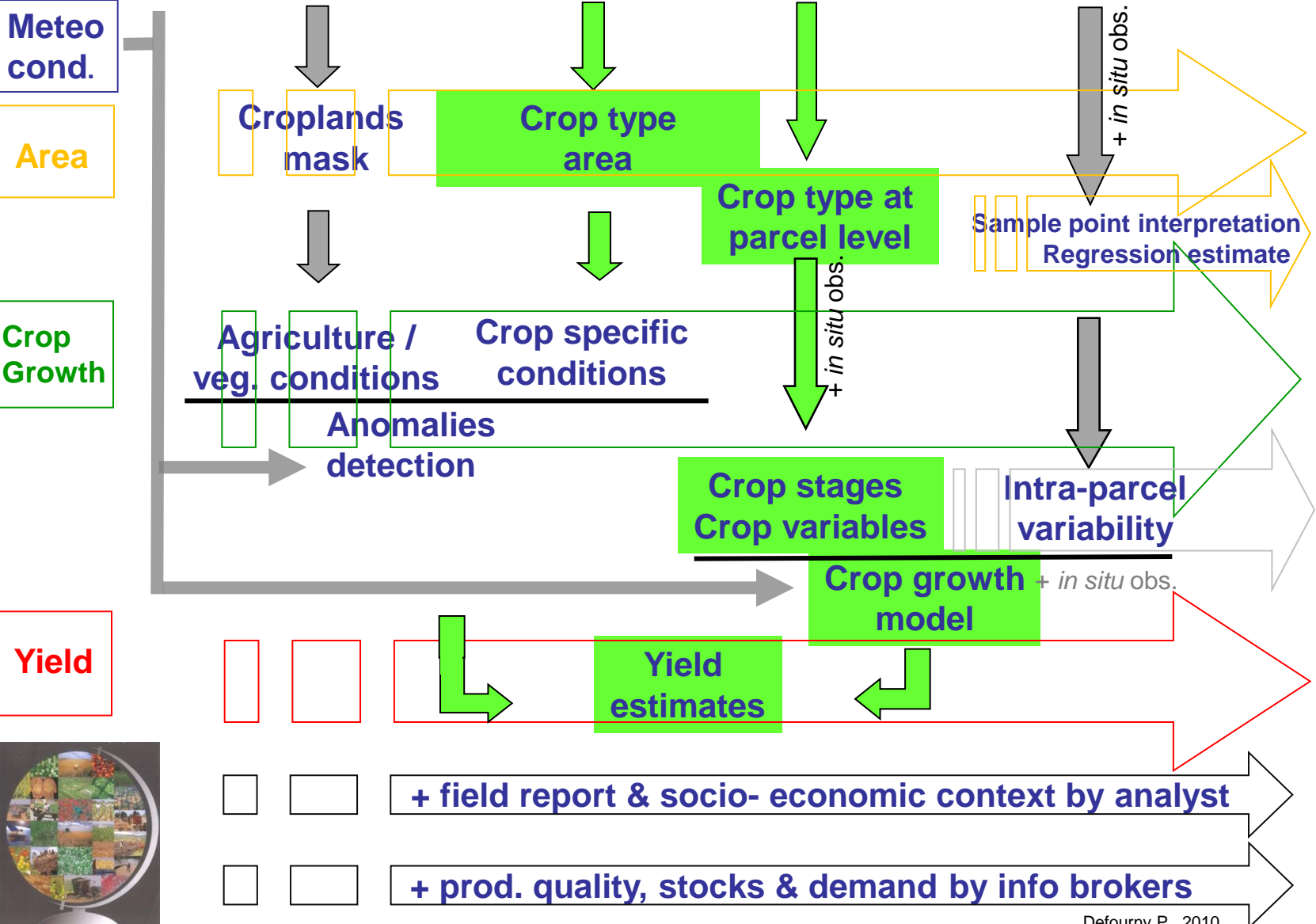
- Timely **crop maps** over large areas and crop specific **biophysical estimate** (LAI, ET) from EO
- Improved crop growth **models**
- **Assimilation** of EO-derived info in crop growth model for crop yield estimate

GLOBAM contribution

EO **5km - 1km** **1km - 250m** **250m - 60m** **60m - 10m** **10m - 1m** **Use**

hourly images daily images 1 to 3 images per 15 days 1 to 2 images per month 1 to 2 images per season

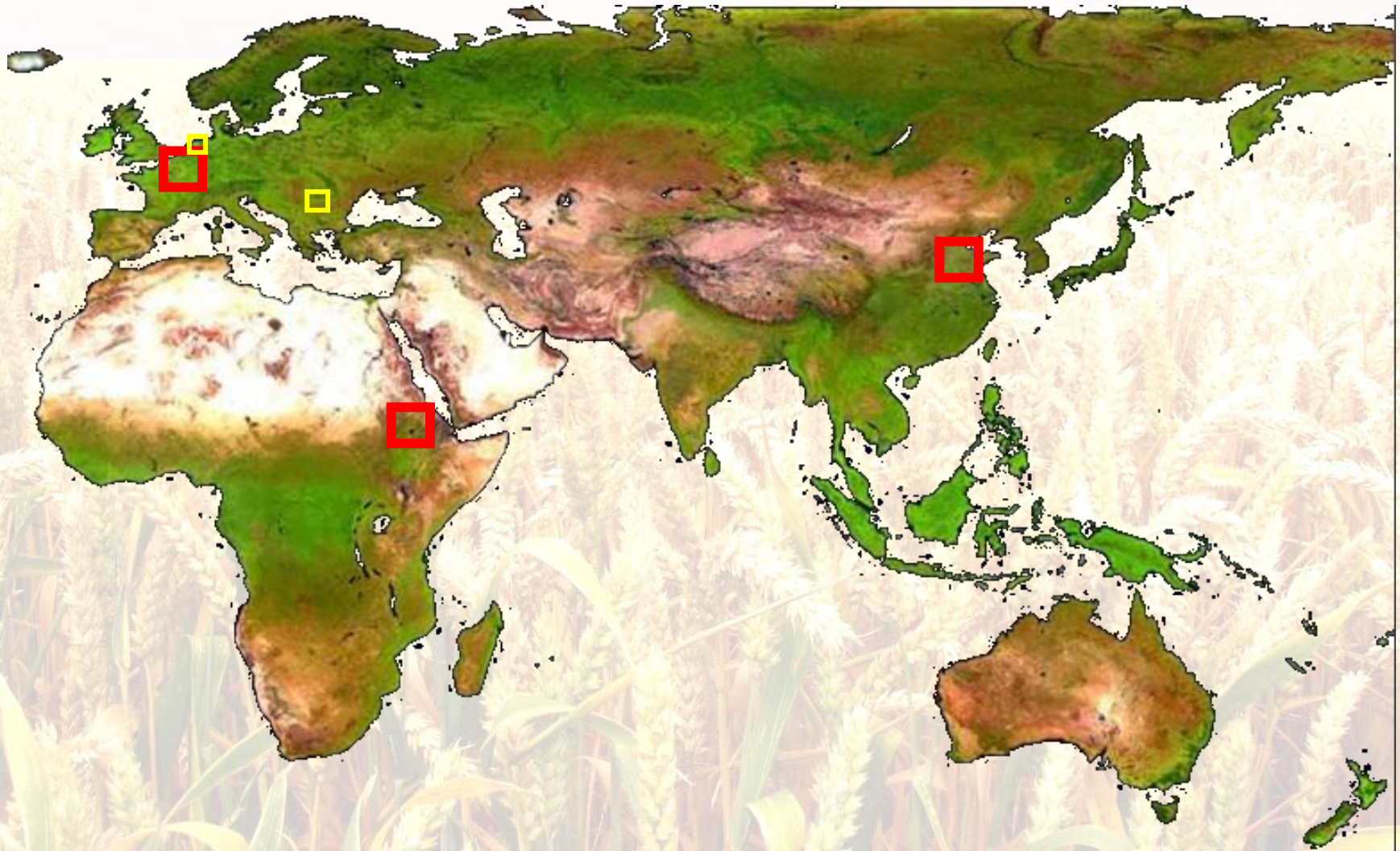
Revisiting capabilities



GLOBAM – a Globally Distributed Agricultural Monitoring Experiment

in different agro-ecological contexts over large sites

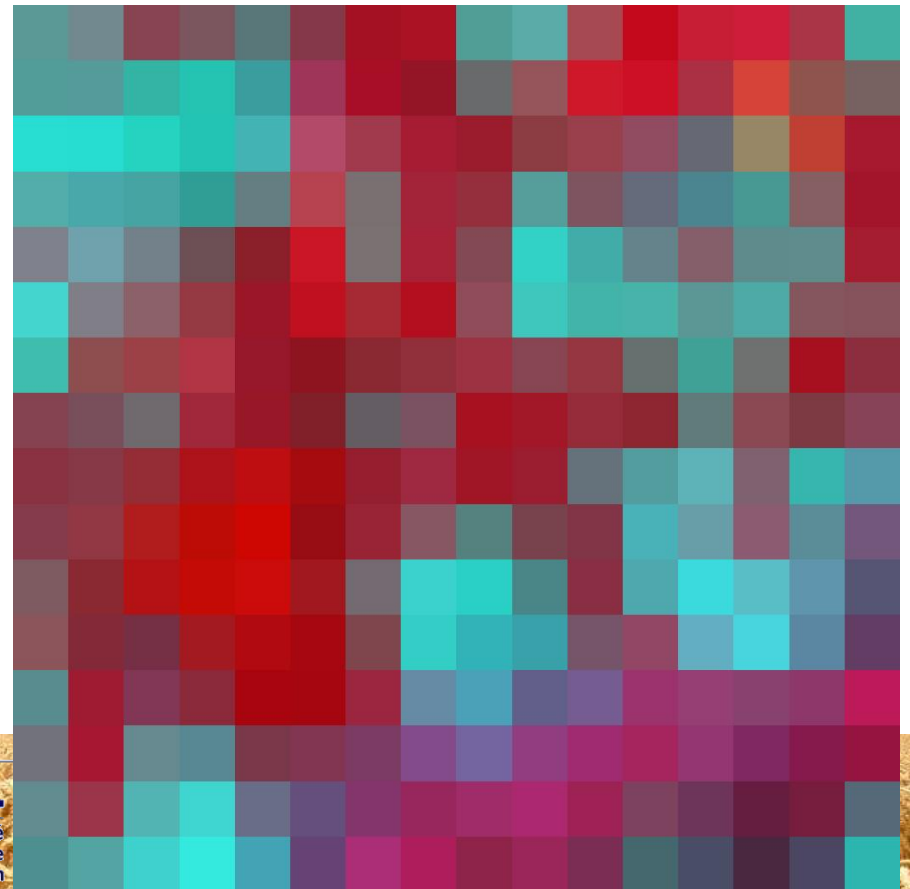
3 sites of 300 x 300 km + ADAM experiment + Flevoland AGRISAR
using Kompsat, SPOT HRV, ETM, DMC, AWiFS, MODIS, MSG and SAR



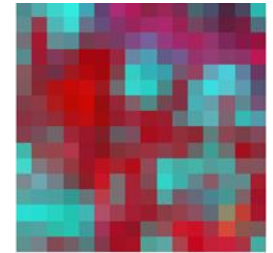
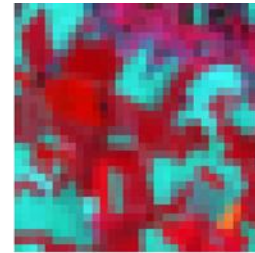
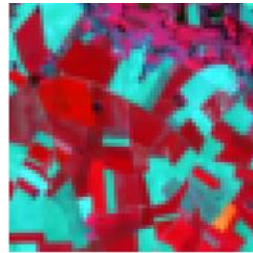
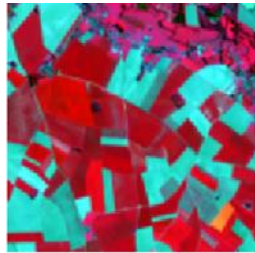
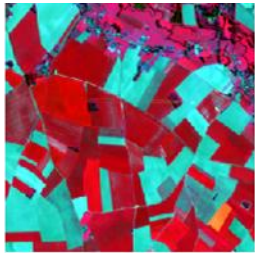
Conceptual development

- What is the appropriate spatial resolution ?
- What is IN a pixel?

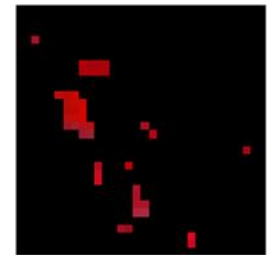
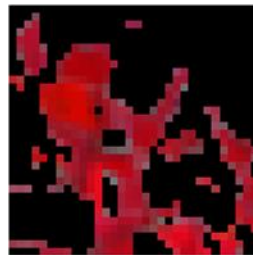
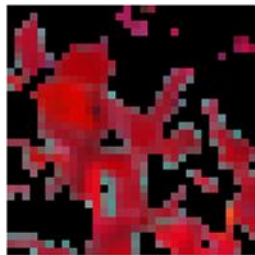
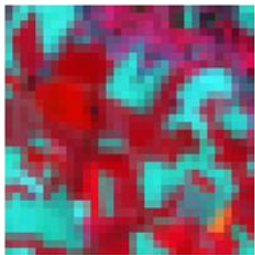
How much signal comes from target land cover?



The balance between *pixel size* and *pixel purity*



Increasing Pixel Size



Increasing Pixel Purity

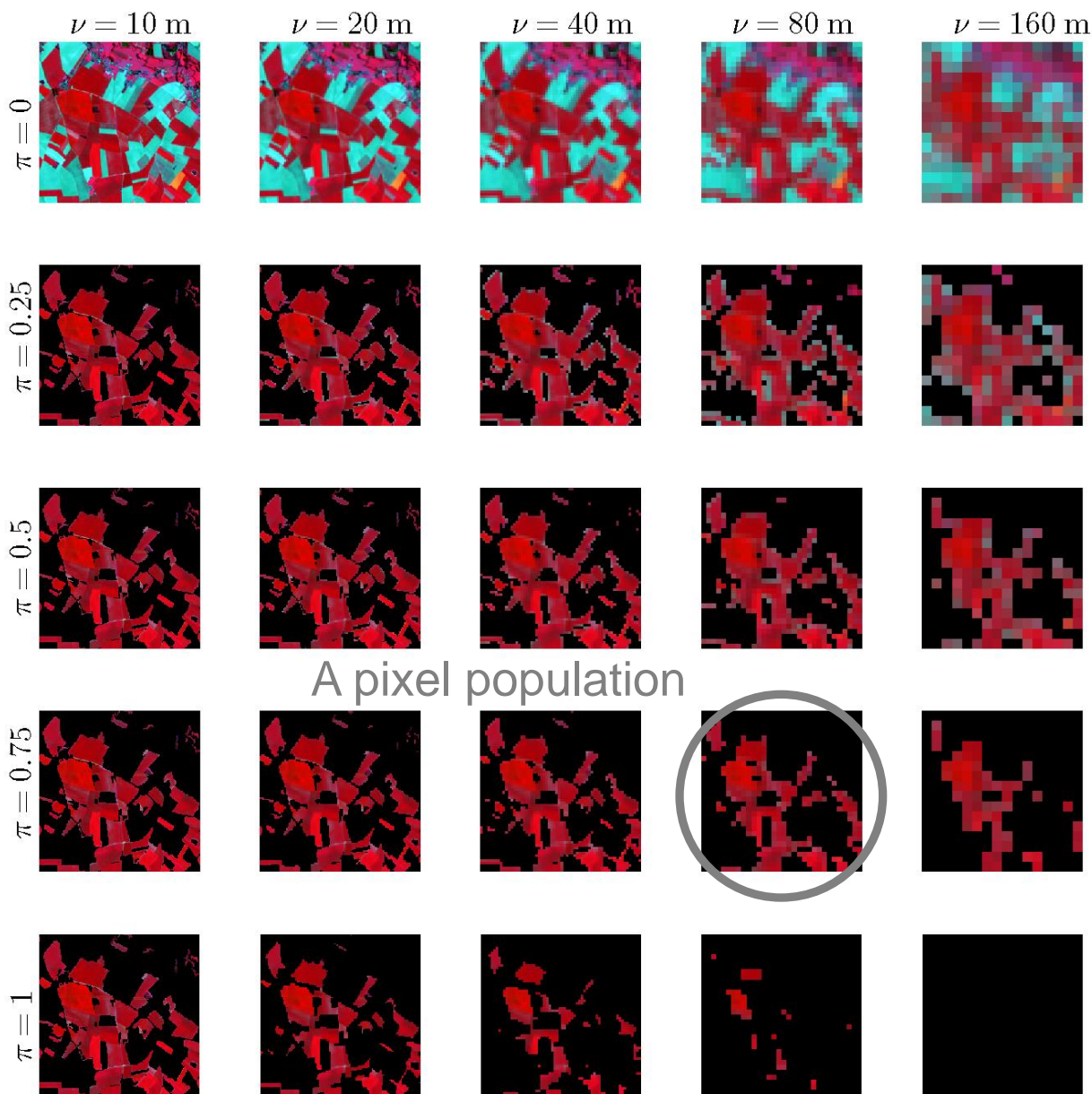


Duveiller & Defourny 2010 RSE

The pixel purity-size space

Increasing Pixel Purity

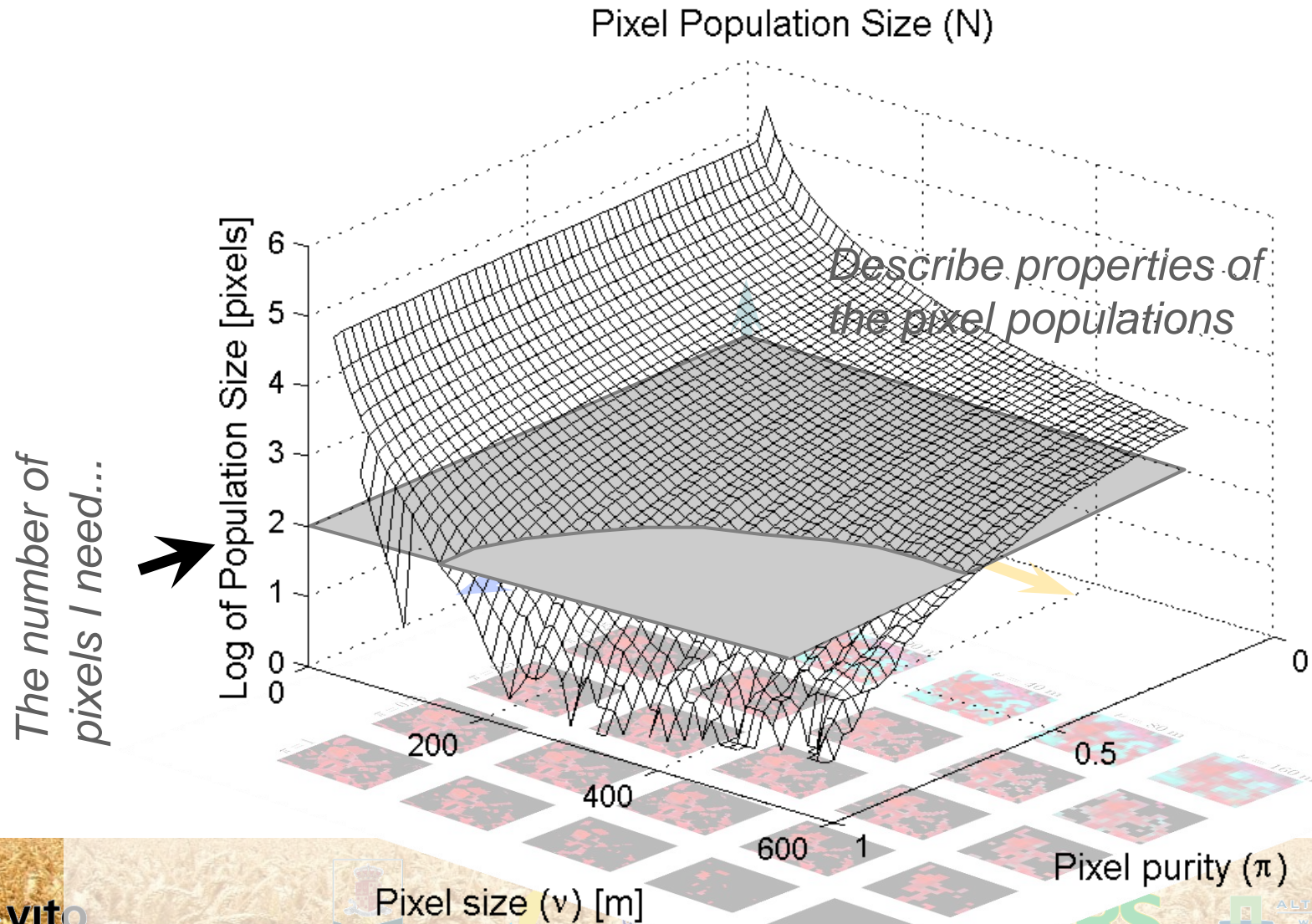
Increasing Pixel Size →



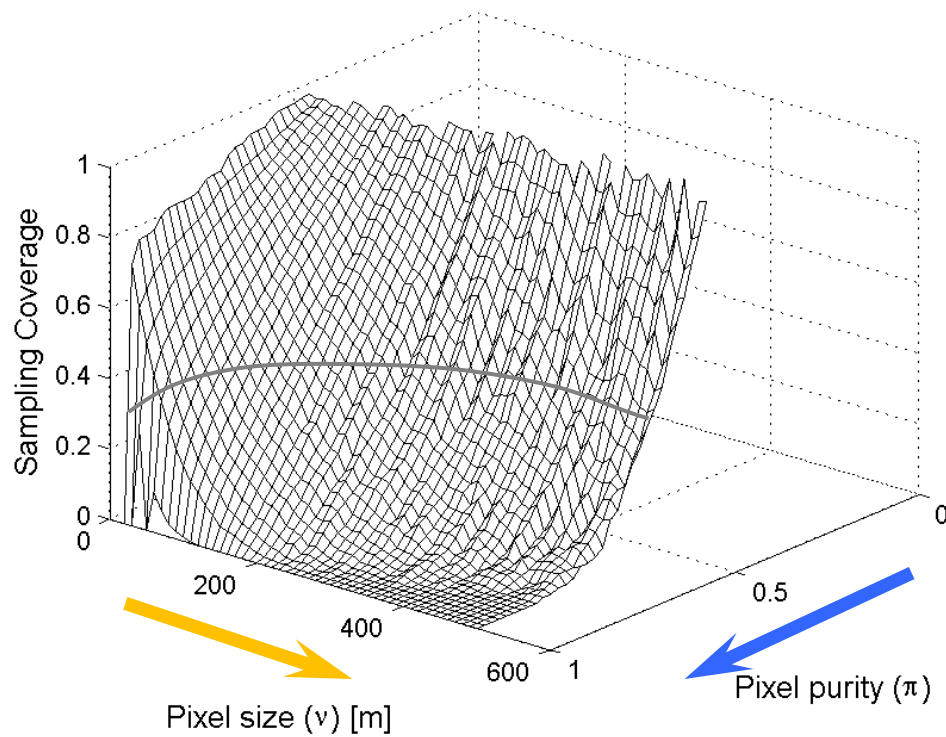
A pixel population



Plotting variables in the purity-size space

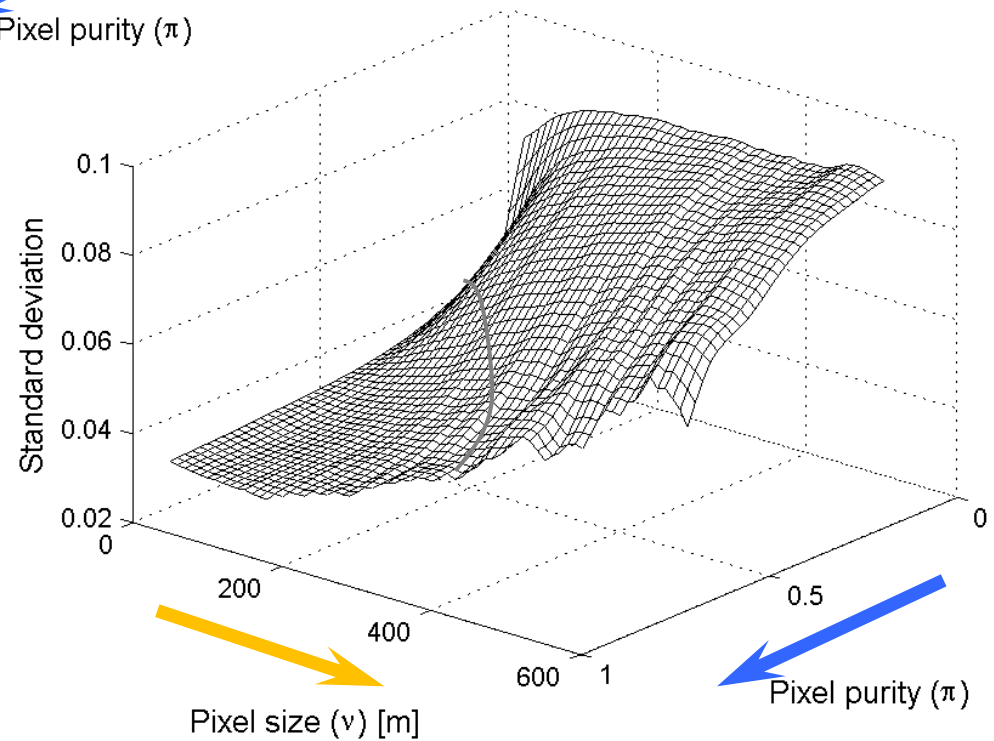


Sampling Coverage (SC)



How much of the target surface is covered by my selected pixels?

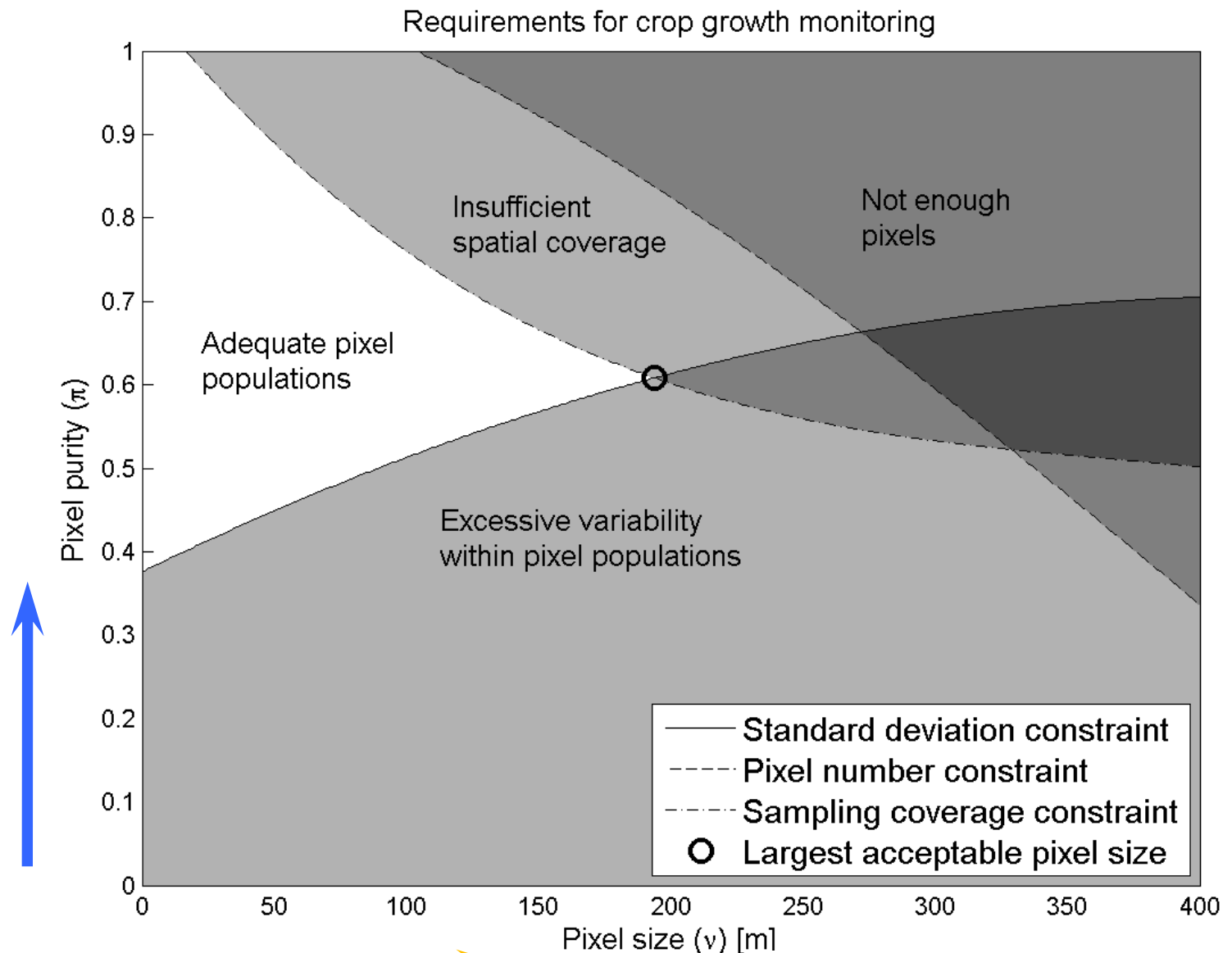
Standard deviation of pixel population (Σ_{NIR})



How variable is the reflectance of my selected pixels?



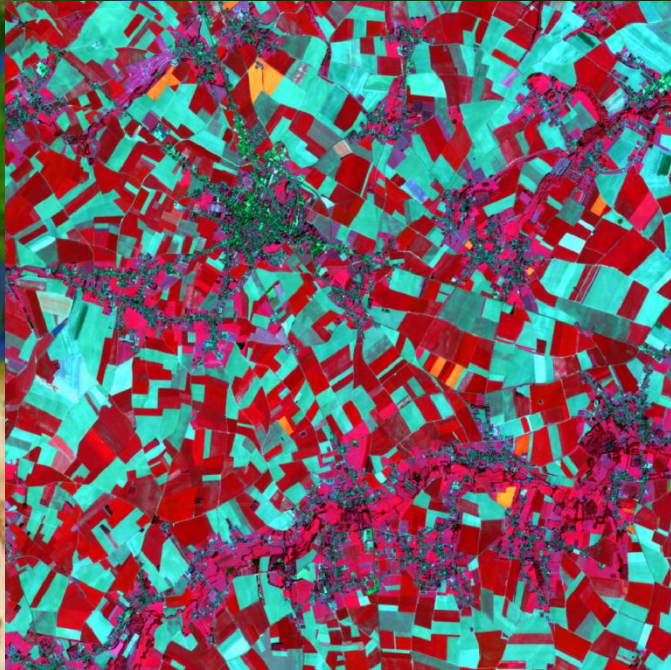
Defining EO sensor requirement... for crop mapping for crop monitoring



Duveiller & Defourny 2010 RSE

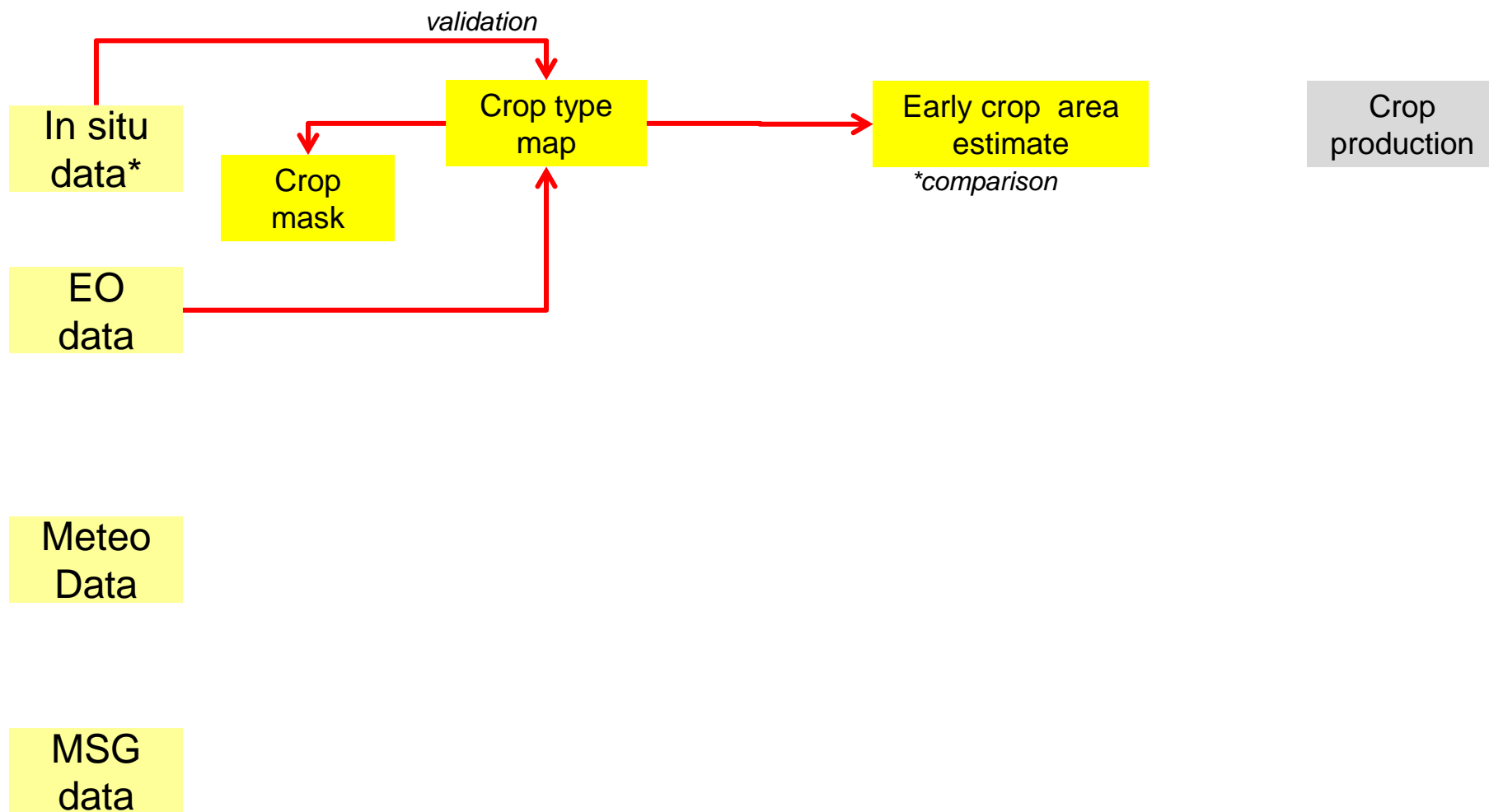


Implemented over different parts of the world with different cultures



Winter cereals in Hesbaye (Belgium)

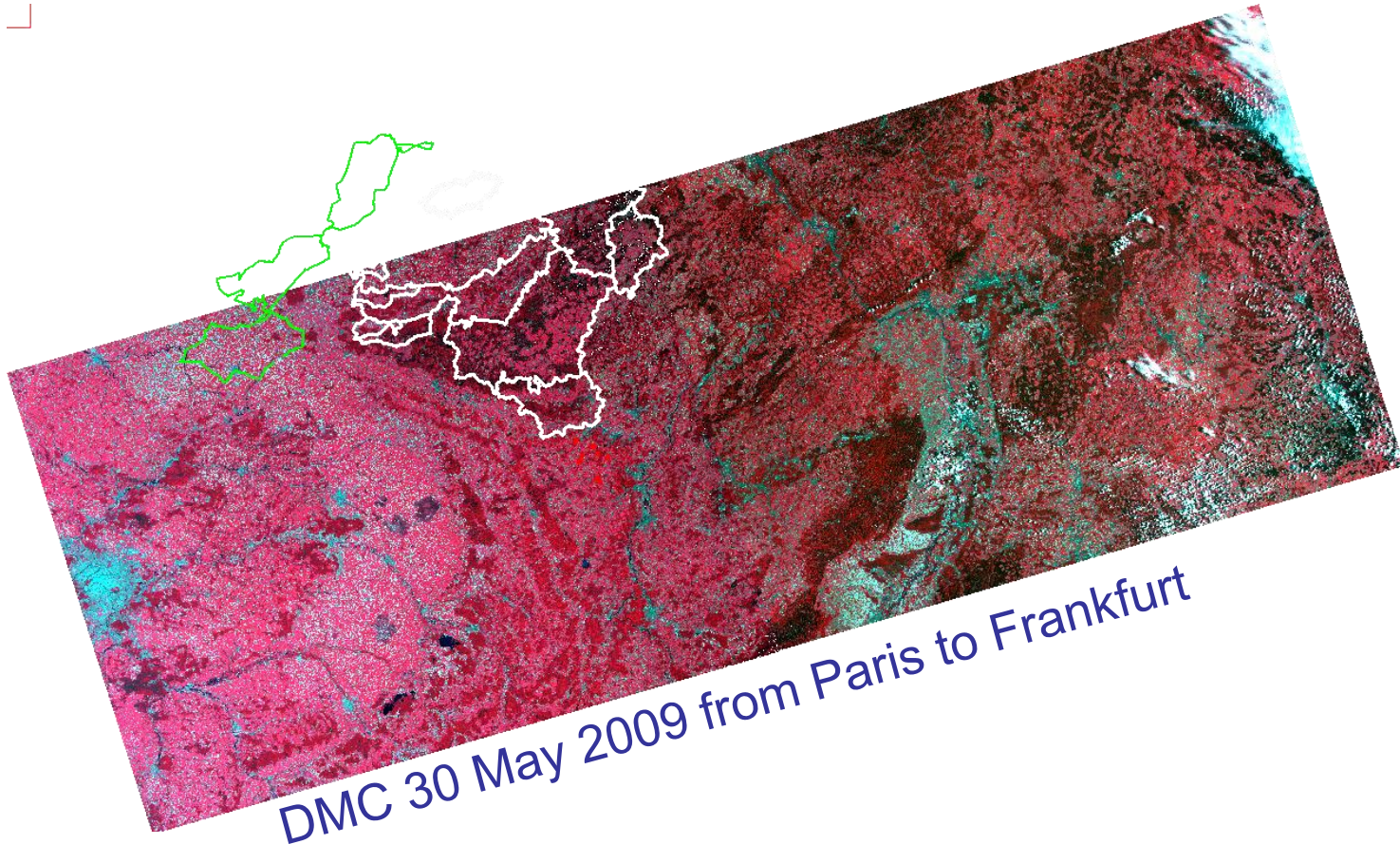
Crop Growth monitoring : 200 m
[100 points, 30 % sampling and 5% std]





GLOBALAM crop mapping – new sensors contribution ?

- Wide Swath High Resolution data : AWIFS - 56 m over 740 km
DMC – 32 m over 660 km



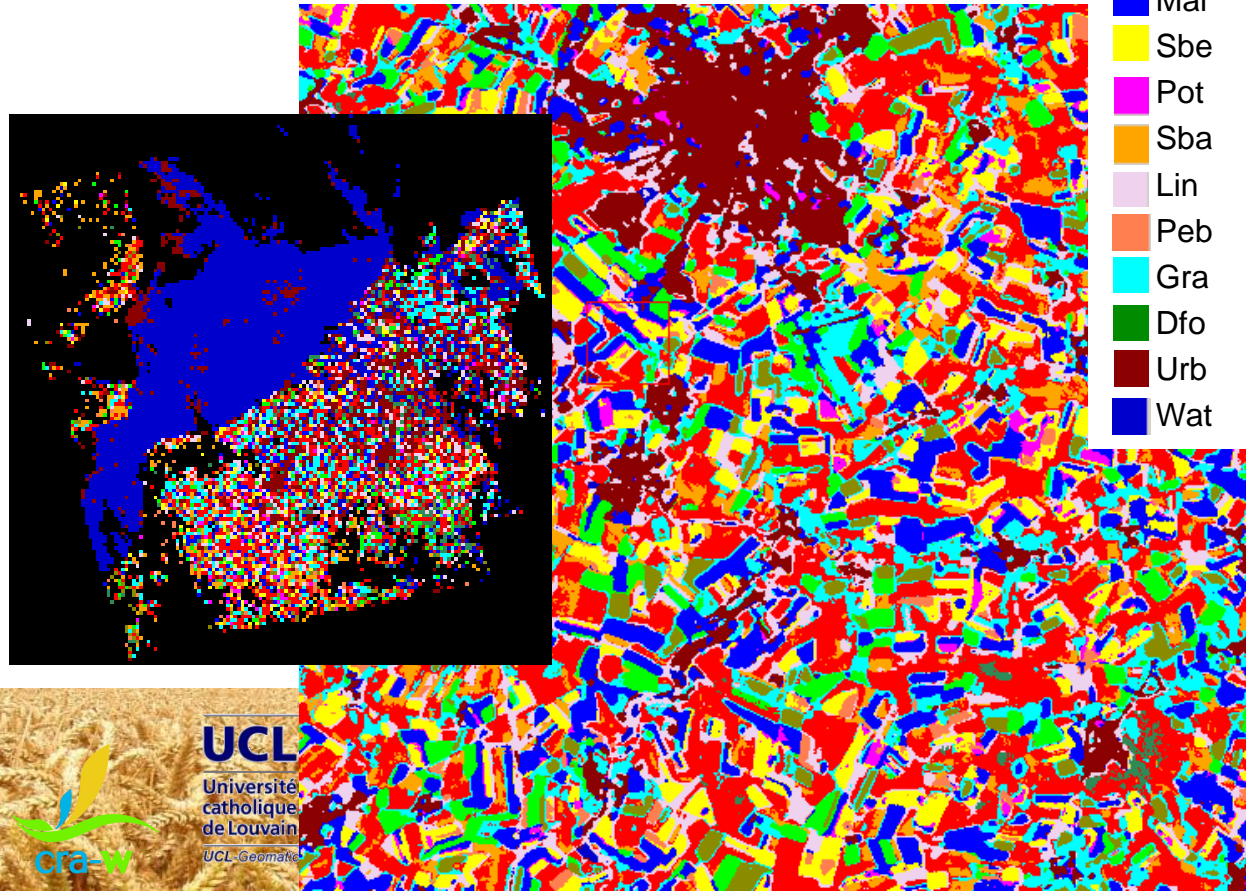
GLOBALAM crop mapping – new sensors contribution ?

● Winter & summer crops

- 5 DMC images : 4 April, 15 April, 29 May, 13 June, 30 June 2009
 - Adapted Maximum Likelihood classification
 - Field observation : 60% for calibration and for 40% validation
- ➔ **Overall accuracy: 70.0% (kappa 0.66)**

Wwh
Wba
Wra
Mai
Sbe
Pot
Sba
Lin
Peb
Gra
Dfo
Urb
Wat

class	prod. acc.	user acc.
wwh	73,00	88,36
wba	83,28	81,82
wra	91,77	93,02
mai	61,52	46,56
sbe	66,71	72,87
pot	53,66	60,42
sba	59,26	11,66
lin	81,02	23,42
peb	44,74	55,91
gra	41,21	43,8
dfo	98,13	95,73
urb	78,08	84,95
wat	76,47	78,37



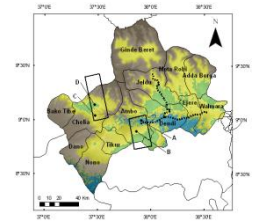
Crop mapping findings in Belg./N. France

- AWiFS /DMC imagery are quite useful but less accurate than Landsat data (SWIR missing) and **requires a stratification to deal with the phenological gradient !**
- Crop map accuracies **relevant for crop mask** but not for area estimate.

Derived Sensors	Mapping area	Accuracy using ground truth data	Accuracy using reference data	Year of exercise
TM/ETM+	Belgium N. France	90%	67%	2007
AWiFS <i>pre-harvest</i>	Belgium N. France	97%	54%	2007
TM/ETM+	Belgium N. France	81%	60%	2009
DMC <i>post-harvest</i>	Belgium N. France	70%	43%	2009

LOBAM crop mapping in Ethiopia

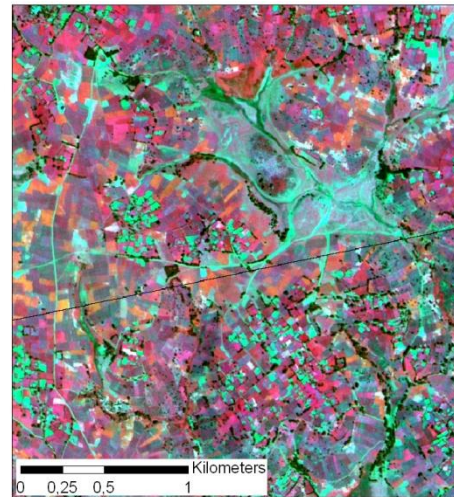
Mapping of the subsistence agricultural area using
very high resolution images still challenging



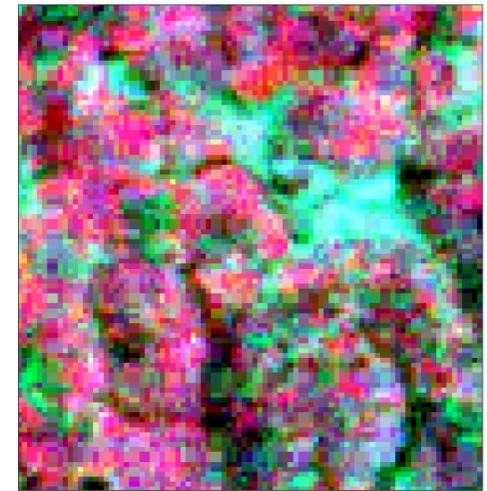
Images tested



Landsat ETM+
(30 m, 185 kmx185 km)

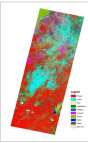


KOMPSAT
(4m, 15kmx15km)



**DMC (32 m,
660 km x660km)**

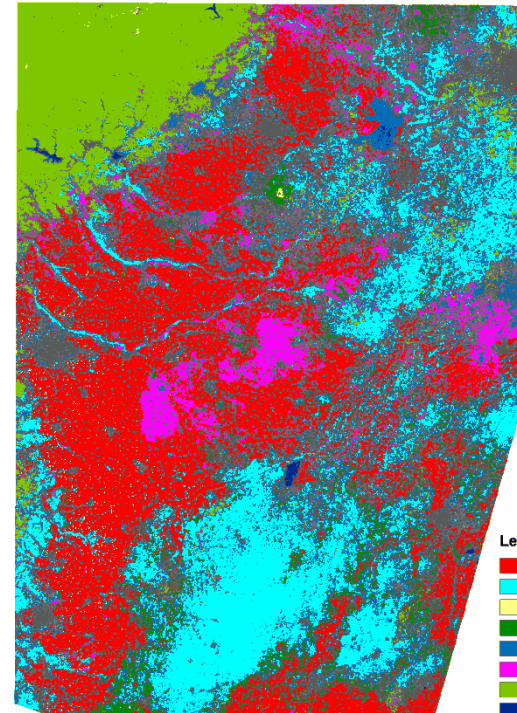
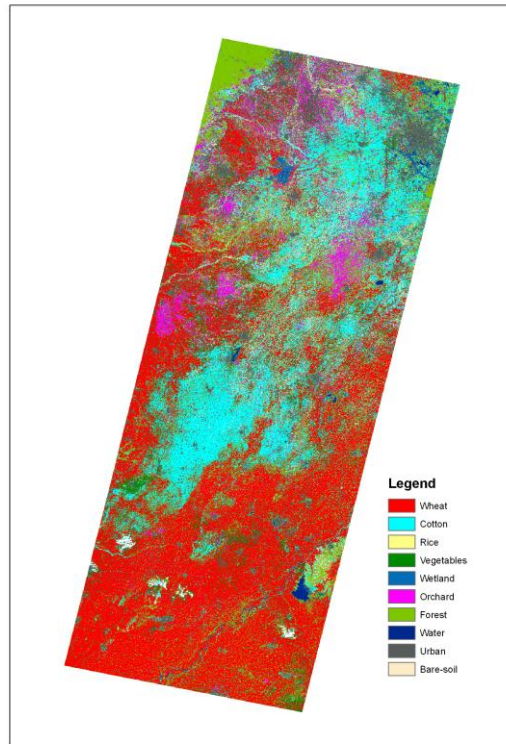
GLOBALAM crop mapping in China (winter wheat season)



'Hard
classification'

Landsat-TM
(30m)

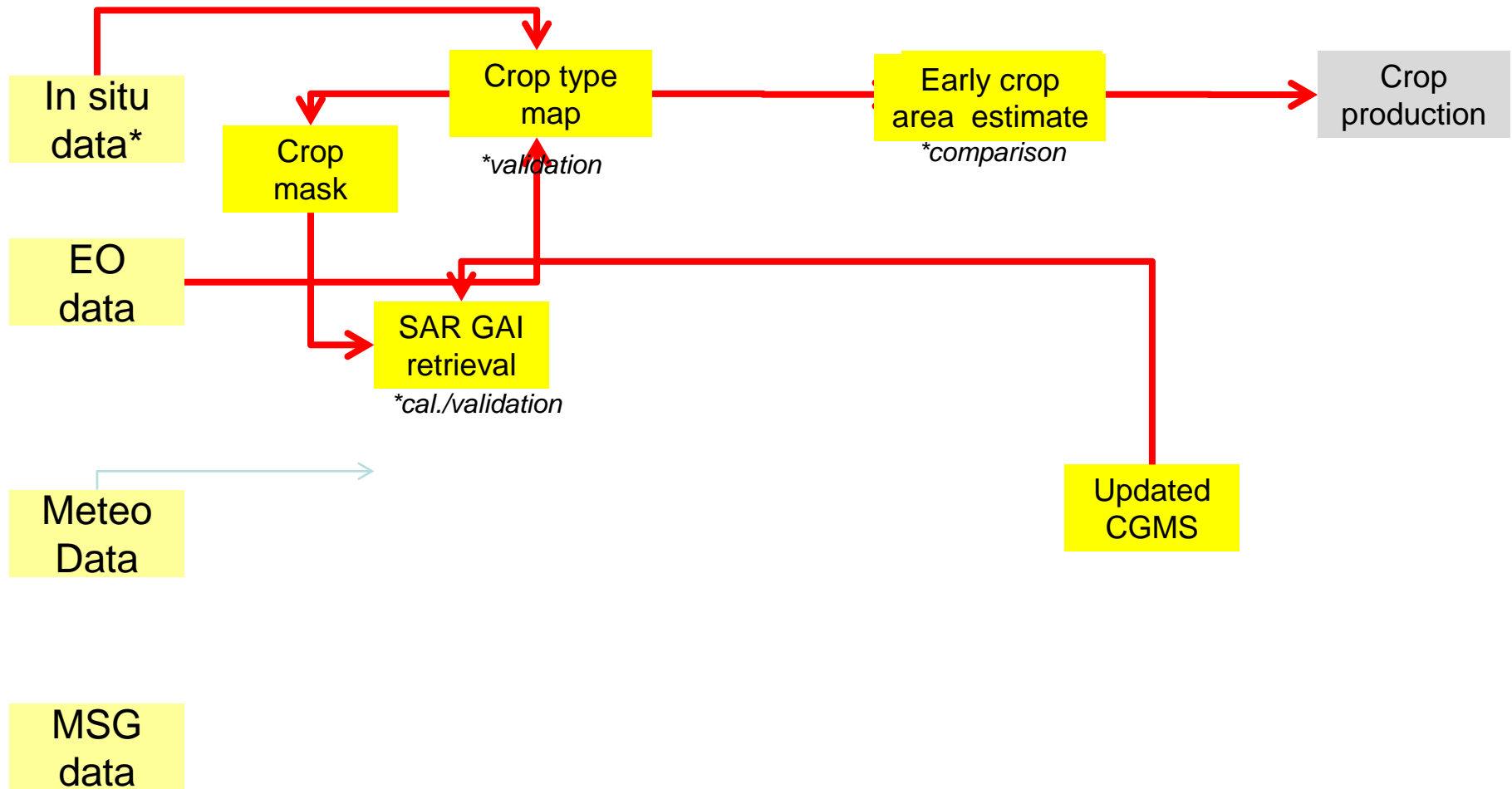
OA: 88%



AWiFS-HJ1
(50m)

OA: 93%

- Wide Swath imagery very performant **even with small fields but thanks to very homogeneous landscape !**



LOBAM field campaign (2007/08/09)

- Top soil moisture

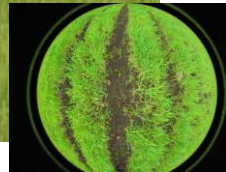


LOBAM field campaign (2007/08/09)

- Crop type
- GPS coord.
- Plant density

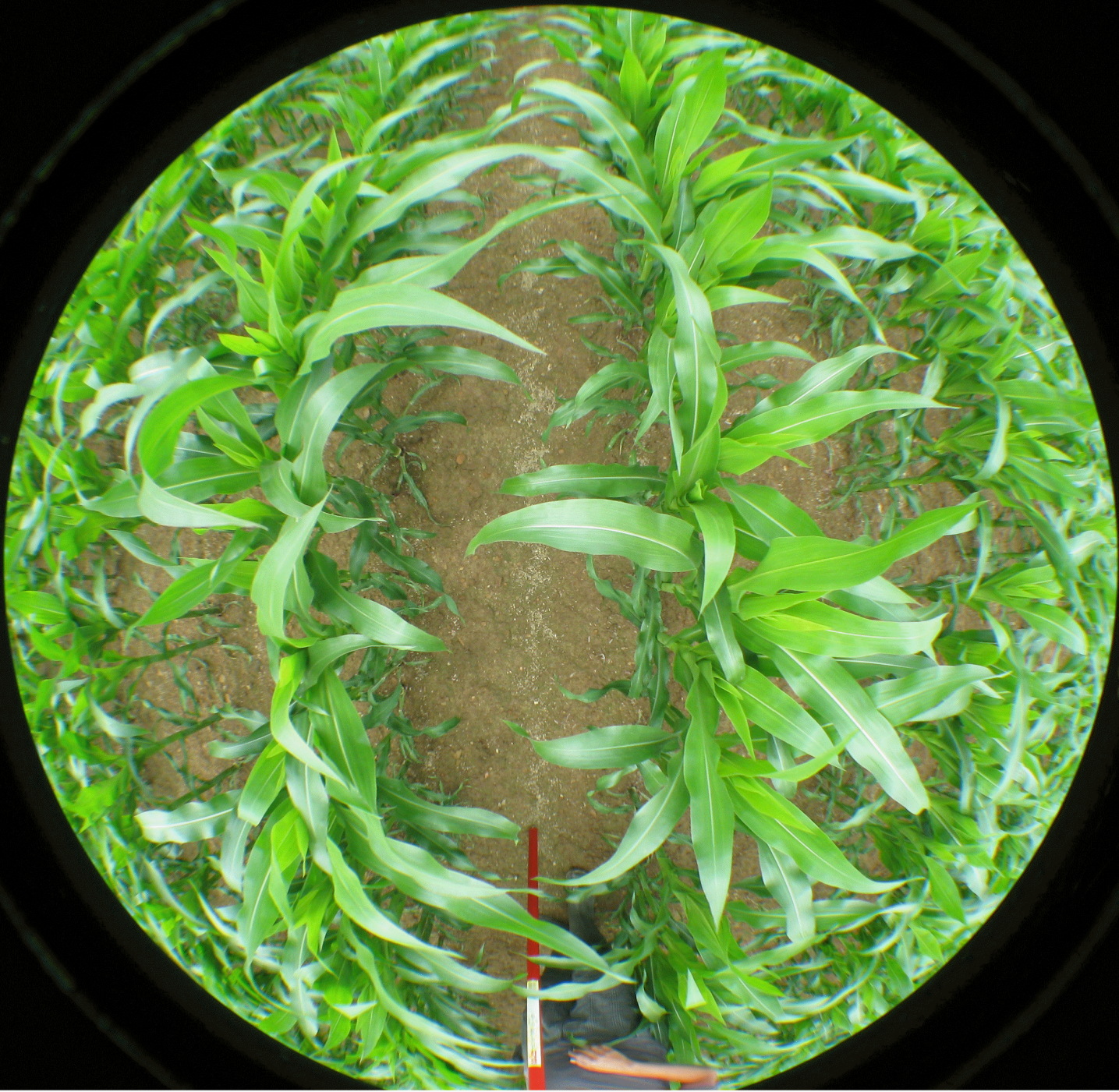


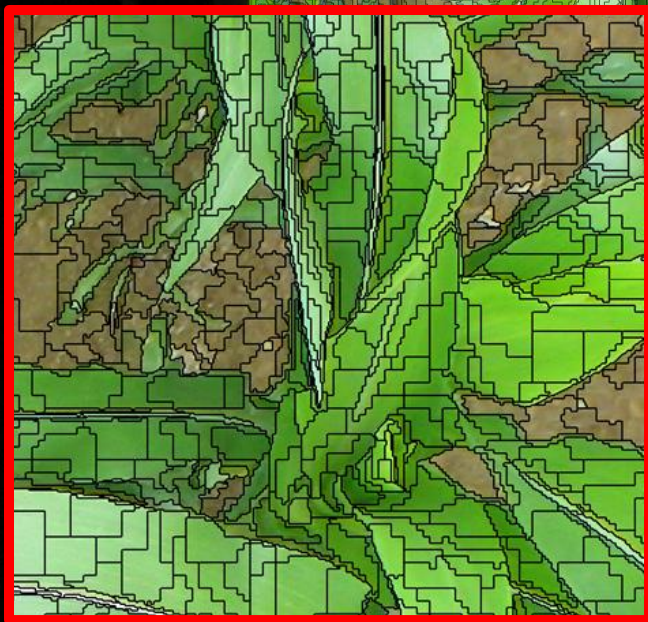
- Leaf Area Index
- Canopy cover

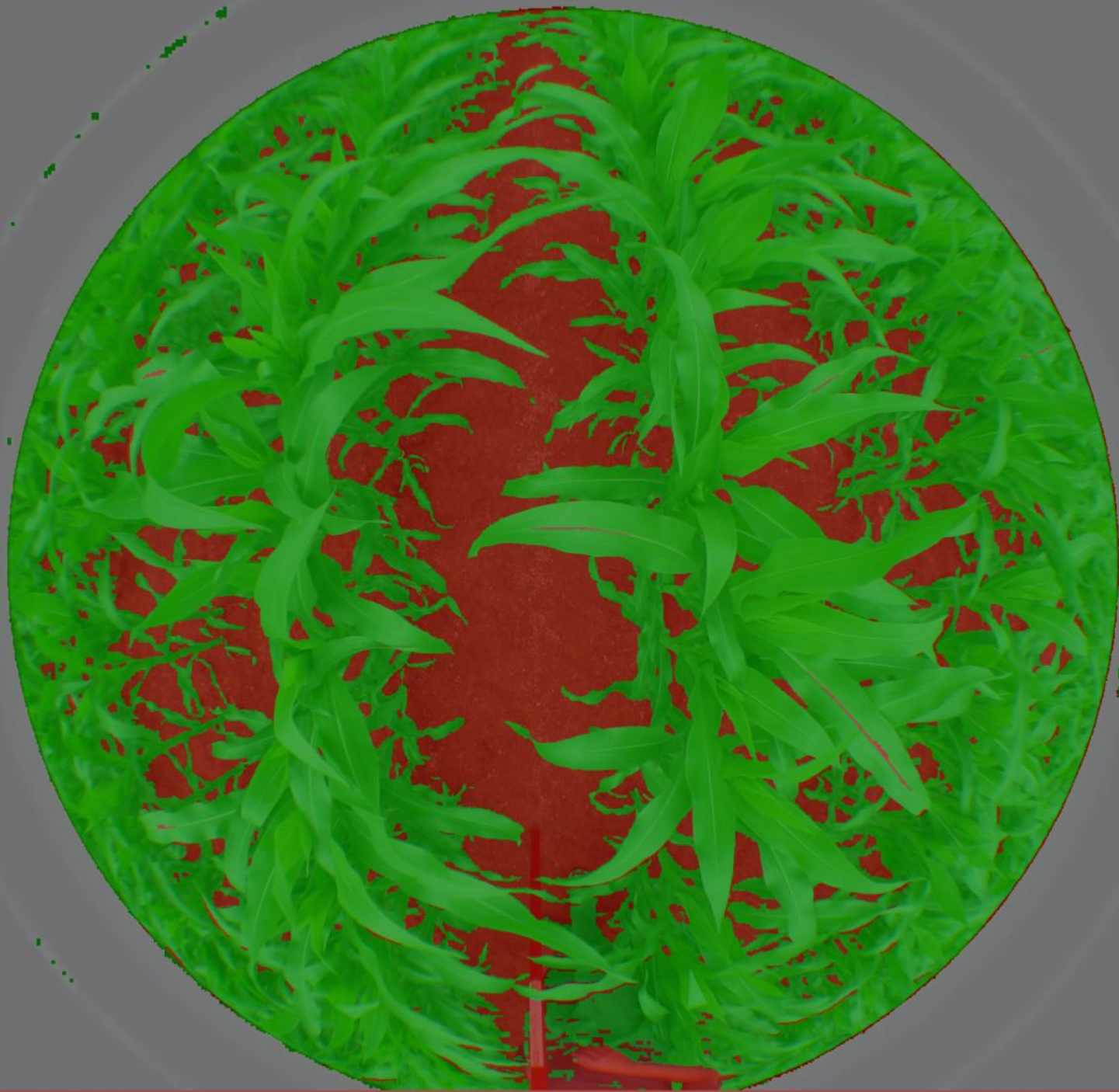


- Yield







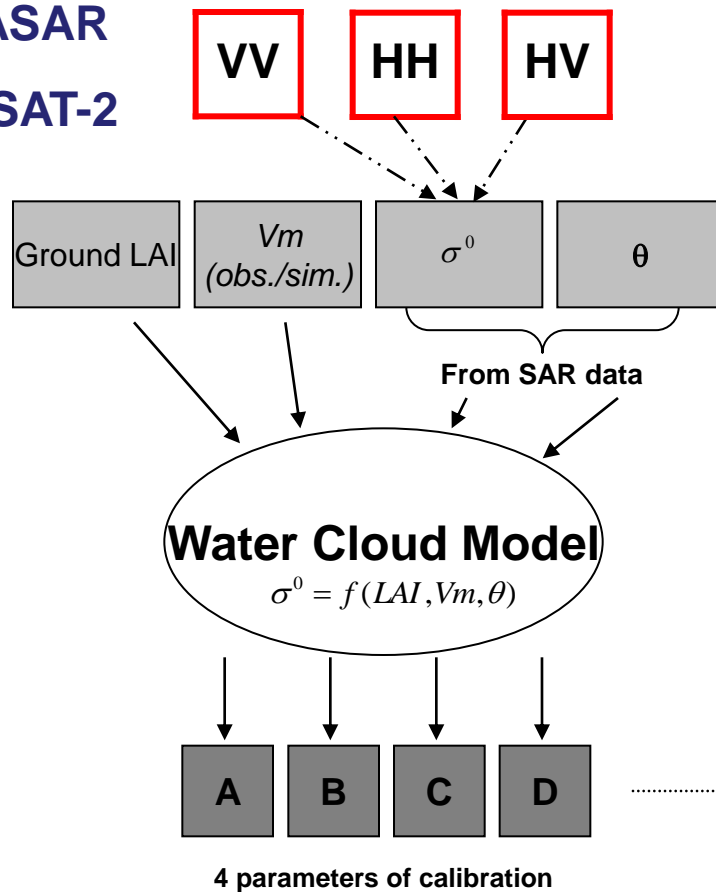


GLOBAM LAI retrieval from SAR

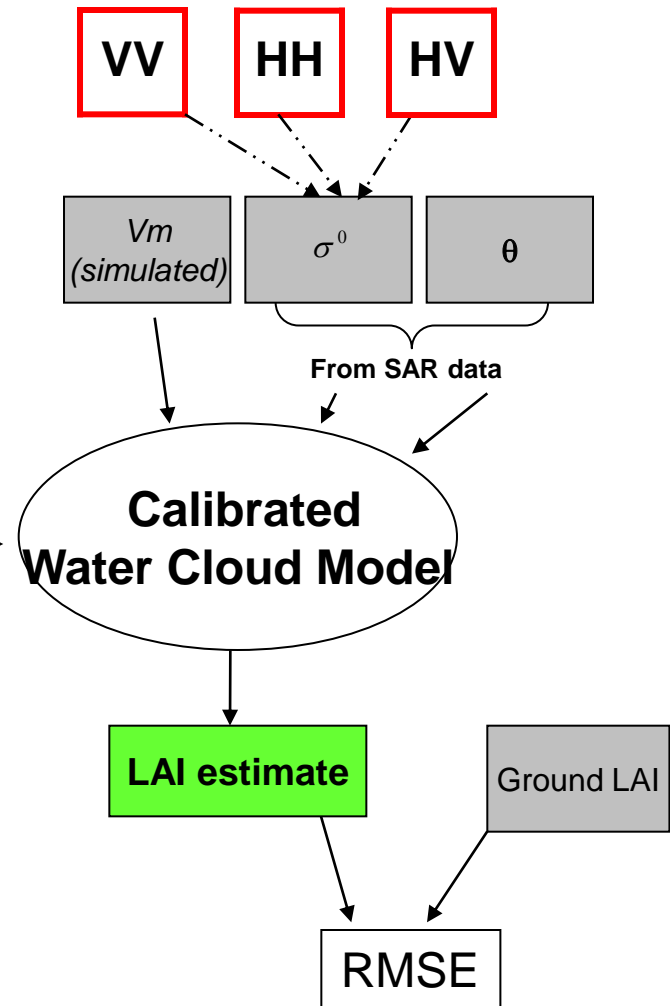
(a) calibration

ERS, ASAR
 RadarSAT-2

4 variables
 needed for the
 calibration



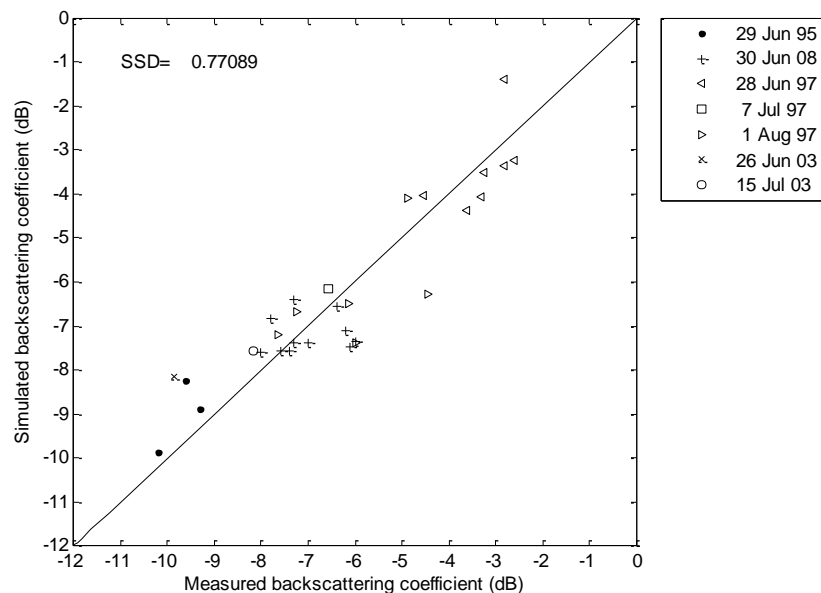
(b) Inversion



LOBAM LAI retrieval from SAR

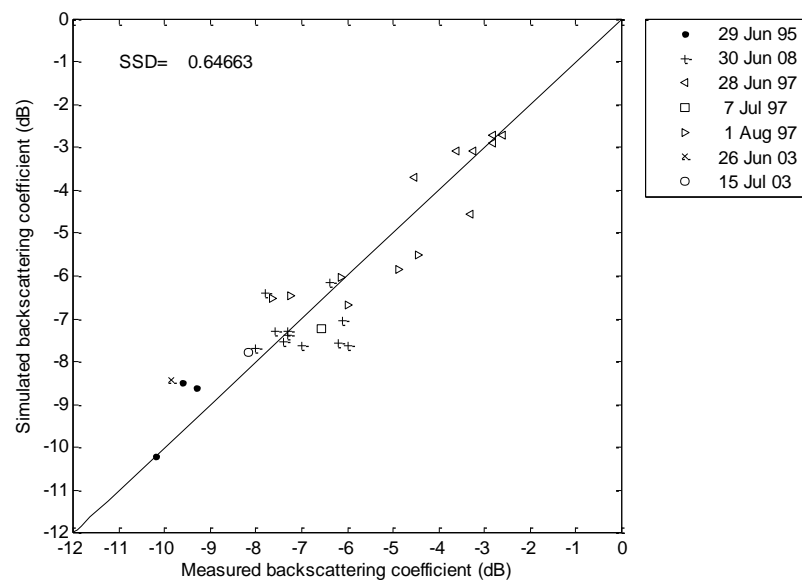
Soil, Water, Atmosphere and Plant (SWAP) model allows to simulate soil moisture accurately to replace field observation

Using measured soil moisture



LAI RMSE = 0.88

Using simulated soil moisture



LAI RMSE = 0.97

n=30

GLOBALAM LAI retrieval from SAR

- More accurate LAI retrieval from **HV polarization**

LAI RMSE = 0.659 (2008 and 2009)

- Good inter-annual robustness of the WCM calibration

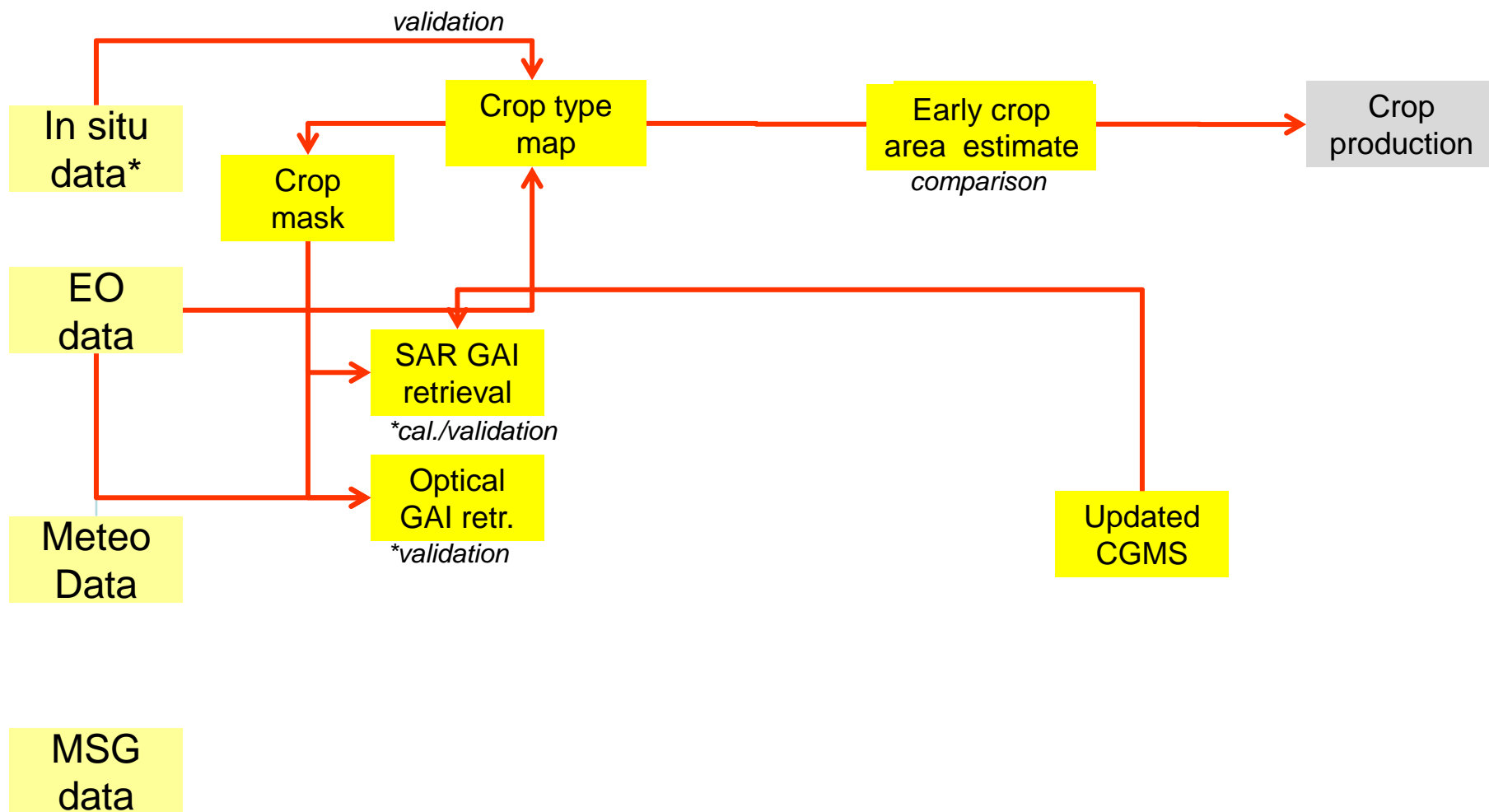
LAI RMSE = 0.67 to 1.2 (5 years data set)

- Efficient use of simulated soil moisture (V_m)

little impact on LAI RMSE

⇒ **Operational potential of SAR retrieval**

⇒ Promising complementarity between LAI derived from SAR and optical data



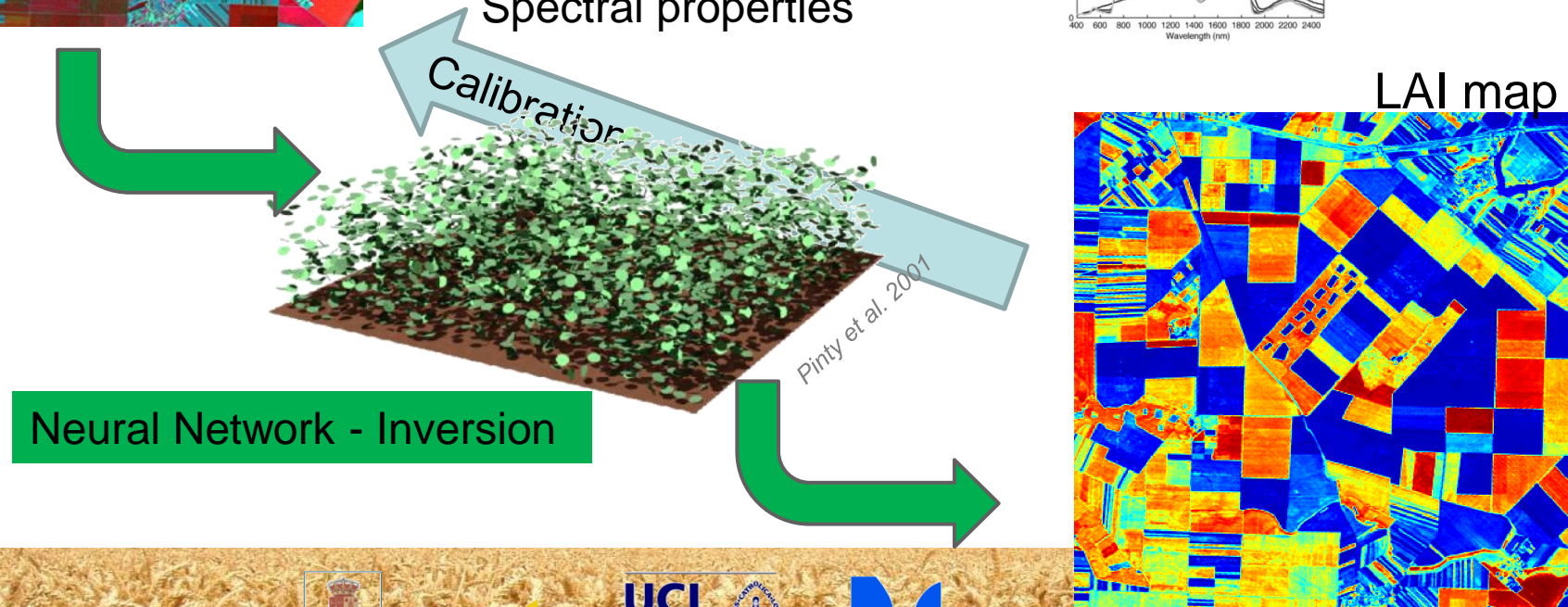
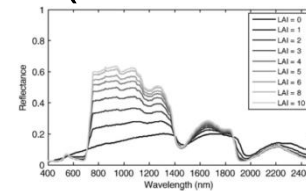
GLOBALAM LAI retrieval from HiRes optical data



Calibrated and atm. corrected images

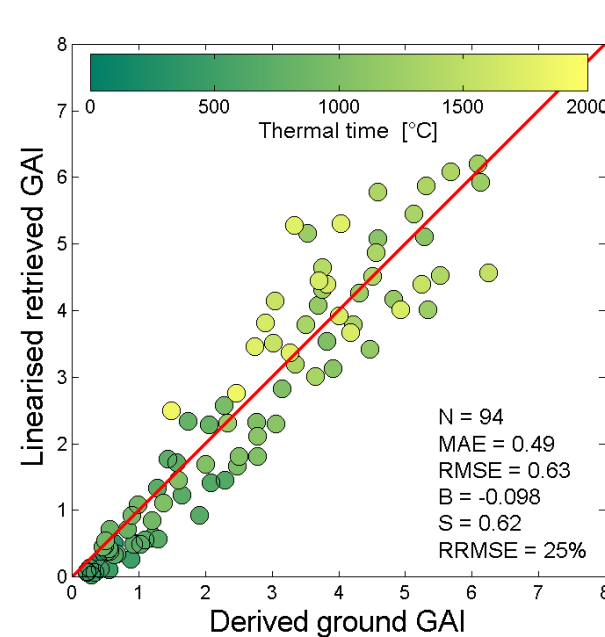
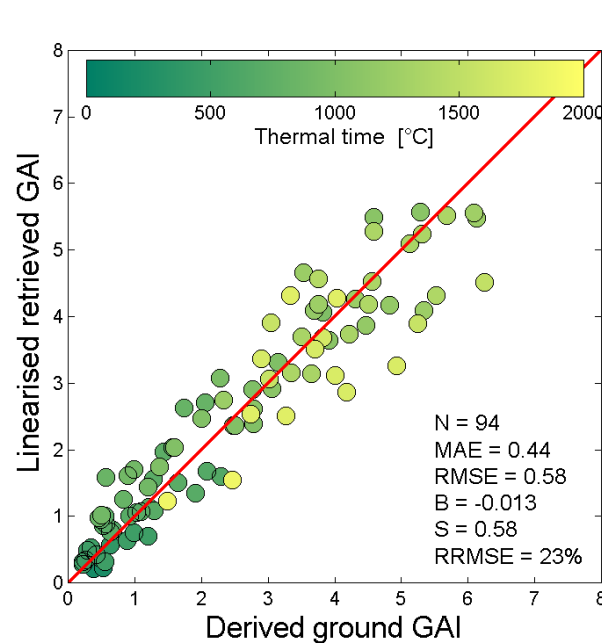
Radiative Transfer Model (PROSAIL)

Observation geometry
Canopy structure (incl. LAI)
Spectral properties



GLOBALAM GAI retrieval from HiRes optical data

- Generic inversion providing great performance
empirical RMSE=0.44 *versus* NNT+RTM RMSE =**0.49**



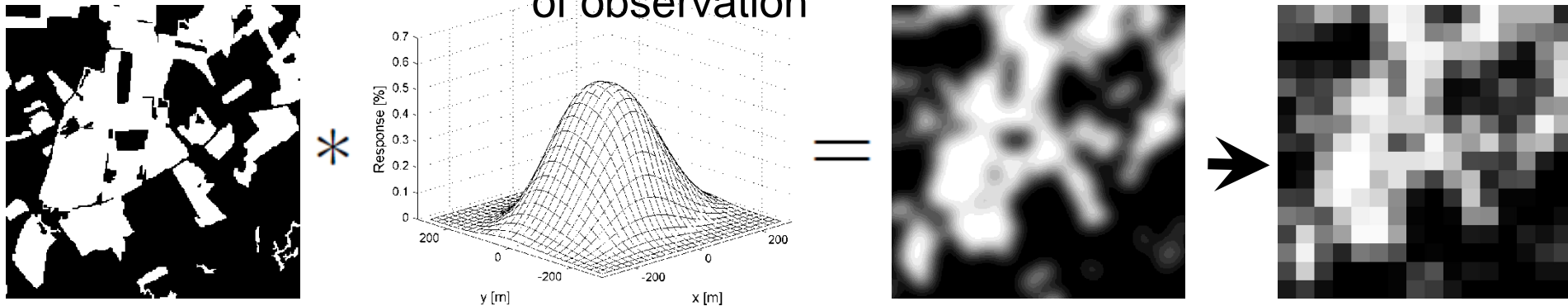
ADAM data set – Fundulea, Romania

Duveiller et al., RSE 2011

GLOBALAM GAI retrieval from MedRes optical data

- Crop specific MODIS LAI inversion thanks to crop purity mask derived crop map

Point Spread Function
indicates footprint
of observation



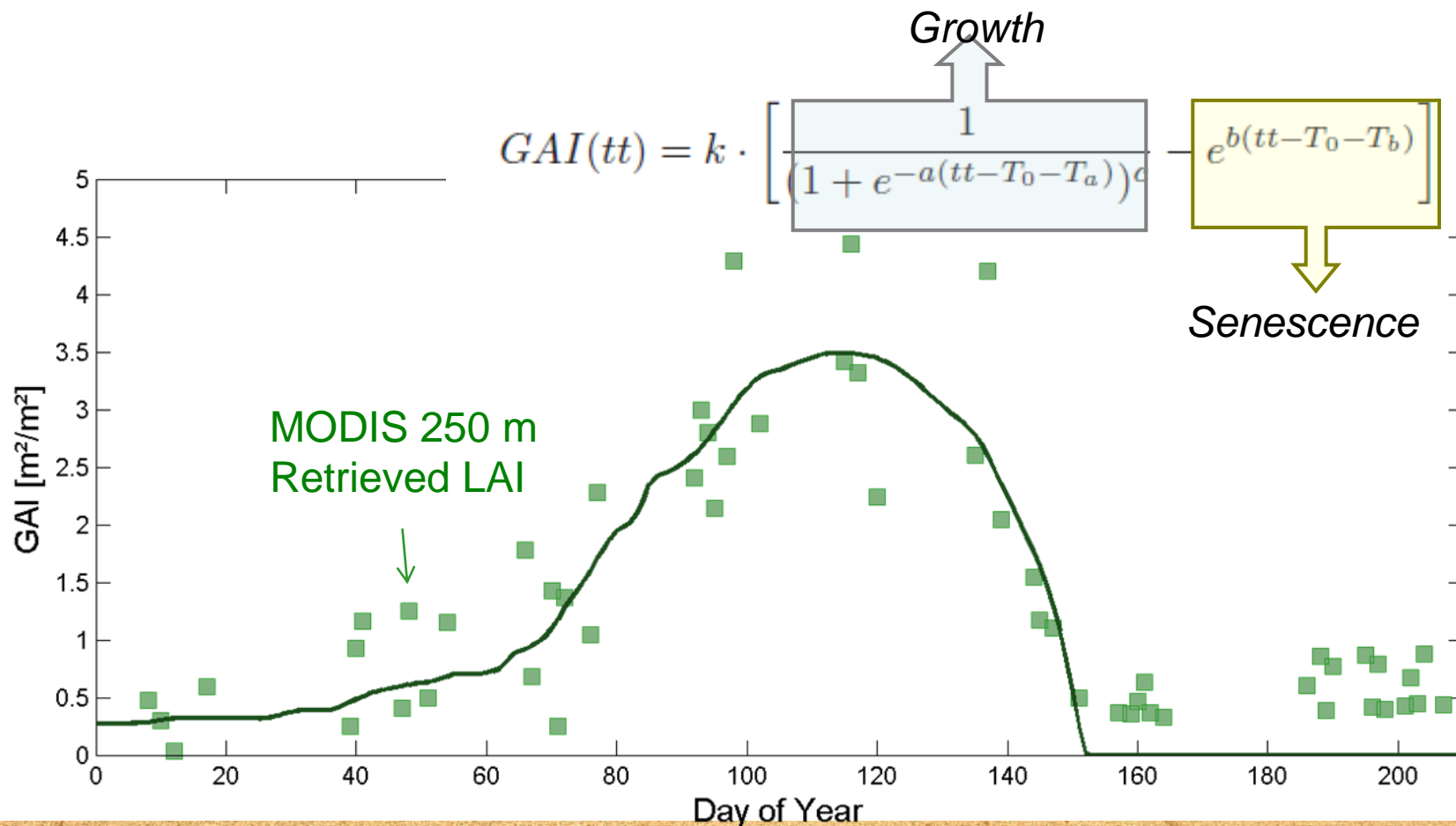
Crop specific mask
delineates winter wheat

MODIS 250 m
resolution

Pixel purity map
for winter wheat

GLOBALAM GAI retrieval from MedRes optical data

- From noisy instantaneous MODIS GAI to continuous GAI profile by Canopy Structural Dynamic Model fitting





GAI = 6

GAI = 3

GAI = 0



GAI = 6

GAI = 3

GAI = 0





GAI = 6

GAI = 3

GAI = 0



GAI = 6

GAI = 3

GAI = 0



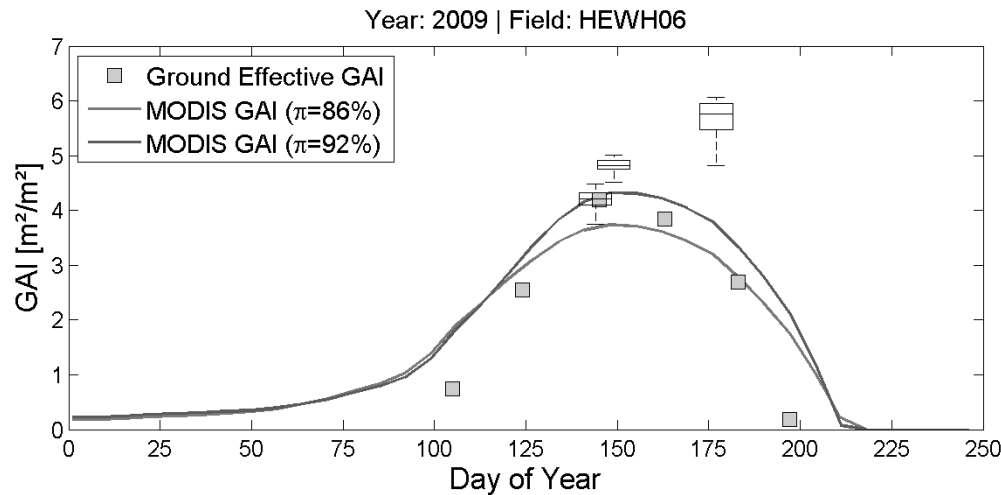
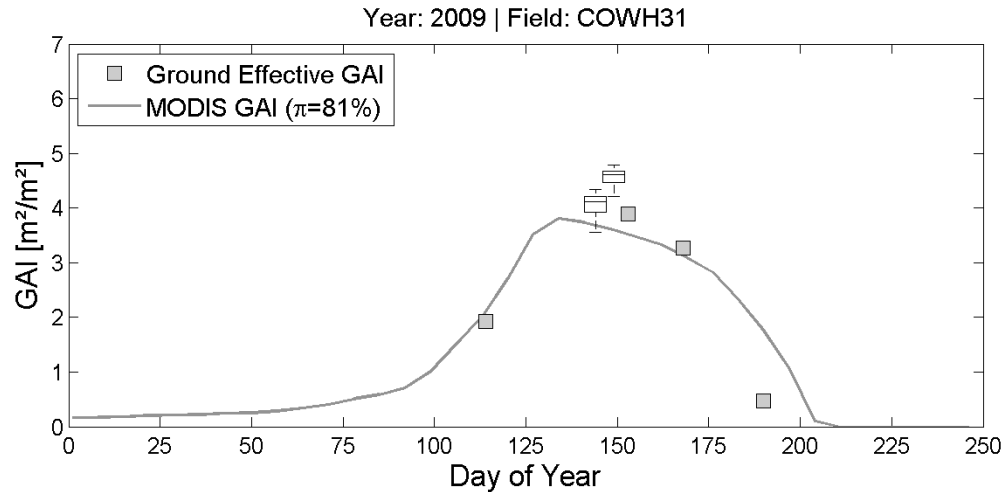


GAI = 6

GAI = 3

GAI = 0

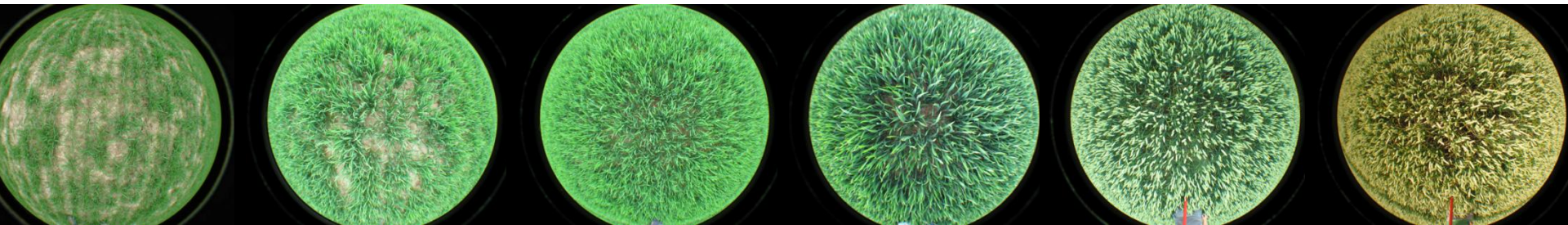
GAI from MODIS – validation from field data



MAE = $0.73 \text{ m}^2/\text{m}^2$
RMSE = $0.95 \text{ m}^2/\text{m}^2$

Duveiller et al. RSE 2011 in press

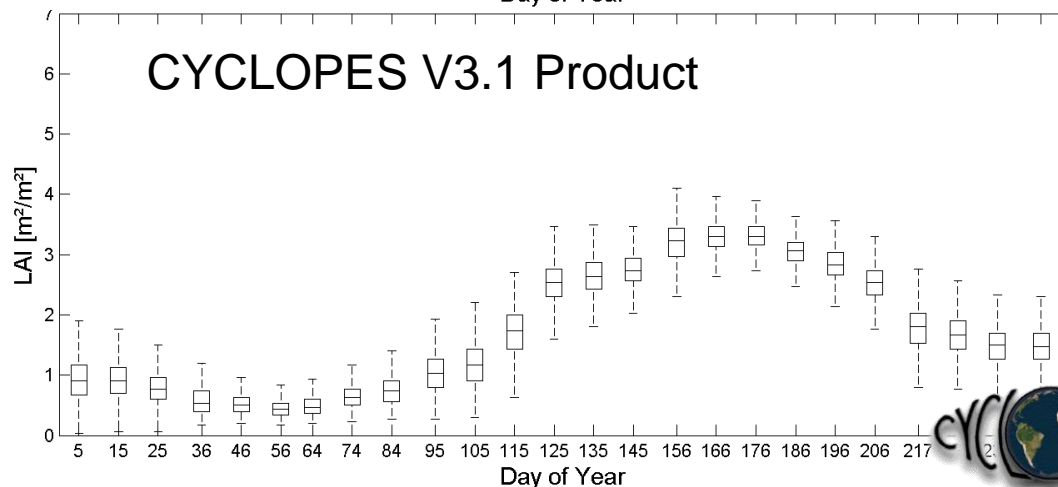
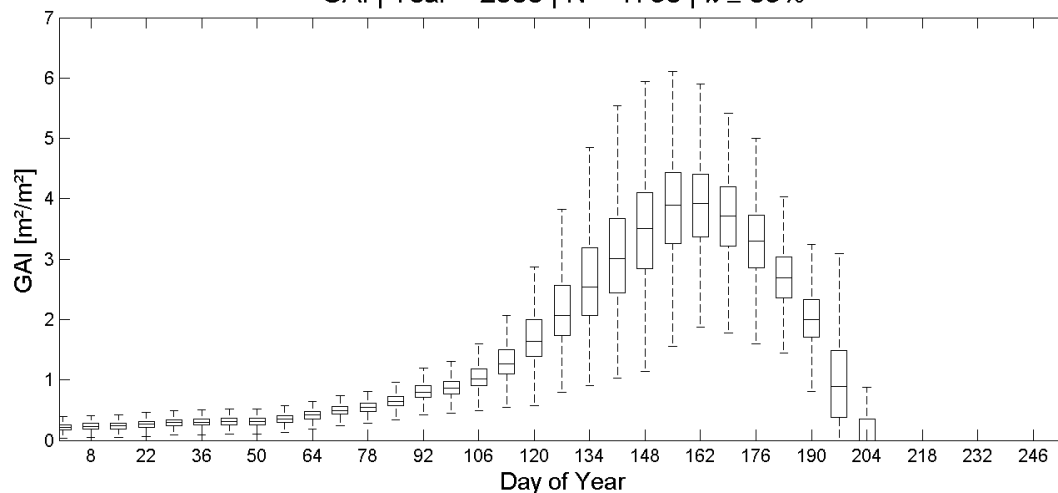
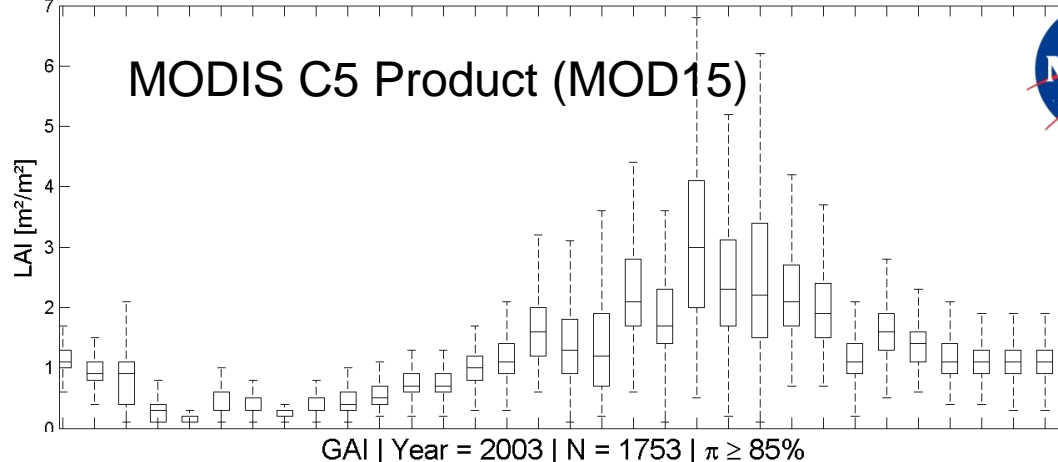
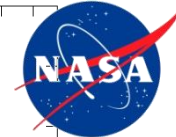
Ground GAI obtained from Digital Hemispherical Photography



GAI from MODIS

Comparison with
existing products
(2003 – purity > 85 %)

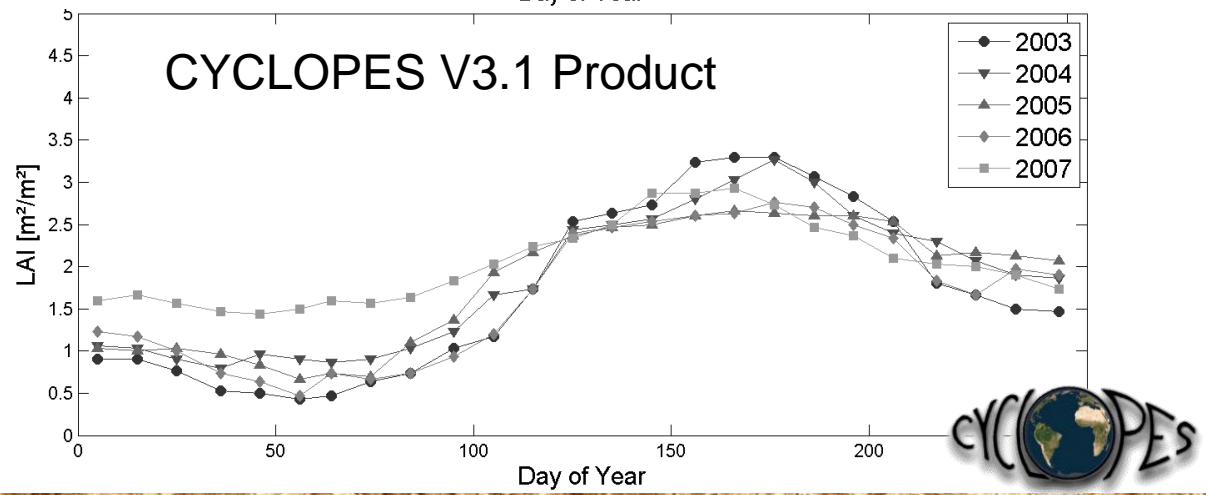
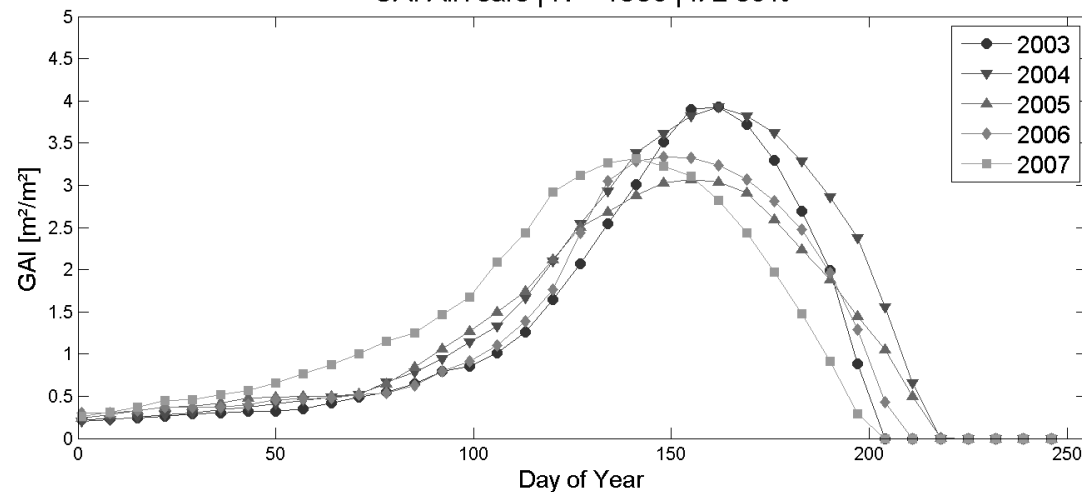
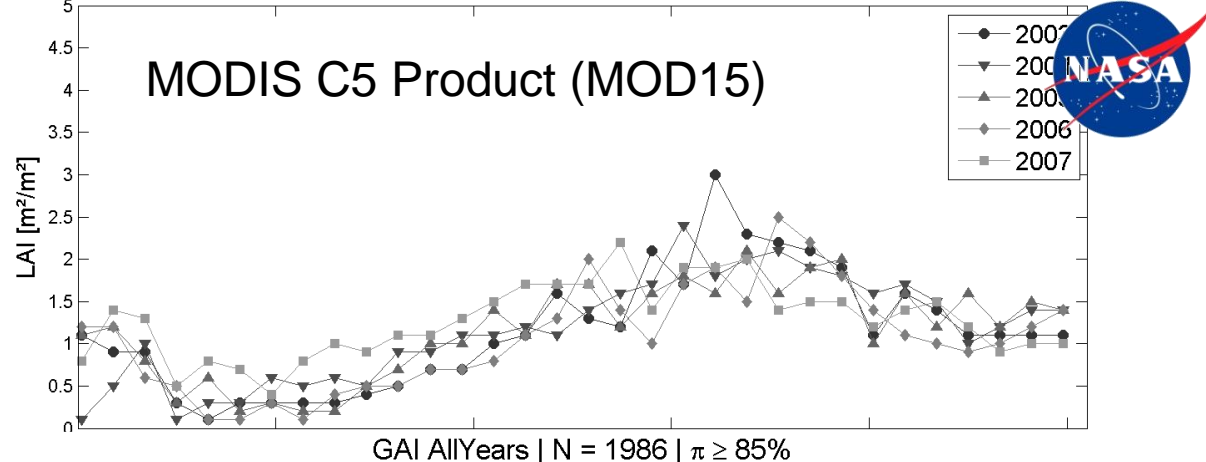
Best temporal consistency
and wide range for
GLOBAM GAI estimate



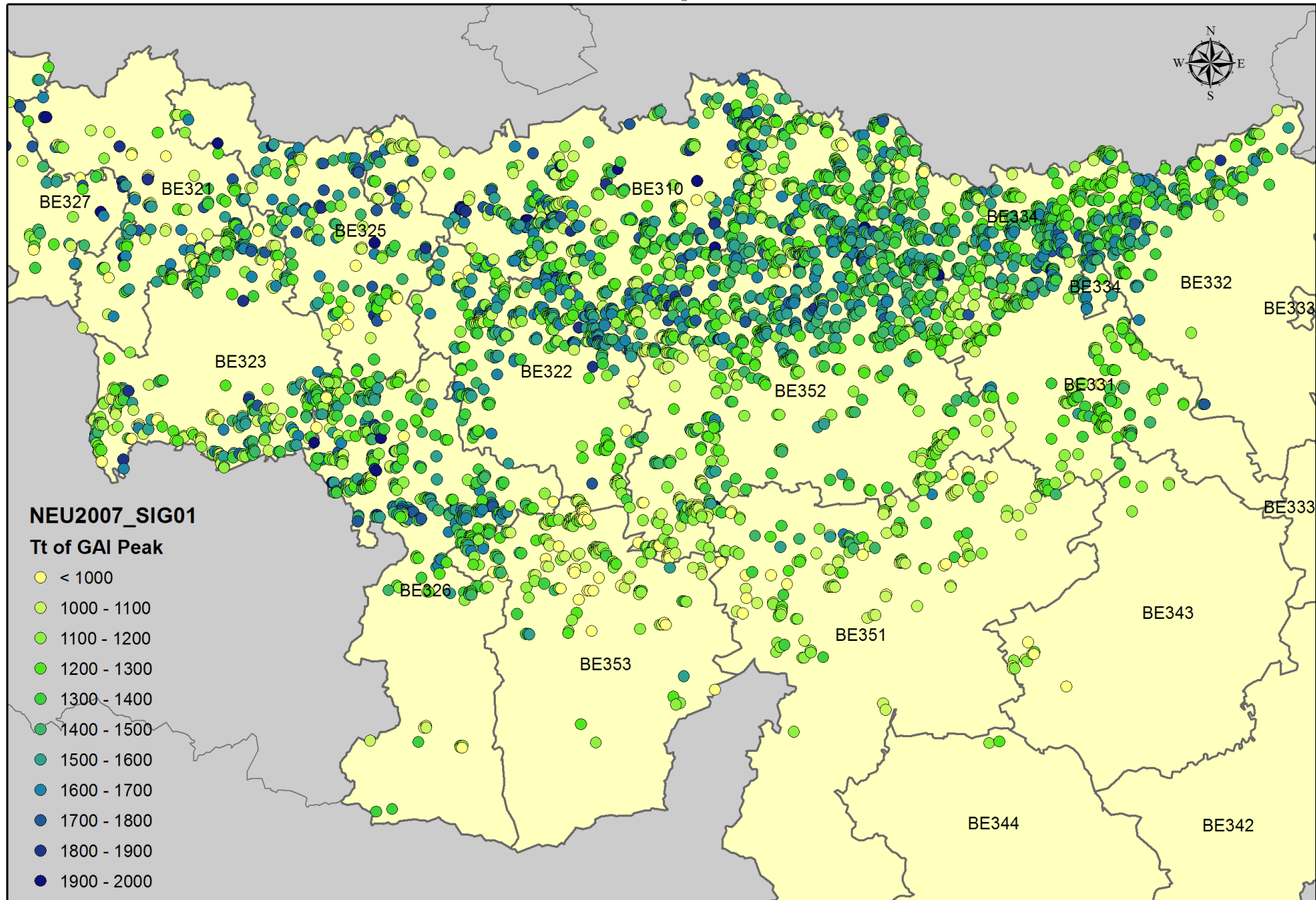
GAI from MODIS

Multi-year comparison
with existing products
(5 years – purity > 85 %)

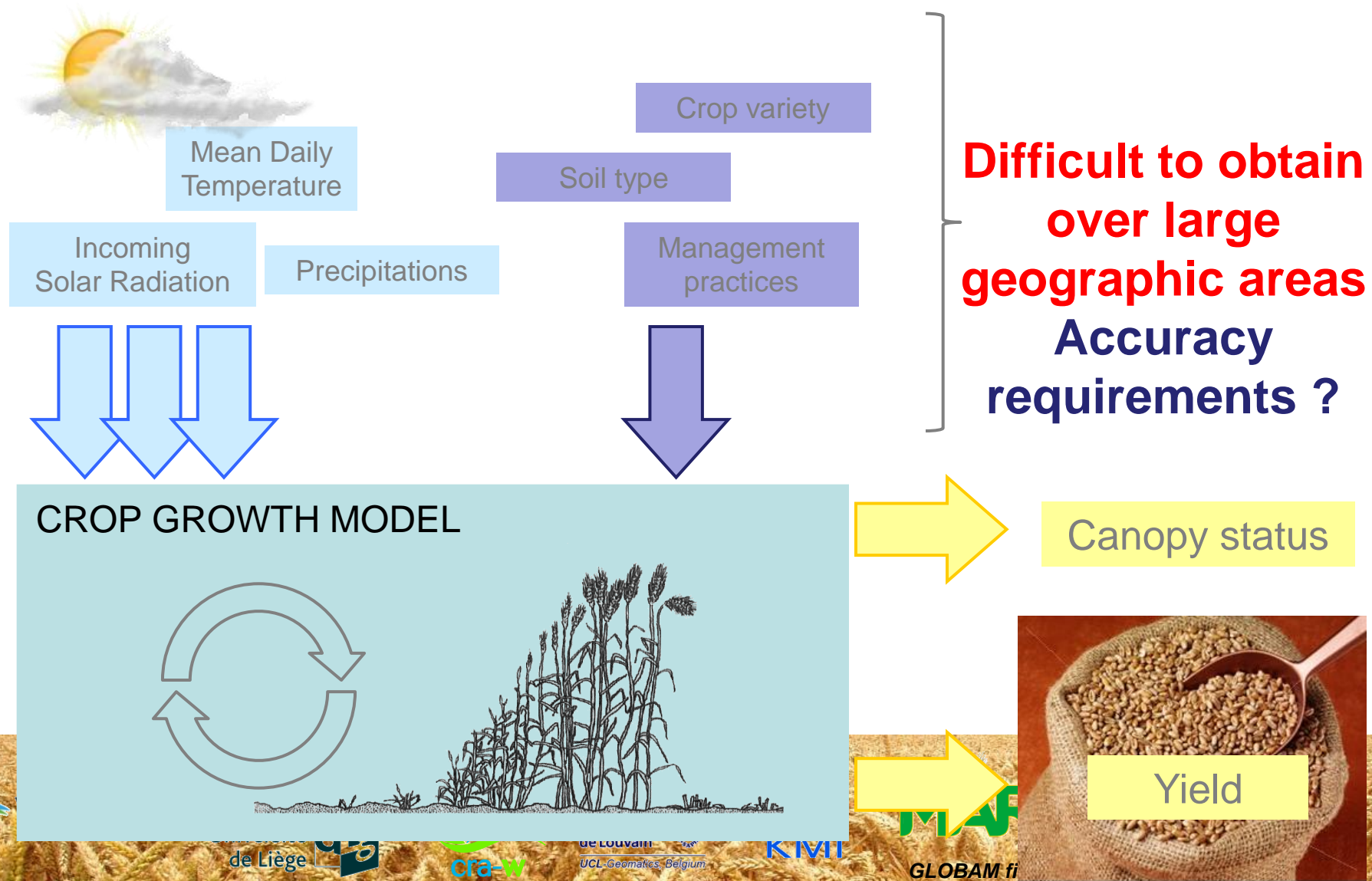
Inter-annual
variability is better
grasped



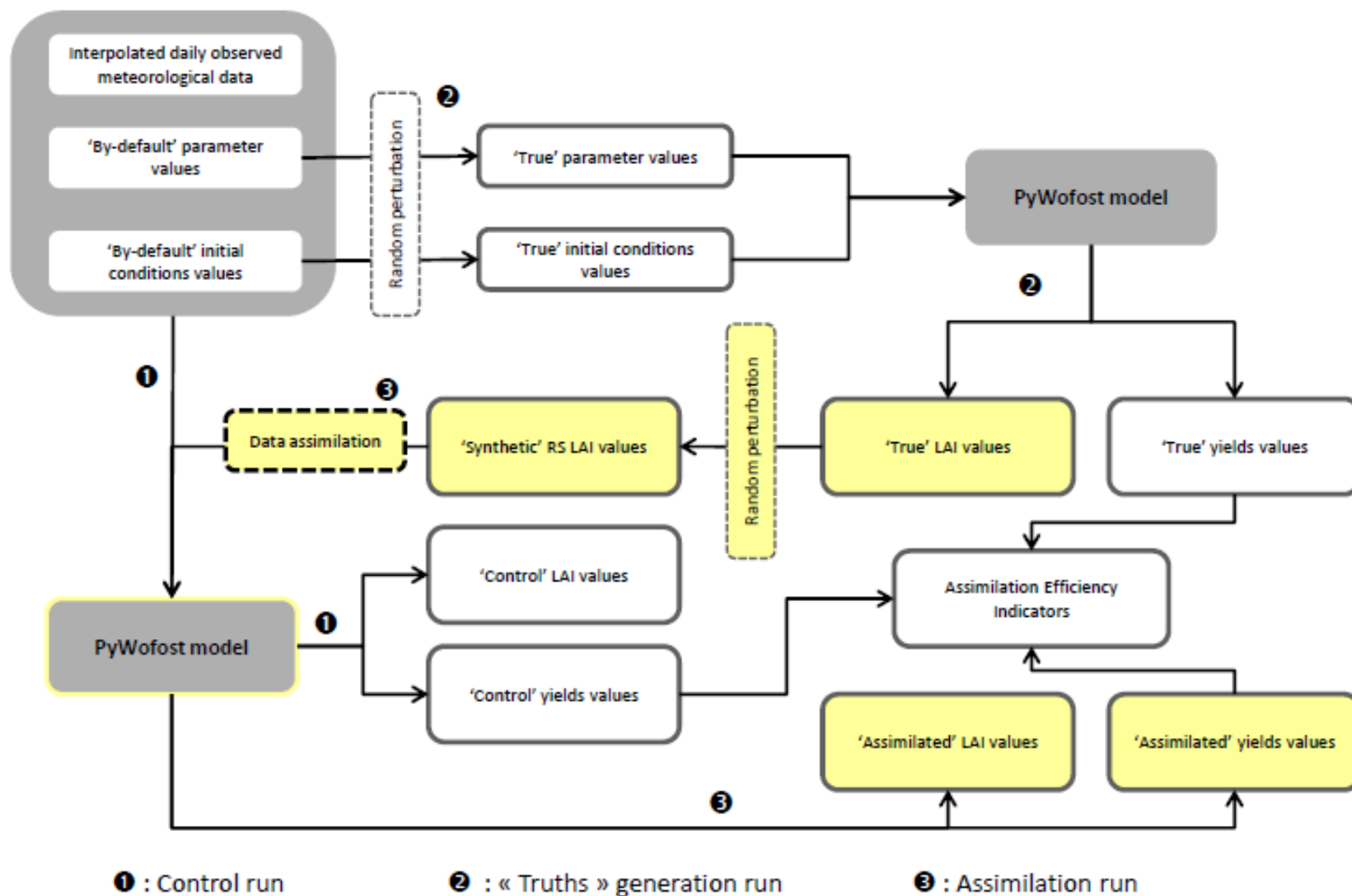
Thermal time of GAI peak - SIGEC 2007



Crop growth models resume our understanding of how crops grow



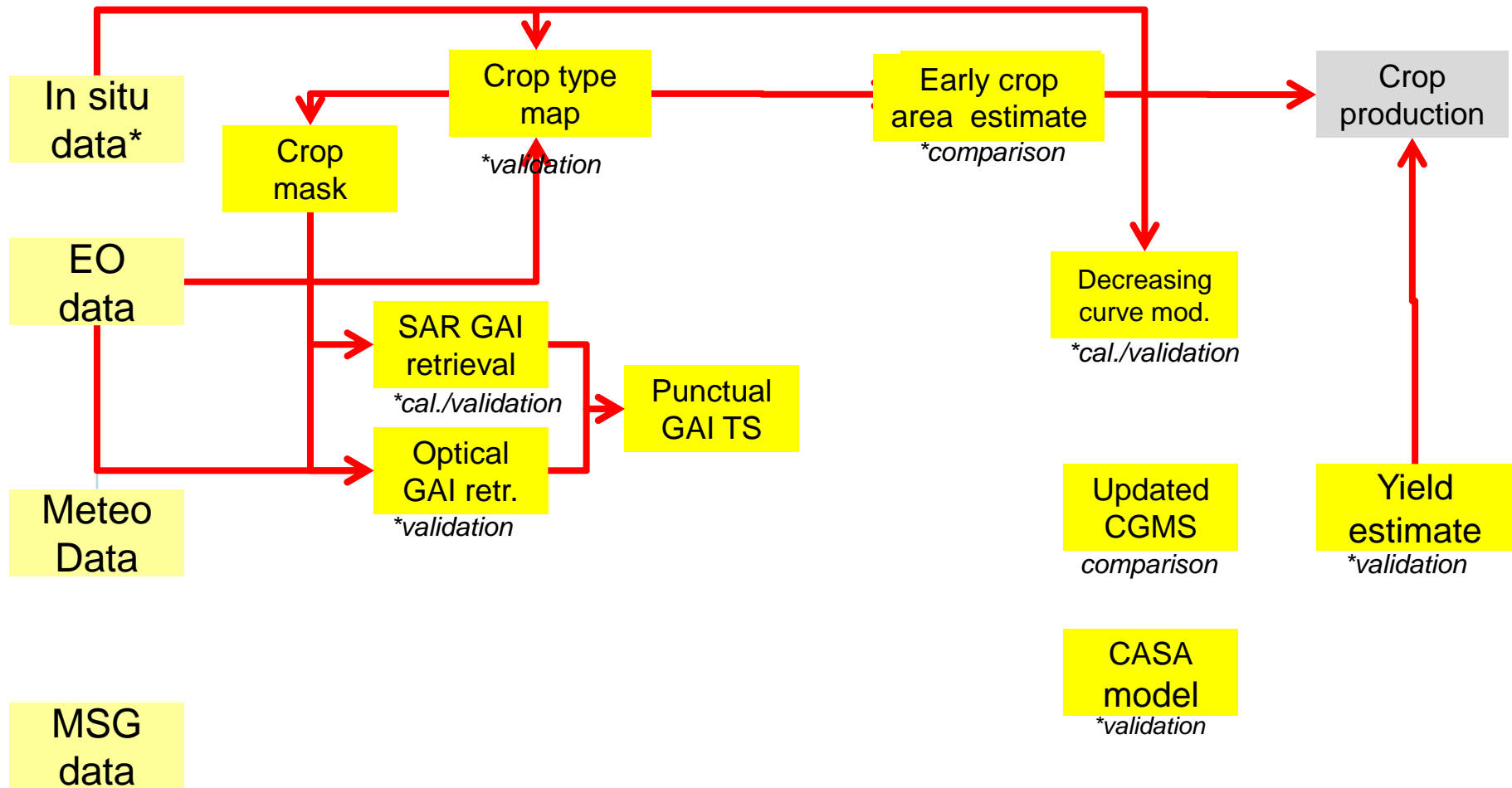
Observing System Simulation Experiment (OSSE)



1 : Control run

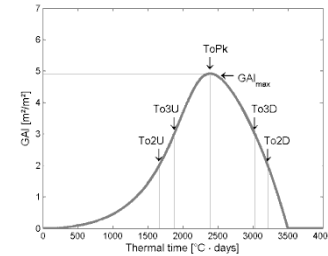
2 : « Truths » generation run

3 : Assimilation run



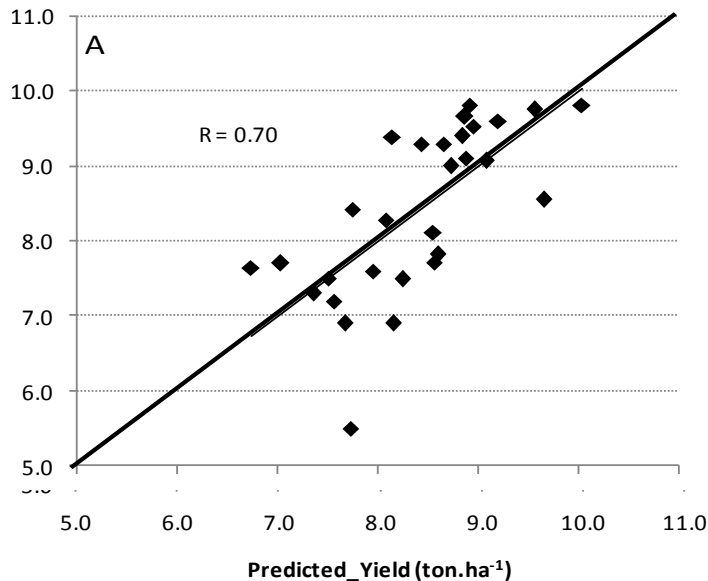
Simplified yield model from GAI

based on senescence phase of EO-retrieved GAI



Official_Yield (ton.ha⁻¹)

Correlation R= 0.70



$$GAI(tt) = \frac{A}{\left(1 + \left(\exp(-k(tt - m))\right)\right)}$$

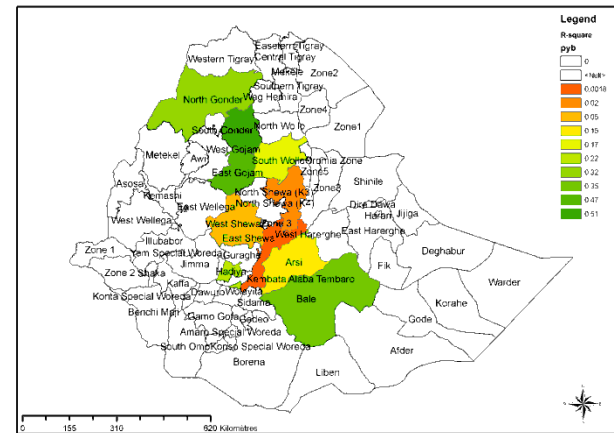
A = maximum value of GAI,
 m = inflection point in the decreasing part
 k = relative senescence rate
 tt = thermal time

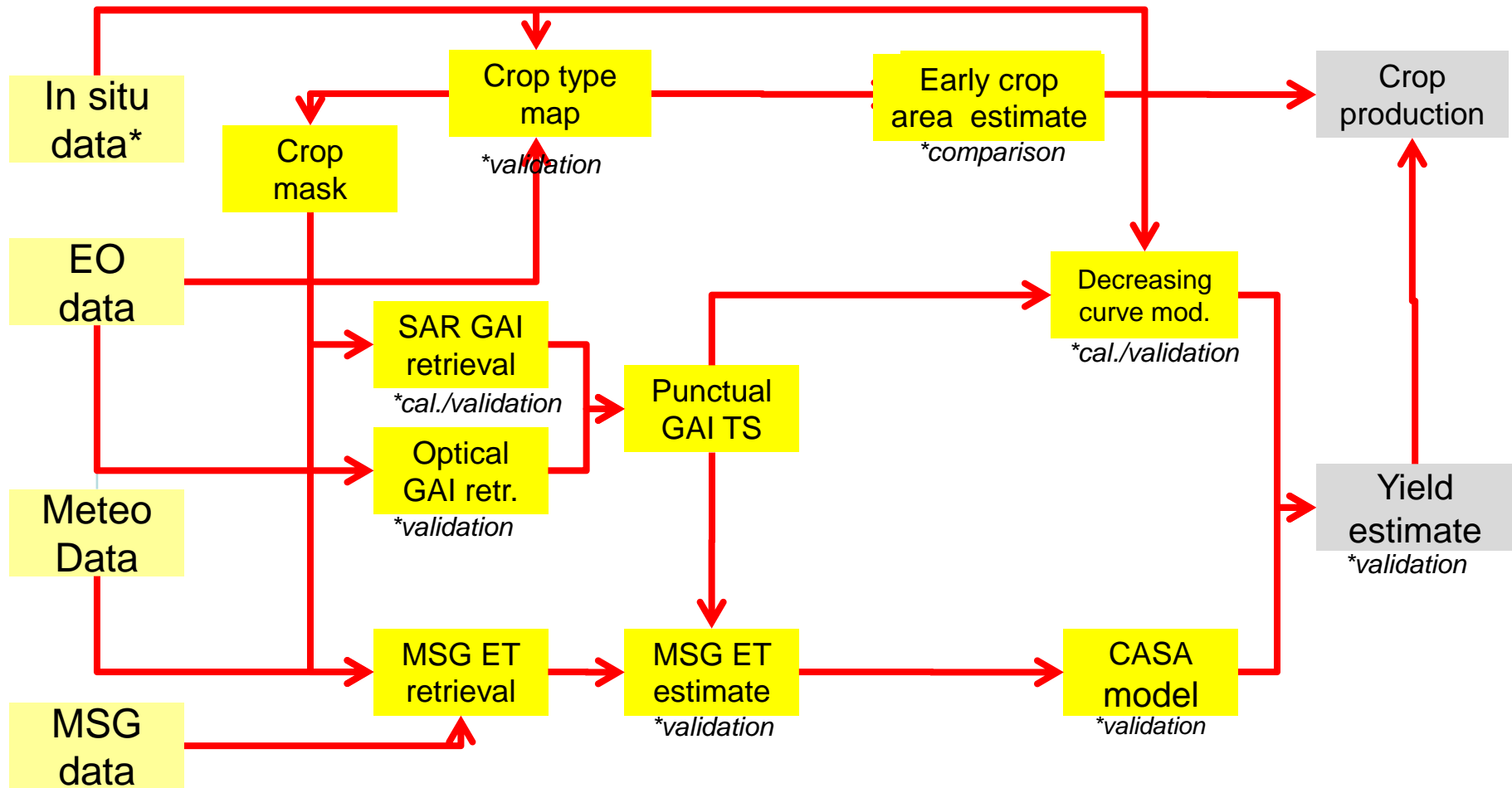
- Modified logistic function to describe GAI senescence phase and then provide wheat yield estimates

CGMS and simple FAO model for Ethiopia

- Poor results from CGMS ($R = 0.3$ to 0.5 – 3 zones sign. out of 11)
- Better results from FAO AgroMetShell water balance model

	AMS R^2	CGMS R^2	RMSE-AMS	RMSE-CGMS
ET0302	0.43	0.49	133.7	142.7
ET0306	0.62	0.41	174.2	279.8
ET0702	0.55	0.39	124.5	187.1

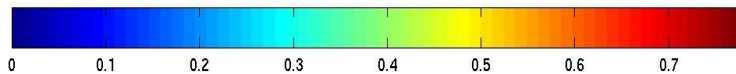
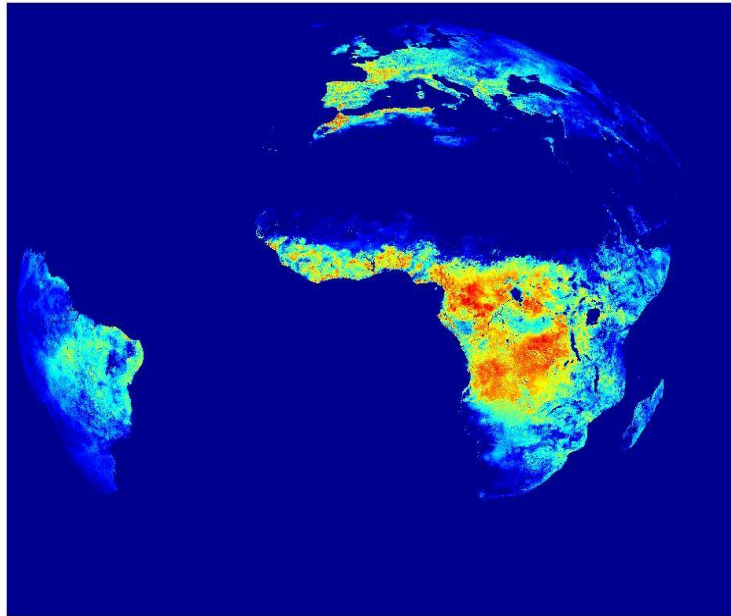




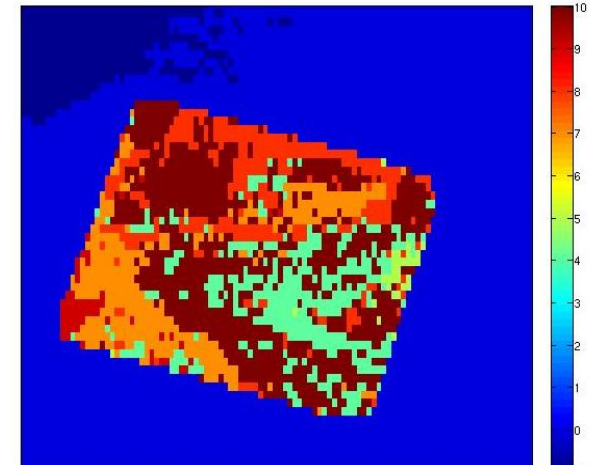
GLOBAL MSG evapotranspiration - from LSA-SAF ET model

LSA-SAF ET
[mm/h]

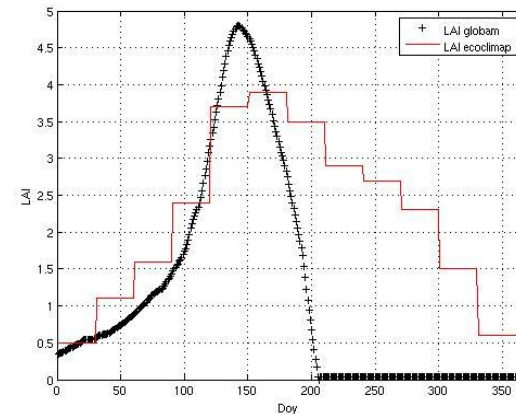
2010/04/28/1200



<http://landsaf.meteo.pt/>



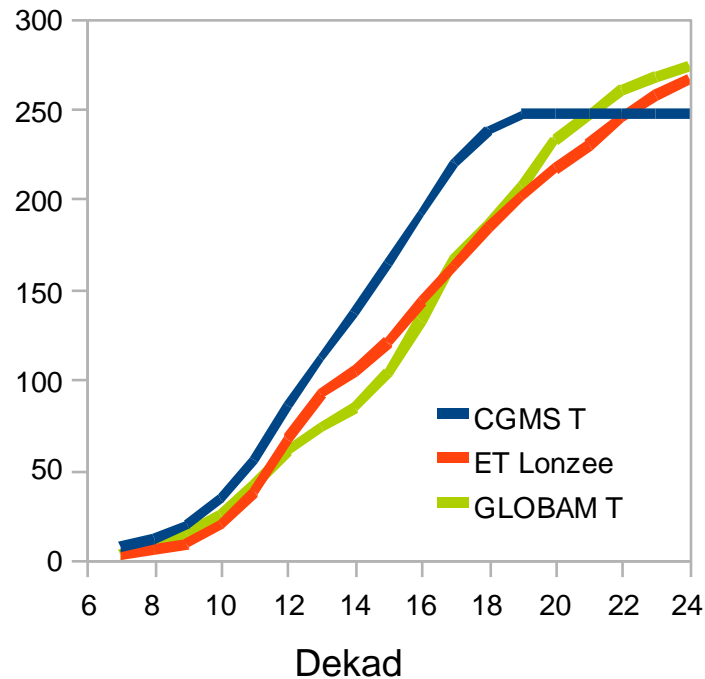
ET crop specific thanks to Landsat crop mask in MSG grid



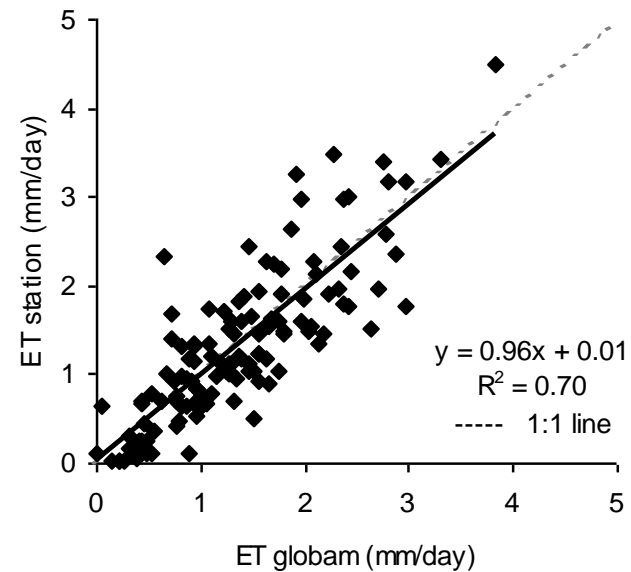
2007 MODIS GAI obtained versus Ecoclimap DB

LOBAM MSG evapotranspiration – validation on flux tower

Time series comparison



Validation

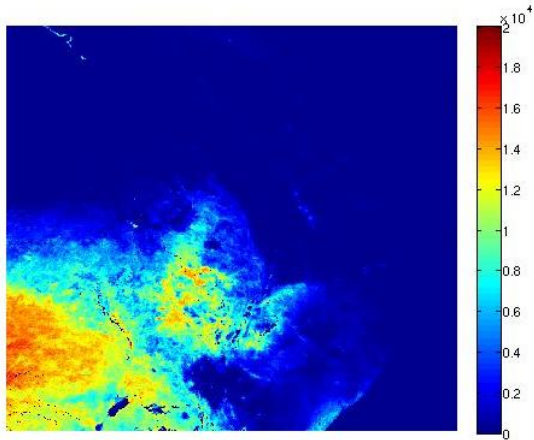


With GLOBAM LAI

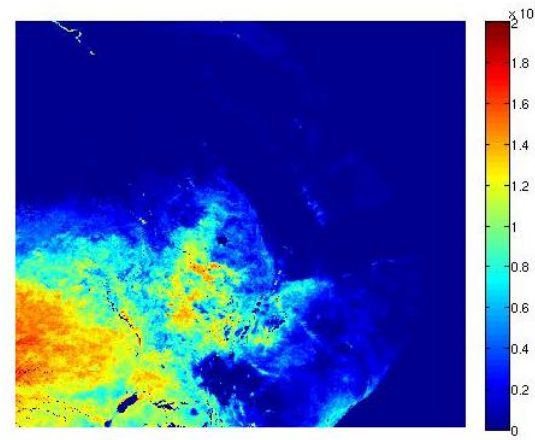
GLOBAL MSG evapotranspiration

Very promising results and efficient CASA model implementation

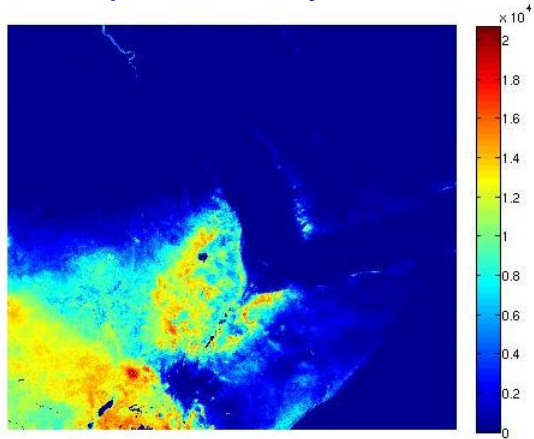
DMP (Kg/ha/day) obtained from CASA



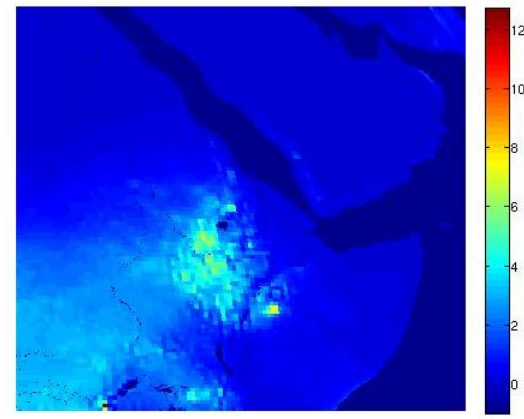
DMP from CASA without water stress modulator

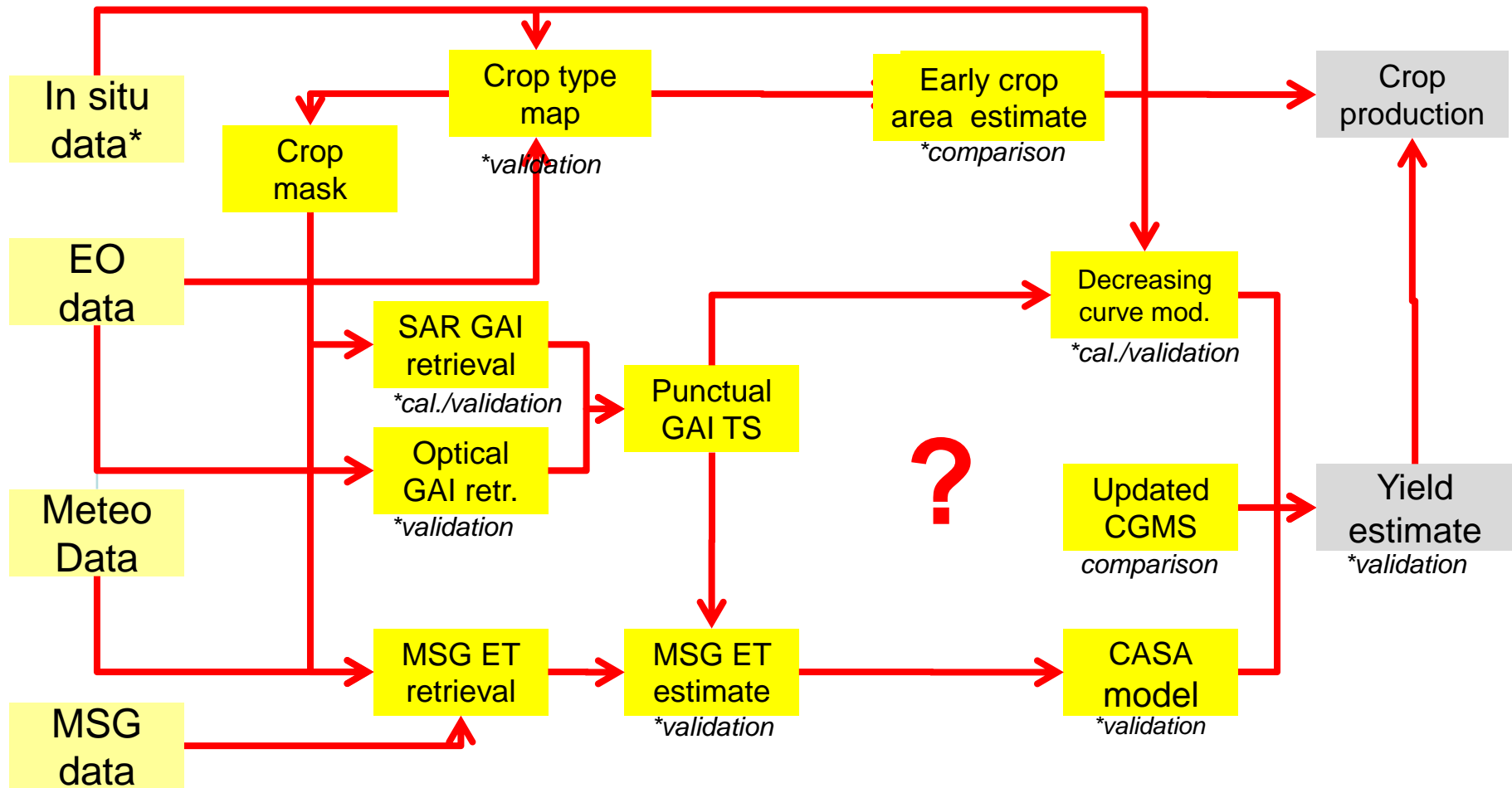


DMP provided by VITO



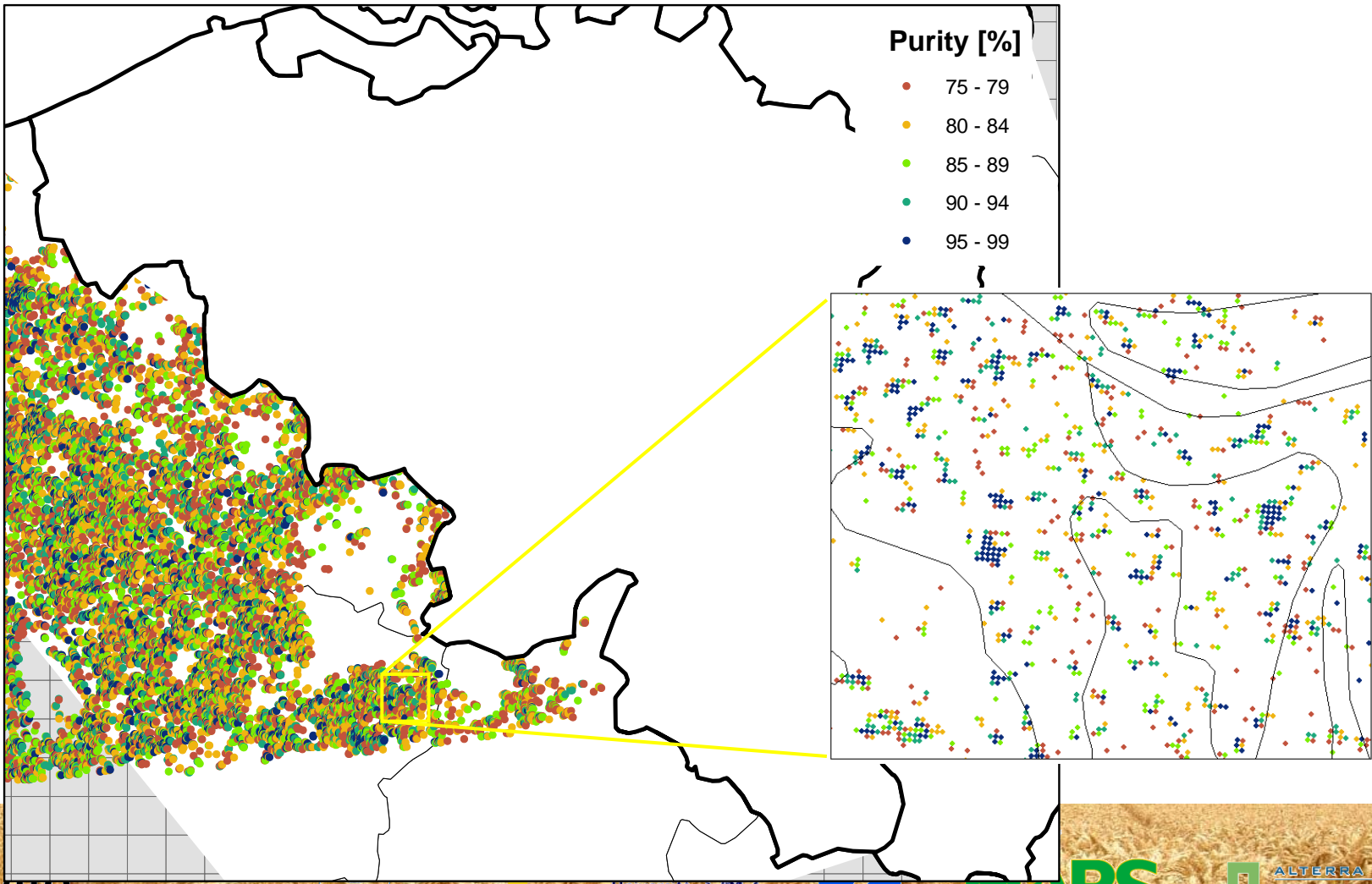
Accumulated rain from ECMWF





GLOBAM 10km grid CGMS recalibrated by MODIS GAI

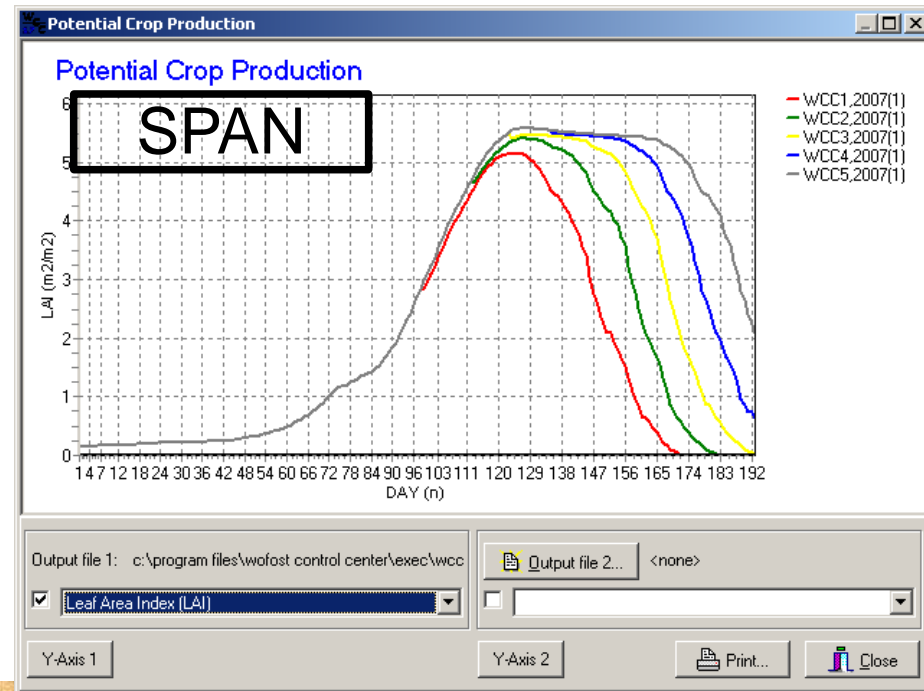
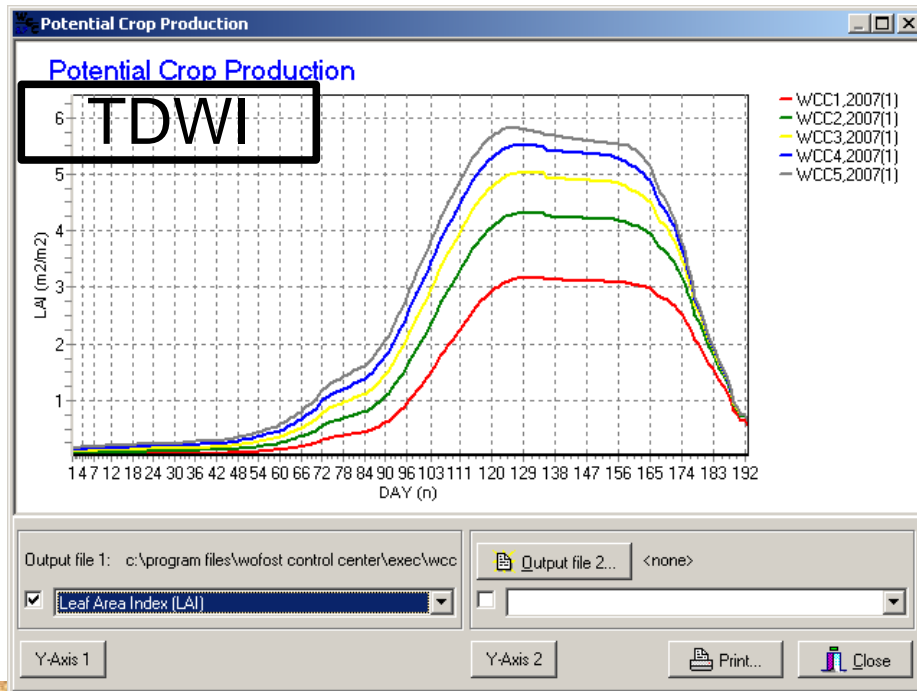
Belgium



GLOBALAM 10km grid CGMS recalibrated by MODIS GAI

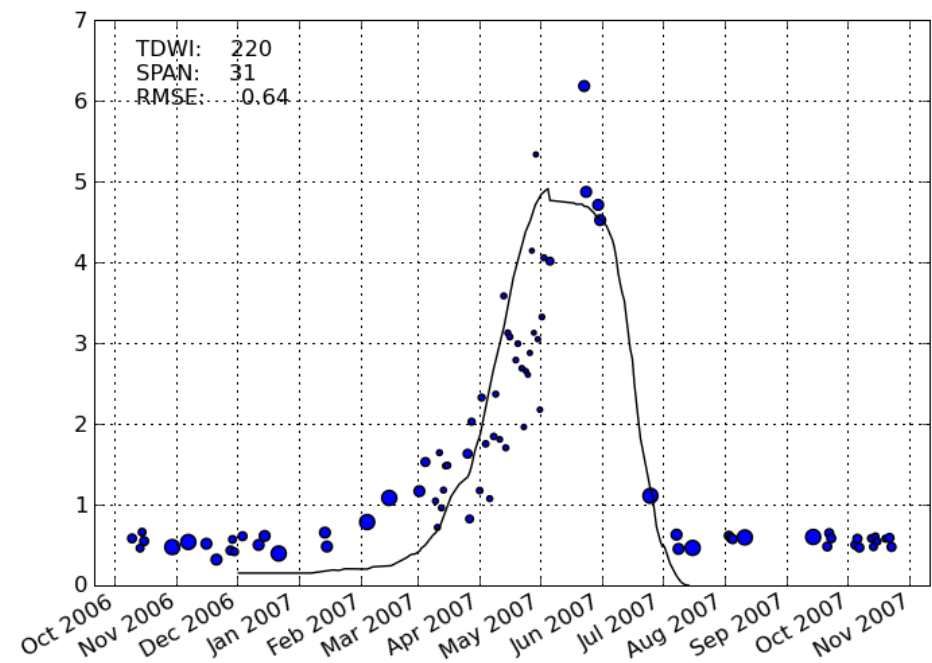
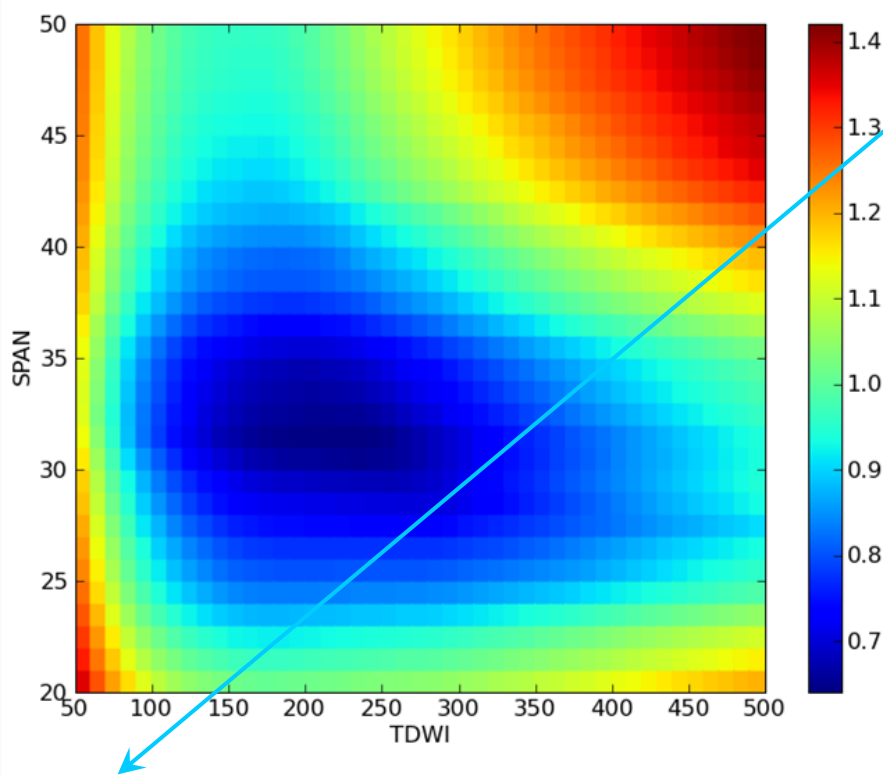
Optimisation of 2 WOFOST parameters from GAI

- Initial dry weight (TDWI)
- Life span of leaves (SPAN)

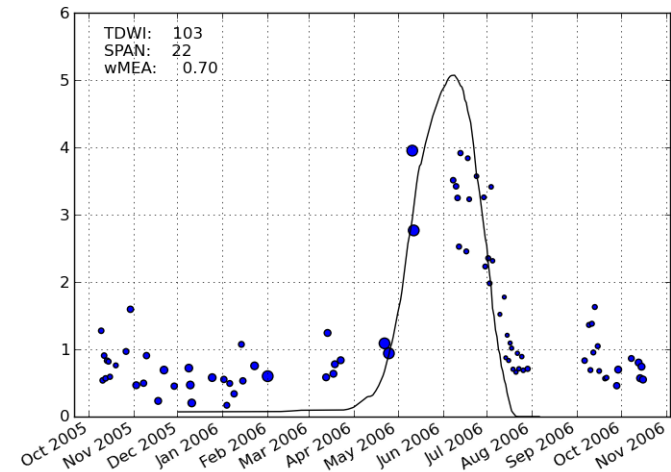
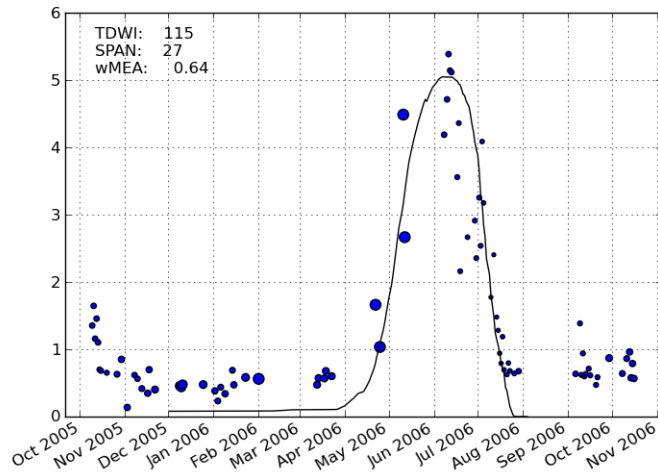
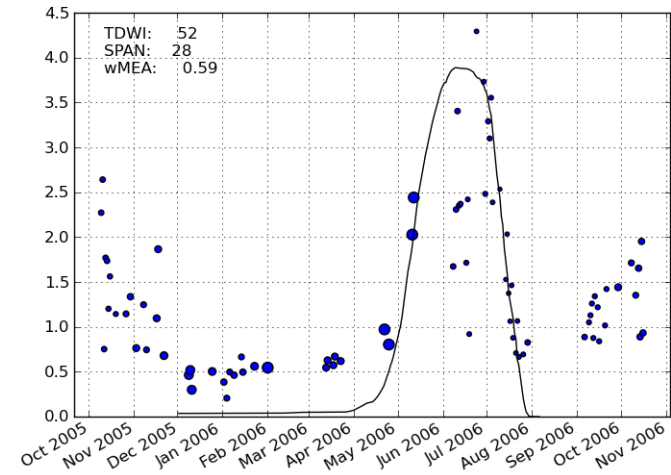
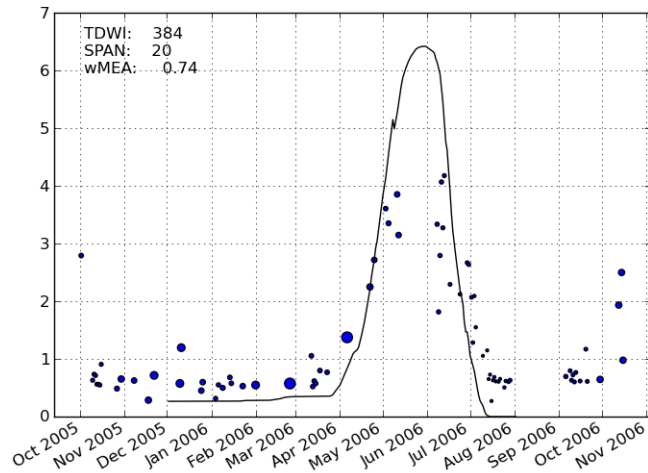


GLOBAM 10km grid CGMS recalibrated by MODIS GAI

Optimum SPAN/TWDI
 for given LAI profile

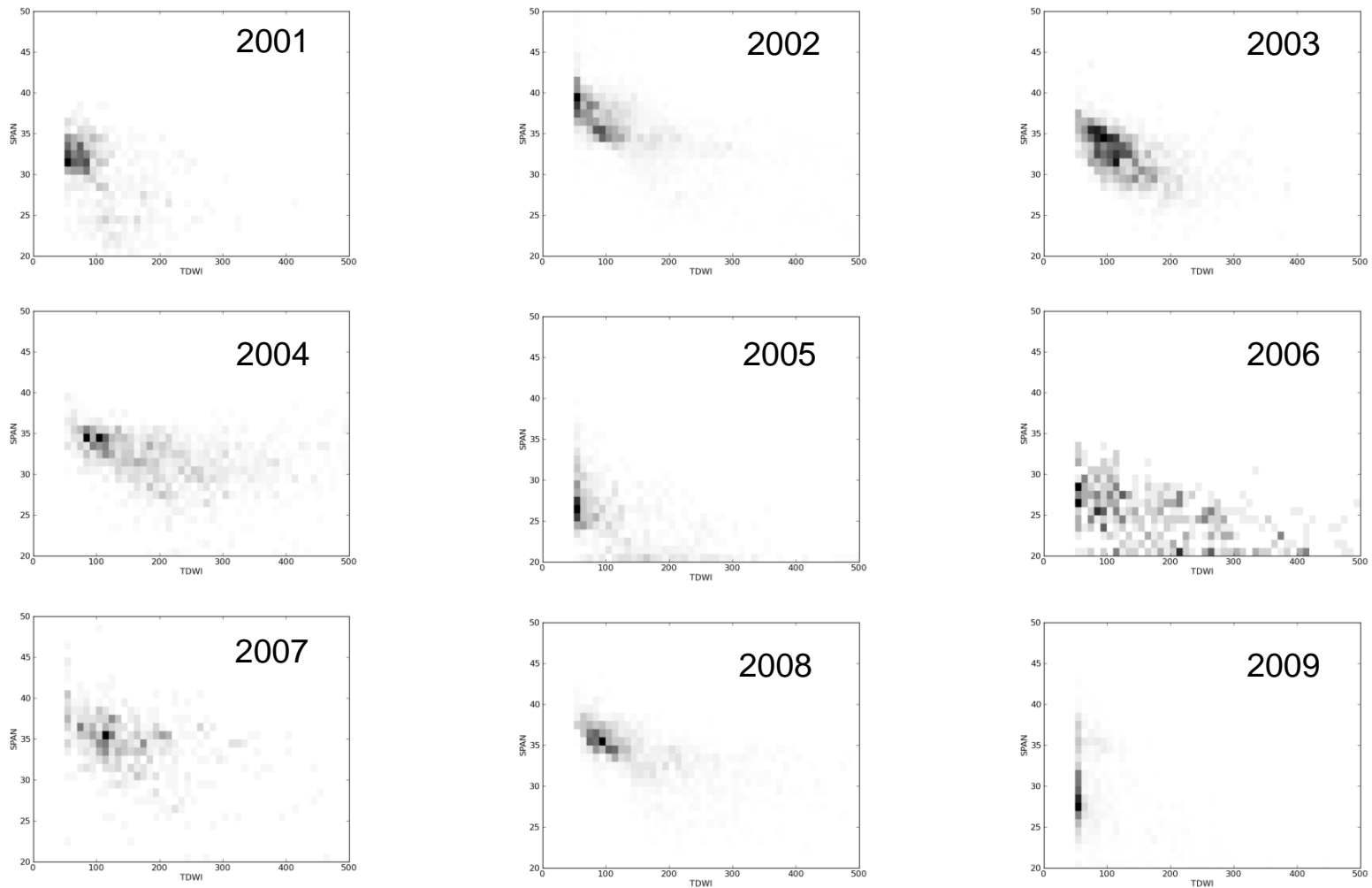


GLOBAM 10km grid CGMS recalibrated by MODIS GAI



GLOBALAM 10km grid CGMS recalibrated by MODIS GAI

high variability of parameter values distributions (10 y.)



GLOBALAM 10km grid CGMS recalibrated by MODIS GAI

Significant improvement of Total Biomass estimation by assimilating GAI profile at Région wallonne level

Region Wallone (BE3)						t-values	
	R-squared	Residual standard deviation	Root mean squared error for prediction	Standard error of prediction		free indicator	linear term
Ensemble Total Biomass	64.65	0.29	0.36	0.36		2.827	2.097
Default Yield	40.73	0.38	0.42	0.48		1.393	1.935
Default Total Biomass	46.85	0.36	0.43	0.44		1.723	1.618
None	24.3	0.4	0.45	0.49	-		1.603
Ensemble Yield	32.19	0.41	0.48	0.51		0.902	1.736




Significance level:

0.1













0.05

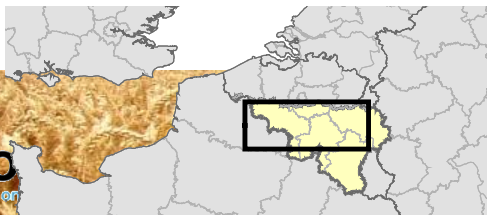
0.025

GLOBAL CGMS recalibrated by GAI 6 years data set

 Improved: 3 yr
 Equal: 2 yr
 Worse: 1 yr

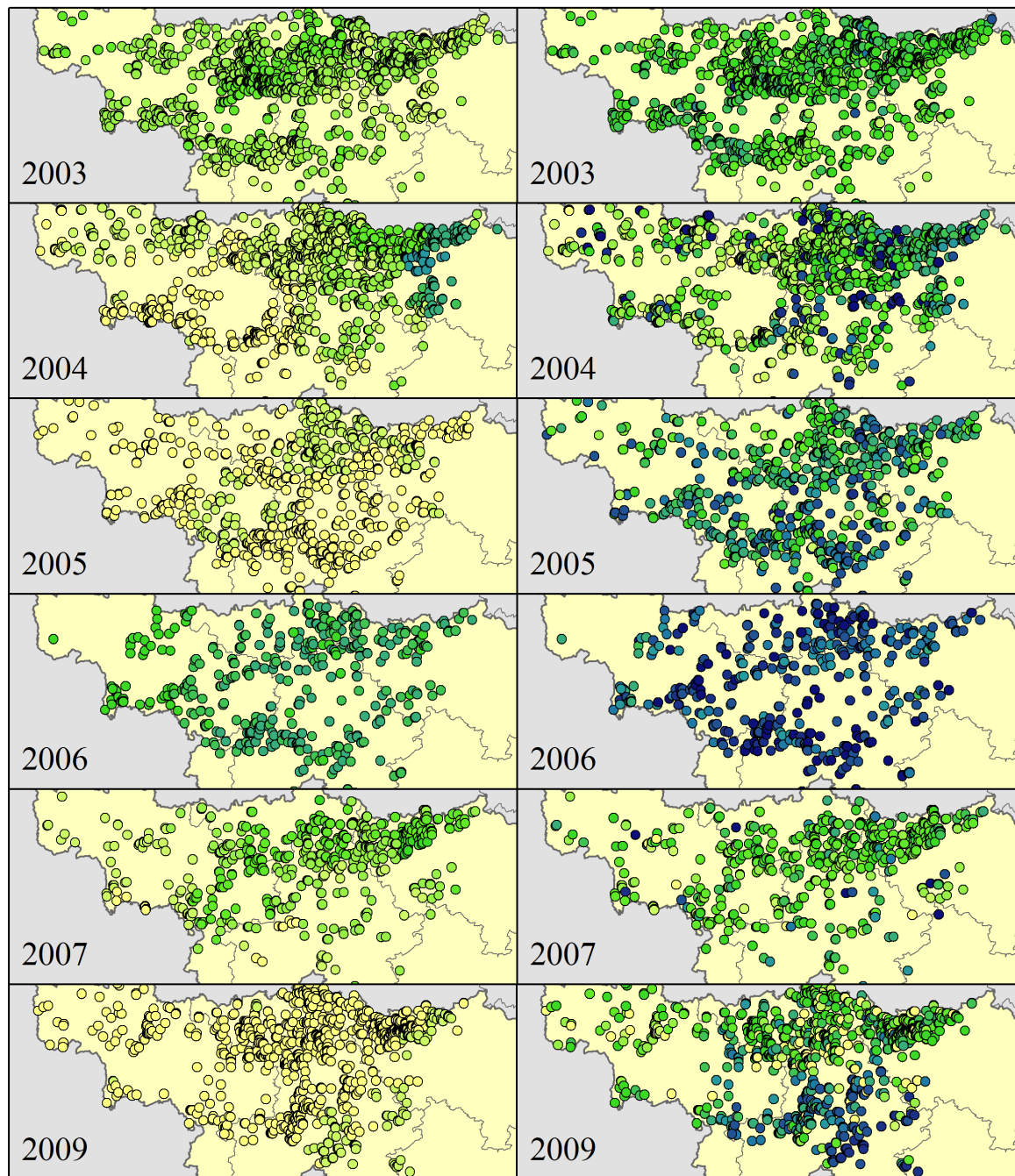
Yield Estimations

 < 5.0 t/ha	 6.5 - 7.0 t/ha	 8.5 - 8.5 t/ha
 5.0 - 5.5 t/ha	 7.0 - 7.5 t/ha	 9.0 - 9.5 t/ha
 5.5 - 6.0 t/ha	 7.5 - 8.0 t/ha	 9.5 - 10.0 t/ha
 6.0 - 6.5 t/ha	 8.0 - 8.5 t/ha	 > 10. t/ha

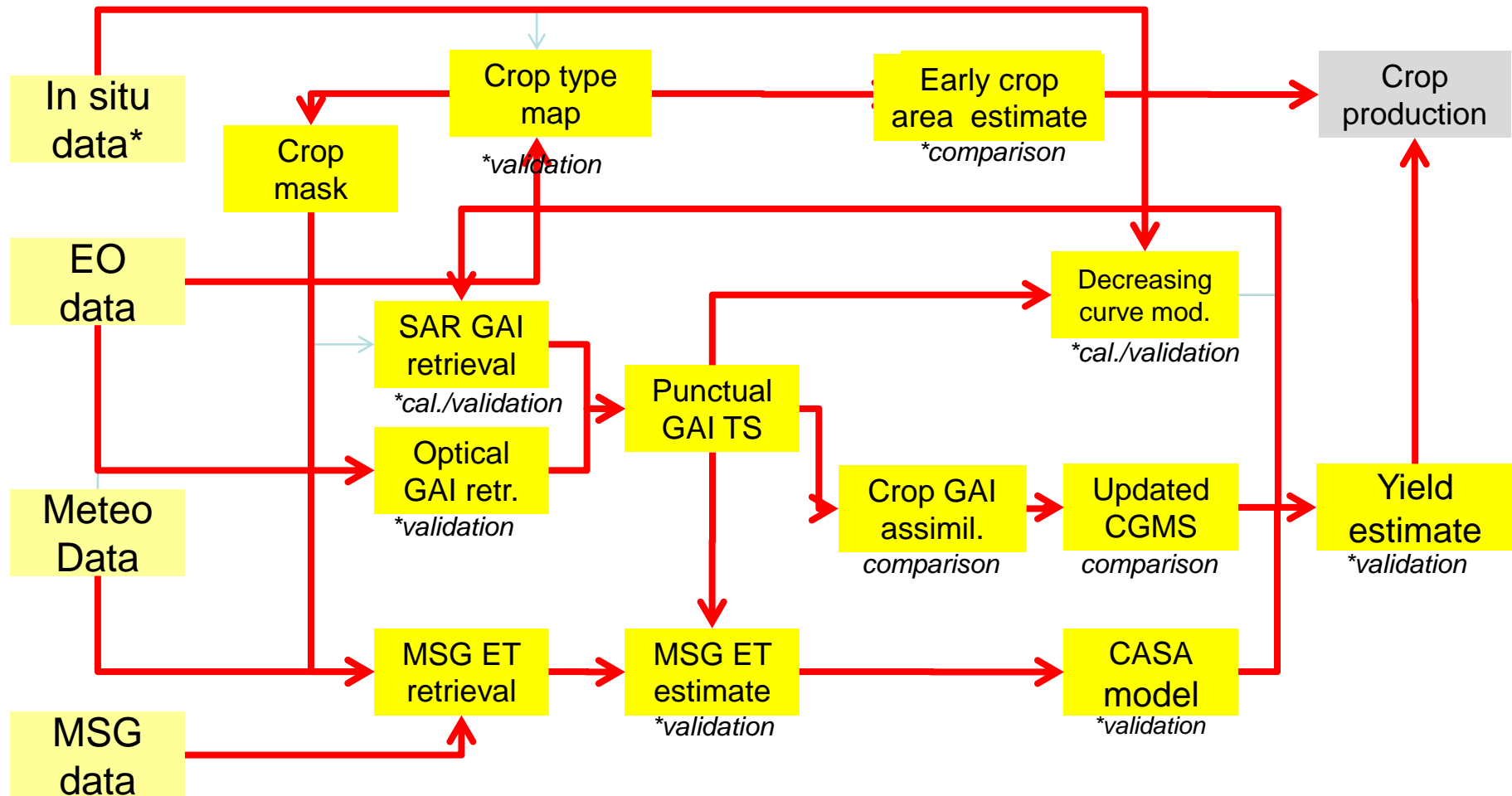


WOFOST default

WOFOST optimized



GLOBALAM : very significant interactions and integration



GLOBALAM conclusions

- Crop specific approach is demonstrated but crop map delivery needs to be secured
- Feasibility of operational retrieval from SAR
- Great performance of physical-based GAI retrieval along the crop season and efficient upscaling using purity map
- GAI time series improve crop yield estimate (CGMS)
- Simplified models required in very complex landscapes
- Operational data provision of Med. Res. good quality time series becomes the major constraints (Proba, S2)

Thank you for attention

