ESA–MOST Dragon Cooperation

中国科技部-欧洲空间局“龙计划”合作

2017 DRAGON 4 SYMPOSIUM

2017年“龙计划”四期学术研讨会

EXPLOITATION OF MULTITEMPORAL AND MULTISENSOR EARTH OBSERVATION DATA FOR ARABLE CROP CLASSIFICATION AND YIELD ASSESSMENT AT THE FARM SCALE

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26–30 June 2017 | Copenhagen, Denmark

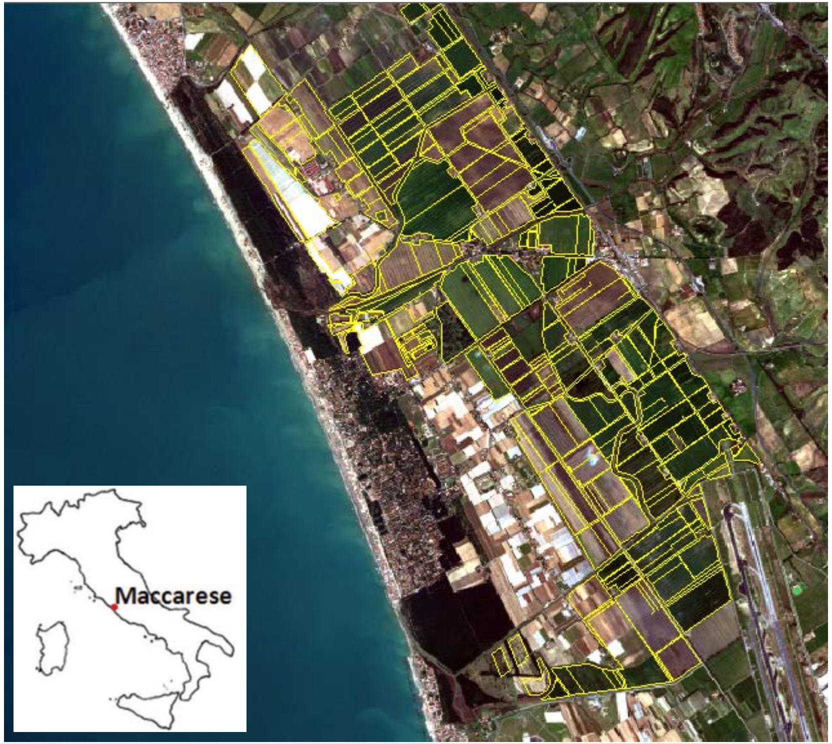
2017年6月26-30日，丹麦 哥本哈根

Topic 1 of the Dragon4 project ID32275

Algorithm Development Exploiting Multitemporal and multisensor Satellite data for improving crop classification, biophysical and agronomic variables retrieval and yield prediction (ADEMS)

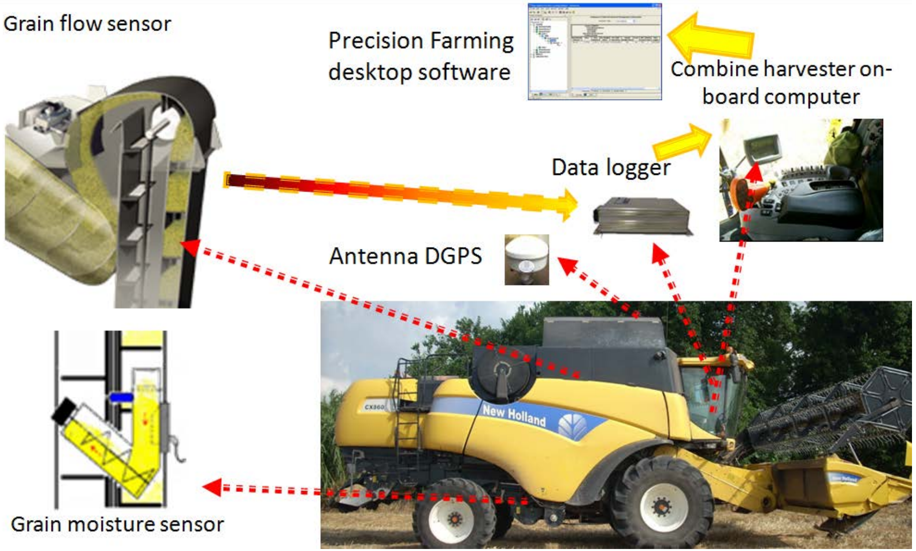
- WP1: Crop classification
- WP2: Retrieval from optical and SAR data
- WP3: Defining errors and uncertainties
- WP4: Data assimilation into crop models
- WP5: Crop yield and quality estimation
- WP6 : Core field validation

Maccarese test site Central Italy

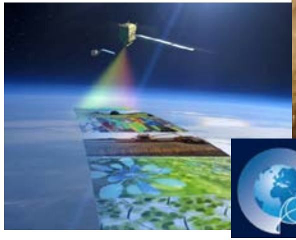


Large private farm 3200 ha flat coastal area

- ❑ large fields (15 – 100 ha plots)
- ❑ precision farming equipment

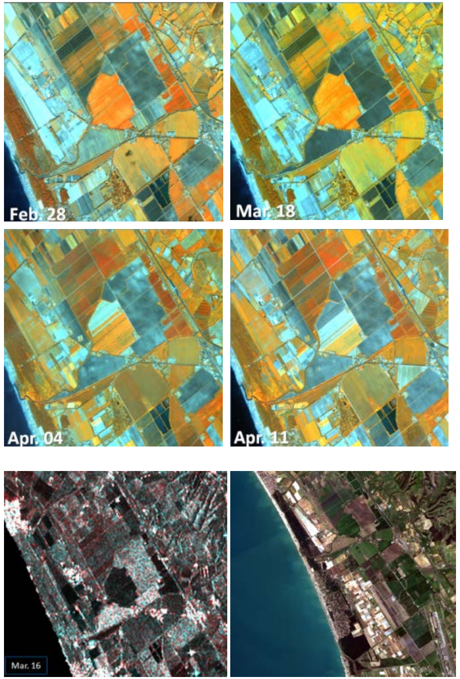


Maccarese test site Central Italy



Crops
Durum wheat
Winter wheat
Maize
Alfalfa
Ryegrass
Triticale
Barley
Rapeseed
Broad bean
Pea
Carrot
Potato

Maccarese 2015 satellite images dataset

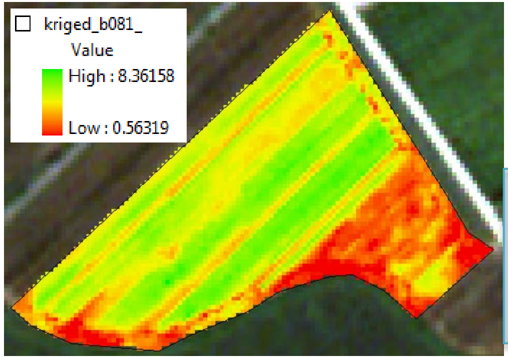


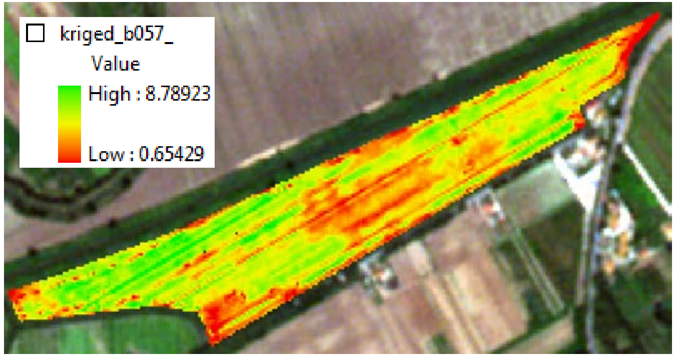
	CSK ping-pong (HH-VV)	CSK Himage	Alos (HH-VV)	RapidEye (5m, 5 ch)	Landsat	ZY-3 (6m, 4ch)	Chris	Hyperion	Ground truth (*)
Jan.	03, 11, 23, 27		7, 12, 19	28	6				11, 13, 27, 28
Feb.	28		11, 18, 27		23				24
Mar.	08, 16, 24		9, 31	18		23	13		3, 20
Apr.	10	Four images/ month	1, 6, 10	04, 11	12				
May	03		11, 13, 18, 22, 27, 29	11	14, 30			7	
June	20		2, 10, 17, 24, 29	3, 10, 30^h					30
July	06		3	5, 15	15			11	7
Total n.	**12**		**23**	**10 (5)**	**6**	**1**	**2**		

Maccarese 2015 ground data

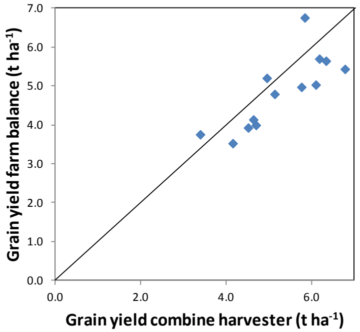
Li-Cor Plant Canopy Analyzer LAI-2000, chlorophyll (Dualex), biomass

Wheat yield ground data from combine harvester





Raw data correction
Local variogram
Block kriging

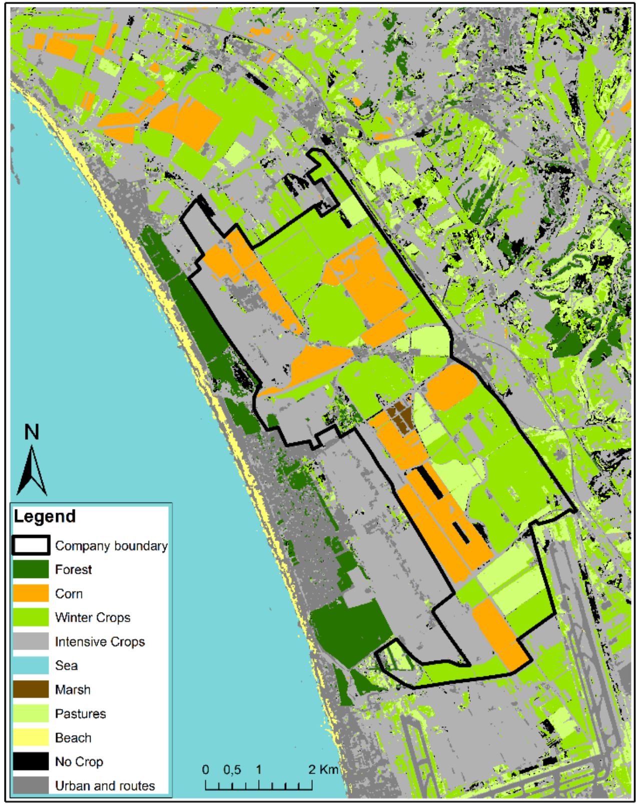


Classification

Classification of land was done using:
- 10 images **RapidEye** (free clouds);
- Field data provided by the Maccarese farm

Four types of crops were identified:
- Winter crops
- Summer crops
- Pastures
- No cultivation.

IMAGES SET:
Rapideye_2015-02-28
Rapideye_2015-03-18
Rapideye_2015-04-01
Rapideye_2015-05-11
Rapideye_2015-06-03
Rapideye_2015-06-10
Rapideye_2015-07-05
Rapideye_2015-07-15
Rapideye_2015-08-29
Rapideye_2015-09-10



Subsequently, 6 other classes of coverage were identified in the study area: Forest, Sea, Swamp, Beach, Urban and routes, Intensive cultivation.

Supervised classification of Maxima Likelihood was carried out. Identified ROI were used for classification and quality assessment

Classification

The confusion matrix was computed.

Overall Accuracy:	98,86%
Kappa Coefficient:	0,9678

		Ground Truth (%)										Total
		FOREST	WINTER CROPS	SUMMER CROPS	SEA	NO CULTIVATION	SWAMP	PASTURE	BEACH	URBAN & ROUTES	INTENSIVE CROPS	
Class (%)	**FOREST**	**97.86**	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	2.62
	WINTER CROPS	0.14	**97.61**	0.02	0.00	6.19	0.00	1.04	0.00	0.00	0.00	4.72
	SUMMER CROPS	0.00	0.00	**91.13**	0.00	0.81	6.09	0.00	0.00	0.00	0.00	2.58
	SEA	0.00	0.00	0.00	**99.93**	0.00	0.00	0.00	0.00	0.00	0.00	79.87
	NO CULTIVATION	0.37	0.00	0.00	0.00	**81.50**	13.25	0.08	0.00	0.00	0.00	0.60
	SWAMP	0.00	0.00	0.00	0.00	0.00	**66.03**	0.00	0.00	0.00	0.00	0.32
	PASTURE	0.00	1.30	0.00	0.00	5.54	0.00	**89.66**	0.00	0.00	0.00	1.81
	BEACH	0.00	0.00	0.00	0.01	0.00	0.00	0.00	**92.67**	0.00	0.00	0.61
	URBAN & ROUTES	0.06	0.00	0.00	0.06	0.00	0.75	0.27	6.45	**89.90**	0.08	1.32
	INTENSIVE CROPS	1.57	1.09	8.85	0.00	5.95	13.89	8.92	0.88	10.10	**99.92**	5.55
Total		100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	**100.00**

Classification

Clump filters were applied to crop classes to improve visualization.
Classes of interest: winter crops, summer crops, pastures were exported as masks.

A following supervised classification of maximum likelihood was applied to identify the types of crops within each class:

-*Winter crops*: Durum Wheat, Soft Wheat, Triticale, Barley

-*Summer crops*: Corn, Corn Silage, Corn ear Paste.

-*Pastures*: Alfalfa, Vicia, Grass.

Classification

Winter Crops – Confusion Matrix

CLASS		Ground Truth (Pixels)				TOTAL
		barley	soft wheat	durum wheat	triticale	
Class (Pixels)	barley	**100.00**	0.00	0.00	7.21	15.78
	soft wheat	0.00	**82.53**	0.00	0.00	12.41
	durum wheat	0.00	0.00	**98.25**	13.09	47.06
	triticale	0.00	17.47	1.75	**79.70**	24.74
Total		100.00	100.00	100.00	100.00	**100.00**

Overall Accuracy:	91,16%
Kappa Coefficient:	0,8709

Summer Crops – Confusion Matrix

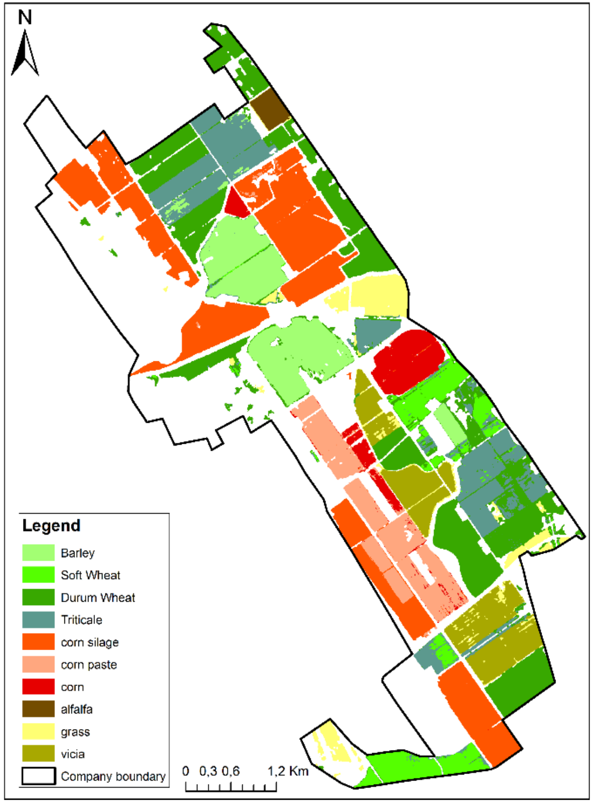
CLASS		Ground Truth (Pixels)			TOTAL
		corn silage	corn paste	corn	
Class (Pixels)	corn silage	**100.00**	0.00	0.00	50.30
	corn paste	0.00	**79.32**	0.42	24.66
	corn	0.00	20.68	**99.58**	25.04
Total		100.00	100.00	100.00	**100.00**

Overall Accuracy:	94%
Kappa Coefficient:	0,896

Pasture – Confusion Matrix

CLASS		Ground Truth (Pixels)			TOTAL
		alfalfa	grass	vicia	
Class (Pixels)	alfalfa	**100.00**	0.00	0.00	19.06
	grass	0.00	**100.00**	1.02	34.38
	vicia	0.00	0.00	**98.98**	46.56
Total		100.00	100.00	100.00	**100.00**

Overall Accuracy:	99,52%
Kappa Coefficient:	0,9924



Yield estimation: data assimilation approach previous work (Dragon3):

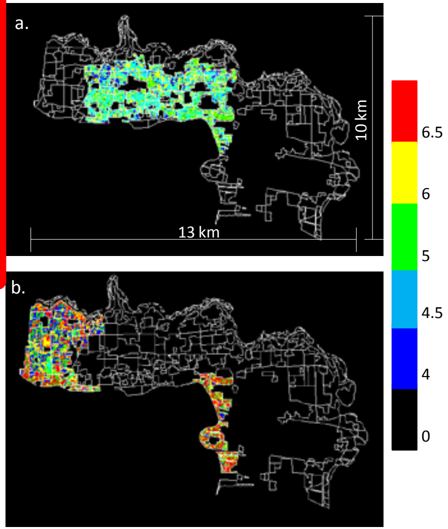
Step 1
LAI and Canopy Cover estimation from PROSAIL-ANN algorithm

Step 2a
EnKF-SAFY
Assimilation of LAI into SAFY using Ensemble Kalman Filter

Step 2b
PSO-Aquacrop
Assimilation of CC into Aquacrop using Particle Swarm Optimization

Step 3
Yield estimation at the field scale
Validation with ground measurements

Step 4
Yield estimation at district scale
Validation with official statistical data



Silvestro et al., 2017. Remote Sensing, 9, 509; doi:10.3390/rs9050509

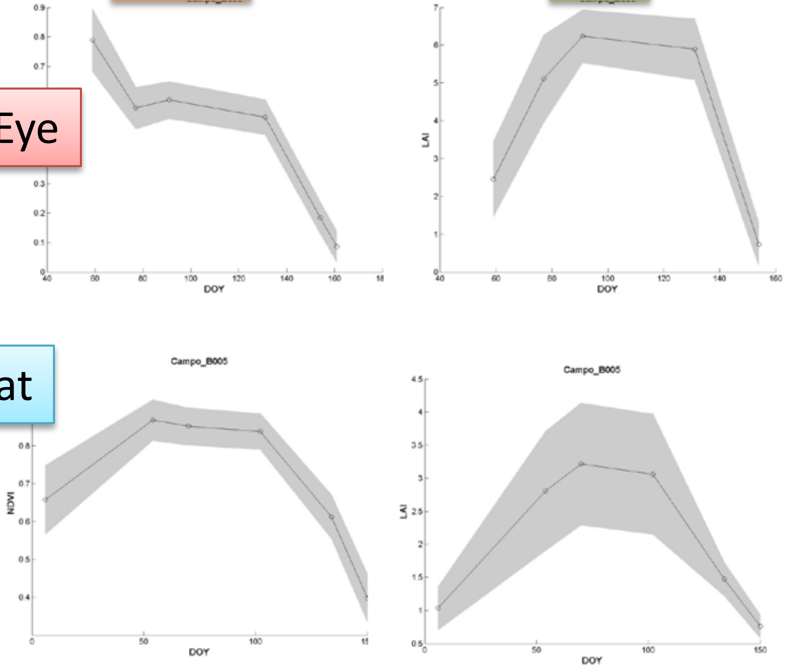
Maccarese 2015 trend NDVI and estimated LAI field average and std.dev

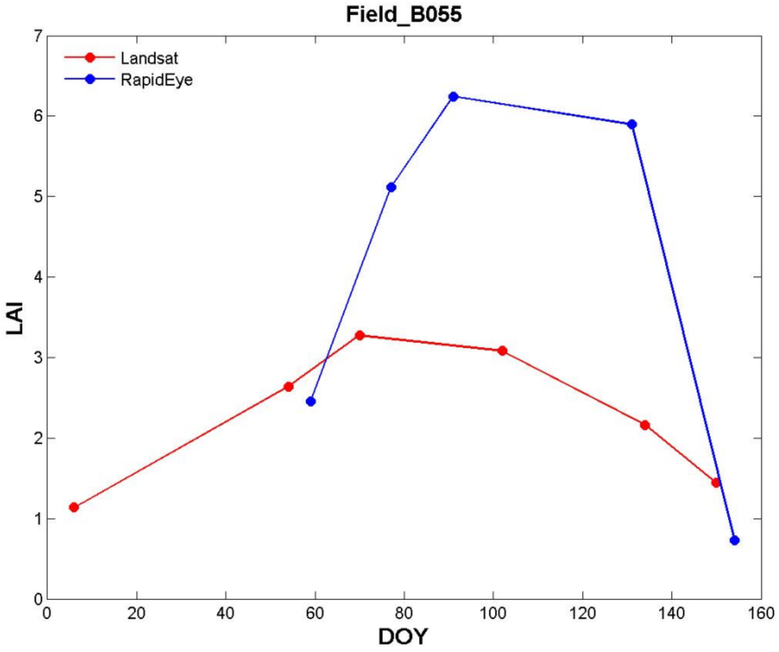
NDVI

LAI

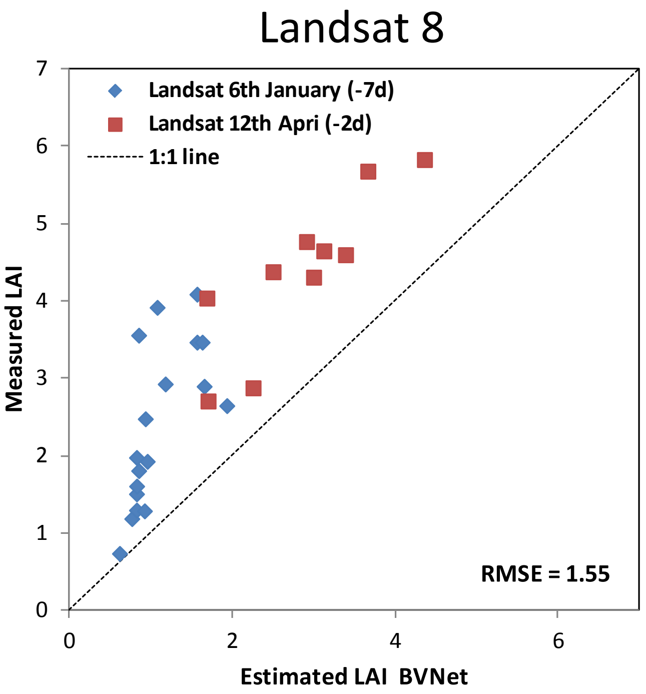
RapidEye

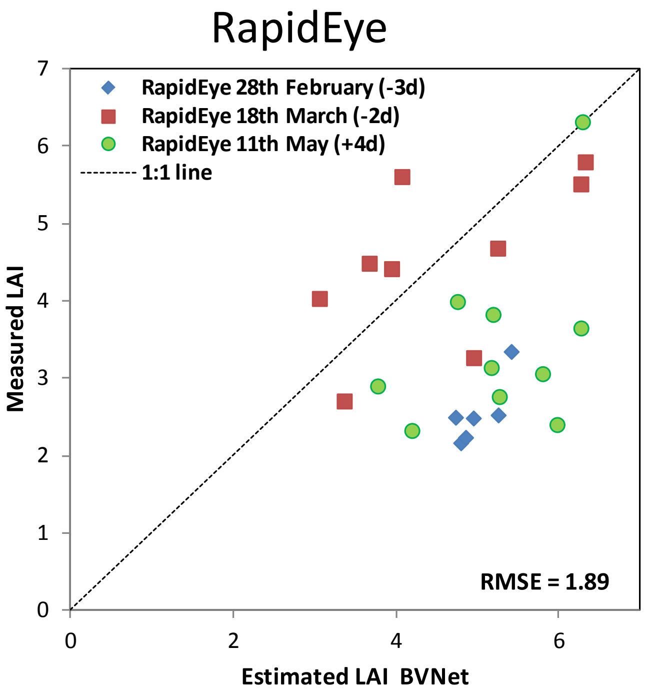
Landsat

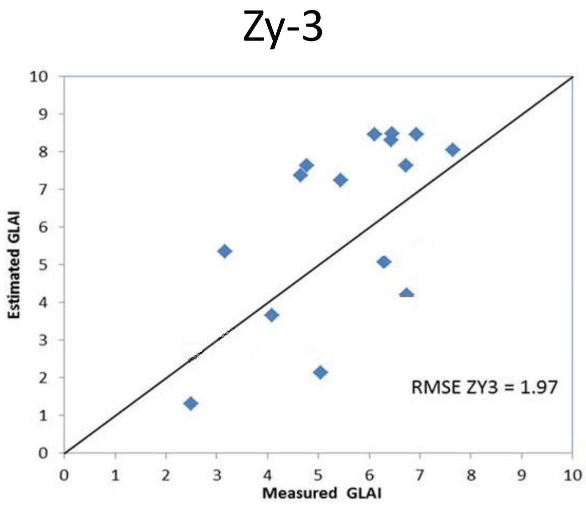




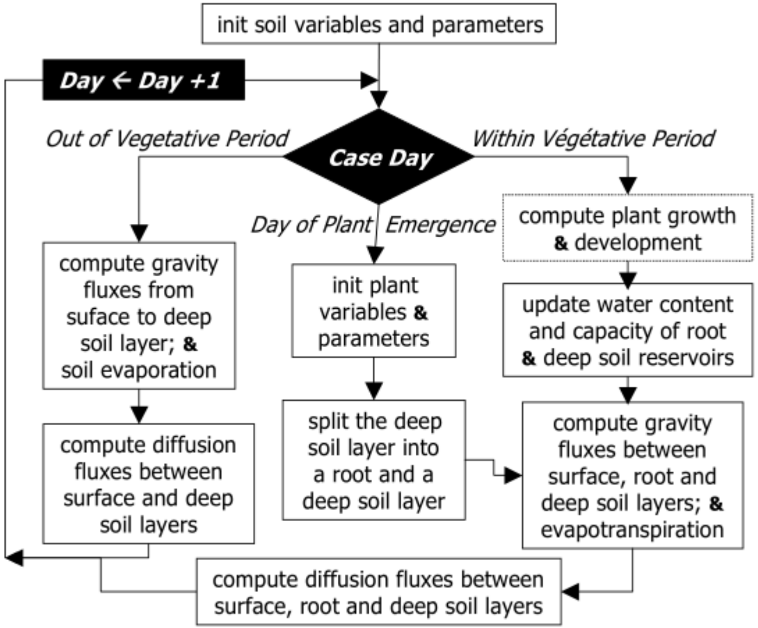
LAI retrieval using BVNet







SAFY and SAFYE



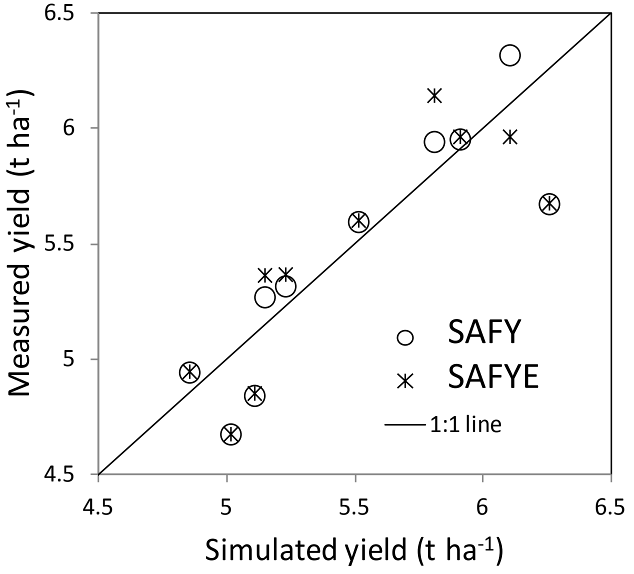
SAFY

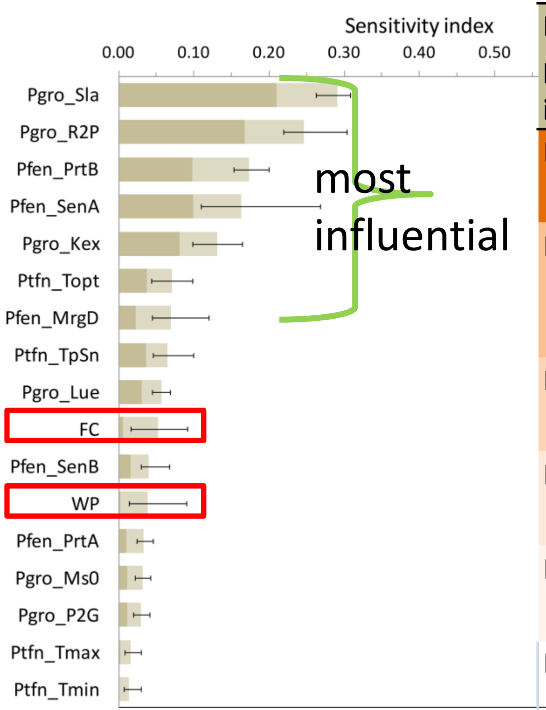
- driving variables: Rad, Temp
- no water balance
- no direct account of crop stress

SAFYE

- driving variable: Rad, Temp, ET_0, soil properties
- water balance according to FAO 56
- takes into account water stress

Sensitivity analysis: SAFYE additional parameters mostly non-influential

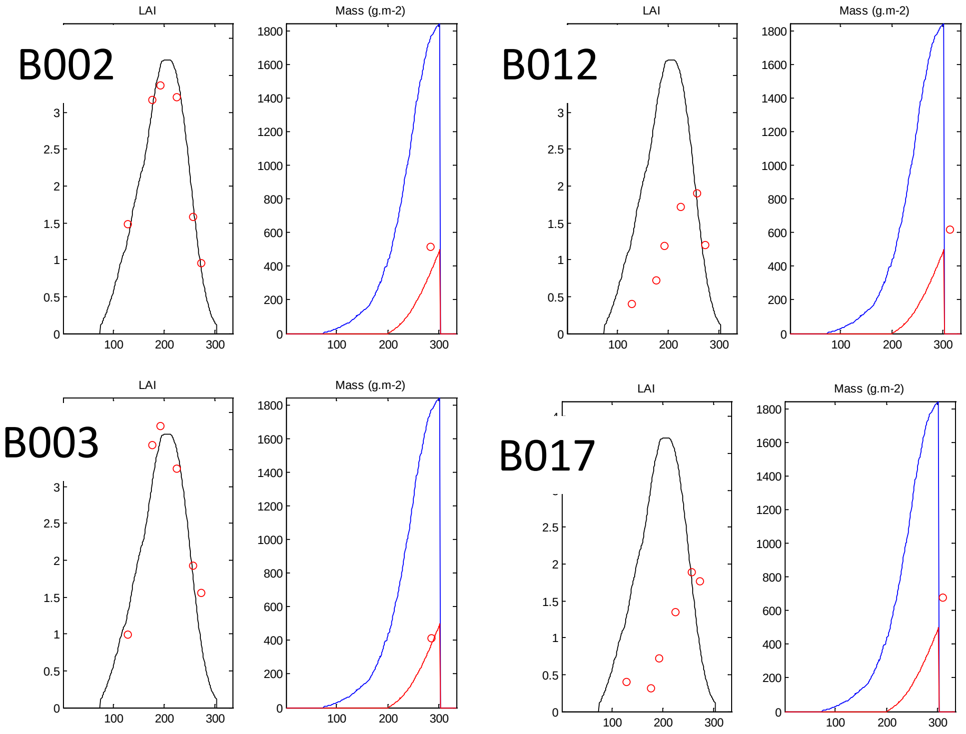


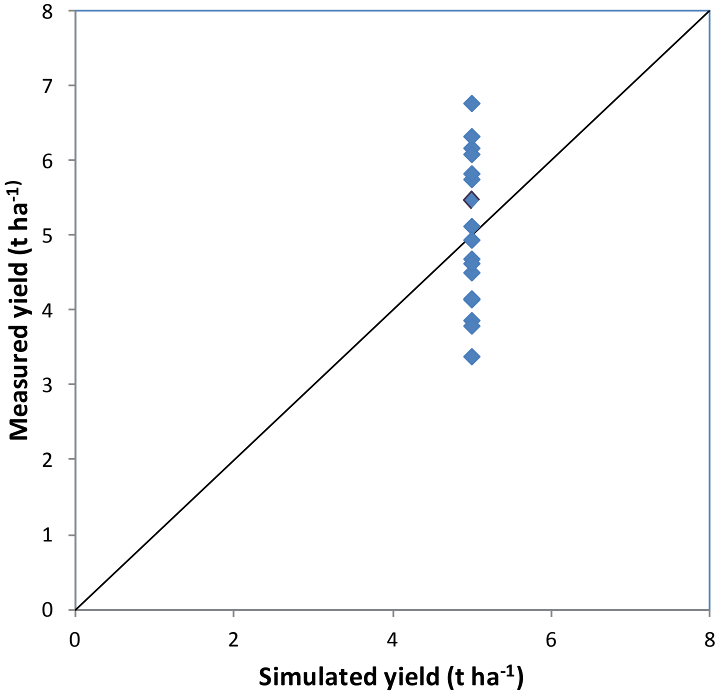


Name of parameter or input variable	Description
Pgro_Sla	Specific Leaf Area ($m^2 g^{-1}$)
Pgro_R2P	Climatic efficiency: ratio of incoming photosynthetically active radiation (PAR) to global radiation
Pfen_SenA	Temperature threshold to start senescence (°C)
Pfen_PrtB	Partition to leaf function parameter 2 (PLb)
Pgro_Kex	Light extinction coefficient in canopy
Pfen_MrgD	Day of the year of emergence

Silvestro et al., 2017. Submitted to *PLOSone* (major revisions at 15/5/2017)

SAFY calibration dataset Maccarese 2015



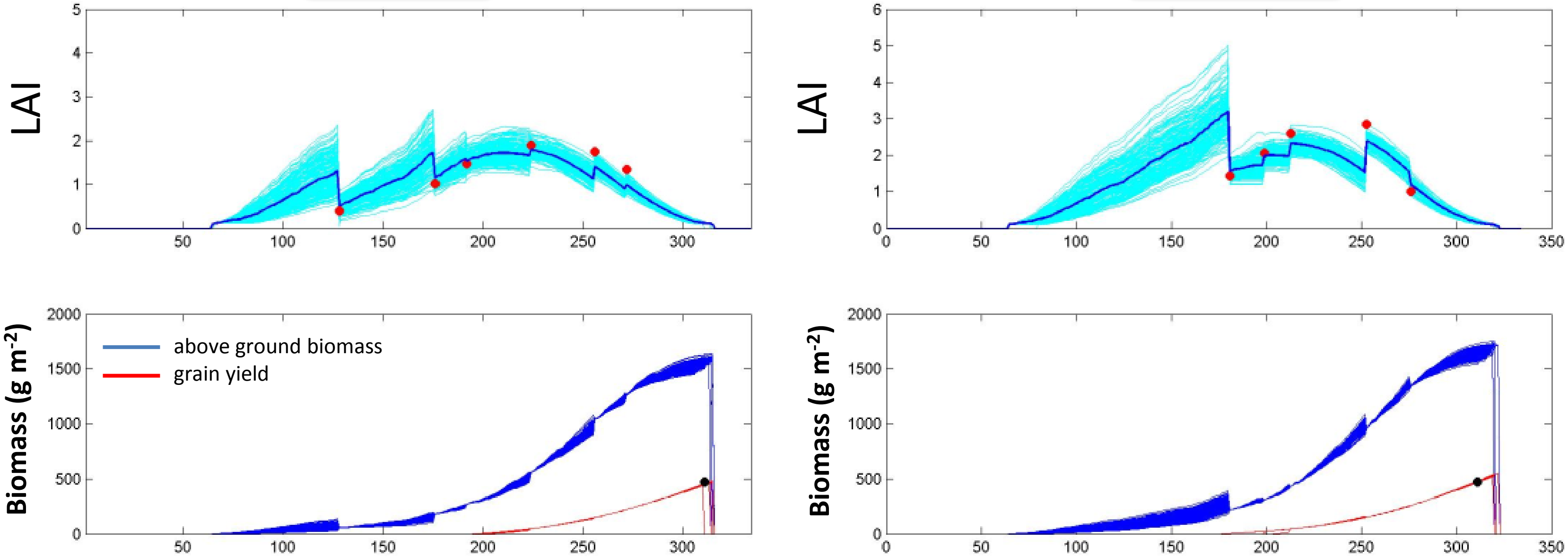


EnKF assimilation process

Landsat

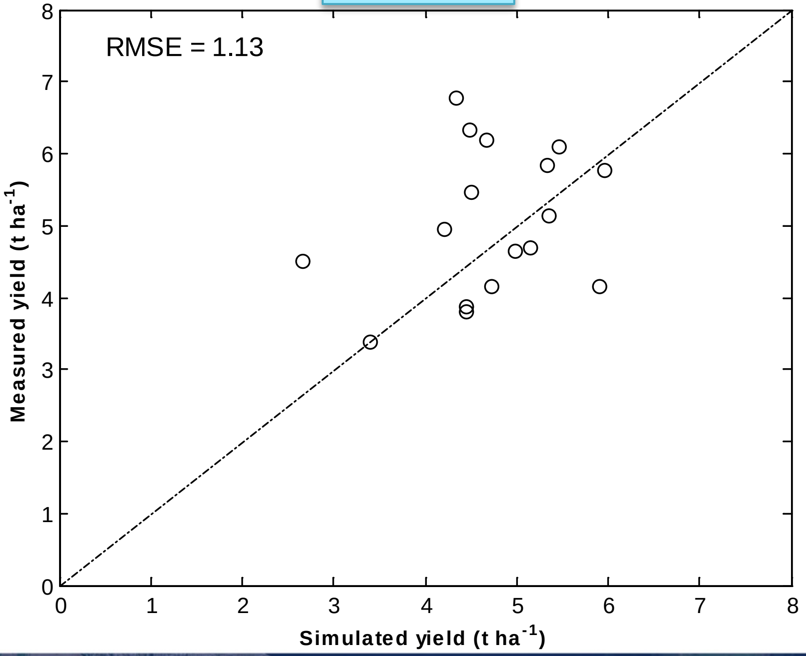
Field B011

RapidEye

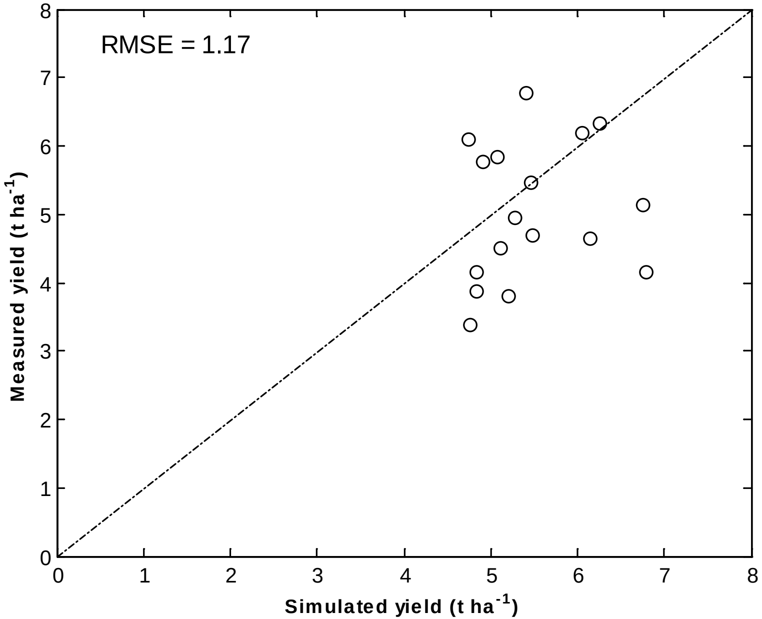


SAFY assimilation results

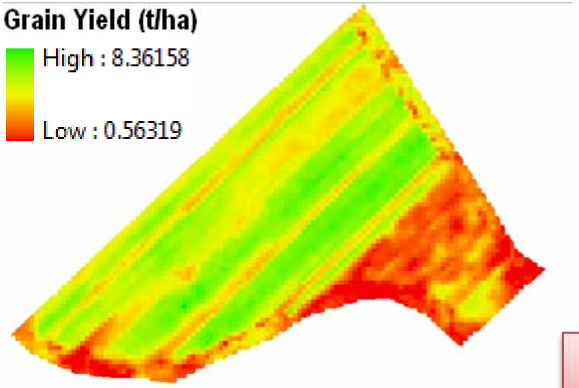
Landsat



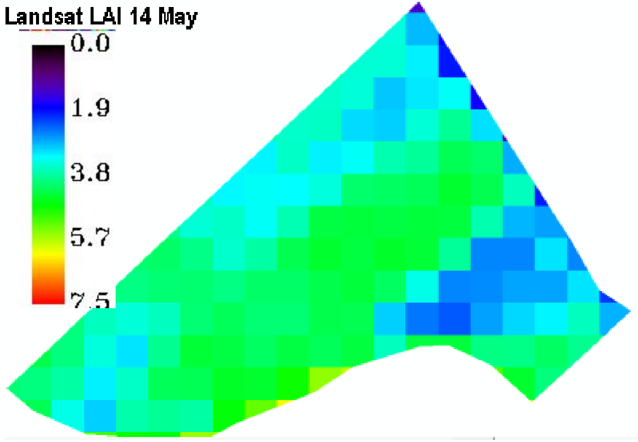
RapidEye



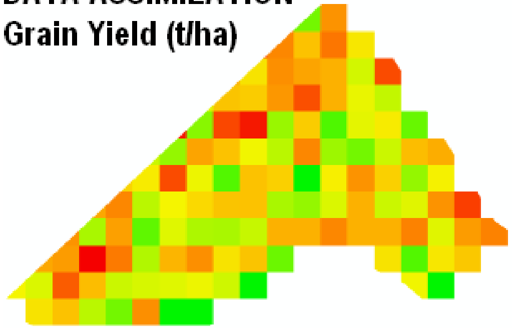
Capturing within-field spatial variability ?



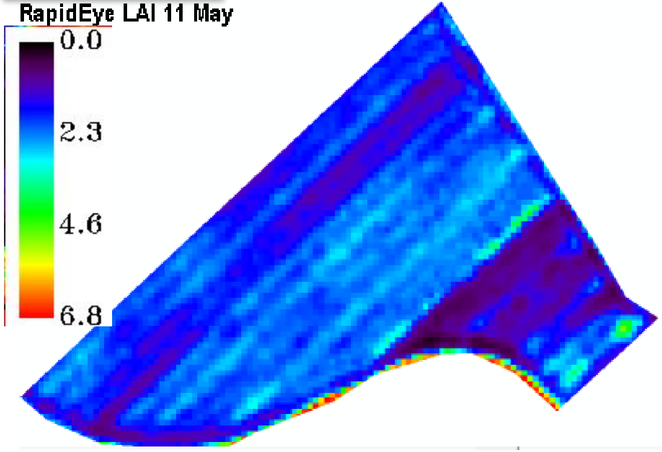
Landsat



DATA ASSIMILATION
Grain Yield (t/ha)



RapidEye

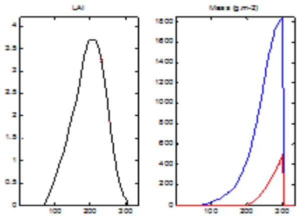


What is the influence of the number of images available on yield estimation? Test with SAFY synthetic data

20 random parameter extractions

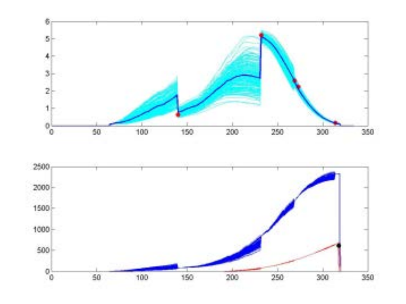
Parameter	Min	Max	media	st deviatic
Pgro_R2P	0.55	0.65	0.6	0.06
Pfen_MrgD	308	328	318	31.8
Pfen_SenA	1272	1472	1372	137.2
Pgro_Sla	0.024	0.028	0.026	0.0026
Pfen_PrtB	0.0012	0.0014	0.0013	0.00013
Pgro_Kex	0.6	0.8	0.77	0.077

Run SAFY and generate LAI and yields



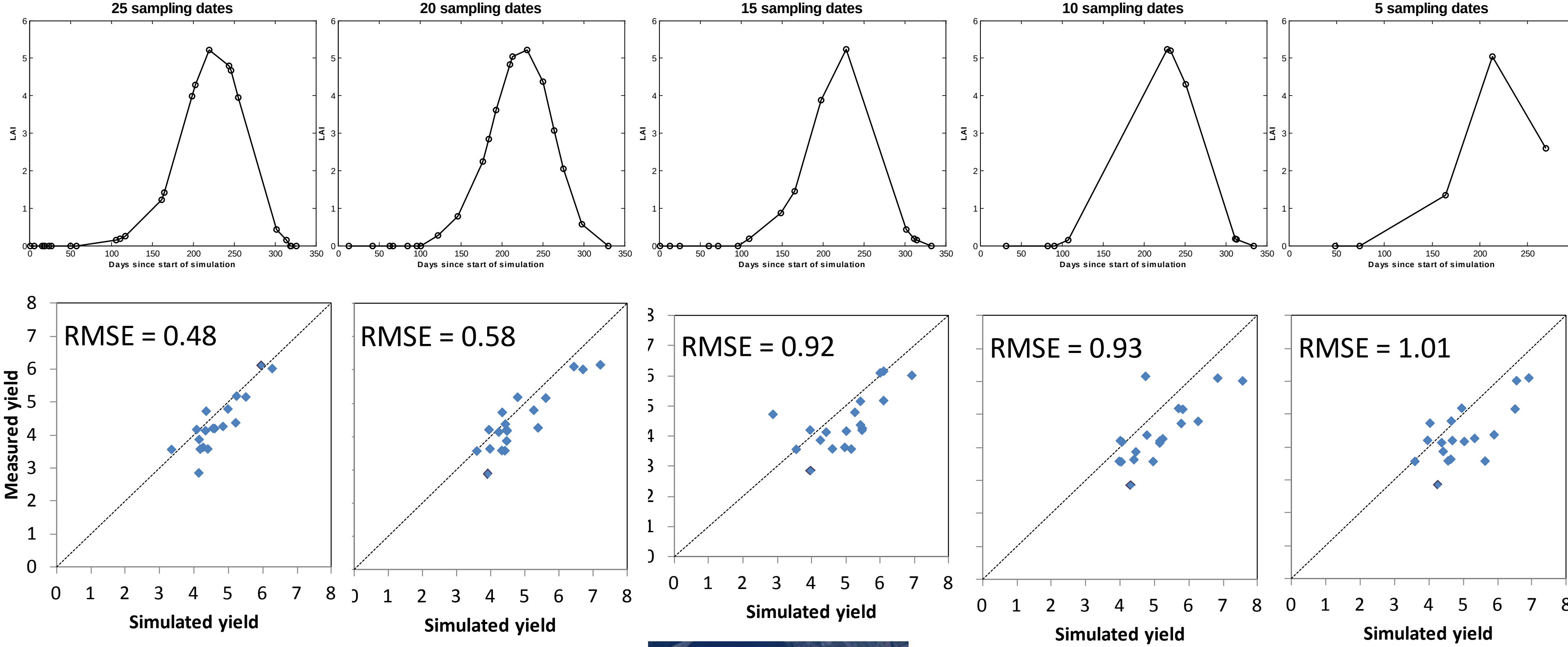
Extract a sample of n. LAI “observations”

Use LAI “observations” in the assimilation of SAFY



Compared with yields after assimilation with originally simulated values

What is the influence of the n. of images available ?



Conclusions...& work to do for the young scientist

- use better quality data: radiometric & atmospheric correction, ground data
- improve the biophysical variables retrieval method: e.g. more efficient use of temporal and spatial constraints information in the ANN algorithm; test with better quality data (Sentinel-2, Venus ?); ground campaigns in 2018
- carry out a thorough study of the sensitivity of the EnKF method to all contributing factors using synthetic data: n. of observation dates; error on biophysical variables, model calibration....
- improve SAFYE processes and carry out a more thorough assessment of SAFY vs. SAFYE
- Develop and test EnKF with SAFY for other crops (e.g. maize)
- Add N related processes to SAFY in order to address grain quality issues

THANKS FOR YOUR ATTENTION !