11th Advanced Training Course on Land RS

Crop type mapping and crop specific growth monitoring

Diane Heymans, Sophie Bontemps, Pierre Defourny

UCLouvain

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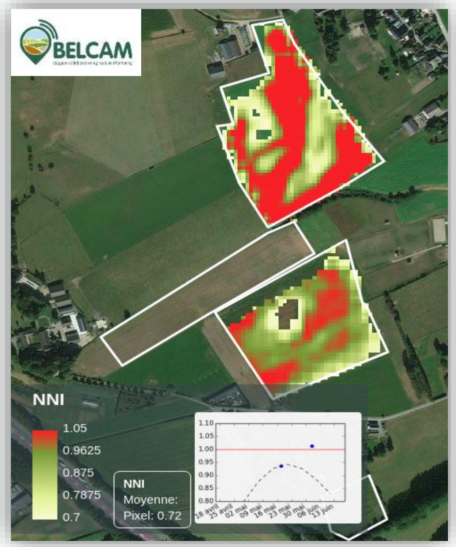
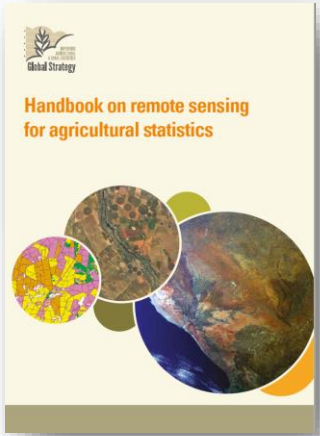
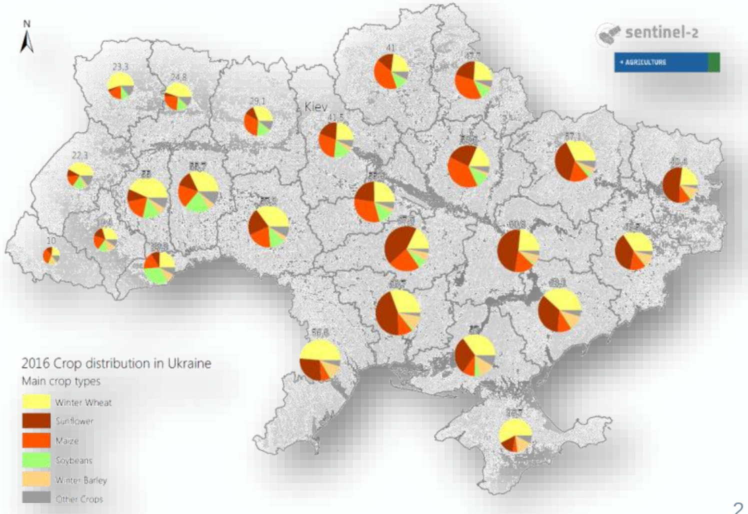
Importance of agriculture monitoring







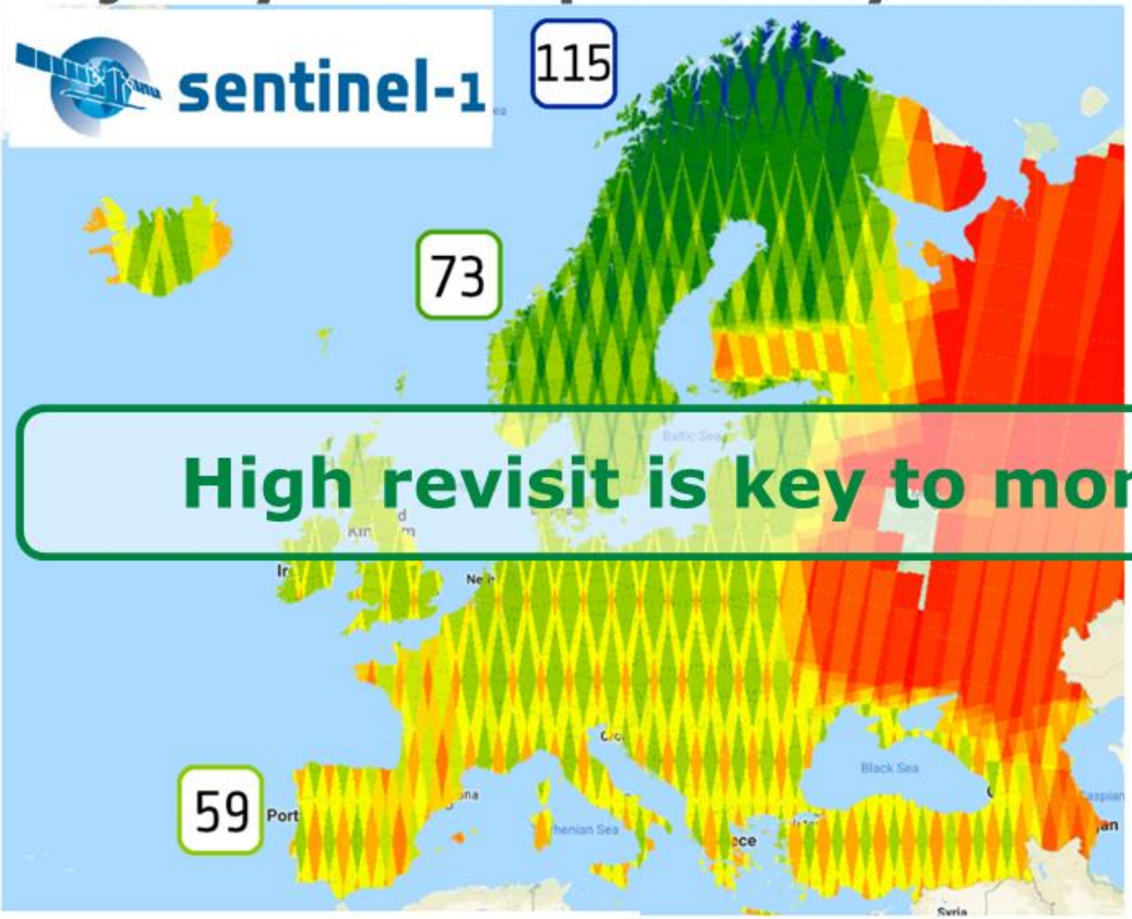
Presentation outline

- **Introduction of agriculture monitoring with optical and radar data**
- What is a crop? What is a crop map?
- Crop classification by remote sensing
  - Classification
  - Features extraction
  - Segmentation
  - Post-processing
- Crop specific growth monitoring
  - Phenological stage retrieval
  - Agricultural practices monitoring

Sentinels as a game changer, especially for agriculture

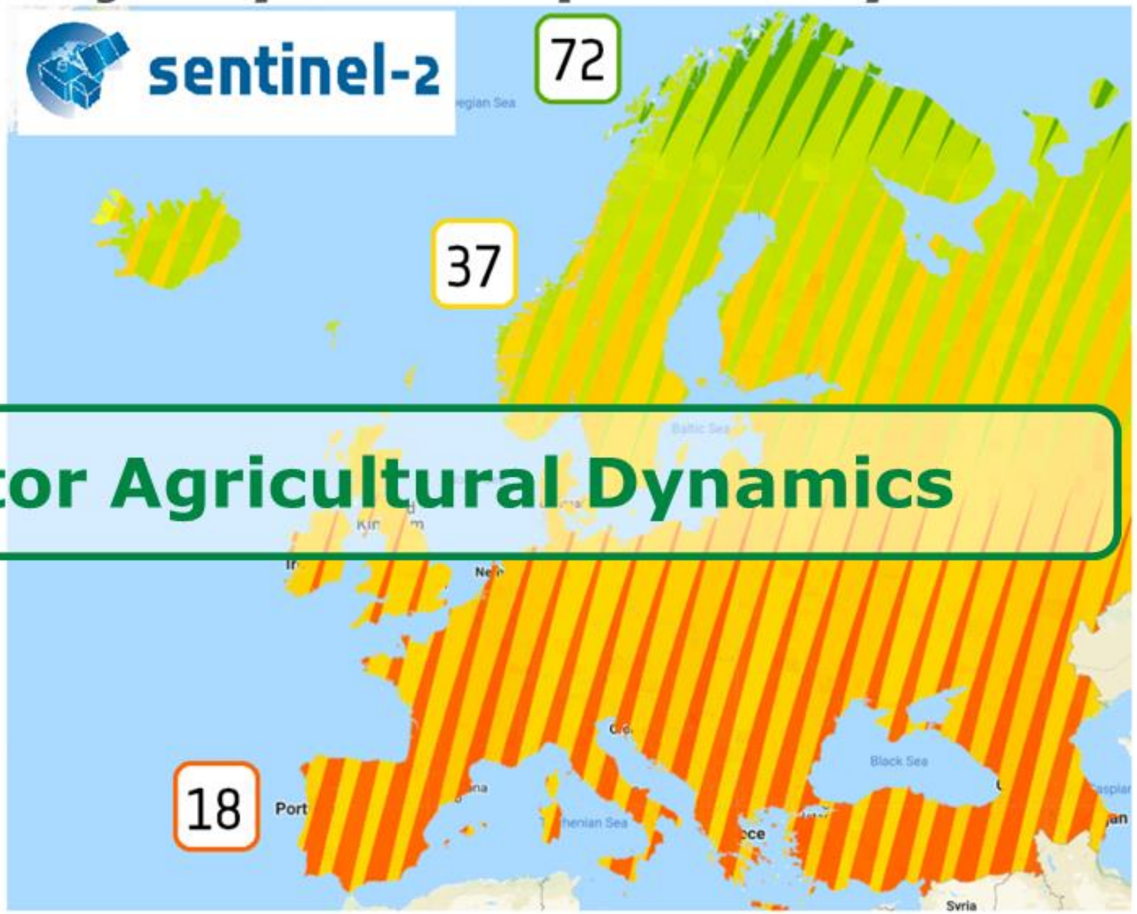
esa

Majority of Europe >2 day revisit



S-1A & -1B (July-Sept 2018)

Majority of Europe >3 day revisit



S-2A & -2B (July-Sept 2018)

High revisit is key to monitor Agricultural Dynamics

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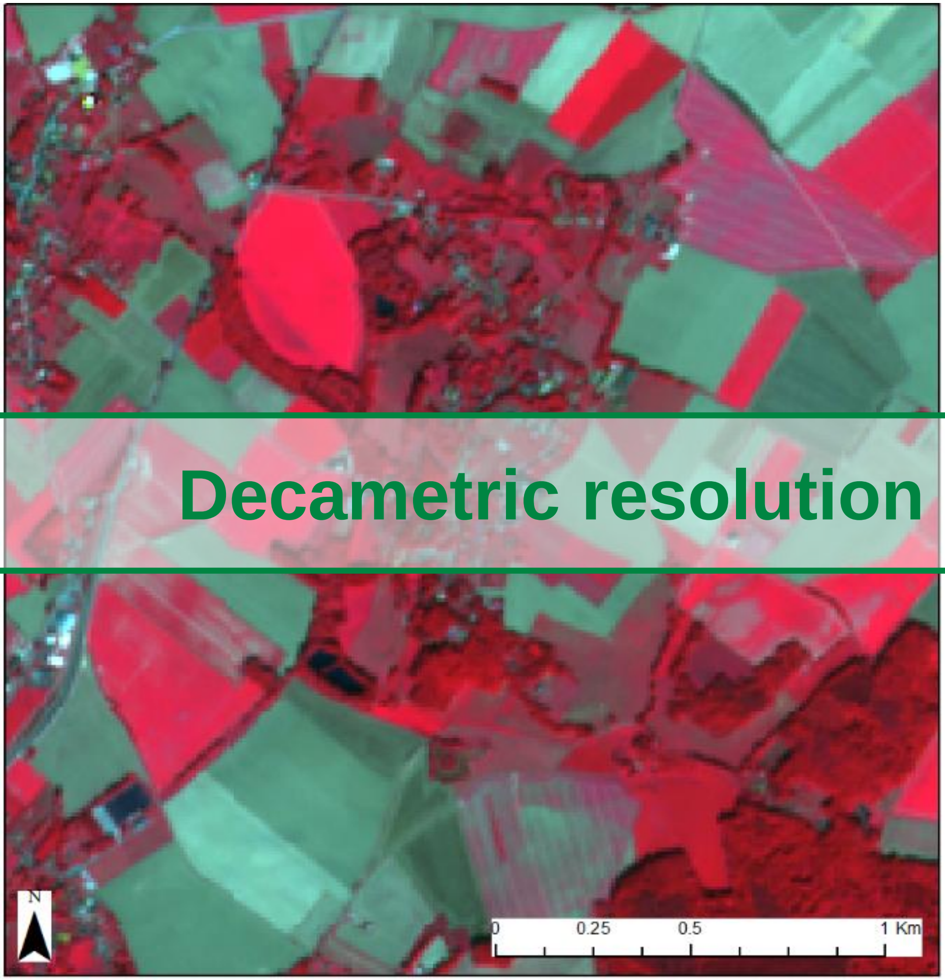
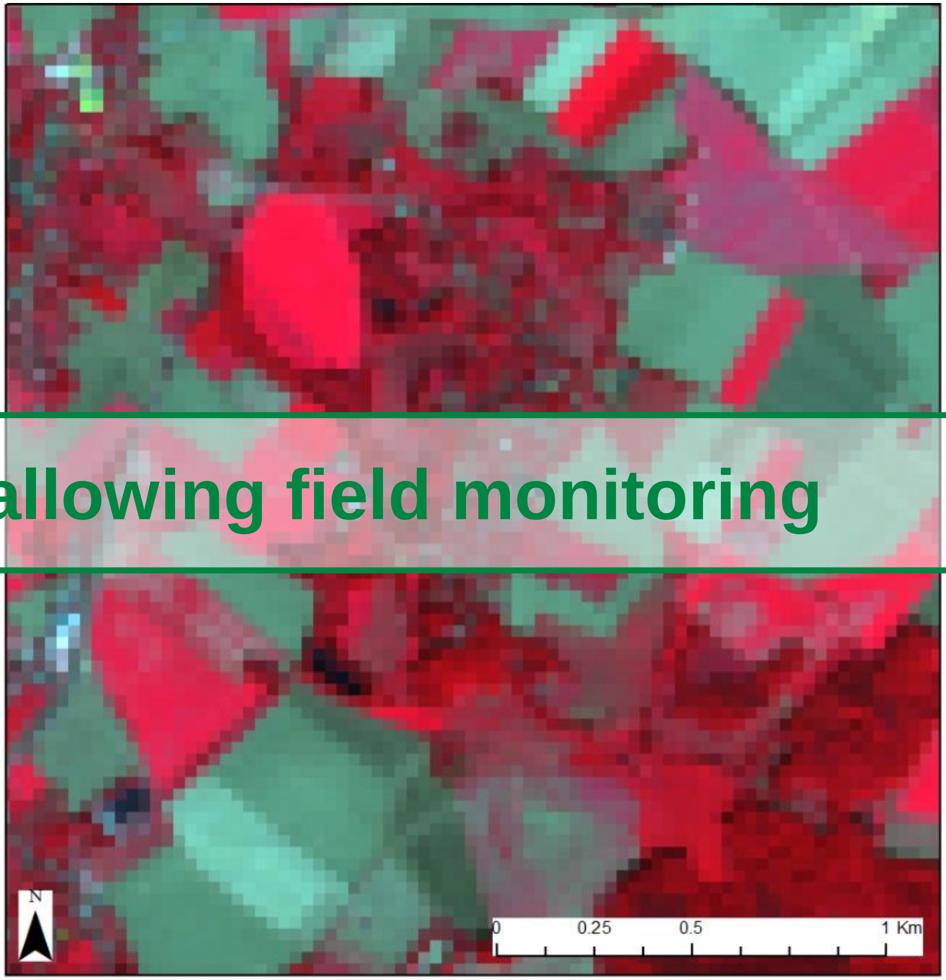
Sentinels as a game changer, especially for agriculture

10 m

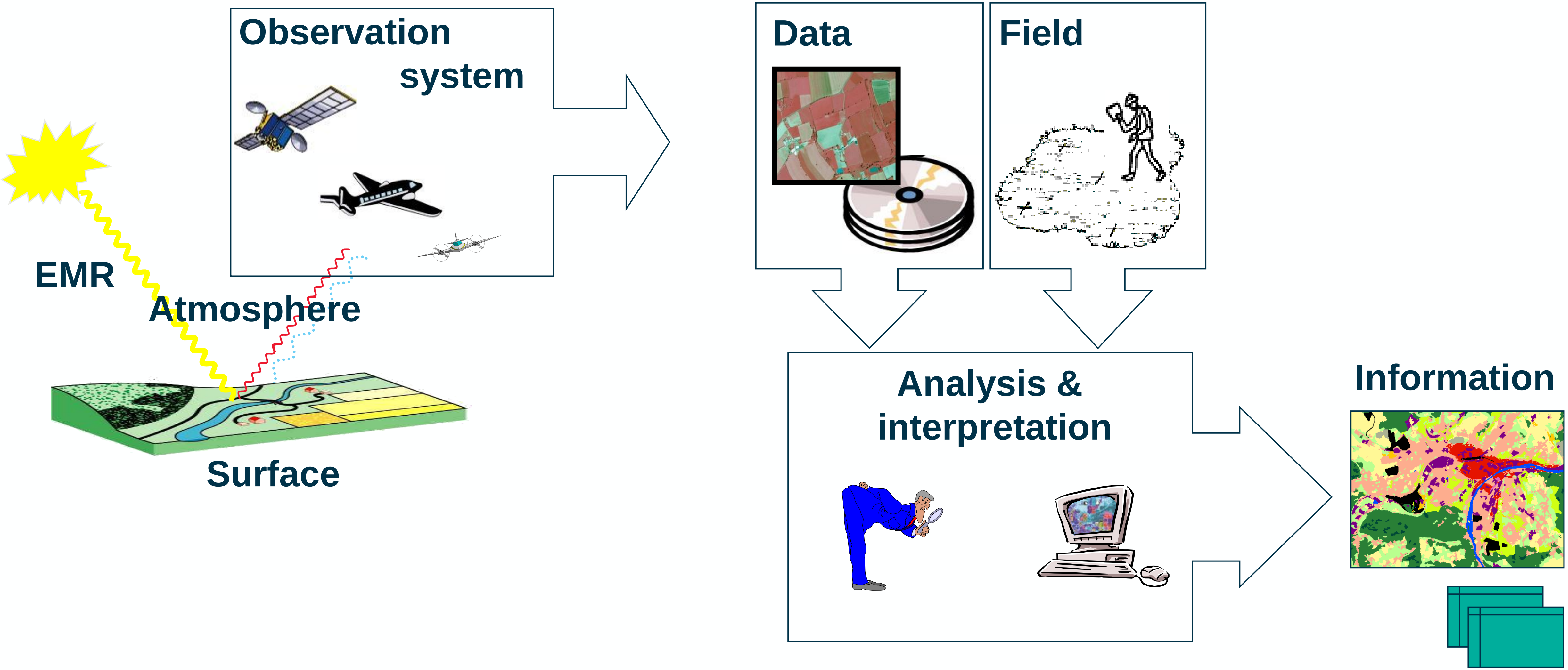


30 m

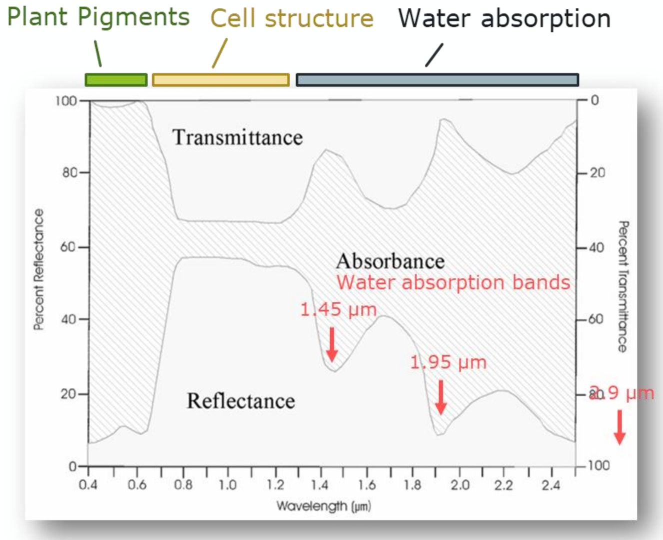


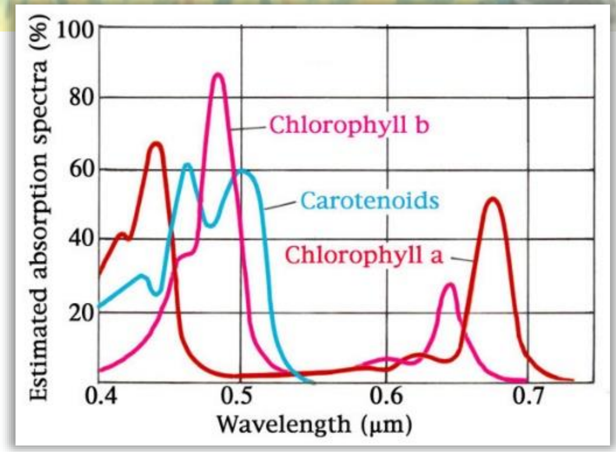
Decametric resolution allowing field monitoring

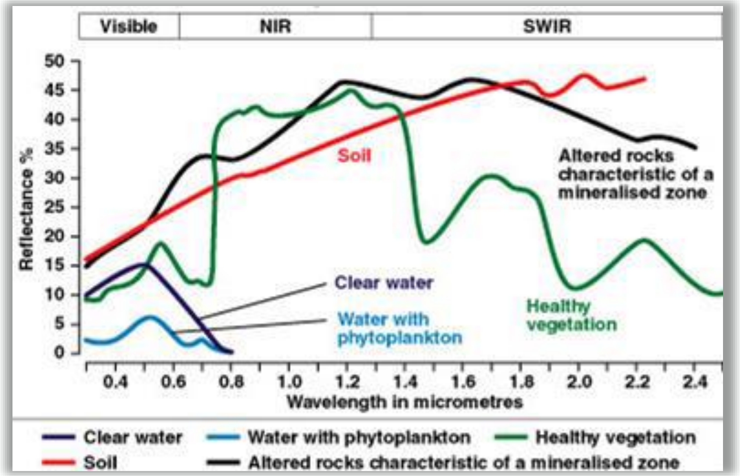
Classification by remote sensing



Spectral signatures and vegetation indices (optical image)







Vegetation indices - often based on 2 spectral bands (red and IR). Convenient way to resume information

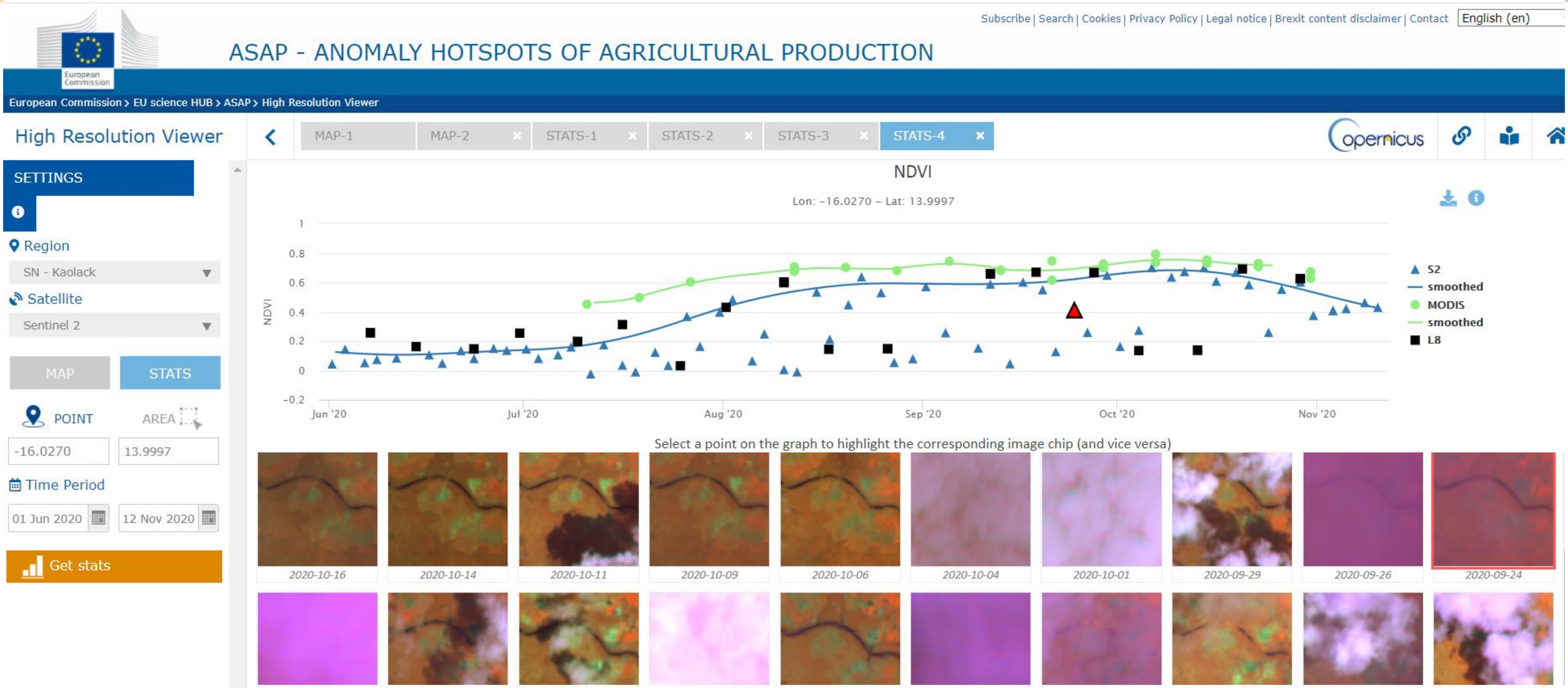
Chlorophyll Green index	$\frac{\text{NIRnarrow}}{\text{Green + Rededge1}}$
Global Environment Monitoring Vegetation Index	$n \times (1 - 0.25n) - \frac{\text{Red} - 0.125}{1-\text{Red}}$ $n = \frac{2 \times (\text{NIRnarrow}^2 - \text{Red}^2) + 1.5 \times \text{NIRnarrow} + 0.5 \times \text{Red}}{\text{NIRnarrow} + \text{Red} + 0.5}$
Greenness Index	$\frac{\text{Green}}{\text{Red}}$
Green normalized difference vegetation index	$\frac{\text{NIRnarrow - Green}}{\text{NIRnarrow + Green}}$
Leaf Anthocyanid Content	$\frac{\text{Rededge3}}{\text{Green - Rededge1}}$
Leaf Carotenoid Content	$\frac{\text{Rededge3}}{\text{Blue - Rededge1}}$
Leaf Chlorophyll Content	$\frac{\text{Rededge3}}{\text{Rededge1}}$
Moisture stress index	$\frac{\text{SWIR1}}{\text{NIRnarrow}}$
Normalized Difference of Red-edge and SWIR2	$\frac{\text{Rededge2 - SWIR2}}{\text{Rededge2 + SWIR2}}$
Normalized Difference Tillage Index	$\frac{\text{SWIR1 - SWIR2}}{\text{SWIR1 + SWIR2}}$
Normalized difference vegetation index	$\frac{\text{NIRnarrow -Red}}{\text{NIRnarrow+ Red}}$
Red-edge normalized difference vegetation index	$\frac{\text{NIRnarrow - Rededge1}}{\text{NIRnarrow + Rededge1}}$

Vegetation indices using Sentinel-2 Red-Edge bands

Ratio Vegetation Index	RVI	$\frac{R}{NIR}$
Vegetation Index Number	VIN	$\frac{NIR}{R}$
Transformed Vegetation Index	TVI	$\sqrt{NDVI + 0.5}$
Green Vegetation Index	GVI	$(-0.283MSS4 - 0.660MSS5 + 0.577MSS6 + 0.388MSS7)$
Soil Brightness Index	SBI	$(0.332MSS4 + 0.603MSS5 + 0.675MSS6 + 0.262MSS7)$
Yellow Vegetation Index	YVI	$(-0.899MSS4 + 0.428MSS5 + 0.076MSS6 - 0.041MSS7)$
Non Such Index	NSI	$(-0.016MSS4 + 0.131MSS5 - 0.425MSS6 + 0.882MSS7)$
Soil Background Line	SBL	$(MSS7 - 2.4MSS5)$
Differenced Vegetation Index	DVI	$(2.4MSS7 - MSS5)$
Misra Soil Brightness Index	MSBI	$(0.406MSS4 + 0.600MSS5 + 0.645MSS6 + 0.243MSS7)$
Misra Green Vegetation Index	MGVI	$(-0.386MSS4 - 0.530MSS5 + 0.535MSS6 + 0.532MSS7)$
Misra Yellow Vegetation Index	MYVI	$(0.723MSS4 - 0.597MSS5 + 0.206MSS6 - 0.278MSS7)$
Misra Non Such Index	MNSI	$(0.404MSS4 - 0.039MSS5 - 0.505MSS6 + 0.762MSS7)$
Perpendicular Vegetation Index	PVI	$\sqrt{(\rho_{sol} - \rho_{végé})^2_R + (\rho_{sol} - \rho_{végé})^2_{NIR}}$
Ashburn Vegetation Index	AVI	$(2.0MSS7 - MSS5)$
Greenness Above Bare Soil	GRABS	$(GVI - 0.09178SBI + 5.58959)$
Multi-Temporal Vegetation Index	MTVI	$(NDVI(date\ 2) - NDVI(date\ 1))$
Greenness Vegetation and Soil Brightness	GVSB	$\frac{GVI}{SBI}$
Adjusted Soil Brightness Index	ASBI	$(2.0\ YVI)$
Adjusted Green Vegetation Index	AGVI	$GVI - (1 + 0.018GVI)YVI - NSI/2$
Transformed Vegetation Index	TVI	$\frac{(NDVI + 0.5)}{\lvert NDVI + 0.5 \rvert}\sqrt{\lvert NDVI + 0.5 \rvert}$
Differenced Vegetation Index	DVI	$(NIR - R)$
Normalized Difference Greenness Index	NDGI	$\frac{(G - R)}{(G + R)}$
Redness Index	RI	$\frac{(R - G)}{(R + G)}$
Normalized Difference Vegetation Index	NDVI	$\frac{(NIR - R)}{(NIR + R)}$
Perpendicular Vegetation Index	PVI	$\frac{(NIR - aR - b)}{\sqrt{a^2 + 1}}$
Soil Adjusted Vegetation Index	SAVI	$\frac{(NIR - R)}{(NIR + R + L)}(1 + L)$
Transformed SAVI	TSAVI	$\frac{[a(NIR - aR - b)]}{(R + aNIR - ab)}$
Transformed SAVI	TSAVI	$\frac{[a(NIR - aR - b)]}{[R + aNIR - ab + X(1 + a^2)]}$
Atmospherically Resistant Vegetation Index	ARVI	$\frac{(NIR - RB)}{(NIR + RB)}$ $RB = R - \gamma(B - R)$
Global Environment Monitoring Index	GEMI	$GEMI = \eta(1 - 0.25\eta) - \frac{(R - 0.125)}{(1 - R)}$ $\eta = \frac{[2(NIR^2 - R^2) + 1.5NIR + 0.5R]}{(NIR + R + 0.5)}$
Transformed Soil Atmospherically Resistant Vegetation Index	TSARVI	$\frac{[a_{rb}(NIR - a_{rb}RB - b_{rb})]}{[RB + a_{rb}NIR - a_{rb}b_{rb} + X(1 + a^2_{rb})]}$
Modified SAVI	MSAVI	$\frac{2NIR + 1 - \sqrt{(2NIR + 1)^2 - 8(NIR - R)}}{2}$
Angular Vegetation Index	AVI	$\tan^{-1}\left\{\frac{\lambda_3 - \lambda_2}{\lambda_2}[NIR - R]^{-1}\right\} + \tan^{-1}\left\{\frac{\lambda_2 - \lambda_1}{\lambda_2}[G - R]^{-1}\right\}$

List of indices by sensor

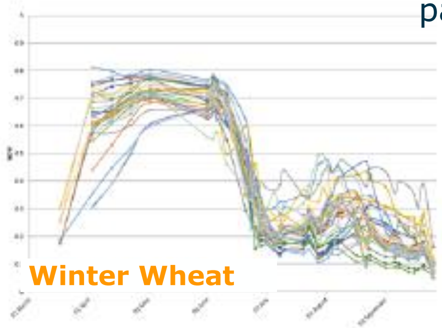
Spectral indices – temporal profile much affected by atmospheric perturbations

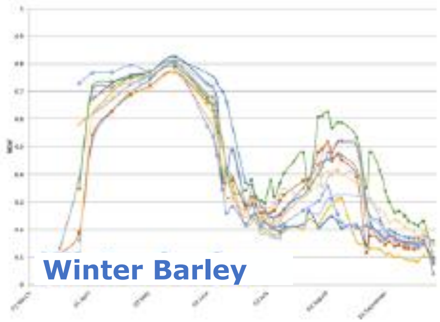


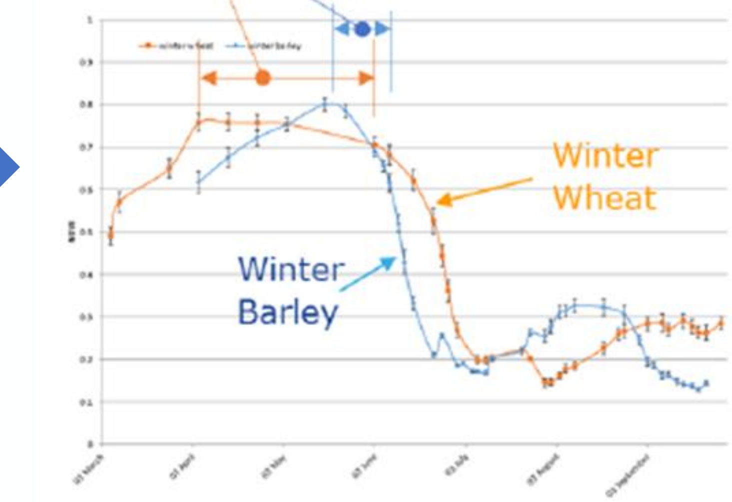
https://mars.jrc.ec.europa.eu/asap/hresolution/?region=0

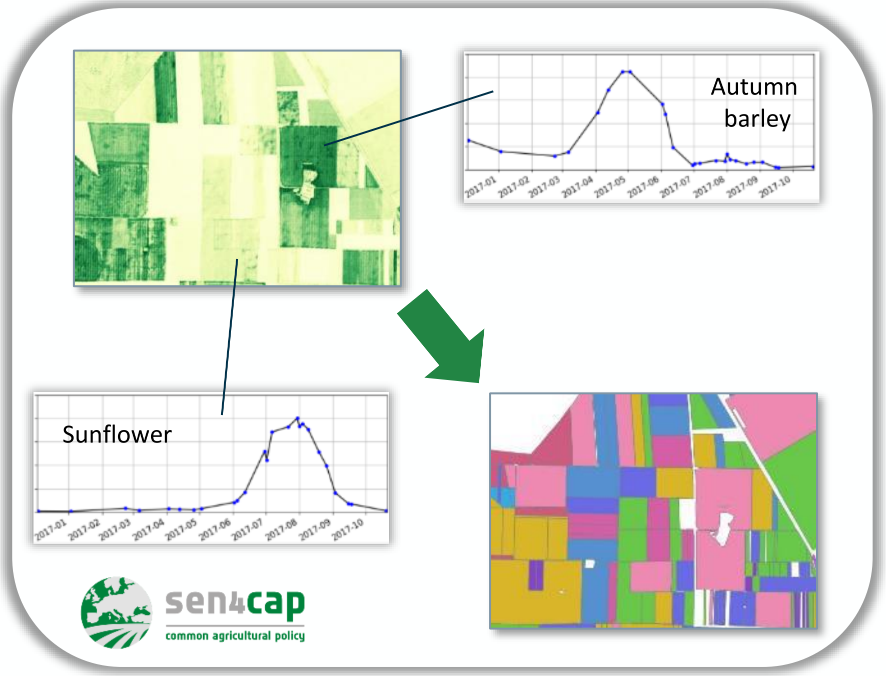
VI temporal signature – time series analysis

NDVI time profiles at parcel-scale



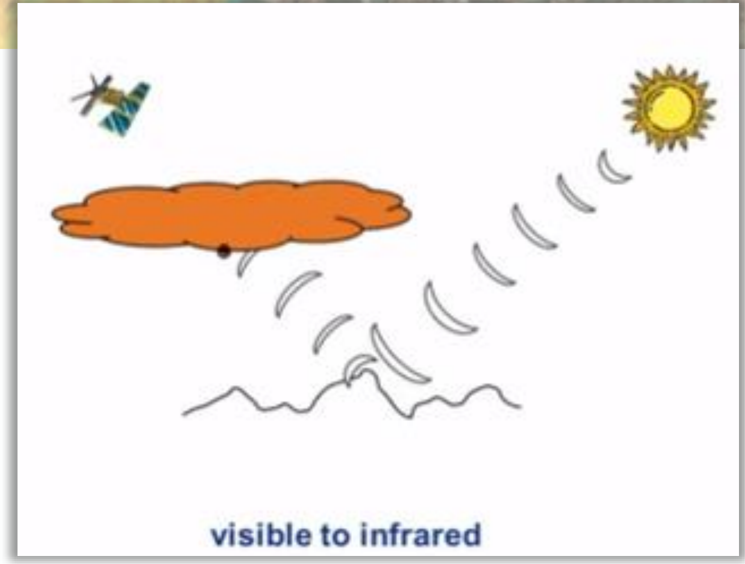


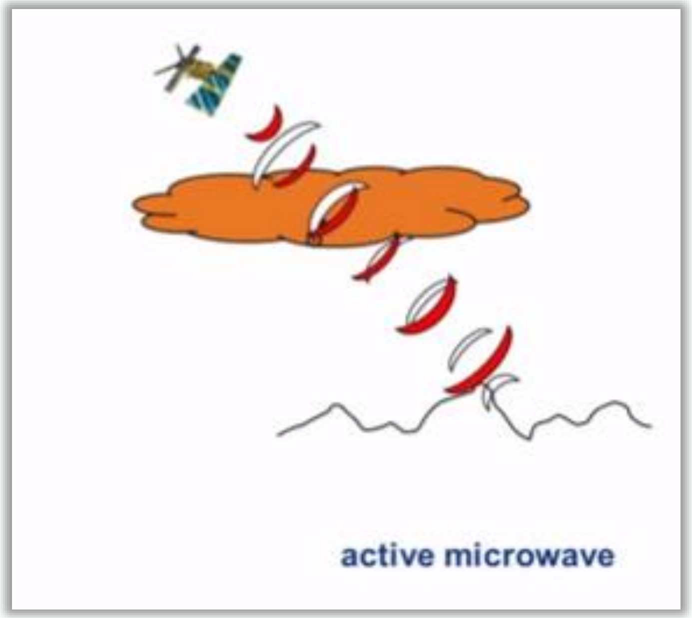


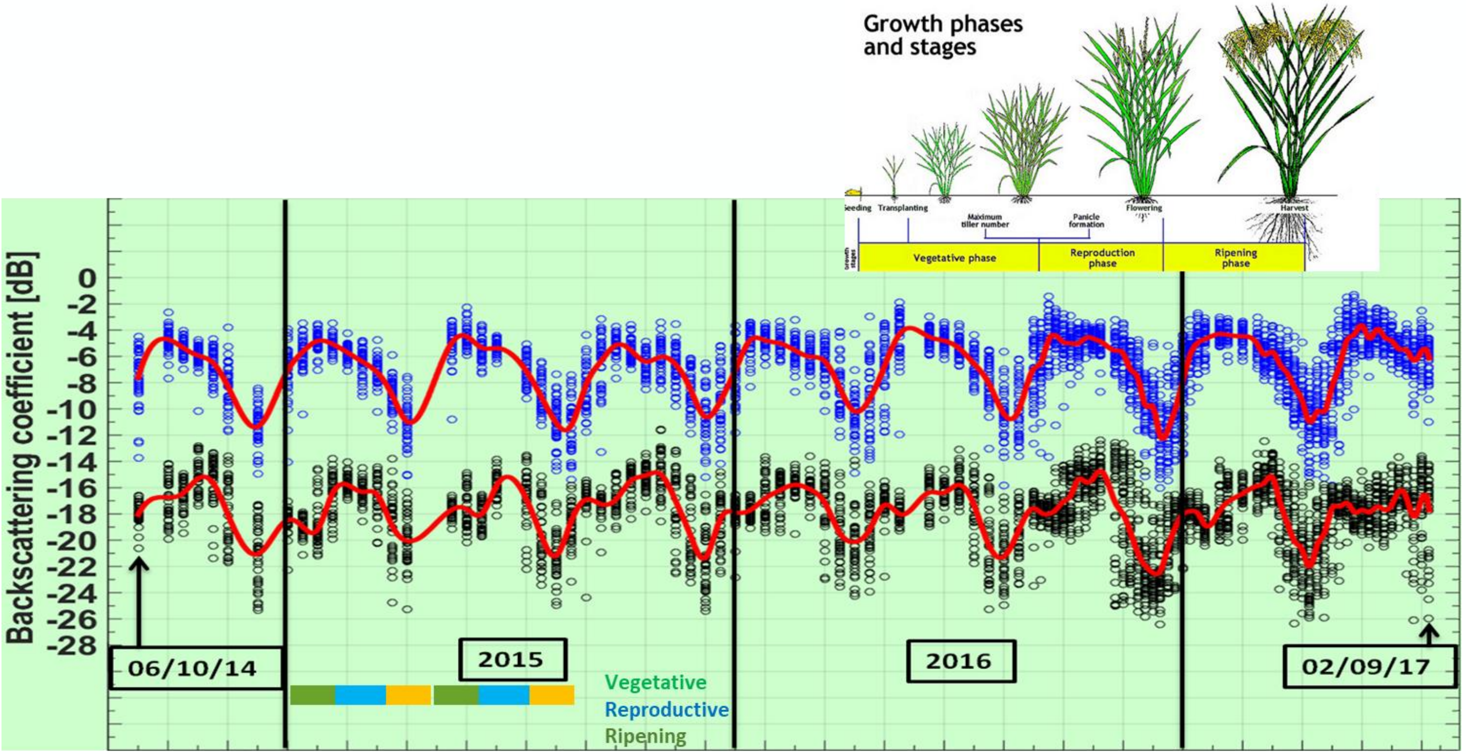


JRC Technical Reports, DS/CDP/2018/18

Optical vs Synthetic Aperture Radar (SAR)







Density of SAR time series is key

- SAR backscattering
- SAR coherence

(Geomatics)

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Backscattering and Coherence

➢ SAR backscattering (after calibration, sigma nought σ0)

The **SAR backscattering** is a measure of the outgoing radar signal that the target redirects directly back towards the radar antenna. It is a measure of the reflective strength of a target. The normalised measure of the radar return from a distributed target is called the backscatter coefficient, or **sigma nought** (σ_0), and is defined as per unit area on the ground. In general, due to the high dynamic of the SAR backscatter coefficient, **the amplitude** = sqrt(σ_0) is preferred for visualization purposes.

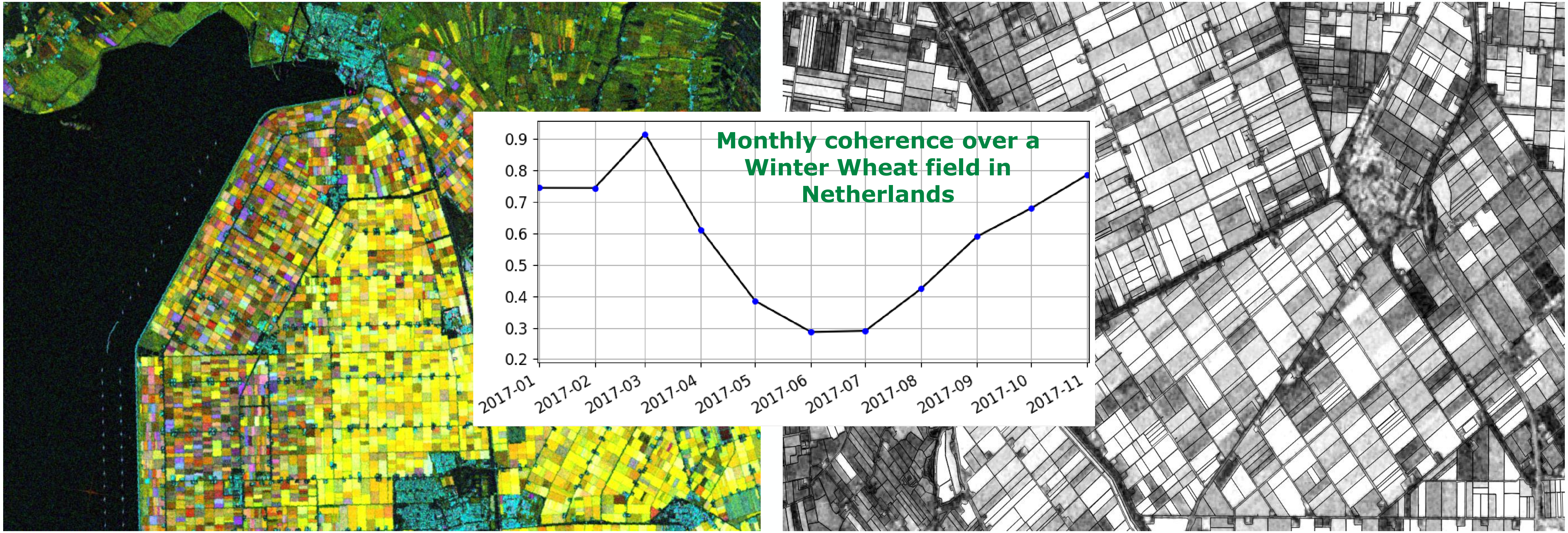
Definitions of SAR terms can be found in https://earth.esa.int/handbooks/asar/CNTR5-2.html

➢ SAR Coherence

The coherence, which assume values in the range [0.0, 1.0], gives an **estimation of changes in the scene taking into account variation of the phase of the backscattered radar signal:** high coherence (close to 1.0) implies that the scene is steady (e.g. urban areas, bare soil, rocks and so on), low coherence indicates changes between the two acquisition dates.

The coherence is calculated from a couple of SAR images acquired from the same orbit (in order to have significant coherence values the images must be acquired with similar sight of view). The high revisit time of Sentinel-1 mission allows to calculate **short term coherence** from couples of images acquired one **6 days** from the other.

SAR for agriculture monitoring



S1 RGB color composite (blue: mean of the July coherence; green: mean of the March coherence; red: seasonal standard deviation)

Mean of the coherence value of March 2017 over Netherlands

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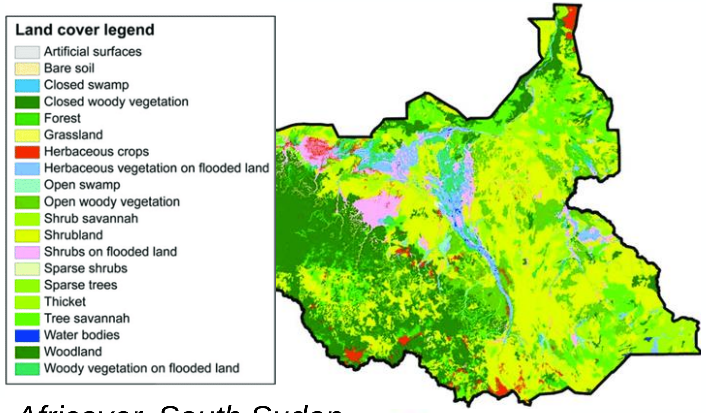
What is a crop?

A crop is any cultivated plant, fungus, or alga that is harvested for food, clothing, livestock fodder, biofuel, medicine, or other uses

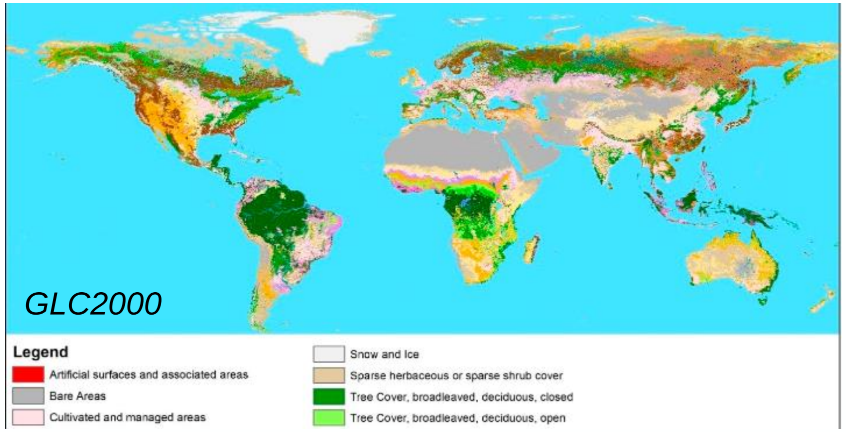
Cultivated land is not, strictly speaking, a land cover class, but rather a **land use class**. But, due to its importance, cropland is integrated in all existing land cover typologies

General LC map, with « crop class »

All existing general land cover map includes one or several crop classes

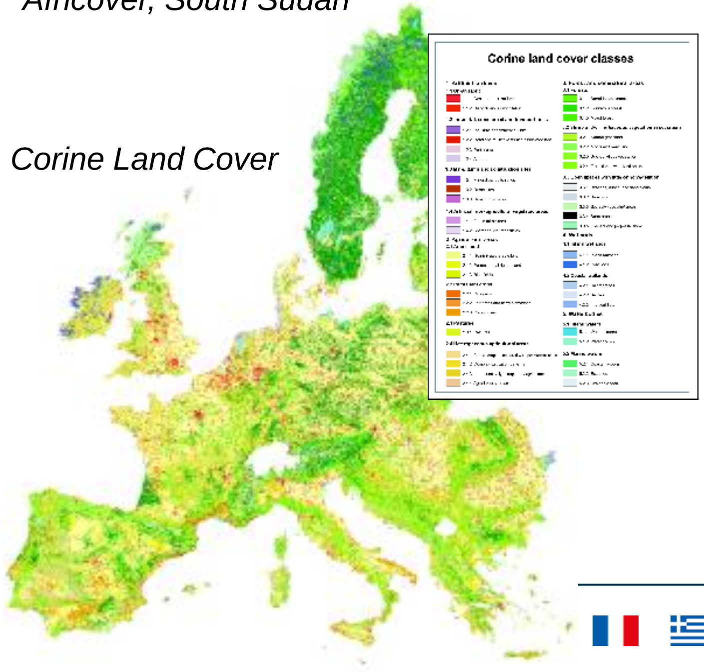


Africover, South Sudan

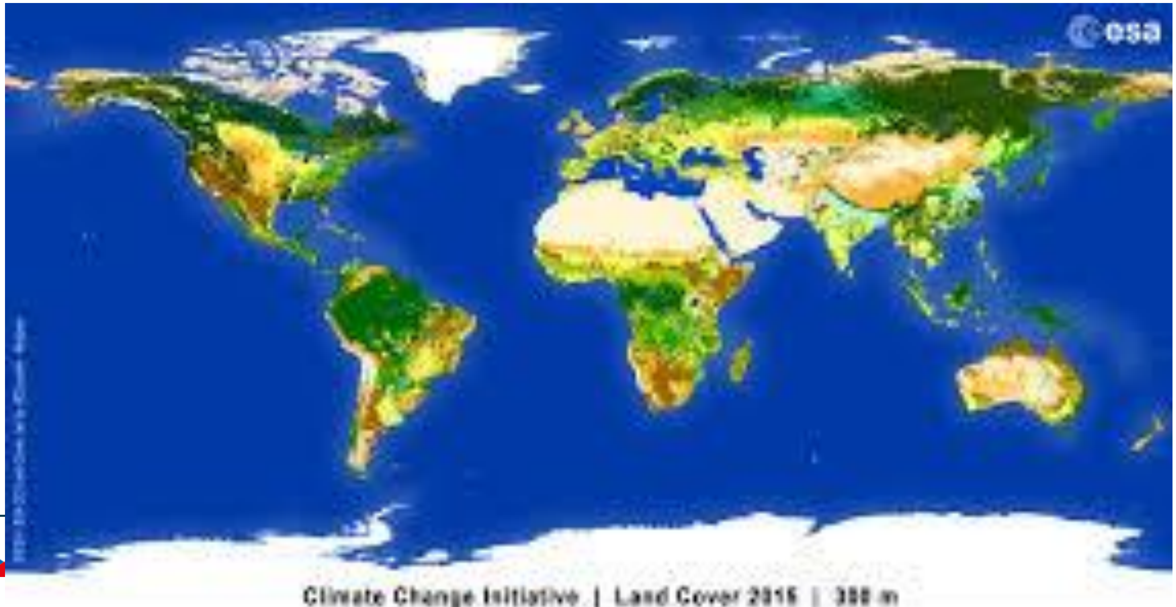


MODIS LC

Corine Land Cover

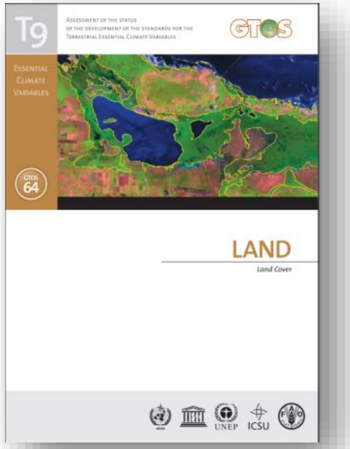


SERVIR

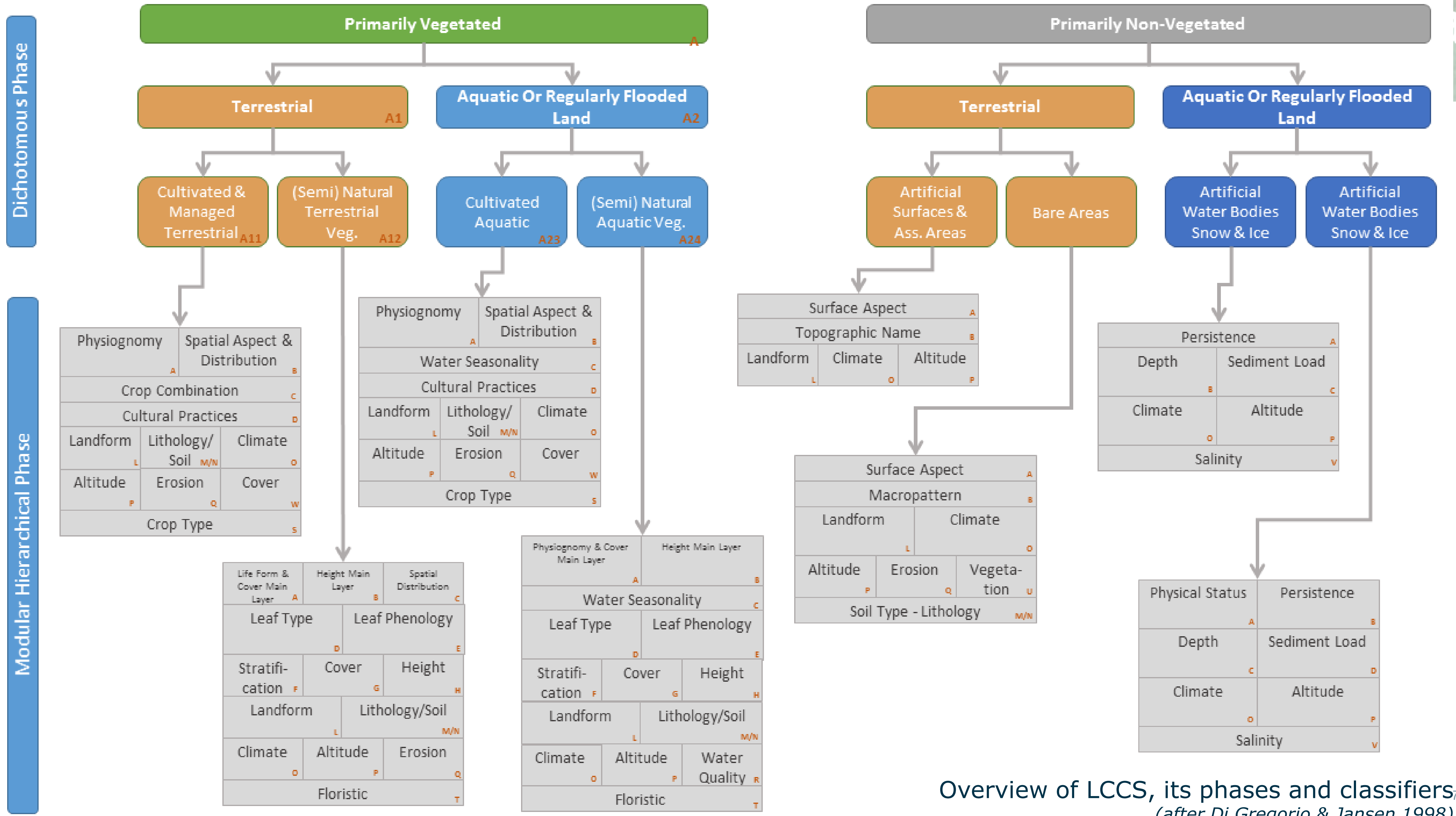


Land Cover Classification Systems – FAO LCCS

- Developed by FAO and UNEP in response to a need for harmonized and standardized collection of land cover data
- A world-wide reference system (LCCS as ISO standard)
- Combine a high level of flexibility (ability to describe land cover features all over the world at any scale or level of detail) with an absolute level of standardization of the class definition between different users
    - Vegetation life form: trees, shrubs, herbaceous vegetation (separated into grasslands and agricultural crops), lichen and mosses, non vegetated
    - Leaf type (needle-leaf, broad-leaf) and leaf longevity (deciduous, evergreen)
    - Density of life form and leaf characteristics in percent cover
    - Non-vegetated cover types (bare soil/rock, built up, snow, ice, open water)
    - Terrestrial areas versus aquatic/regularly flooded
    - Artificiality of cover and land use



Source:
- http://www.fao.org/land-water/land/land-governance/land-resources-planning-toolbox/category/details/en/c/1036361/
- http://www.gofcgold.wur.nl/sites/lucc.php



Overview of LCCS, its phases and classifiers

(after Di Gregorio & Jansen 1998)

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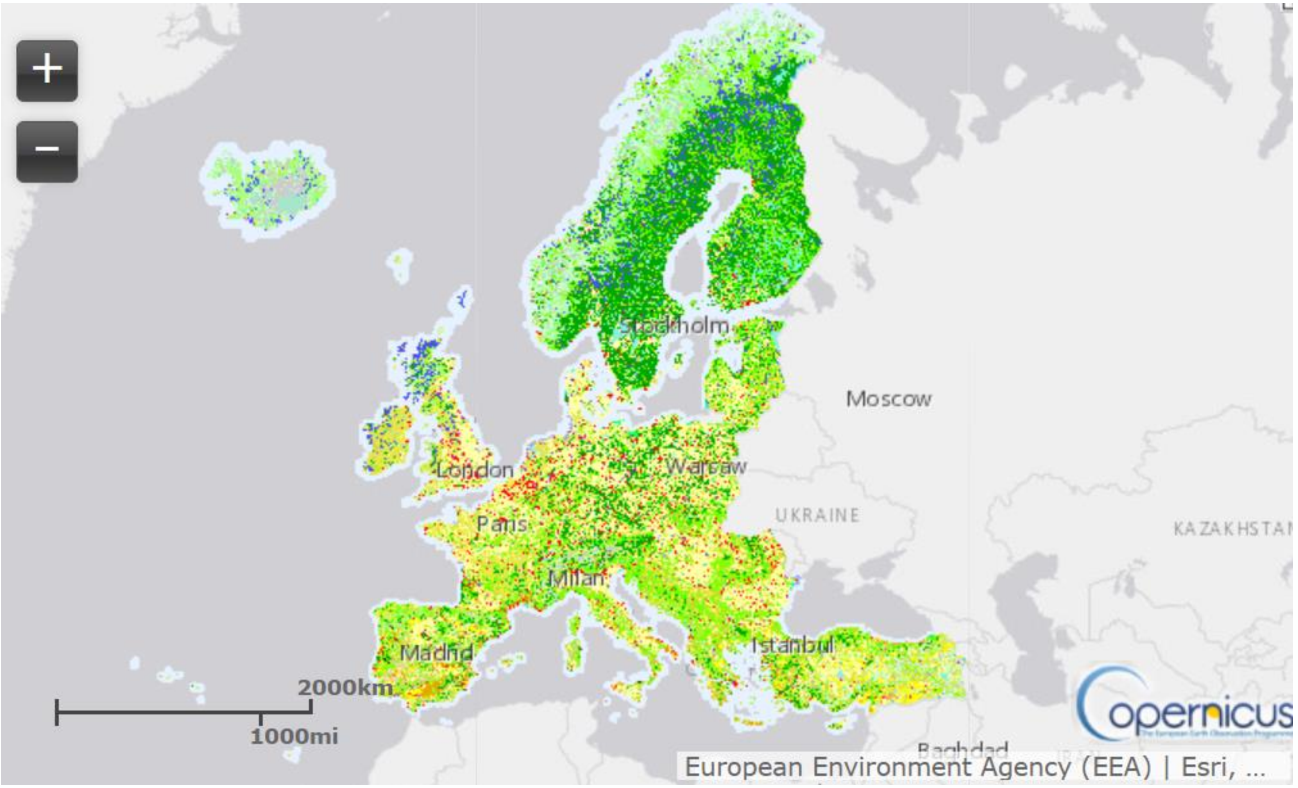
Land Cover Classification Systems - CORINE

- CORINE = Coordination of Information on the Environment: program initiated by the European Commission in 1985
  - Main objective is to provide a homogeneous vector database about land cover => classification system for the EU environment



- ✓ Mapping methodology: computer-assisted visual interpretation of satellite images and maps digitalization
- ✓ Scale: 1:100,000
- ✓ Minimum Mapping Unit (MMU): 25 hectares
- ✓ Minimum width of linear elements: 100 meters
- ✓ 44 land cover classes

https://land.copernicus.eu/pan-european/corine-land-cover/clc2018

Examples of CORINE Land Cover Classes

GRID_CODE	CLC_CODE	LABEL1	LABEL2	LABEL3	RGB
1	111	Artificial surfaces	Urban fabric	Continuous urban fabric	230-000-077
2	112		Urban fabric	Discontinuous urban fabric	255-000-000
3	121		Industrial; commercial and transport units	Industrial or commercial units	204-077-242
4	122		Industrial; commercial and transport units	Road and rail networks and associated land	204-000-000
5	123		Industrial; commercial and transport units	Port areas	230-204-204
6	124		Industrial; commercial and transport units	Airports	230-204-230
7	131		Mine; dump and construction sites	Mineral extraction sites	166-000-204
8	132		Mine; dump and construction sites	Dump sites	166-077-000
9	133		Mine; dump and construction sites	Construction sites	255-077-255
10	141		Artificial; non-agricultural vegetated areas	Green urban areas	255-166-255
11	142		Artificial; non-agricultural vegetated areas	Sport and leisure facilities	255-230-255
12	211	Agricultural areas	Arable land	Non-irrigated arable land	255-255-168
13	212		Arable land	Permanently irrigated land	255-255-000
14	213		Arable land	Rice fields	230-230-000
15	221		Permanent crops	Vineyards	230-128-000
16	222		Permanent crops	Fruit trees and berry plantations	242-166-077
17	223		Permanent crops	Olive groves	230-166-000
18	231		Pastures	Pastures	230-230-077
19	241		Heterogeneous agricultural areas	Annual crops associated with permanent crops	255-230-166
20	242		Heterogeneous agricultural areas	Complex cultivation patterns	255-230-077
21	243		Heterogeneous agricultural areas	Land principally occupied by agriculture	230-204-077
22	244		Heterogeneous agricultural areas	Agro-forestry areas	242-204-166
23	311	Forest and semi natural areas	Forests	Broad-leaved forest	128-255-000
24	312		Forests	Coniferous forest	000-166-000
25	313		Forests	Mixed forest	077-255-000
26	321		Scrub and/or herbaceous vegetation associations	Natural grasslands	204-242-077
27	322		Scrub and/or herbaceous vegetation associations	Moors and heathland	166-255-128
28	323		Scrub and/or herbaceous vegetation associations	Sclerophyllous vegetation	166-230-077
29	324		Scrub and/or herbaceous vegetation associations	Transitional woodland-shrub	166-242-000
30	331		Open spaces with little or no vegetation	Beaches; dunes; sands	230-230-230
31	332		Open spaces with little or no vegetation	Bare rocks	204-204-204
32	333		Open spaces with little or no vegetation	Sparsely vegetated areas	204-255-204
33	334		Open spaces with little or no vegetation	Burnt areas	000-000-000
34	335		Open spaces with little or no vegetation	Glaciers and perpetual snow	166-230-204

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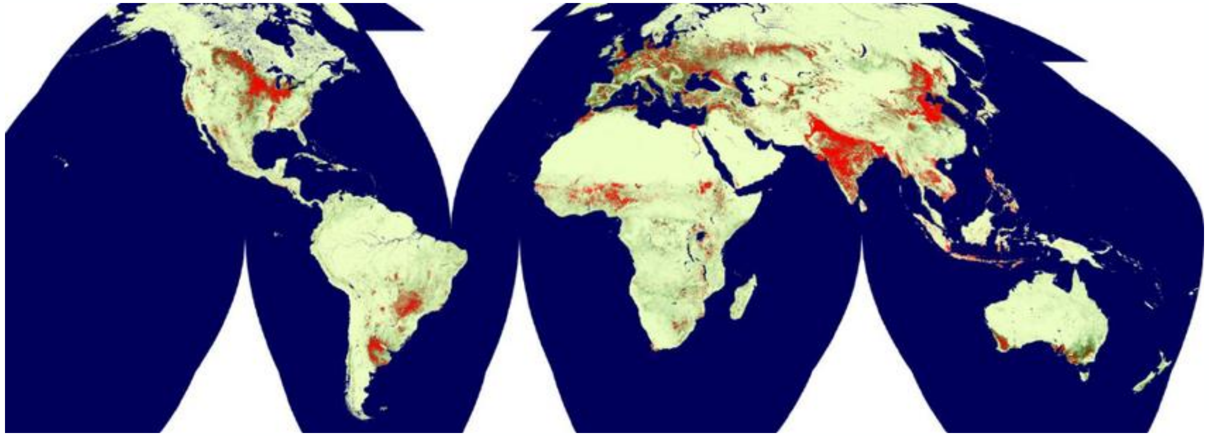
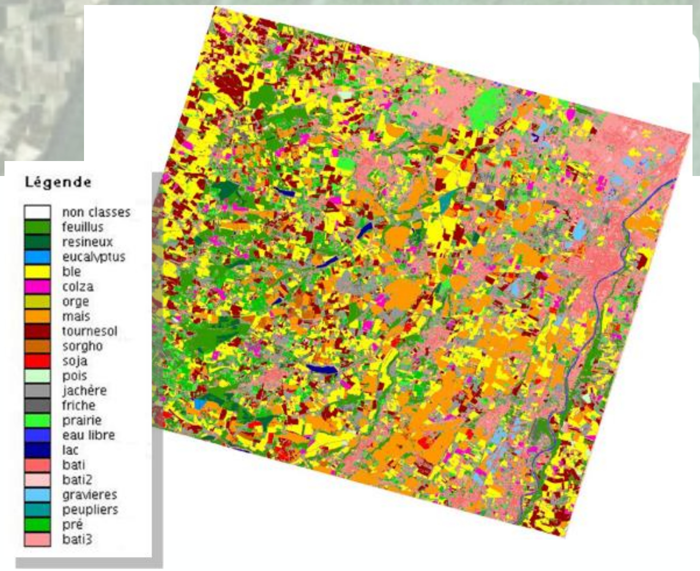
Cropland vs no cropland & crop type maps

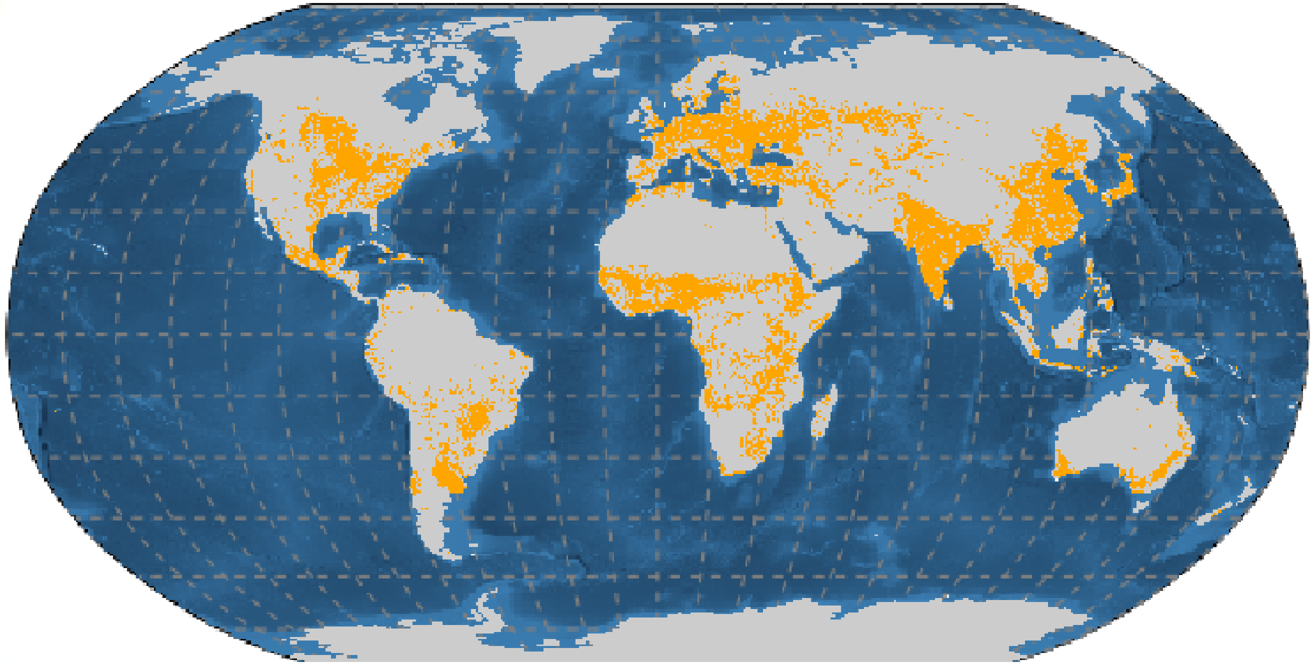
Global MODIS 250 m cropland product

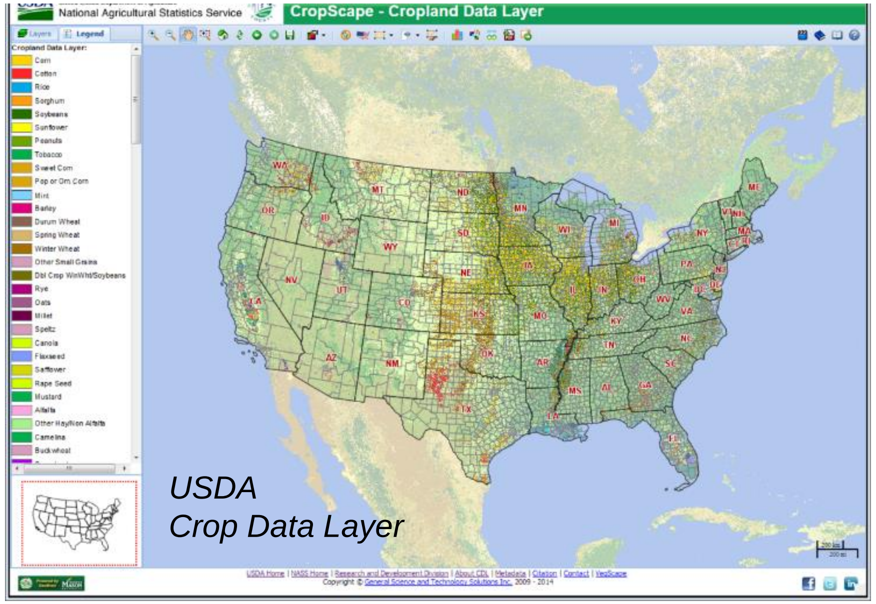




CESBIO (Toulouse, France)

Unified Cropland Layer 250m (Waldner et al. 2016)





USDA Crop Data Layer

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Land mapping by remote sensing driven by technology

Mapping = interpretation of radiance (measured by the sensors in watt/m².str) in terms of land cover class, but no direct inference => series of complex processes

Evolution:

- First operational mapping systems based on on-screen interactive **visual interpretation of one or two images acquired at specific periods of the year**, and mainly relied on expert interpretation
- Progressively supported by image processing tools, which are either interactively run or applied once for all
- Moving from best-image or pair-of-images selection to **full-time series processing**
- Digital processing tends to reduce labour-intensive data handling to focus interactive human intervention on the most critical steps

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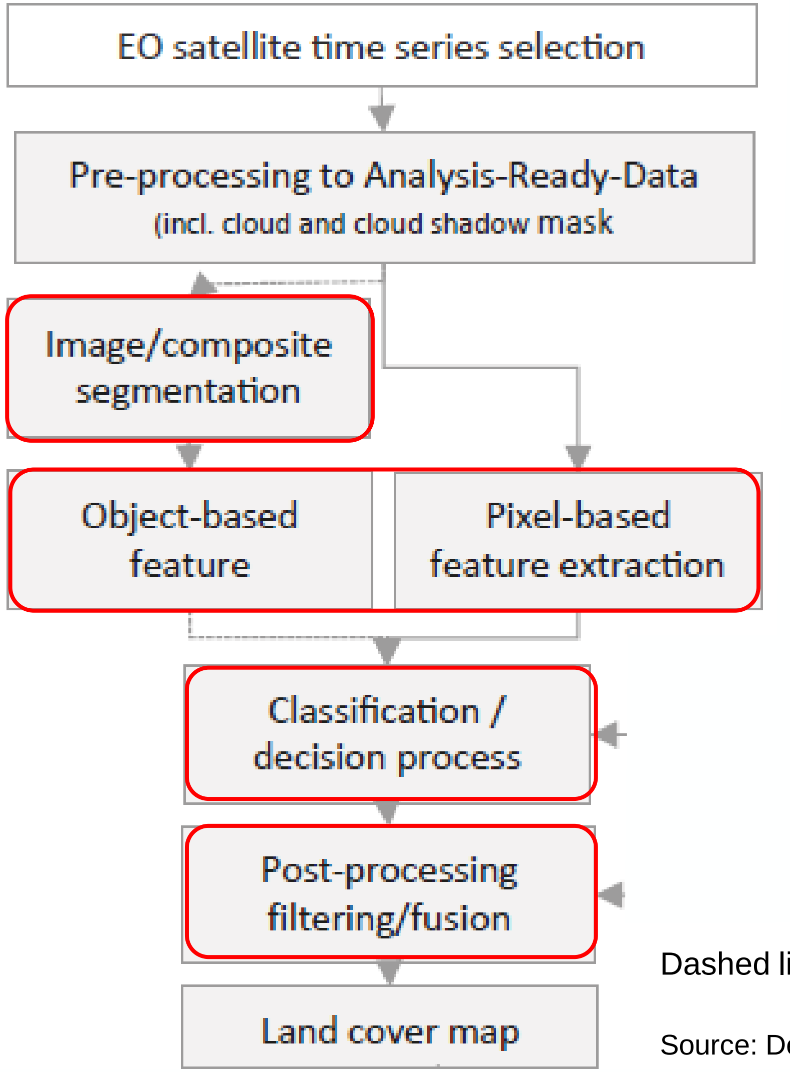
Generic workflow for land classification with EO data



Dashed lines correspond to alternative pathways

Source: Defourny in Delincé

For each step, there are several conceptual and algorithmic choices

Strong influence of the **quality and quantity** of the **remote sensing input** and of the **calibration data set**

But in the end, crop mask accuracy varies more from one agricultural region to another rather than from one state-of-the-art method to another *(Waldner et al. 2016)*

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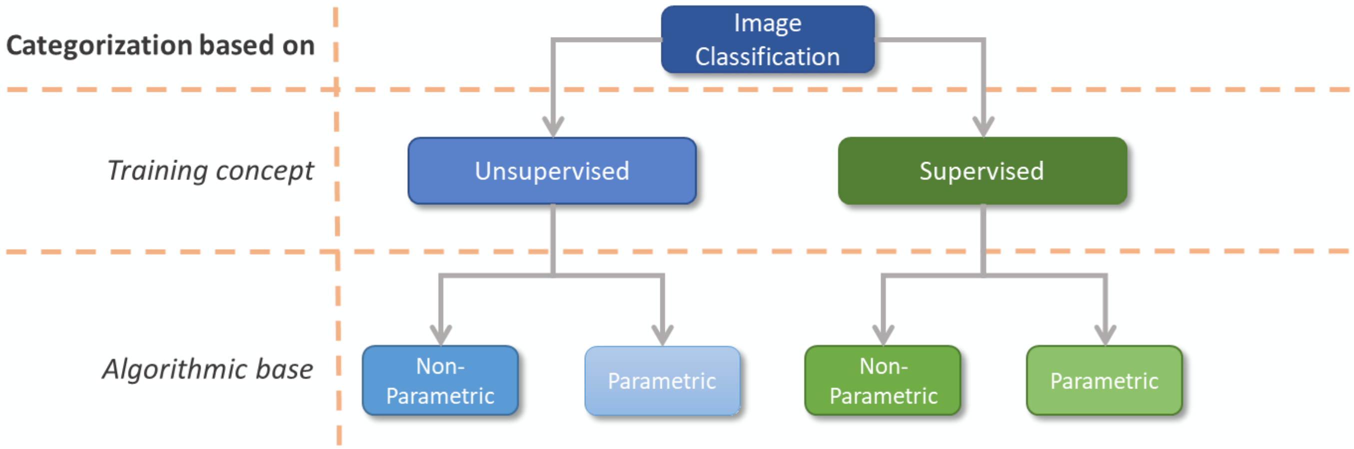
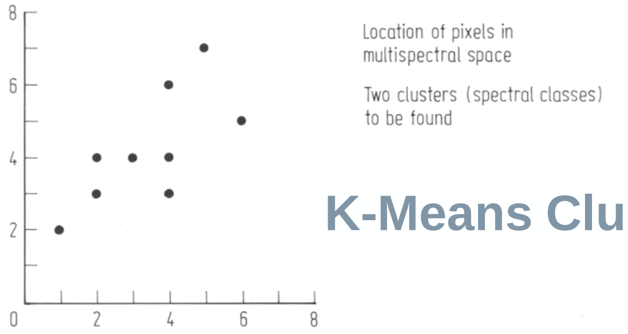
Classification algorithms

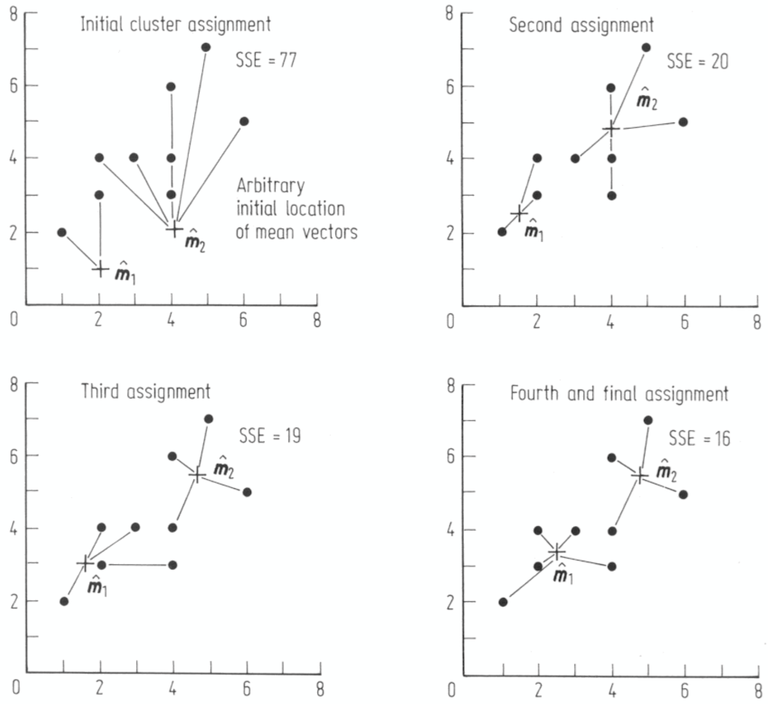
- Training concept
  - Unsupervised
    - Without training of the classifier
    - Purely based on statistical parameters of the distribution of the spectral properties in multi-spectral data set
    - Examples: Isodata Clustering, K-Means Clustering
  - Supervised
    - With training of the classifier using training areas
    - Examples: Maximum Likelihood, Minimum Distance, K-Nearest Neighbor, Artificial Neural Network
- Algorithmic base
  - Non-parametric
    - No a priori assumptions on statistical distribution, may be used for many different distributions (more robust)
    - Examples: Artifical Neural Networks, Nearest Neighbors
  - Parametric
    - Assumes specific statistical distribution of the data (e.g. normal distribution)
    - Examples: (Isodata, K-Means, Maximum Likelihood)



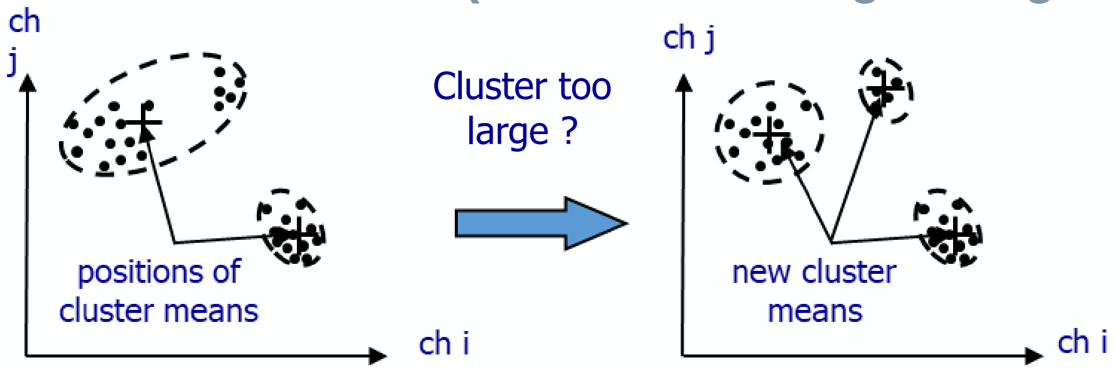
Unsupervised algorithms



K-Means Clustering

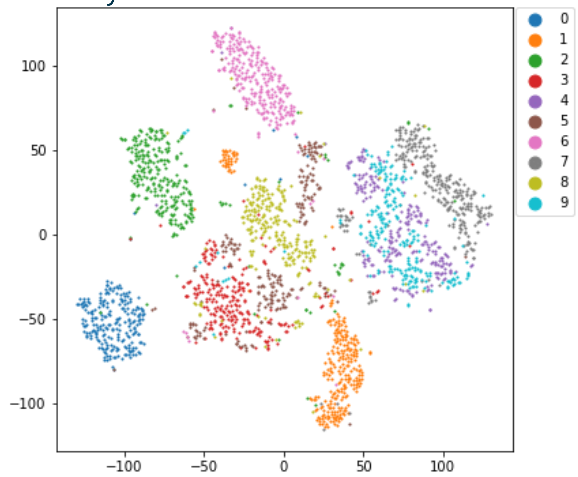


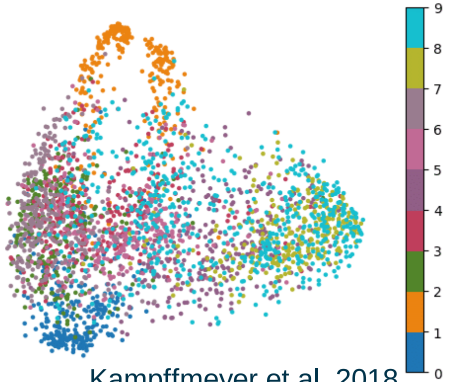
ISODATA (Iterative Self-Organising Data Analysis)



No calibration data needed, but expert knowledge required to label clusters

Boytsov et al. 2017





Kampffmeyer et al. 2018

Van der Maaten and Hinton, 2008

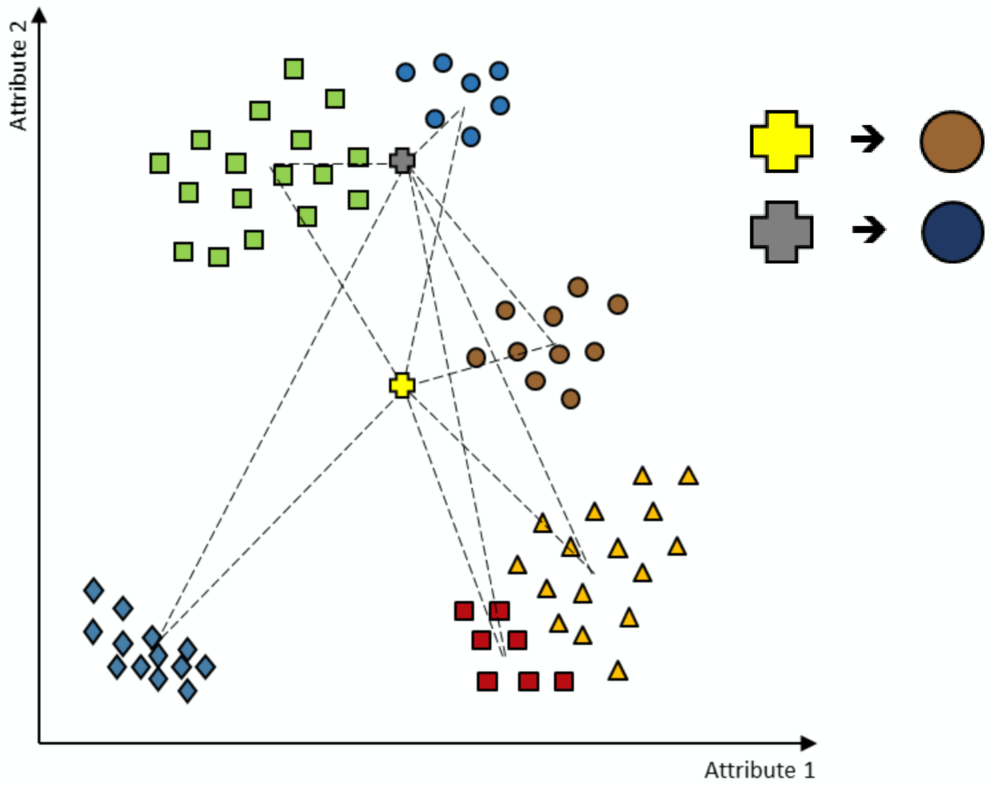
UCLouvain

Supervised algorithms

Training pixel

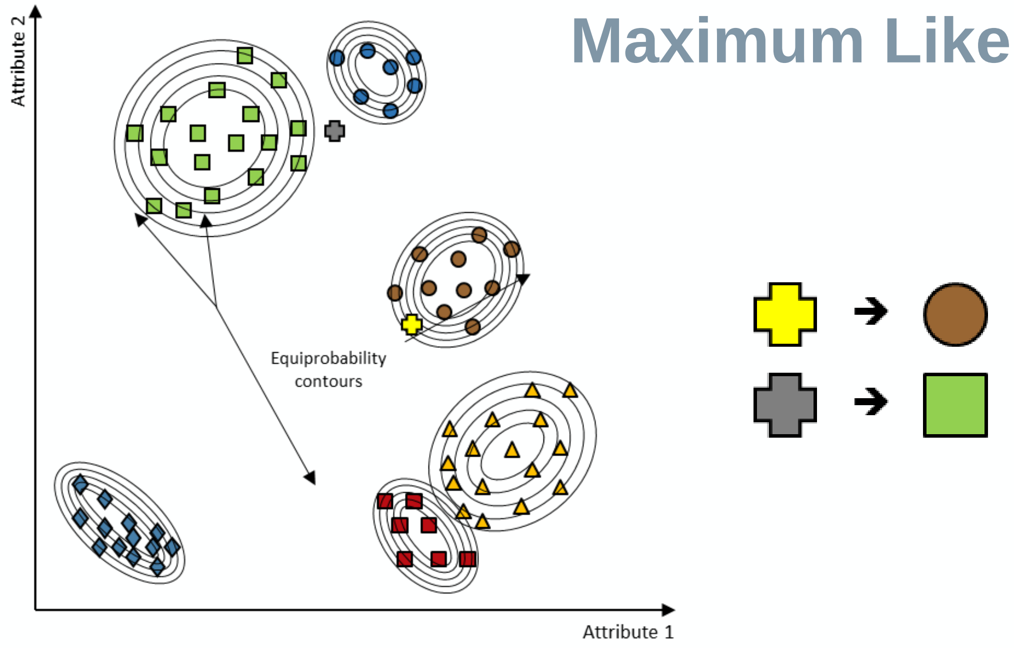
Pixel under investigation

Minimum-Distance-to-Mean



Mean point is calculated for pixels of known classes (training data) and unknown pixels are then assigned to the class which is arithmetically closest

Maximum Likelihood



- Target classes statistically described by their multivariate probability density functions
- Each density function represents the probability that the spectral pattern of a class falls within a given region in multidimensional spectral space
- The spectral signature of each pixel is then assigned to the class of which it has the highest likelihood of being a member

Supervised algorithms

- Focuses only on training data at the edge of the class distributions (= support vectors)
- When classes cannot be separated, the training data are projected into a higher-dimensional space using kernel techniques for a **better fitting of a linear hyperplane**
- Repeated for each pair of classes to divide the data into the predefined number of classes
- Optimal rules used to assign all image data into the predefined target classes

Support Vector Machines (SVM)

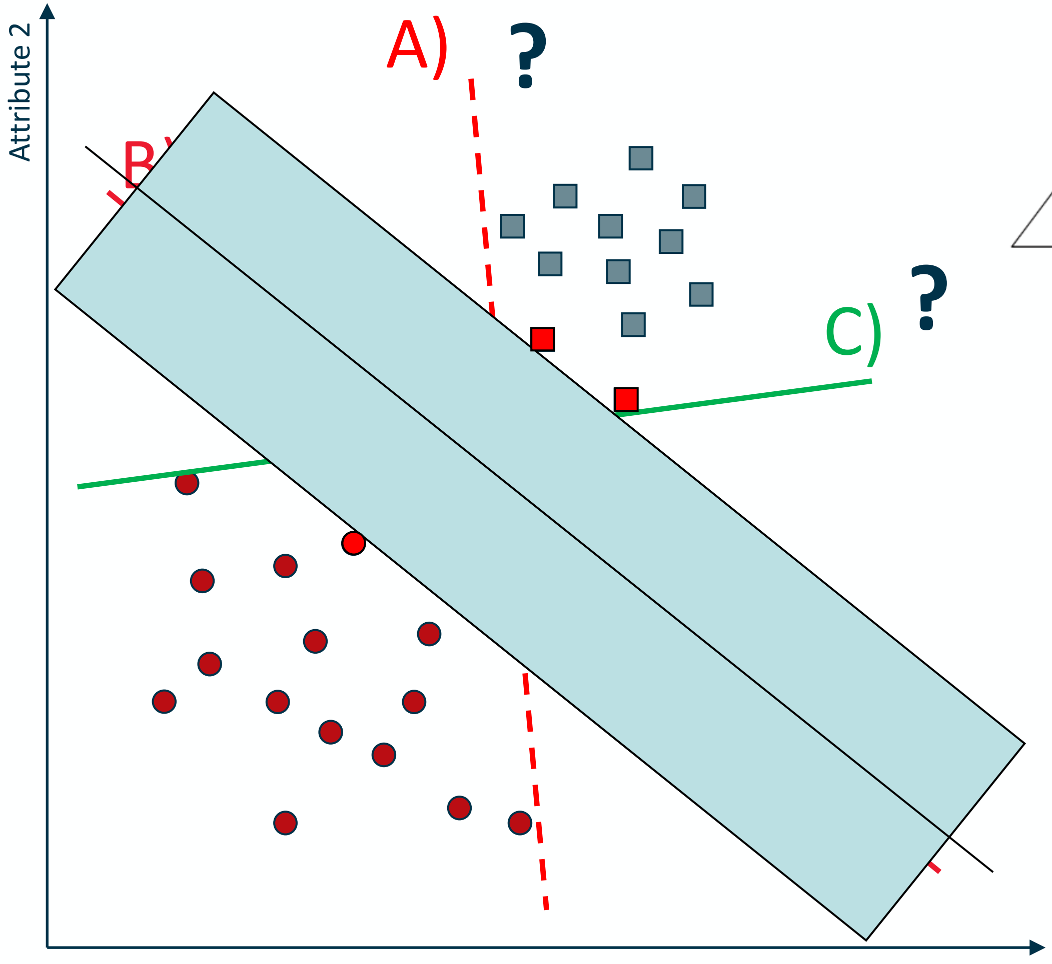
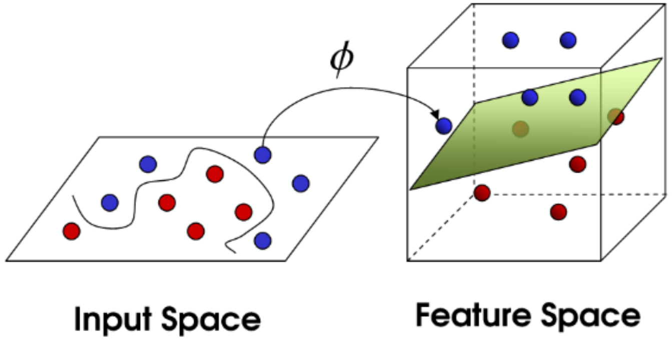


Fig. 9: SVM Classifier

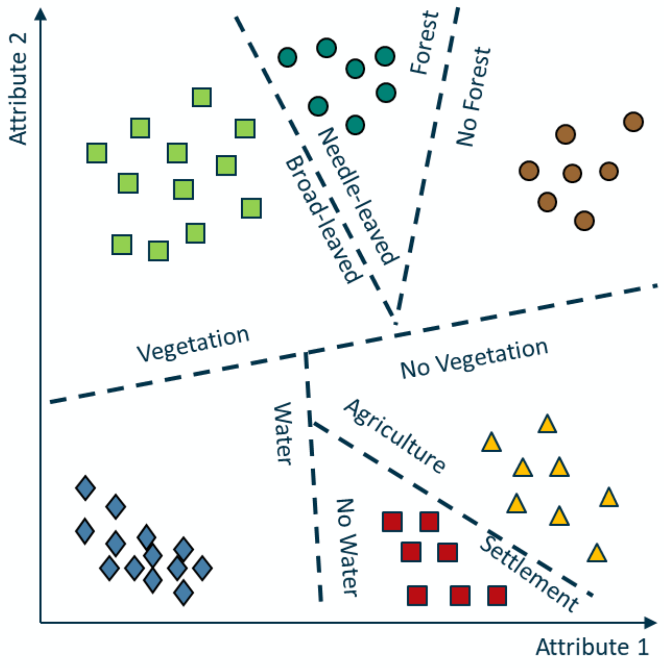


Which line divides the classes best?

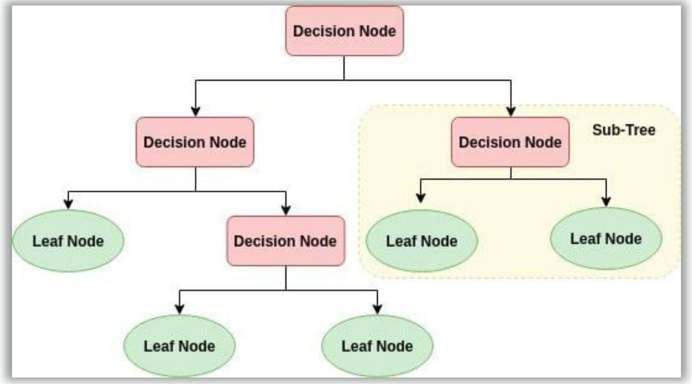
Support Vectors
Training Pixel Class **A**
Training Pixel Class **B**

Supervised algorithms

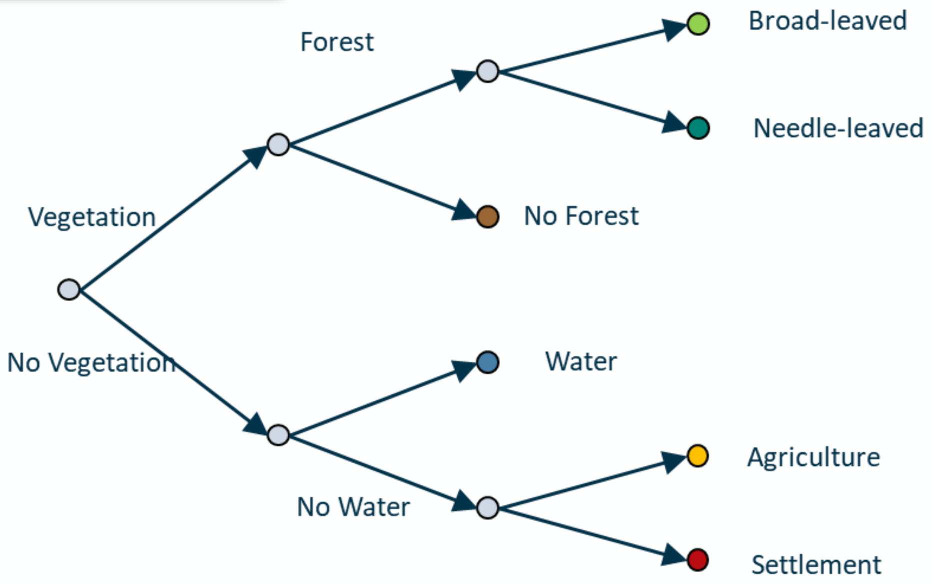
- Trees = output of a sequence of tests
- Rules built by recursive partitions to get regions (nodes) increasingly homogeneous with respect to their class variable



Decision Trees (DT)



- Sequence:
  - Generation of DTs based on training samples
  - Transformation of DTs into another representation of knowledge representation, called production rules (easy to understand and possibly editable by human experts)

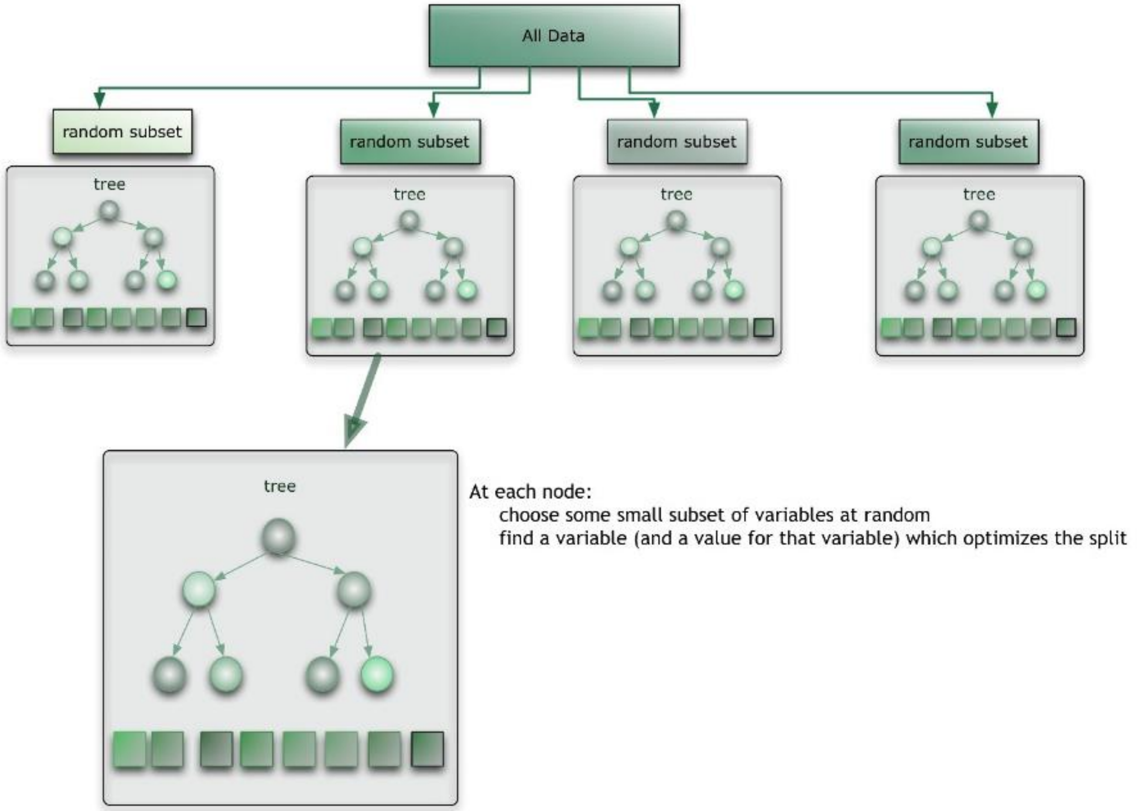


UCLouvain

Supervised algorithms

- Improved implementation of Decision Trees: ensemble-learning algorithm that combines multiple classifications of the same data to produce higher classification accuracies
- Sequence:
  - Bagging: individual trees are grown from different subsets of training data (random subsampling of the original data for growing each tree)
  - Classification fit to each bootstrap sample
  - Splitting continues until further subdivision no longer reduces the Gini index => finding the best features combination for each class discrimination
  - Most frequent class decided from all trees with a single majority vote

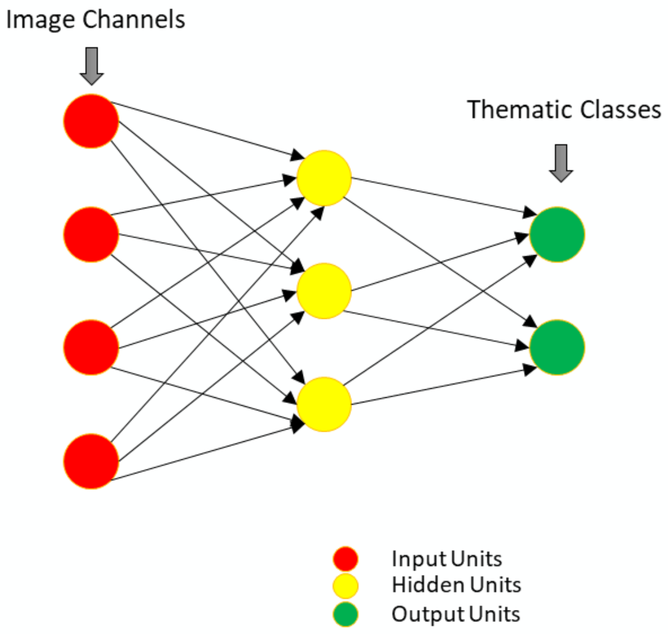
Random Forest (RF)



Supervised algorithms

Artificial Intelligence (AI) – Neural Network (NN)

- Mimick human brain which is able to process vast quantities of data from a variety of sources
- ANN = based on a collection of connected units called “artificial neurons”
  - acquiring knowledge from its environment through a self-learning process
  - adaptively constructing linkages between input (EO features) and output (LC classes)



1) Training data used to define the rules (network) that produce the best classification results
2) Rules used to assign features data to the training class of which it has the **highest probability** (fuzzy membership grade) of being a member

Convolutional Neural Network (CNN)

-> https://www.youtube.com/watch?v=FmpDIaiMIeA

Supervised classification algorithms - Summary

Algorithm	Strengths/characteristics	Weaknesses
Maximum Likelihood (Parametric)	• Simple application • Easy to understand and interpret • Predicts class membership probability	• Parametric • Assumes normal distribution of data • Large training sample necessary
Artificial Neural Networks (Non-parametric)	• Manages large feature space well • Indicates strength of class membership • Generally high classification accuracy • Resistant to training data deficiencies – requires less training data than Decision Trees (DTs)	• Needs parameters for network design • Tends to overfit data • Black box (rules are unknown) • Computationally intense • Slow training
Support Vector Machines (Non-parametric)	• Manages large feature space well • Insensitive to Hughes effect • Works well with small training data set • Does not overfit	• Needs parameters: regularization and kernel • Poor performance with small feature space • Computationally intense • Designed as binary, although variations exist
Decision Trees (Non-parametric)	• No need for any kind of parameter • Easy to apply and interpret • Handles missing data • Handles data of different types (e.g. continuous, categorical) and scales • Handles non-linear relationships • Insensitive to noise	• Sensitive to noise • Tends to overfit • Does not perform as well as others in large feature spaces • Large training sample required
Random Forests (Non-parametric)	• Capacity to determine variable importance • Robust to data reduction • Does not overfit • Produces unbiased accuracy estimate • Higher accuracy than DTs	• Decision rules unknown (black box) • Computationally intense • Requires input parameters (#trees and #variables per node)

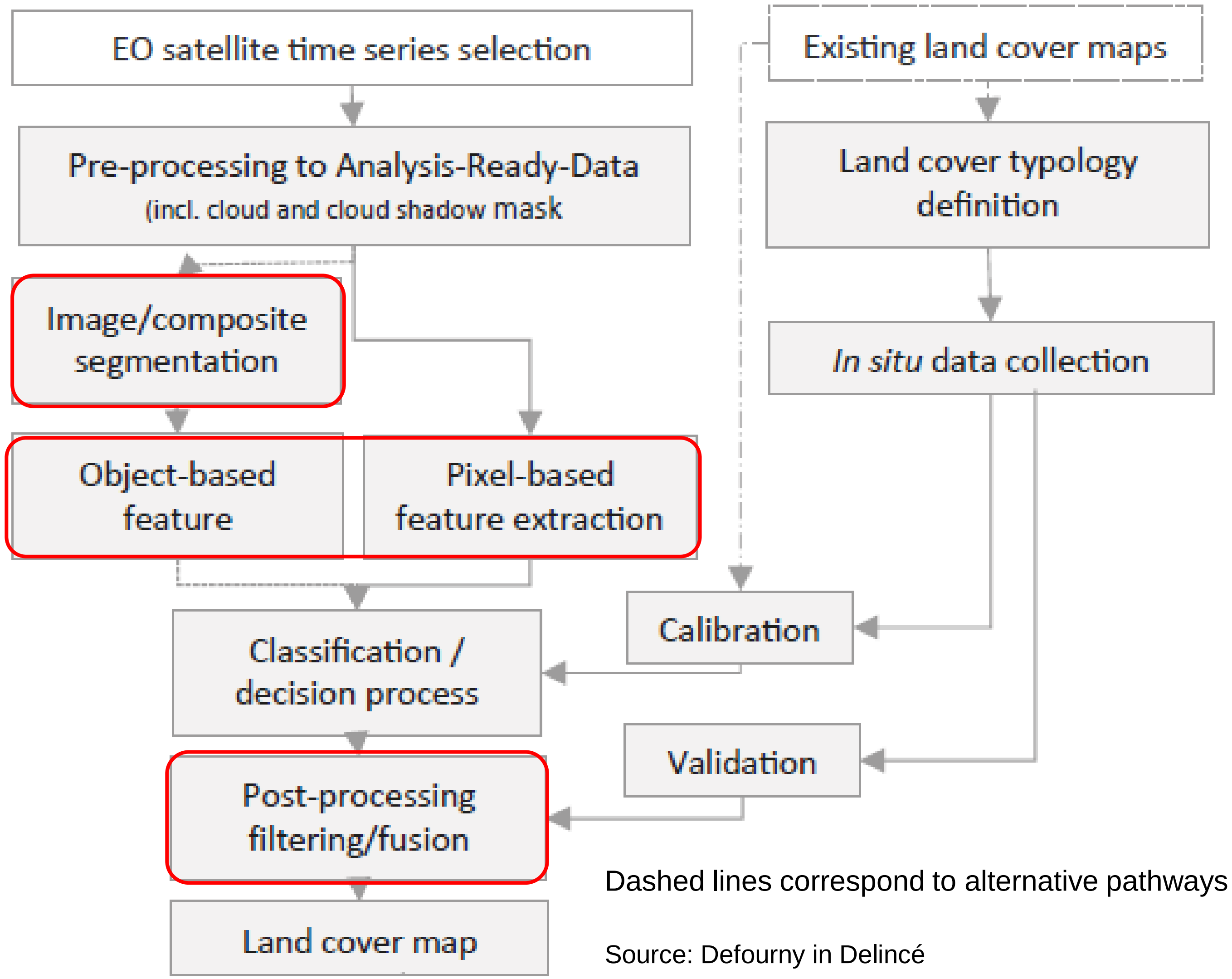
RF or SVM tend to be preferred because of their maturity

Data mining is more and more used

Not a single best solution for all possible situations

Source: Davidson, 2016

Generic workflow for land classification with EO data



Dashed lines correspond to alternative pathways

Source: Defourny in Delincé

Image segmentation

Process of dividing or partitioning the image into “n” regions called segments or objects, which are made by adjacent pixels with similar properties (spectral, spatial and/or temporal)

- Watershed algorithm

Considers the image like a topographic map, with the brightness of each point representing its height, and finds the lines that run along the tops of ridges

- Region growing algorithm

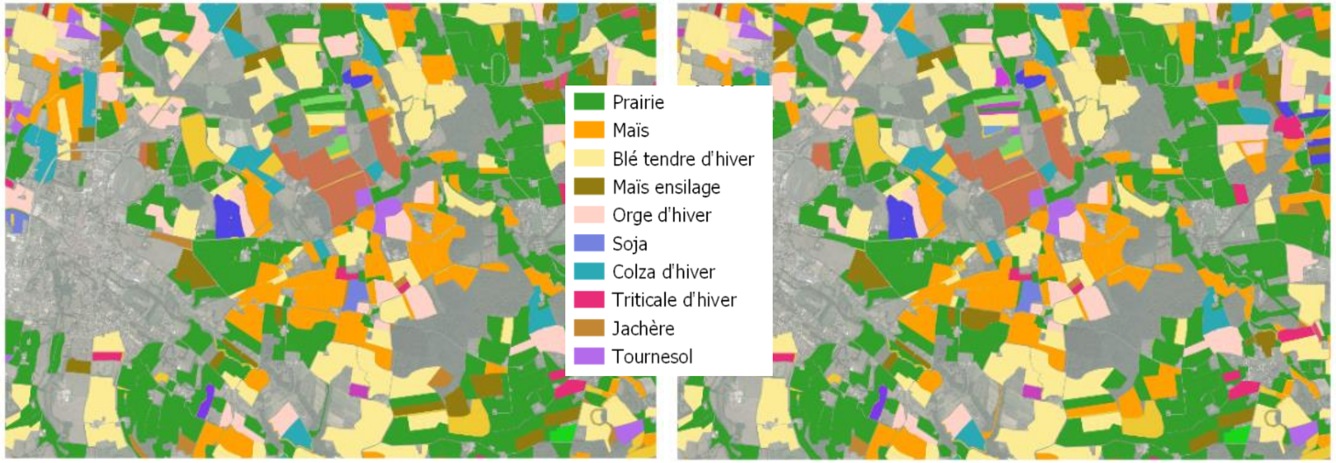
Neighboring pixels are examined and added to a region if no edges are detected. Iterative process

- Other type of algorithm such as neural network

Need a large training dataset

In Europe : Availability of crop boundaries & crop declaration

LPIS : land parcel identification system



Declared crop type

Predicted crop type

Big dataset to handle

UCLouvain

Features extraction

Available data

Satellite data
- Raw measurements
- Pre-processed measurements (atm. cor., calibration): spectral reflectances, radar σ_0
- Combination of bands (e.g. NDVI)
- Phenology index
- …

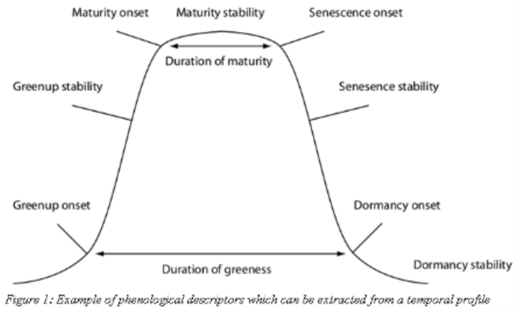
Ancillary data:
- Previous land cover map(s)
- Digital Elevation model
- Soil maps
- …

3 categories

❑ **Radiometric features**
- Reflectances, spectral indices
- Texture (local statistics)

❑ **Temporal features**
- Time descriptors (based on time profiles)
- Phenologic indicators: time descriptors based on prior knowledge about vegetation

❑ **Object features: extracted after images segmentation**
- Radiometric features
- Shape features
- Adjacency features

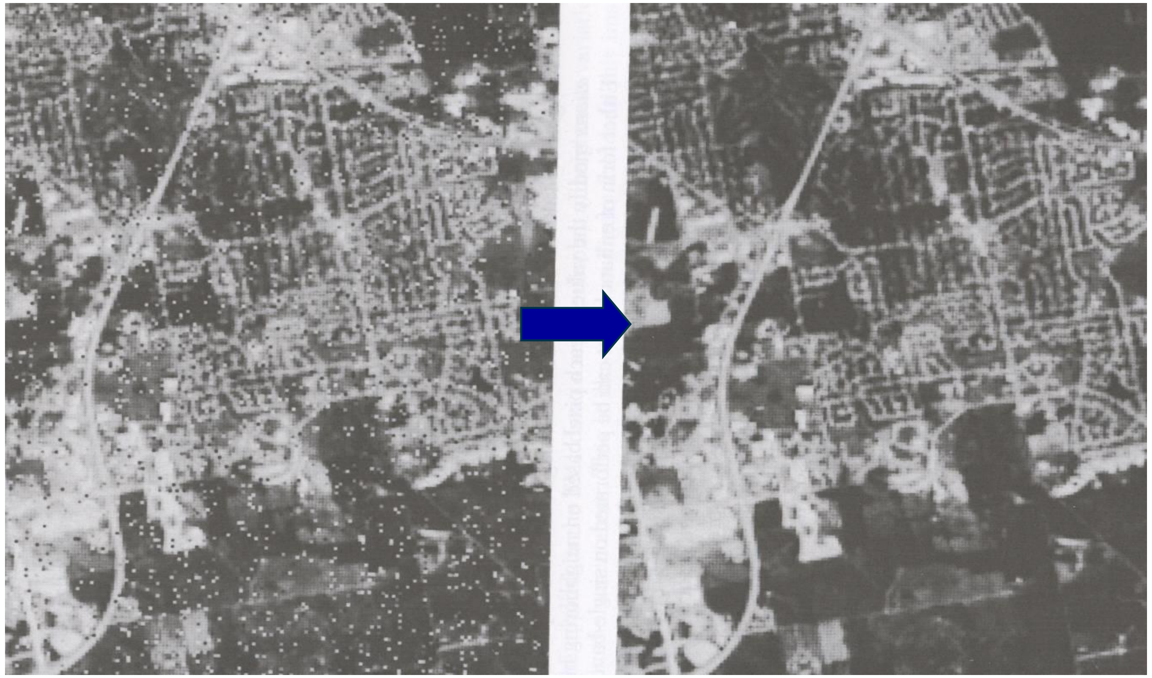


Example of phenological descriptors which can be extracted from a temporal profile

UCLouvain

Post-processing

- Data fusion
- Data filtering: majority voting, selective class-specific filtering, pre-defined transitions, etc.



Accuracy metrics

Overall accuracy is the probability that an individual will be correctly classified by a test

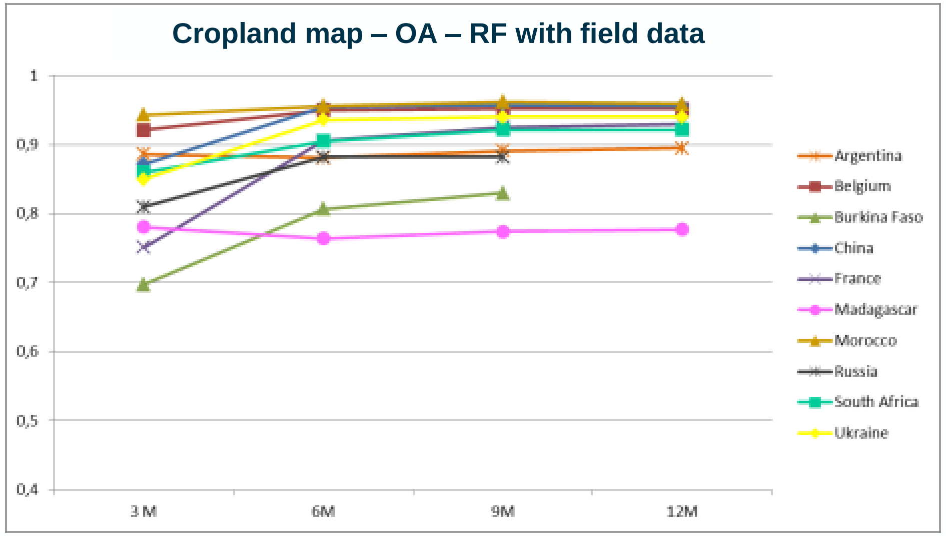
$$OA = \frac{TP + TN}{TP + TN + FP + FN}$$

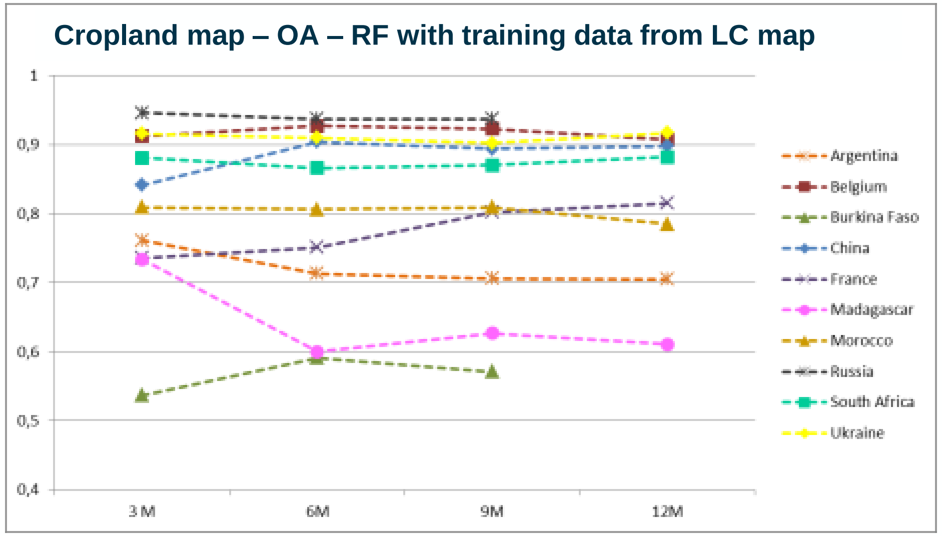
F1 score - F1 Score is the weighted average of Precision and Recall

Confusion matrix

		Predicted condition	
	Total population = P + N	Positive (PP)	Negative (PN)
Actual condition	Positive (P)	True positive (TP)	False negative (FN)
	Negative (N)	False positive (FP)	True negative (TN)

Training data impact on cropland classification



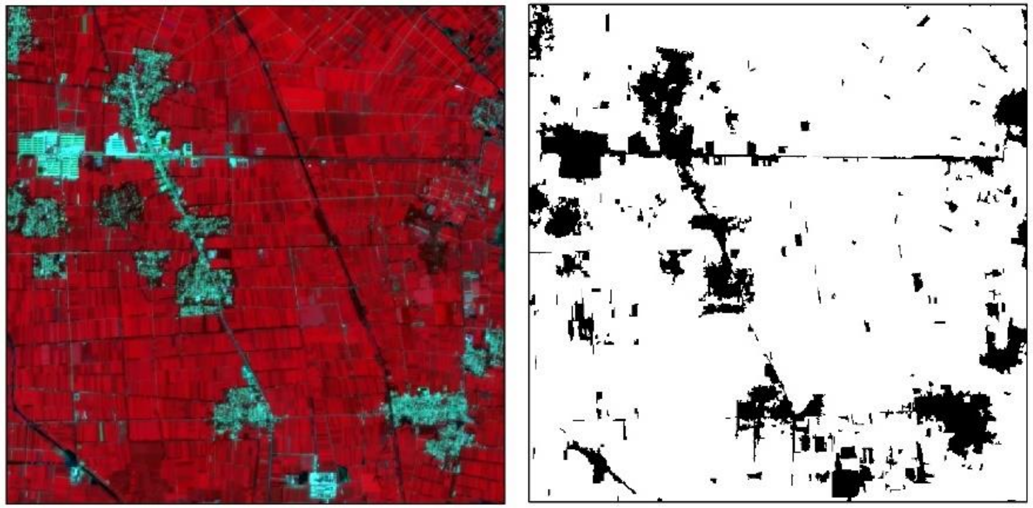


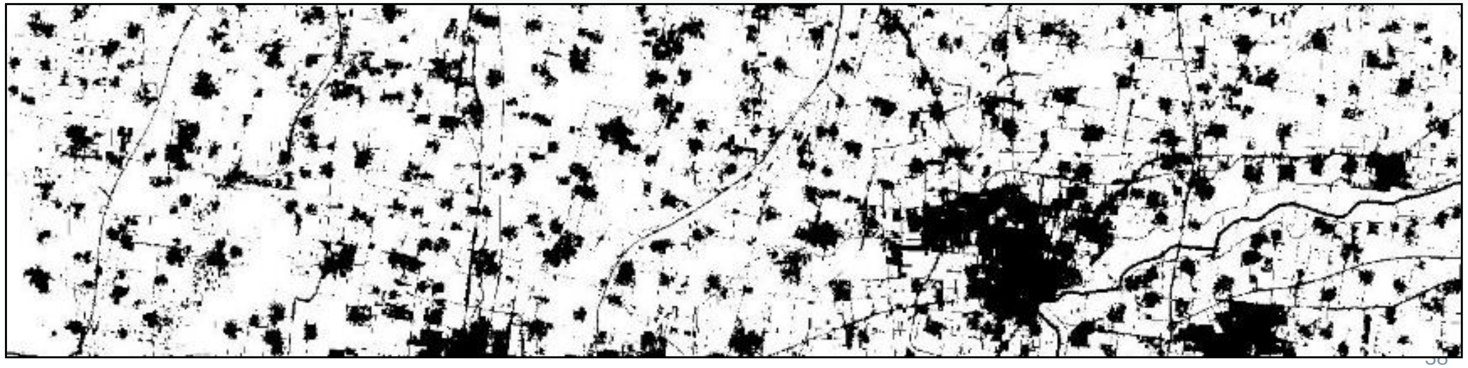
Better performance of RF with field data but still…

Cropland

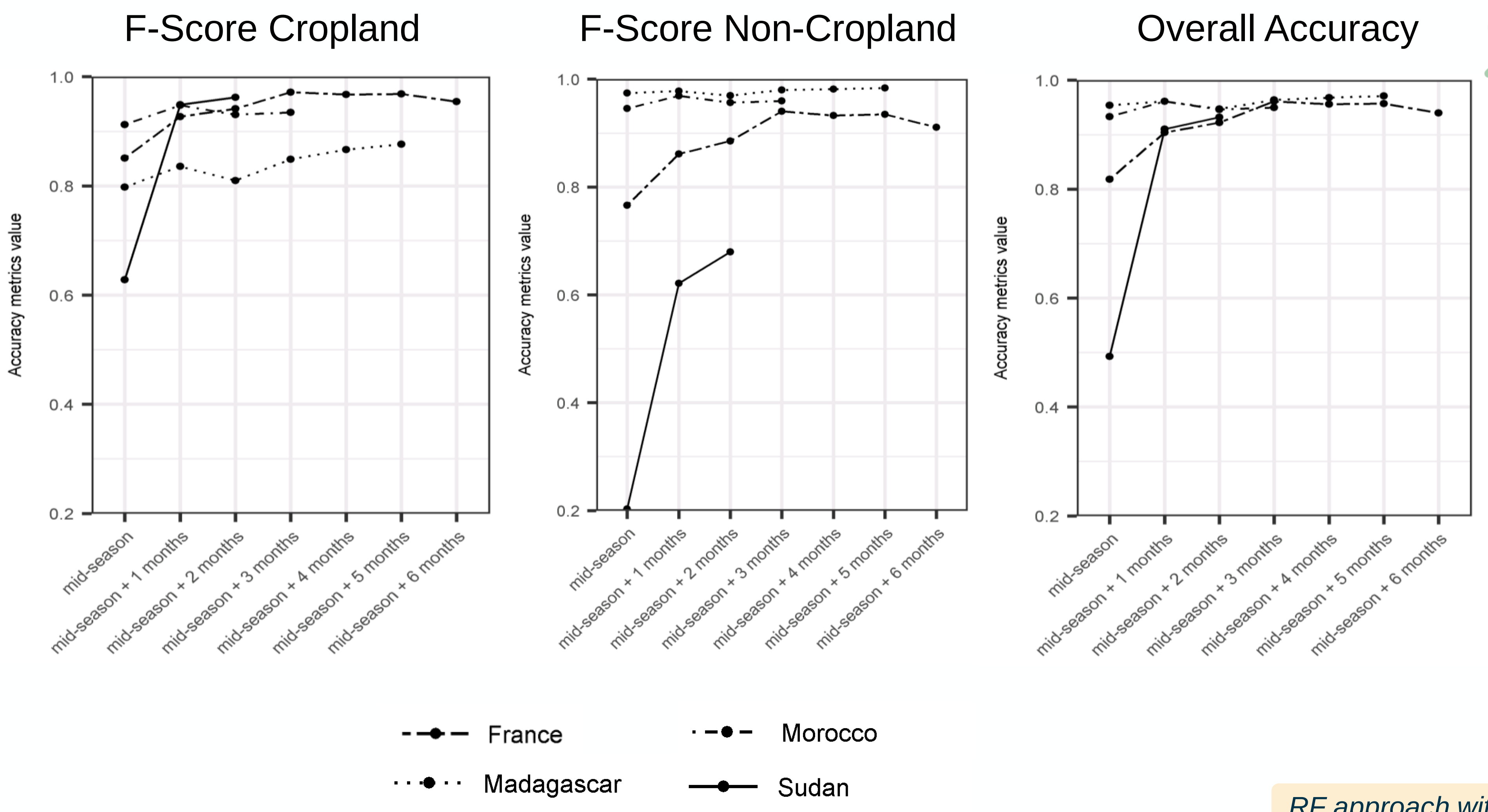
Non cropland

Cropland mask, obtained without in-situ data but using the ESA CCI Land Cover map to extract training dataset (https://maps.elie.ucl.ac.be/CCI/viewer/)





OA from the end of season achieved after 6 months

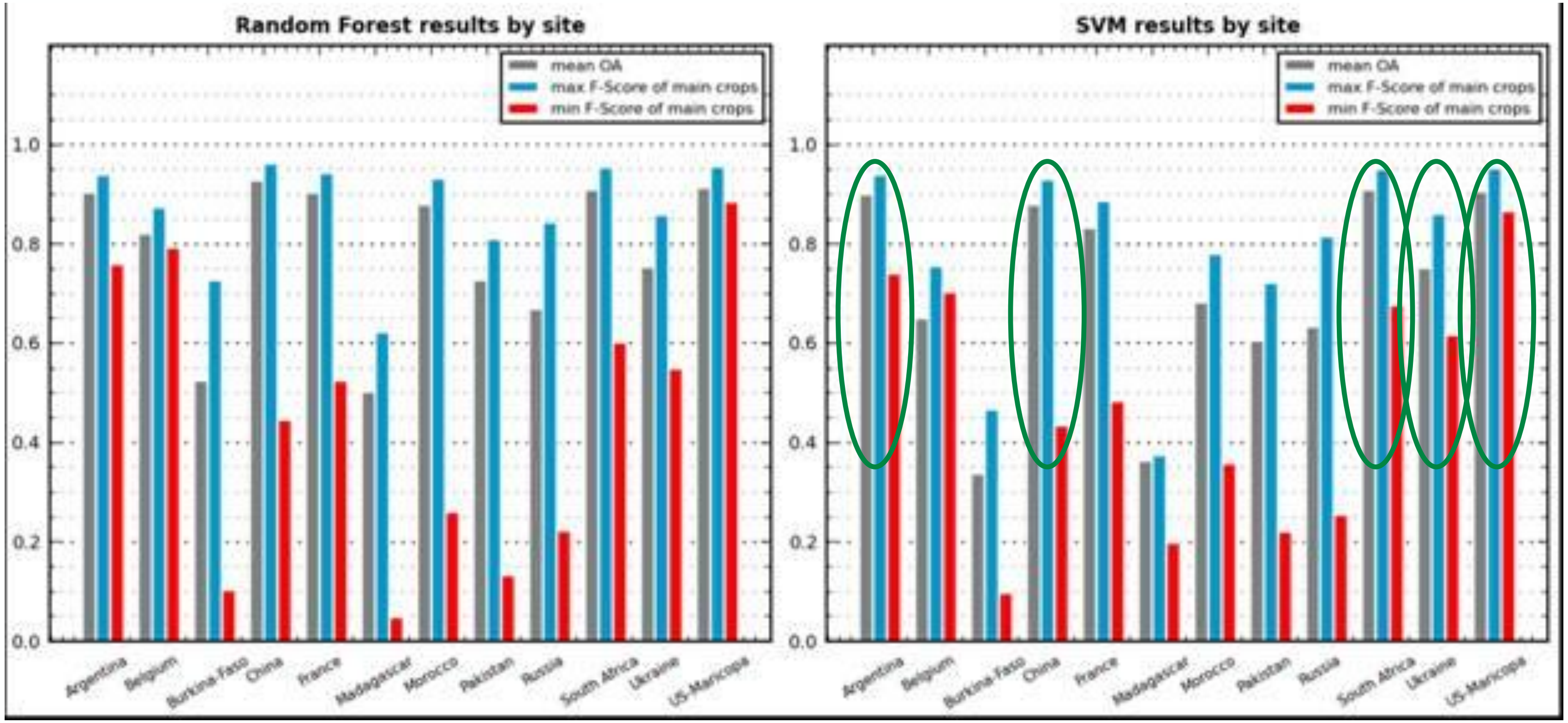


RF approach with field data

Mid-season crop type maps already useable
Better accuracy for end-of-season products (but not always)

		F1 Crop type					OA [%]
		Maize	Straw cereals	Sunflower	Winter Rapeseed	Soyabean	
France	Mid-season	0.84	0.98	0.82	0.90	0.37	86.3
	End-of-season	0.94	0.98	0.96	0.69	0.60	94.1
		Rice	Maize	Sweet Potatoes	Soyabean		
Madagascar	Mid-season	0.66	0.68	0.90	0.34		66.3
	End-of-season	0.69	0.8	0.88	0.34		66.3
		Sorghum	Sesame				
Sudan	Mid-season	0.87	0.20				78.4
	End-of-season	0.91	0.34				84.6
		Winter wheat	Alfalfa	Maize	Sugar beet		
Morocco	Mid-season	0.87	0.67	0.61	0.72		82.2
	End-of-season	0.93	0.60	0.78	0.83		89.3

Random Forest vs Support Vector Machines

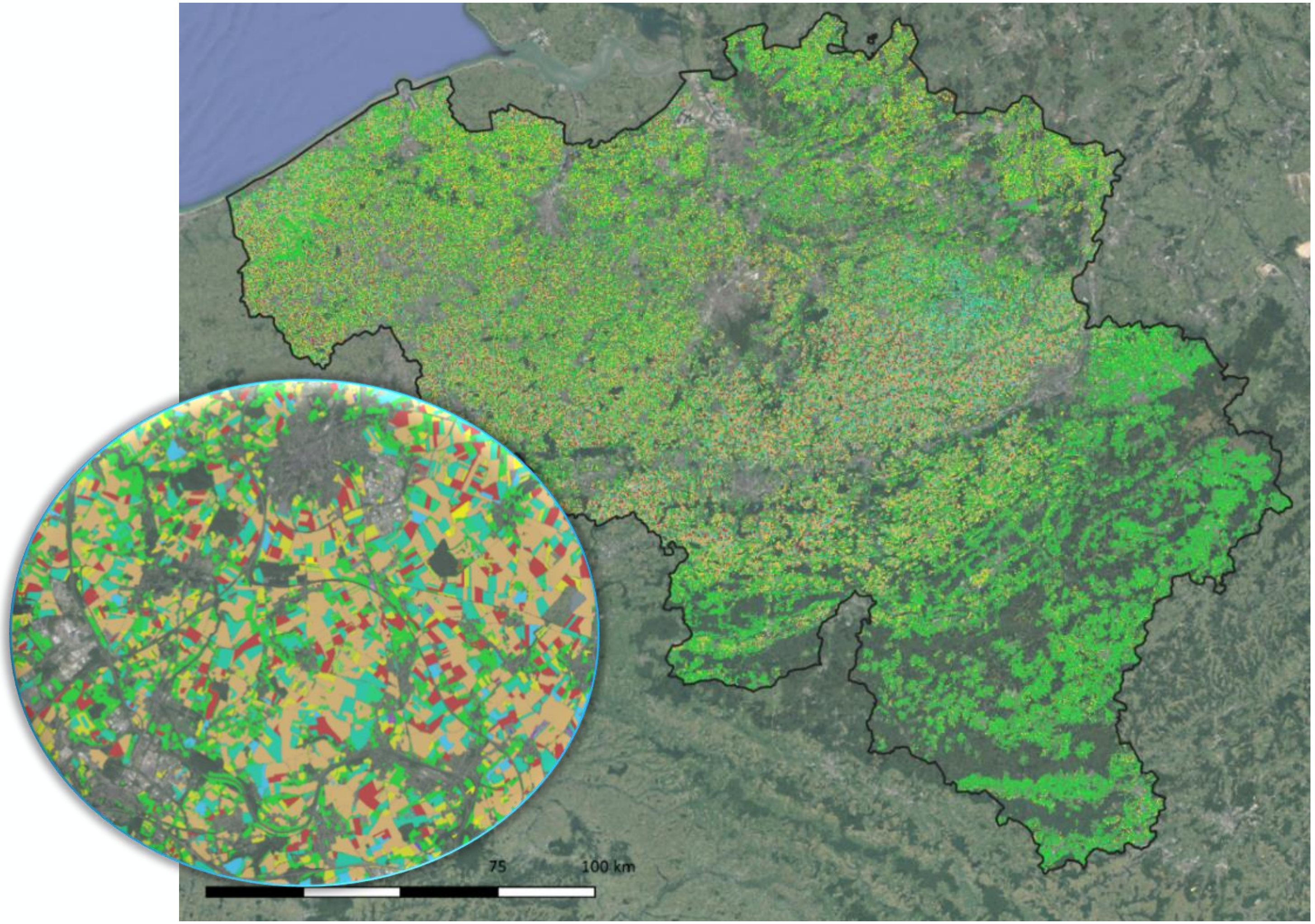


RF classifier yields better results for most of the sites

SVM comparable to RF when the number of classes is small

SVM very sensitive to a balanced share of samples between the classes: it has to be parameterized in such a way that all classes are equally represented => majority classes will be under-sampled

National crop type mapping for CAP monitoring



- **National** dataset available
- 457 933 parcels
- **275 crop classes** (no a priori grouping)
- Grassland and permanent crop included as "crop" classes
- 5% calibration / 95% validation
- By object-classification, RF

sen4cap
common agricultural policy

Corn grain	Carrot (not early)
Winter wheat	Potato (not early)
Spring barley	Potato (early)
Spring oats	Sugar beet
Triticale	Textile flax
Spelt	Peas
Cereals and vegetables	Leek
Winter rape	Ornamental plant
Meadow	Apple
Fodder beet	Pear
Alfalfa	Chicory
Other fodder	Small holder farming
Cauliflower	Other crops

OA = 88,26%

Quite good given the large number of crops (275)

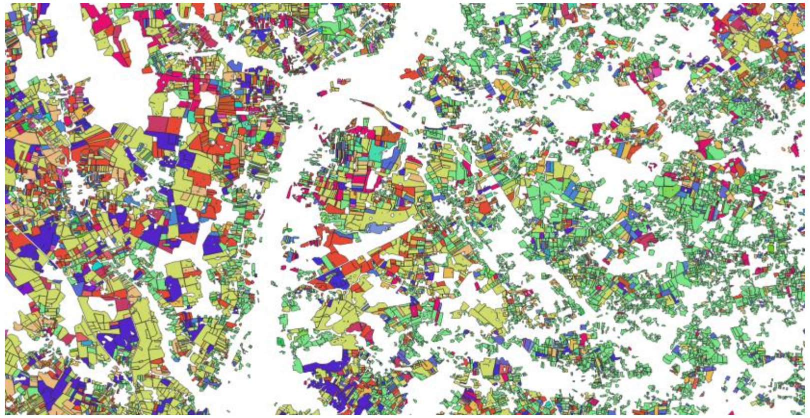
Combining S1 and S2 TS – features selection

Scenario	Features	Average #
a)	S2 time series + NDVI, NDWI, Brightness	~700
b)	S1 time series + ratio VH/VV	~800
c)	S1 temporal features	~200
d)	a) + b)	~1500
e)	a) + c)	~900
f)	a) + b) + c)	~1700

Combining S1 and S2 TS – features selection

Scenario	Features	Average #
a)	S2 time series + NDVI, NDWI, Brightness	~700
b)	S1 time series + ratio VH/VV	~800
c)	S1 temporal features	~200
d)	a) + b)	~1500
e)	a) + c)	~900
f)	a) + b) + c)	~1700

Lithuania



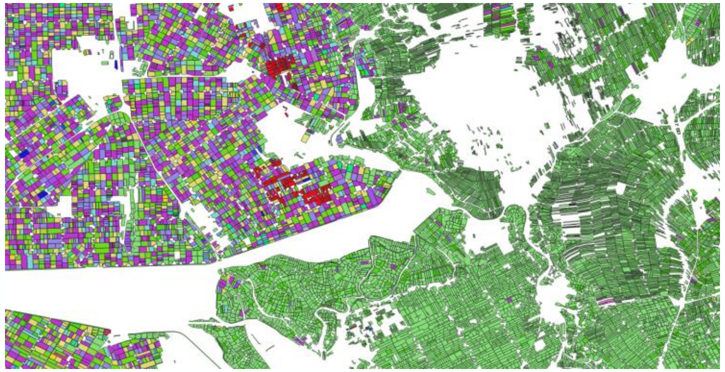
		OA	Kappa	# of crop classes per F-Score category				
				0-0.4	0.4 - 0.65	0.65-0.85	0.85 - 1	Total
SMOTE	a) S2 time series	80	73	17	5	7	4	33
	b) S1 time series + ratio	86	80	9	7	10	6	32
	c) S1 temp. features	84	78	14	5	8	6	33
	a) + b)	**87**	**82**	10	7	8	**8**	33
	a) + c)	85	79	12	8	5	8	33
	a) + b) + c) => all	**87**	**82**	11	6	8	**8**	33

Combining S1 and S2 TS – features selection

Scenario	Features	Average #
a)	S2 time series + NDVI, NDWI, Brightness	~700
b)	S1 time series + ratio VH/VV	~800
c)	S1 temporal features	~200
d)	a) + b)	~1500
e)	a) + c)	~900
f)	a) + b) + c)	~1700

Netherlands

		OA	Kappa	# of crop classes per F-Score category				
				0-0.4	0.4 - 0.65	0.65-0.85	0.85 - 1	Total
SMOTE	a) S2 time series	94	88	13	13	8	8	42
	b) S1 time series + ratio	**97**	92	5	12	12	13	42
	c) S1 temp. features	96	92	4	14	10	13	41
	a) + b)	**97**	**94**	2	15	10	**15**	42
	a) + c)	**97**	93	3	13	11	14	41
	a) + b) + c) => all	**97**	**94**	2	11	**14**	**15**	42



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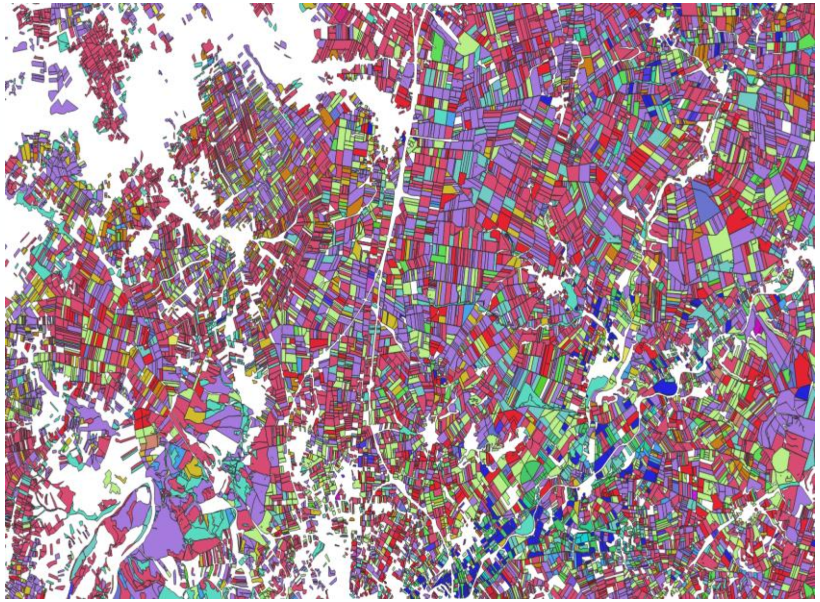
Combining S1 and S2 TS – features selection

Scenario	Features	Average #
a)	S2 time series + NDVI, NDWI, Brightness	~700
b)	S1 time series + ratio VH/VV	~800
c)	S1 temporal features	~200
d)	a) + b)	~1500
e)	a) + c)	~900
f)	a) + b) + c)	~1700



Castilla y Leon

		OA	Kappa	# of crop classes per F-Score category				
				0-0.4	0.4 - 0.65	0.65-0.85	0.85 - 1	Total
SMOTE	a) S2 time series	80	75	10	7	13	5	35
	b) S1 time series + ratio	76	70	12	8	11	4	35
	c) S1 temp. features	75	69	10	8	13	4	35
	a) + b)	**82**	**78**	7	9	9	**10**	35
	a) + c)	**82**	**78**	***12***	6	**12**	7	37
	a) + b) + c) => all	**82**	**78**	***11***	7	**12**	7	37

Presentation outline

- Introduction of agriculture monitoring with optical and radar data
- What is a crop? What is a crop map?
- Crop classification by remote sensing
    - Classification
    - Features extraction
    - Segmentation
    - Post-processing
- **Crop specific growth monitoring**
    - **Phenological stage retrieval**
    - **Agricultural practices monitoring**

Extraction of crop-specific temporal metrics related to the crop phenology

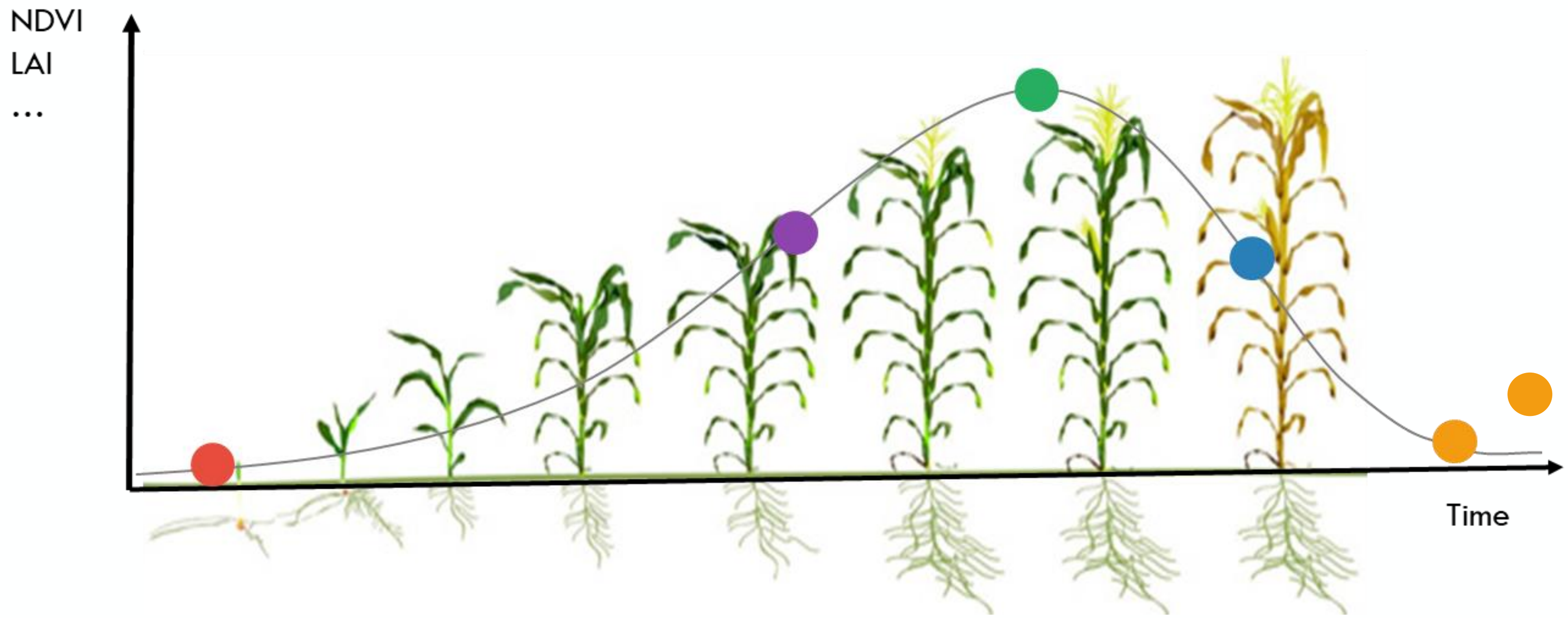
1 Maximum Red
(average of 3 max.)
Bare soil at sowing preparation

2 Max. positive slope
Fastest growth of vegetation

3 Maximum NDVI
(average of 3 max.)
Maximum green biomass

4 Max. negative slope
Fast reduction of vegetation

5 Minimum NDVI
(average of 3 max.)
Harvested crop or non green residues



(Matton et al., 2015, Waldner et al., 2016, Lambert et al., 2016)

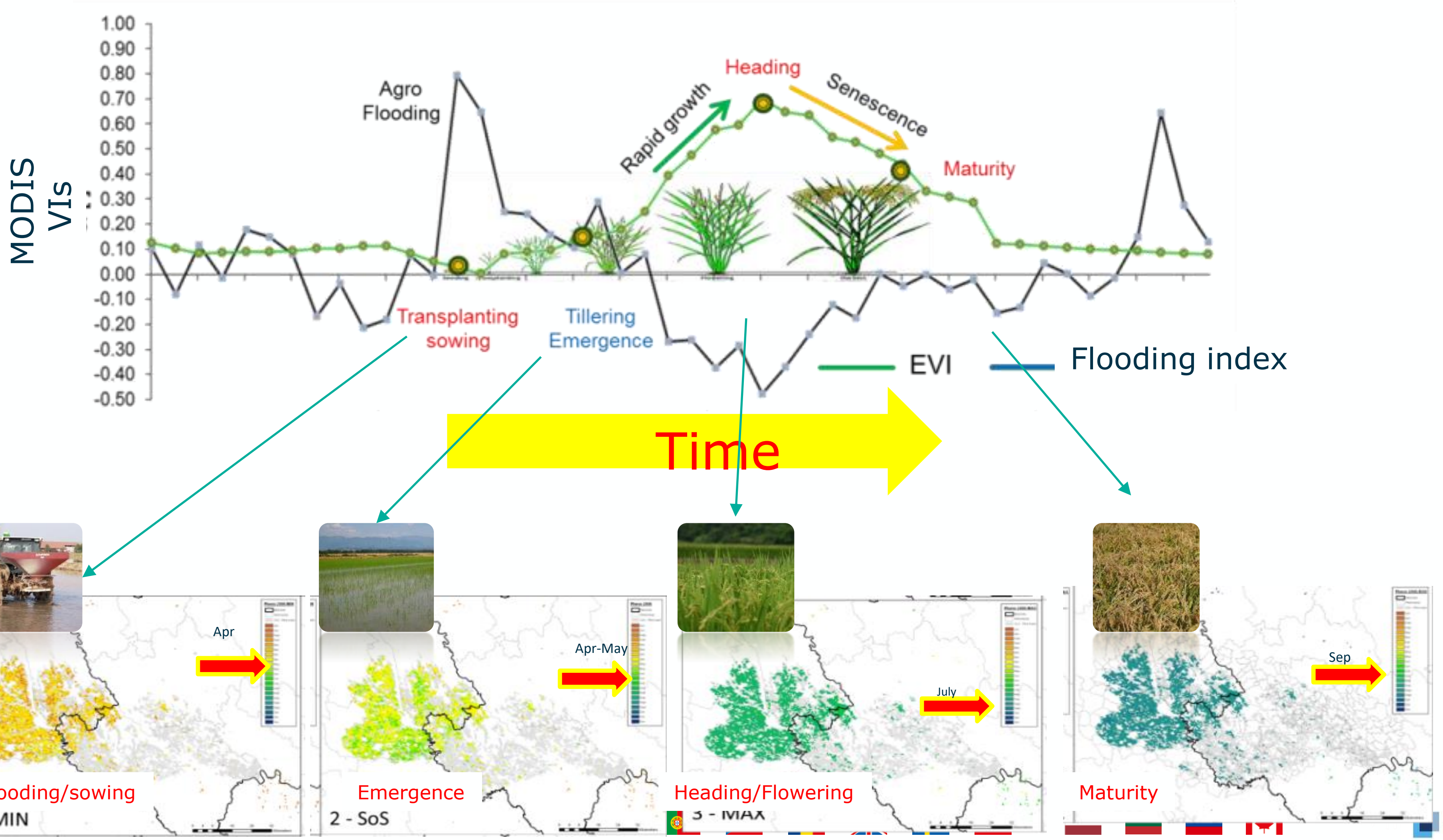
Sen2-Agri

UCLouvain

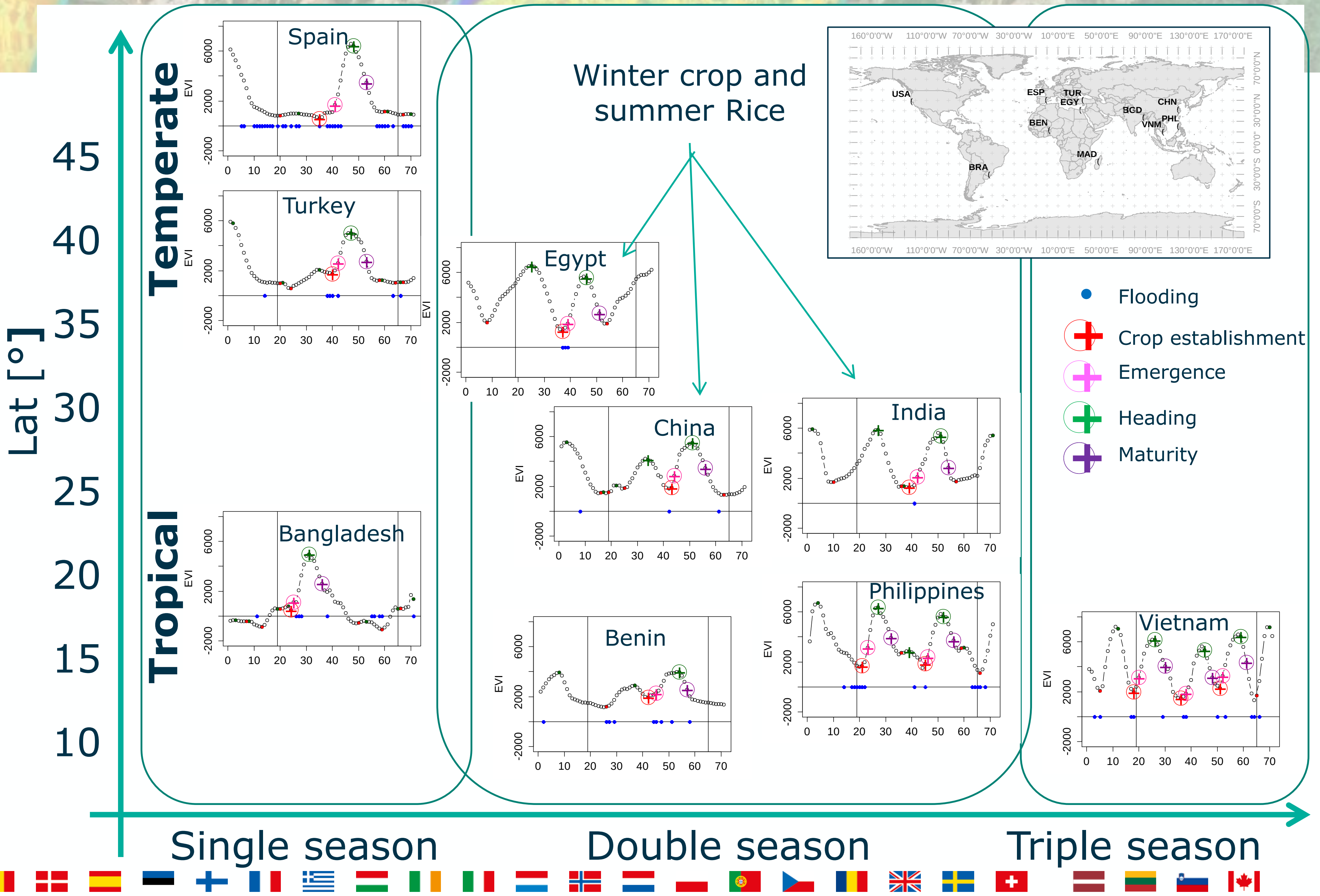
REGIONAL LEVEL APPLICATION 1:
MODIS-BASED DYNAMIC CROP CALENDARS

An example for rice

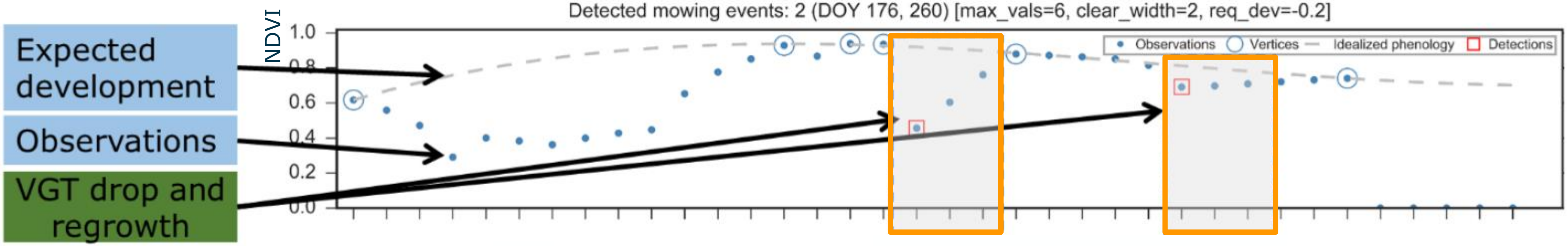
Phenorice concept

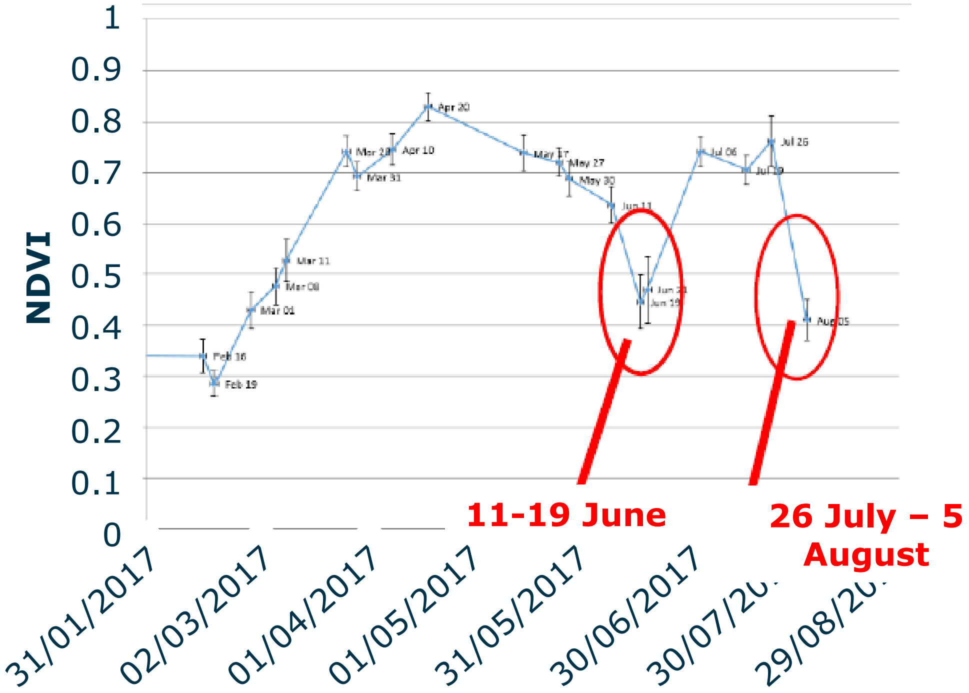


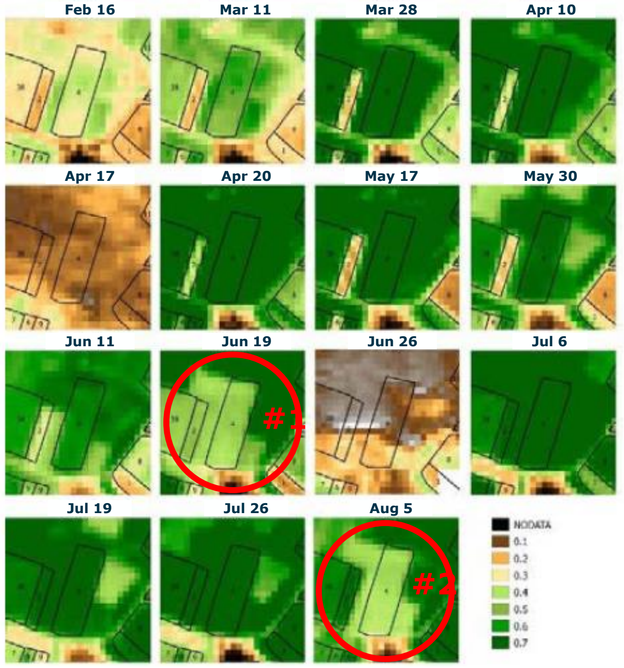
Boschetti et al. 2017


Winter crop and summer Rice
Temperate
Tropical
Lat [°]
45
40
35
30
25
20
15
10
Spain
Turkey
Bangladesh
Egypt
China
India
Benin
Philippines
Vietnam
EVI
USA
ESP
TUR
EGY
BGD
CHN
PHL
VNM
BEN
MAD
BRA
Flooding
Crop establishment
Emergence
Heading
Maturity
Single season
Double season
Triple season

Detection of mowing events in permanent grassland







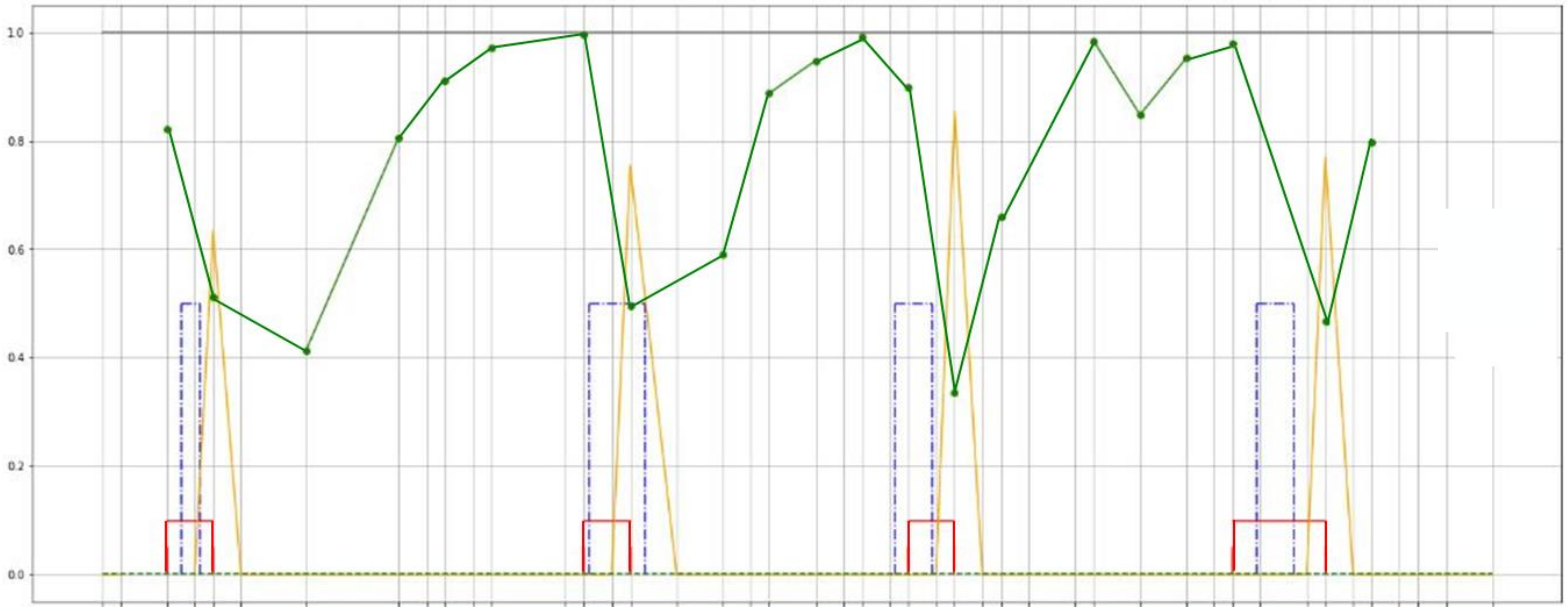
NDVI time series

JRC Technical Reports, DS/CDP/2018/18 & DS/CDP/2017/03 revising R2014/809

Mowing detection example in Spain - Castilla y Leon

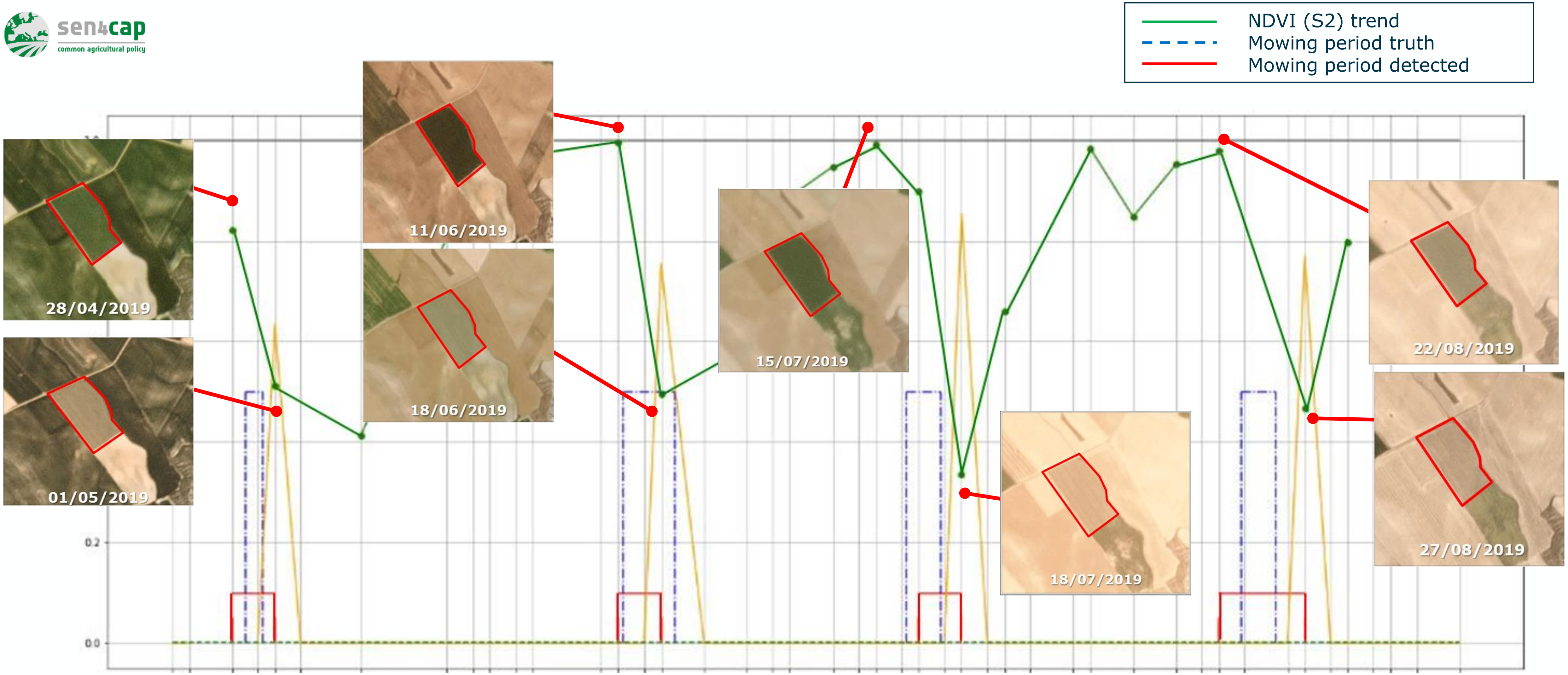
sen4cap
common agricultural policy

NDVI (S2) trend
Mowing period truth
Mowing period detected



NDVI time series & mowing detection on a selected parcel

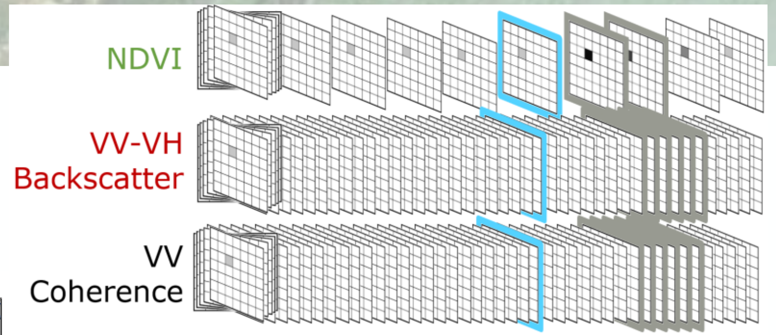
Mowing detection example in Spain - Castilla y Leon

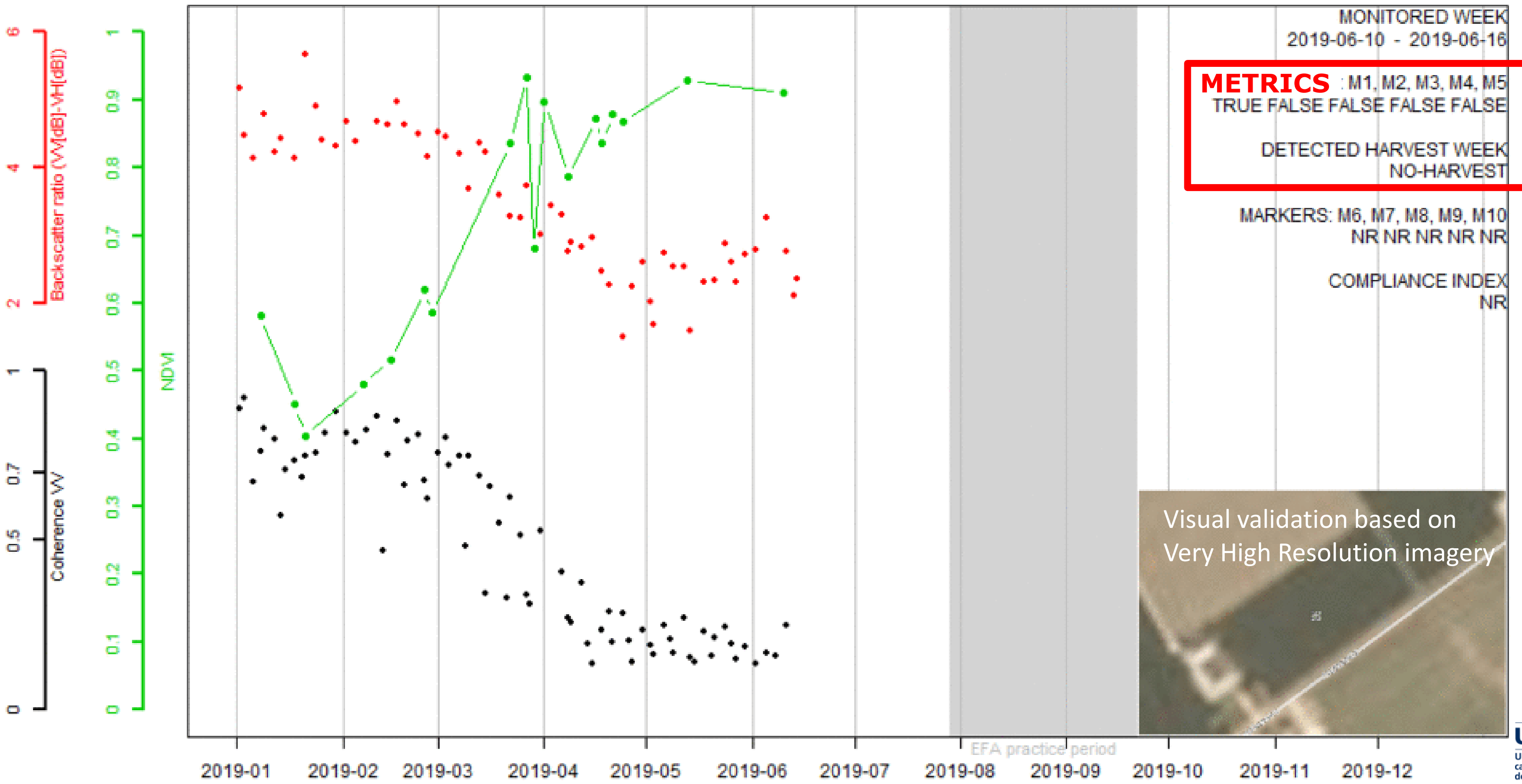


NDVI time series & mowing detection on a selected parcel

Harvest date detection based on 5 metrics computed from 3 parallel time series

Harvest and cover crop monitoring





Harvest detected between 29 July and 4 August

Cover crop in place during the mandatory period and not harvested before its end

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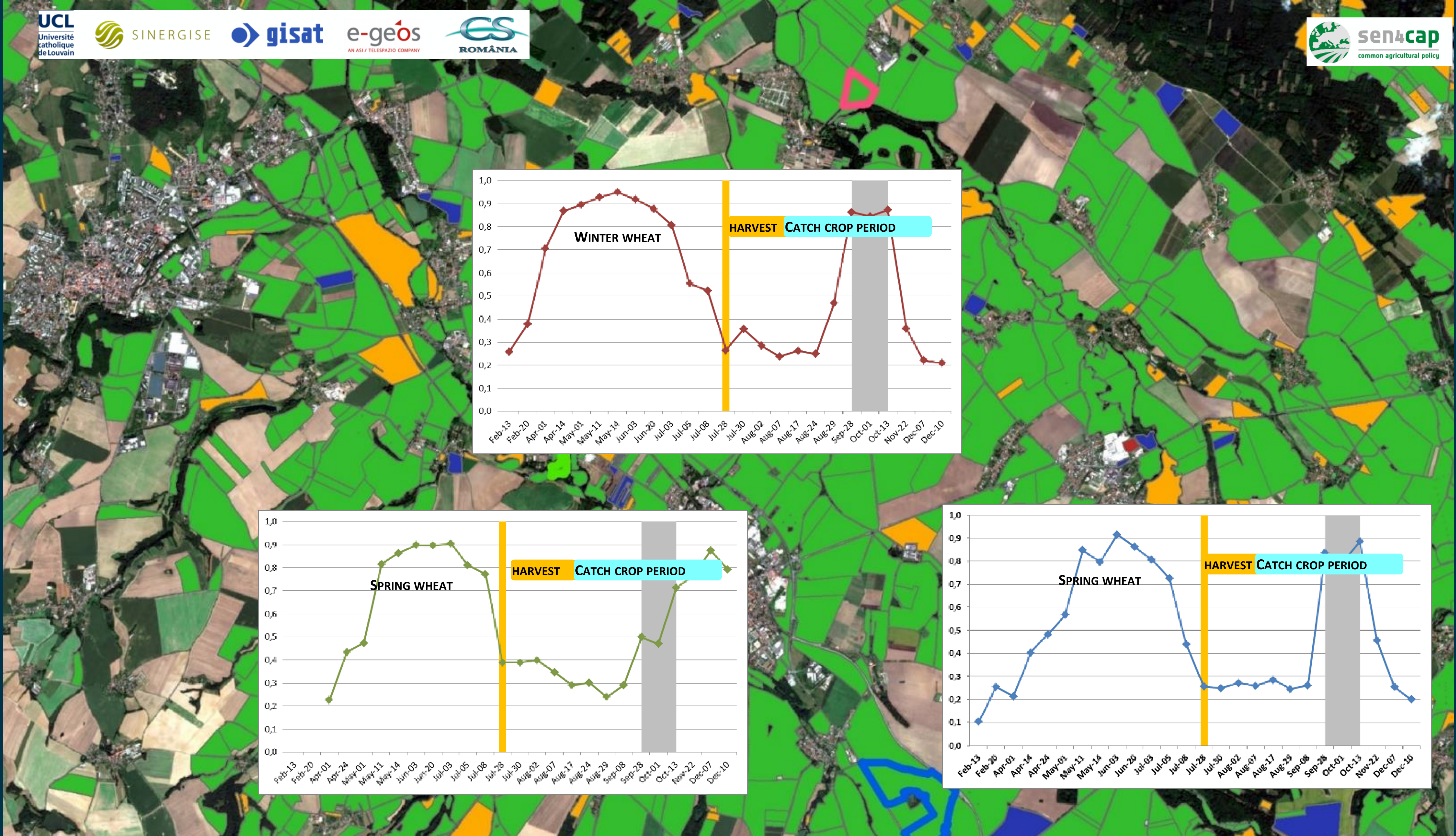
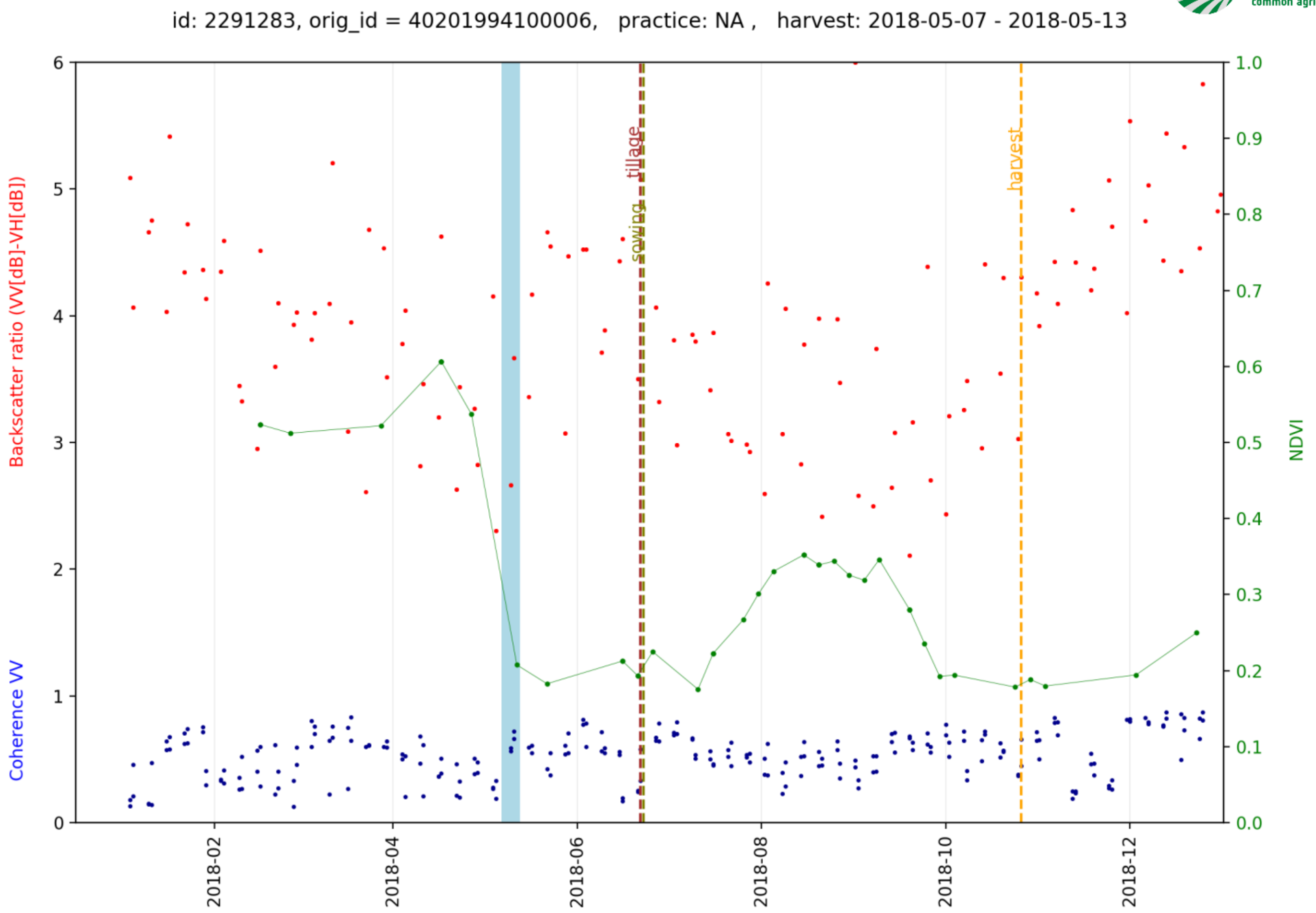

WINTER WHEAT
HARVEST
CATCH CROP PERIOD
Feb-13 Feb-20 Apr-01 Apr-14 May-01 May-11 May-14 Jun-03 Jun-20 Jul-03 Jul-05 Jul-08 Jul-28 Jul-30 Aug-02 Aug-07 Aug-17 Aug-24 Aug-29 Sep-28 Oct-01 Oct-13 Nov-22 Dec-07 Dec-10
SPRING WHEAT
HARVEST
CATCH CROP PERIOD
Feb-13 Feb-20 Apr-01 Apr-24 May-01 May-11 May-14 Jun-03 Jun-20 Jul-03 Jul-05 Jul-08 Jul-28 Jul-30 Aug-02 Aug-07 Aug-17 Aug-24 Aug-29 Sep-08 Sep-28 Oct-01 Oct-13 Nov-22 Dec-07 Dec-10
SPRING WHEAT
HARVEST
CATCH CROP PERIOD
Feb-13 Feb-20 Apr-01 Apr-14 Apr-24 May-01 May-11 May-14 Jun-03 Jun-20 Jul-03 Jul-05 Jul-08 Jul-28 Jul-30 Aug-02 Aug-07 Aug-17 Aug-29 Sep-08 Sep-28 Oct-01 Oct-13 Nov-22 Dec-07 Dec-10

Tillage detection, from optical NDVI / LAI and SAR backscatter / coherence time series

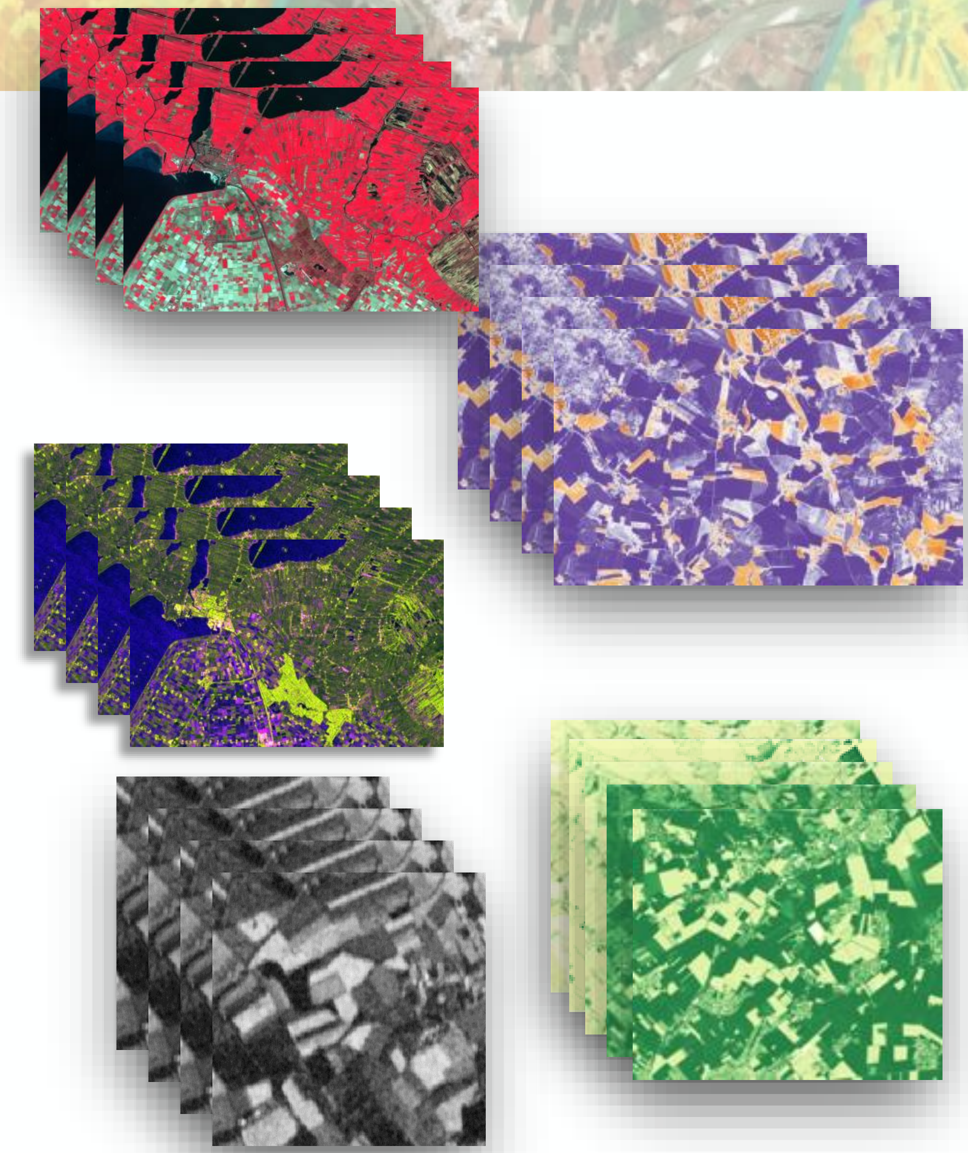
(1) NDVI should remain low throughout this process

(2) The backscatter ratio should remain high/increasing throughout this process

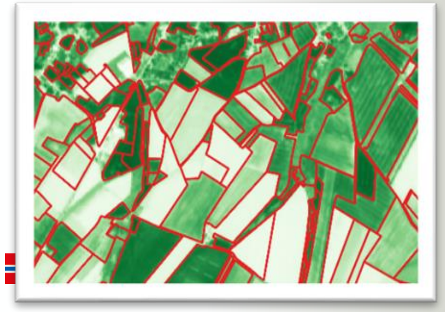
(3) Coherence should increase during/after harvest, decrease after ploughing/tilling and finally increase again to a stable condition



100+ features & markers per week, per parcel



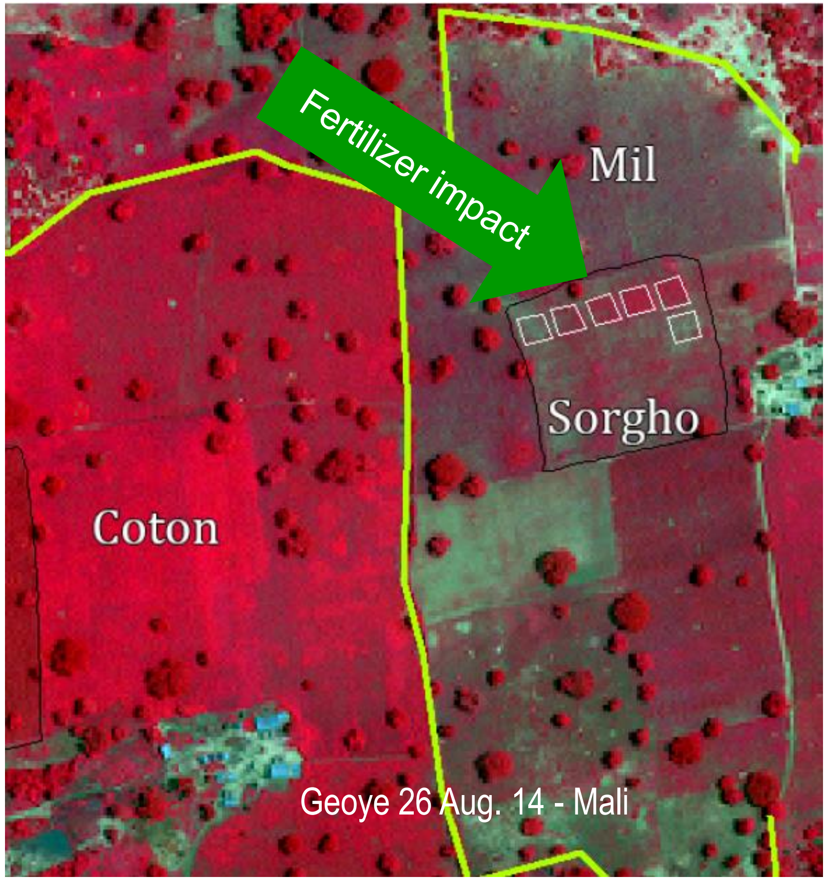
E.g. Spain : **17 millions parcels**
x **60+ metrics** + S2&1 signal
x 40 weeks / year



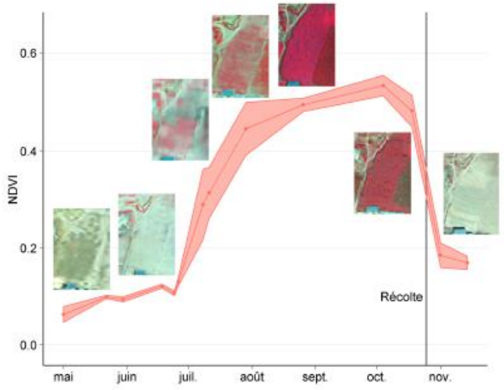
sen4cap
common agricultural policy

Monitoring of agricultural practices in smallhoder farming system by 1(0) m time series – fertilization in Mali

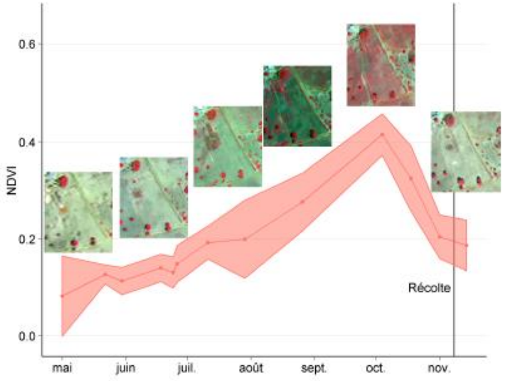
Exploiting (deca)metric time series to capture crop development signal including spatial field heterogeneity (sorghum for 3 different fields)



2-m resolution time series capture large field heterogeneity

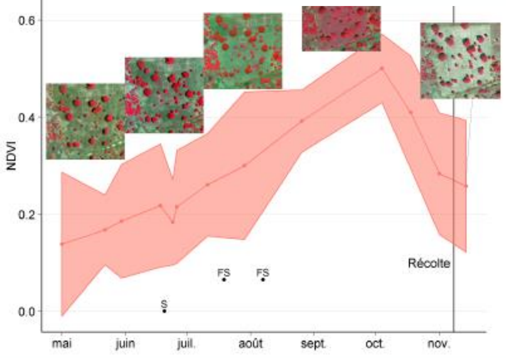


a) Parcel closed to the village, homogeneous and early cropping



b) Parcel close to plateau, without catching-up and hydromorphic conditions

SORGHUM FIELDS



c) Parcel close to plateau, catching-up, for production (S = sowing, FS = fertilization of STARS plots)

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Gates Fundation – STARS Project
Blaes et al., 2016

Monitoring nitrogen status

Nitrogen Fertilisation Information

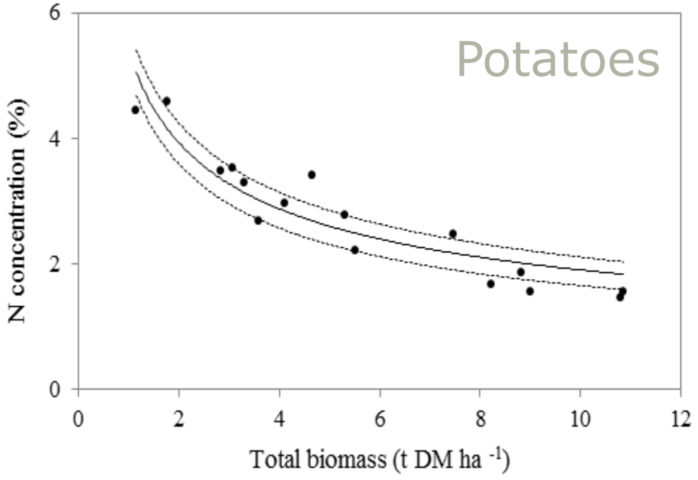
$$NNI = \frac{Na}{Nc}$$

Na = biomass current N content

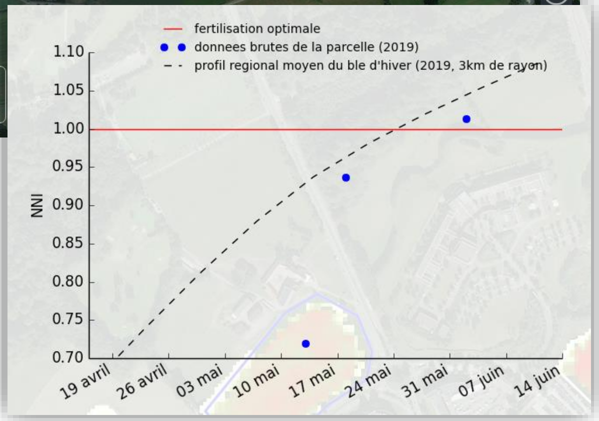
Nc = biomass critical N content

Chlorophyllmeter (SPAD)

Fluorometer (Dualex)



Critical N dilution curve of potato for *cv* Bintje in Belgium (Source : Ben Abdallah *et al.*, 2016)



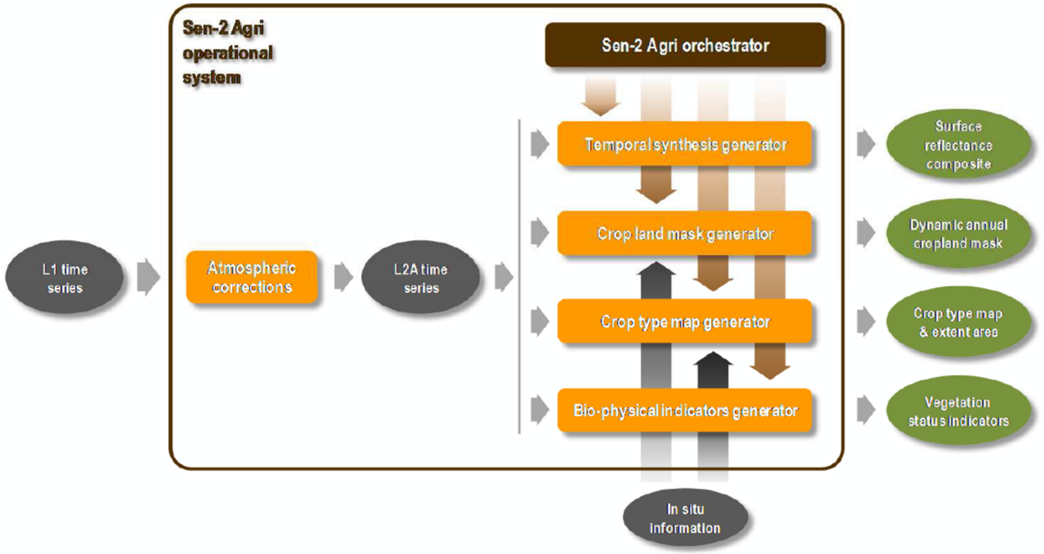
Winter Wheat

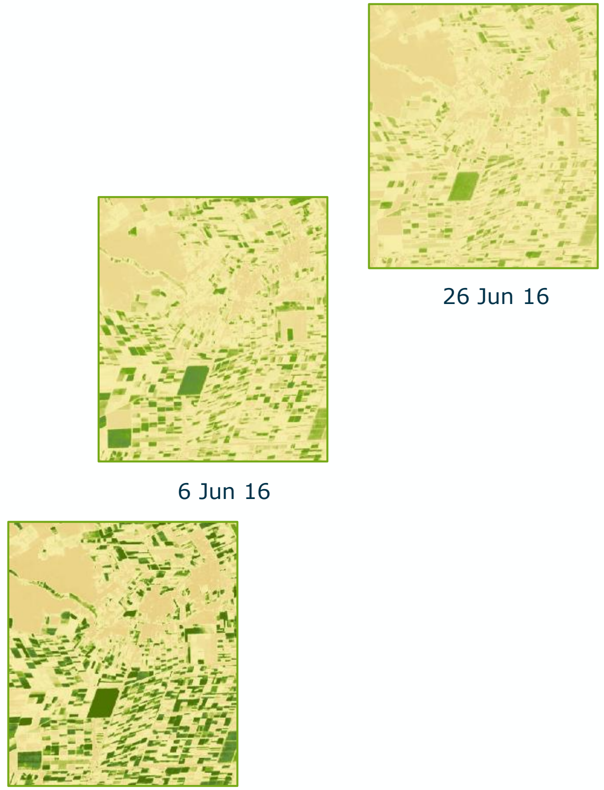
ESA Sen2-Agri / Sen4CAP / Sen4Stat open source toolboxes

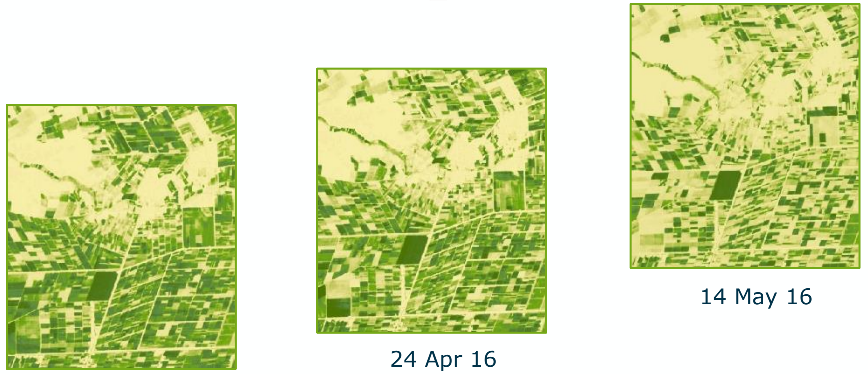
Sen2-Agri
Sentinel-2 for Agriculture

sen4cap
common agricultural policy

Sen4Stat
Sentinels for Agricultural Statistics







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Thank you
Any questions ?