APPLIED REMOTE SENSING TRAINING PROGRAM
TRAIN - EMPOWER - ADVANCE

Agricultural Crop Classification with Synthetic Aperture Radar and Optical Remote Sensing

Part 5: Biophysical Variable Retrieval using Optical Imagery to Support Agricultural Monitoring Practices

P. Defourny & S. Bontemps – Université Catholique of Louvain, Belgium

Training Outline

October 5, 2021

Synthetic Aperture Radar (SAR) Refresher

October 7, 2021

Optical Remote Sensing Refresher and Introduction to SNAP

October 12, 2021

Operational Crop Classification Roadmap using Optical and SAR Imagery (Part 1)

October 14, 2021

Operational Crop Classification Roadmap using Optical and SAR Imagery (Part 2)

October 19, 2021

Biophysical Variable Retrieval using Optical Imagery to Support Agricultural Monitoring Practices

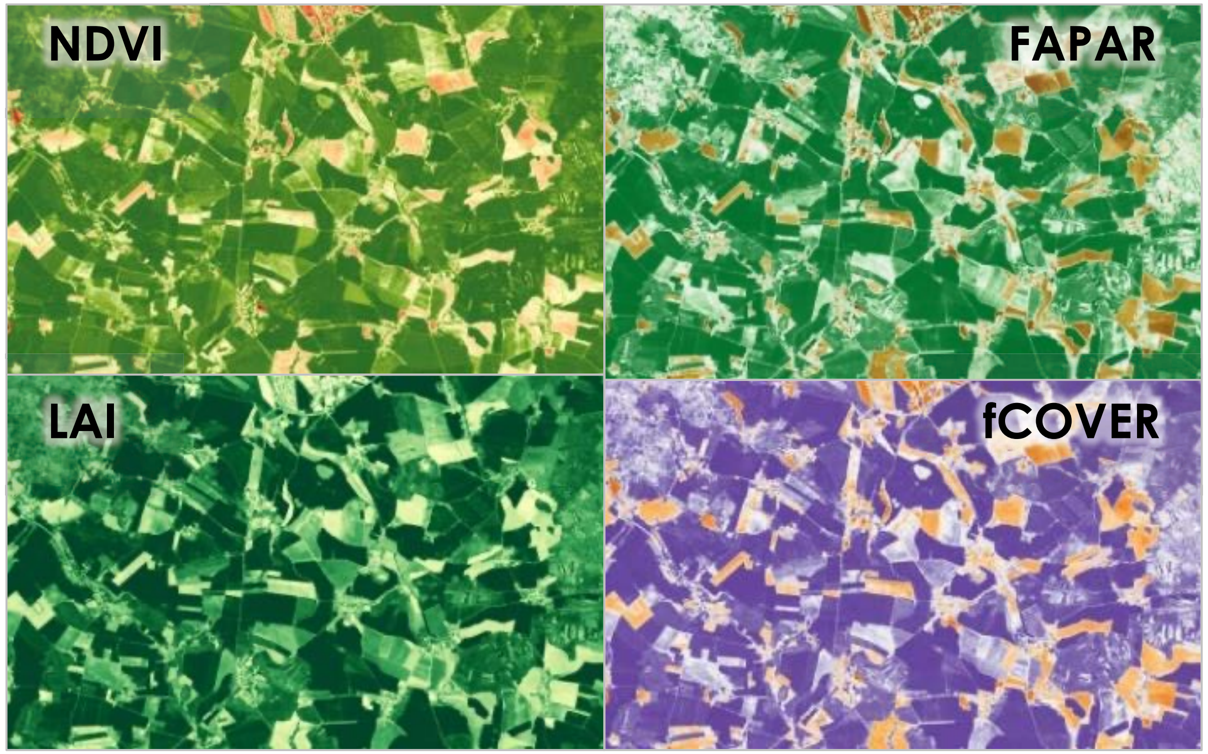
Training Objectives

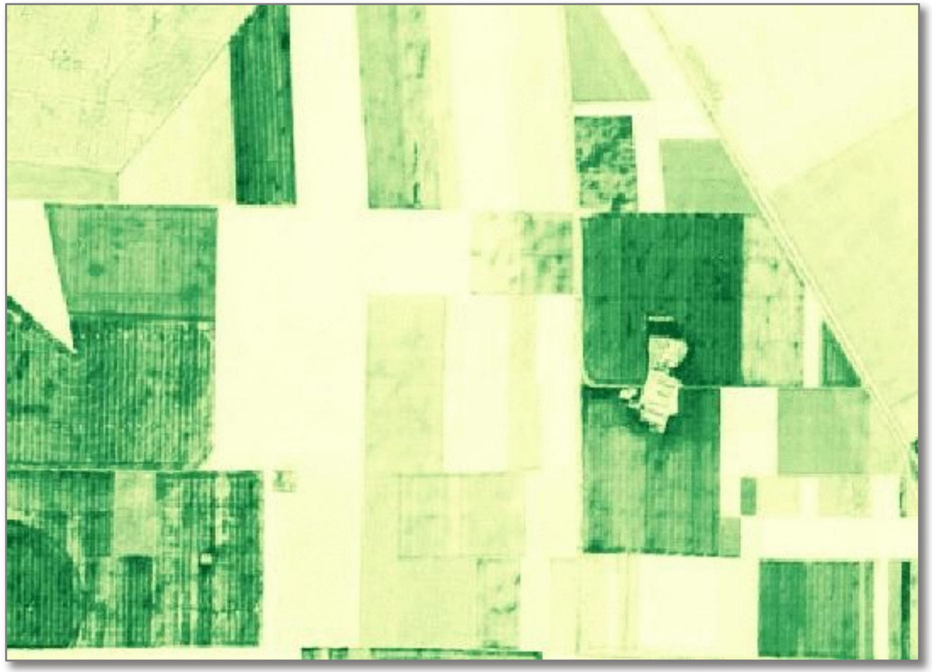
By the end of this training attendees will learn:

- What are the applications of spectral indices for agriculture
- What are the biophysical variables relevant for agriculture
- How to calibrate biophysical variable retrieval models
- How to assess the biophysical variables estimation performances
- What are phenometrics and how are they useful
- How biophysical variables can support monitoring of agricultural practices
- How biophysical variables can support crop yield estimations
- What are the ESA Sen2-Agri, Sen4CAP, and Sen4Stat toolboxes

Table of Contents

Section 1: Spectral Indices (SI) and Biophysical Variables (BV) for Agriculture

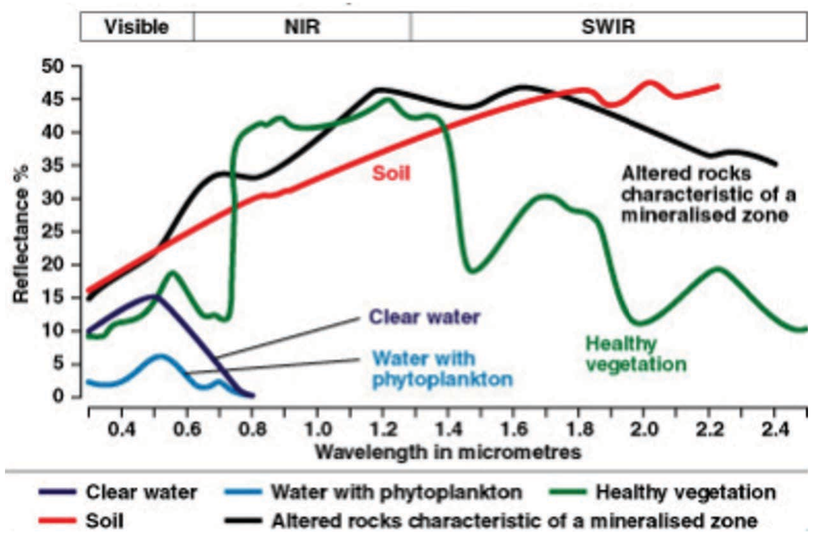


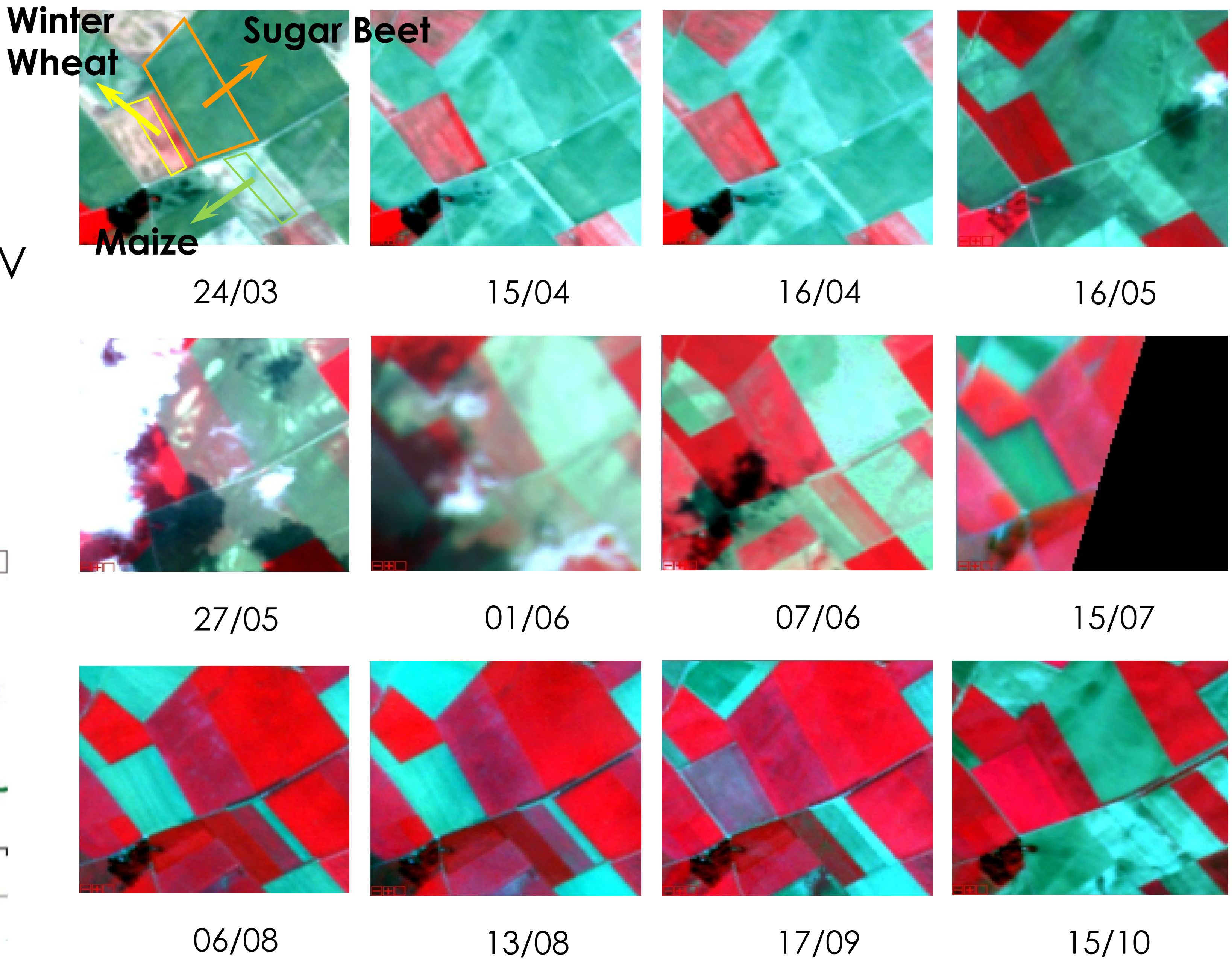


Monitoring Vegetation Development from Spectral Reflectance

Crop assessment by :

- Ground measurements
- Estimation of biophysical variables from satellite/UAV observations
- Spectral or radiometric indices combining several reflectance bands

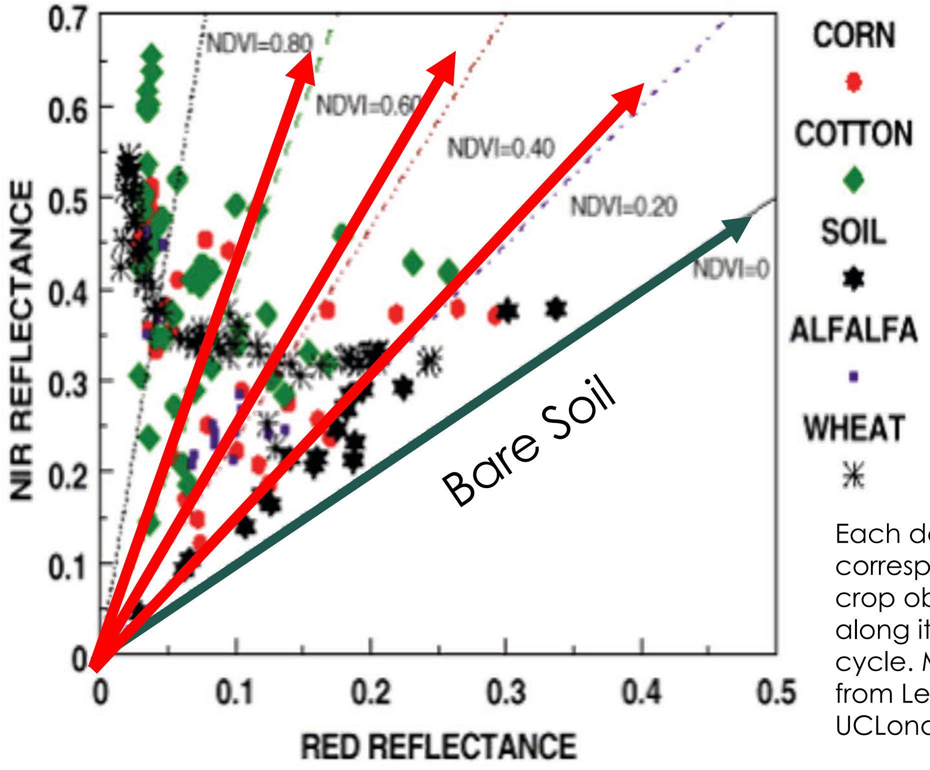




UCLouvain farm (Belgium)– SPOT5

Spectral Indices - To Extract a Specific Signal from a Spectral Signature

Vegetation indices based on red absorption by chlorophyll and high near-infrared reflectance by internal leaf structure enhance the sensitivity to green vegetation while minimizing other effects.



Each dot corresponds to a crop observation along its growth cycle. Modified from Lewis et al. UCLondon

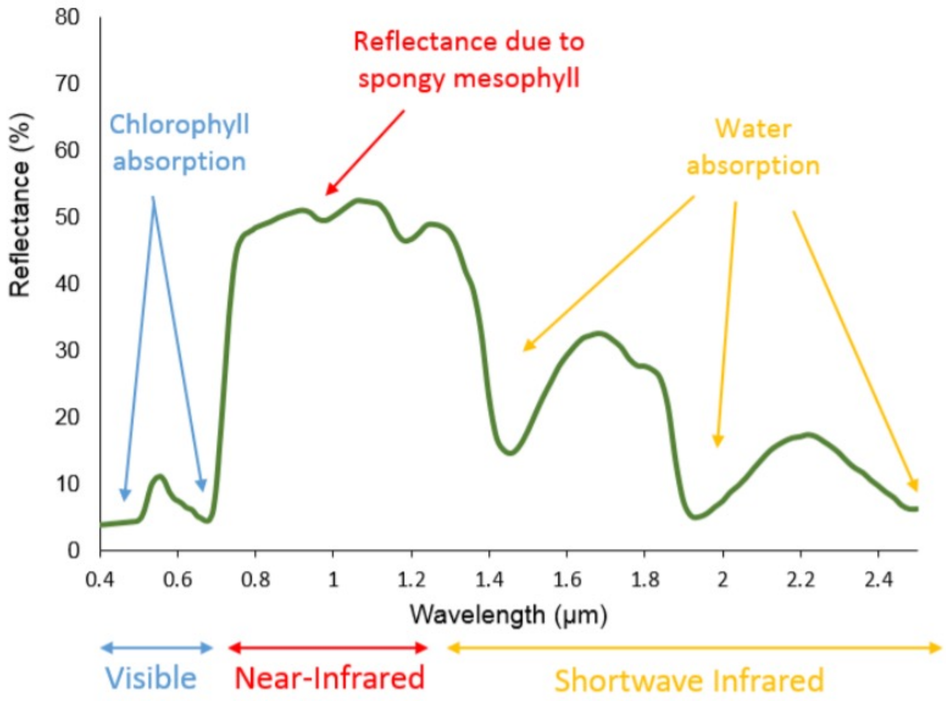
Normalized Difference Vegetation Index
(~ Green Biomass)

$$NDVI = \frac{(\rho_{NIR} - \rho_{RED})}{(\rho_{NIR} + \rho_{RED})}$$

Spectral Indices - To Extract a Specific Signal from a Spectral Signature

Vegetation indices based on red absorption by chlorophyll and high near-infrared reflectance by internal leaf structure enhance the sensitivity to green vegetation while minimizing other effects.

(Soil Moisture, Soil Color, Residual Atmospheric Effects, etc.)

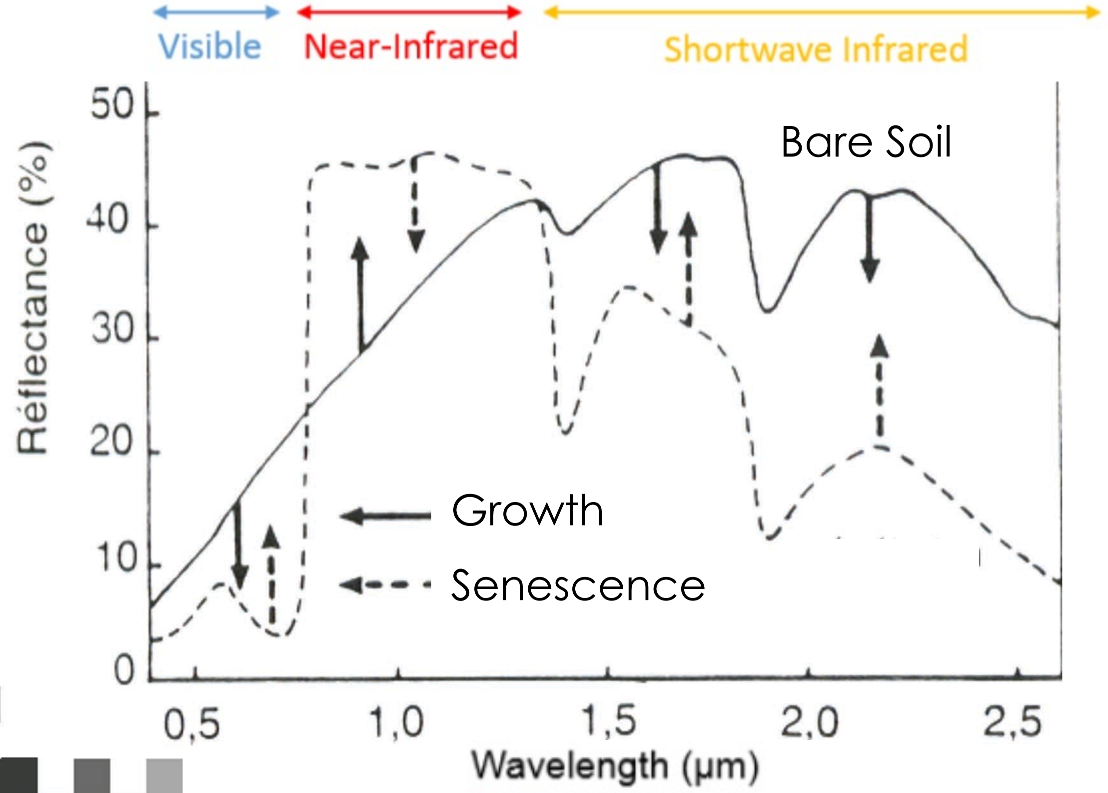


Normalized Difference Water Index
(~ Water Content of Green Vegetation)

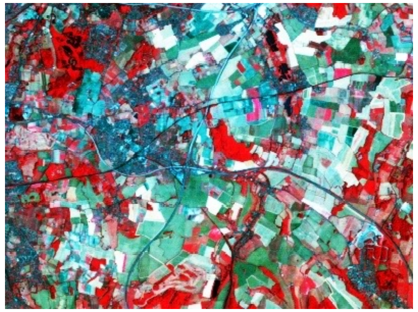
$$NDWI = \frac{(\rho_{NIR} - \rho_{SWIR})}{(\rho_{NIR} + \rho_{SWIR})}$$

Spectral Indices – NDVI as the Most Popular Vegetation Index

A crop cycle corresponds to a progressive transition from a bare soil signature to a closed green vegetation canopy and typically ends with vegetation senescence.



NASA's Applied Remote Sensing Training Program



NIR False Color Image

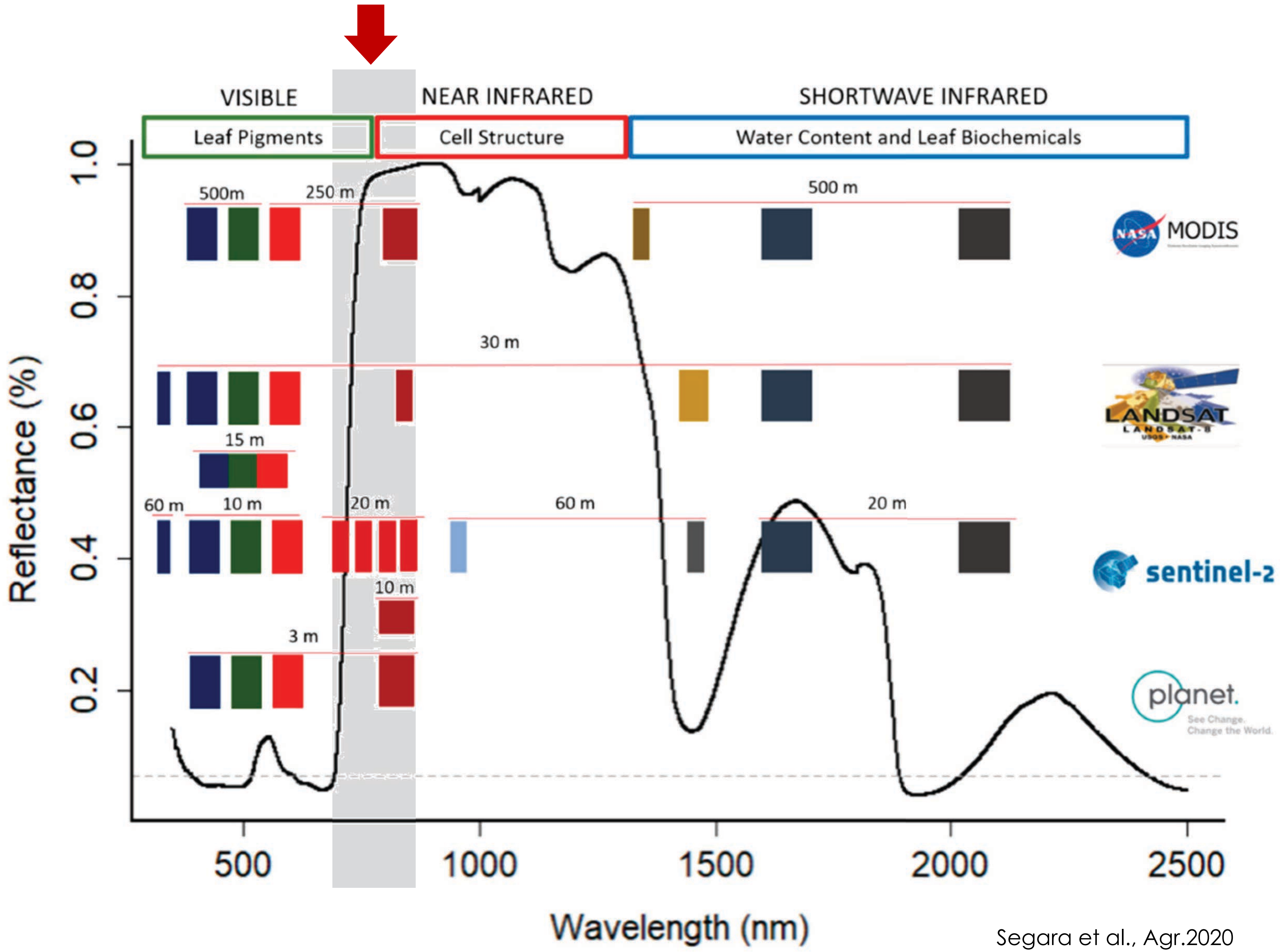
NDVI -1 0 1

Indices	Name	Formula
		Vegetation discrimination
Chlogreen	Chlorophyll Green index	$\frac{\rho_{NIRnarrow}}{\rho_{Green}+\rho_{Rededge1}}$
GI	Greenness Index	$\frac{\rho_{Green}}{\rho_{Red}}$
gNDVI	Green normalized difference vegetation index	$\frac{\rho_{NIRnarrow}-\rho_{Green}}{\rho_{NIRnarrow}+\rho_{Green}}$
MSAVI	Modified soil adjusted vegetation index	$1-2\times a\times NDVI\times WDVi$
MSI	Moisture stress index	$\frac{\rho_{SWIR1}}{\rho_{NIRnarrow}}$
$ND_{RededgeSWIR}$	Normalized Difference of Red-edge and SWIR2	$\frac{\rho_{Rededge2}-\rho_{SWIR2}}{\rho_{Rededge2}+\rho_{SWIR2}}$
NDVI	Normalized difference vegetation index	$\frac{\rho_{NIRnarrow}-\rho_{red}}{\rho_{NIRnarrow}+\rho_{red}}$
NDVIre	Red-edge normalized difference vegetation index	$\frac{\rho_{NIRnarrow}-\rho_{Rededge1}}{\rho_{NIRnarrow}+\rho_{Rededge1}}$
PVI	Perpendicular vegetation index	$\frac{\rho_{NIRnarrow}-a*\rho_{Red}-b}{\sqrt{a^2+1}}$
RededgePeakArea	Red-edge peak area	$\rho_{Red}+\rho_{Rededge1}+\rho_{Rededge2}+\rho_{Rededge3}+\rho_{NIRnarrow}$
RTVIcore	Red-edge Triangular Vegetation Index	$100\times(\rho_{NIRnarrow}-\rho_{Rededge1})-10\times(\rho_{NIRnarrow}-\rho_{Green})$
SAVI	Soil Adjusted Vegetation Index	$\frac{\rho_{NIRnarrow}-\rho_{Red}}{\rho_{NIRnarrow}+\rho_{Red}+L}\times L$ with $L=0.5$
$SR_{NIRnarrowBlue}$	Simple ratio NIR narrow and Blue	$\frac{\rho_{NIRnarrow}}{\rho_{Blue}}$
$SR_{NIRnarrowGreen}$	Simple ratio NIR narrow and Green	$\frac{\rho_{NIRnarrow}}{\rho_{Green}}$
$SR_{NIRnarrowRed}$	Simple ratio NIR narrow and Red	$\frac{\rho_{NIRnarrow}}{\rho_{Red}}$
TSAVI	Transformed Soil Adjusted Vegetation Index	$\frac{a\times(\rho_{NIRnarrow}-a\times\rho_{Red}-b)}{\rho_{NIRnarrow}+\rho_{Red}-a\times b+0{,}08\times(1+a^2)}$
WDVi	Weighted Difference Vegetation Index	$\rho_{NIRnarrow}-a\times\rho_{Red}$

(Radoux et al., RS2016)

Spectral Indices – Vegetation Indices Based on Red-Edge Region

- The red-edge region, corresponding to the red-NIR transition zone, is the basis of several vegetation indices related to the **canopy chlorophyll content** or **canopy nitrogen content**.



Segara et al., Agr.2020

Spectral Indices – Vegetation Indices Based on Red-Edge Region

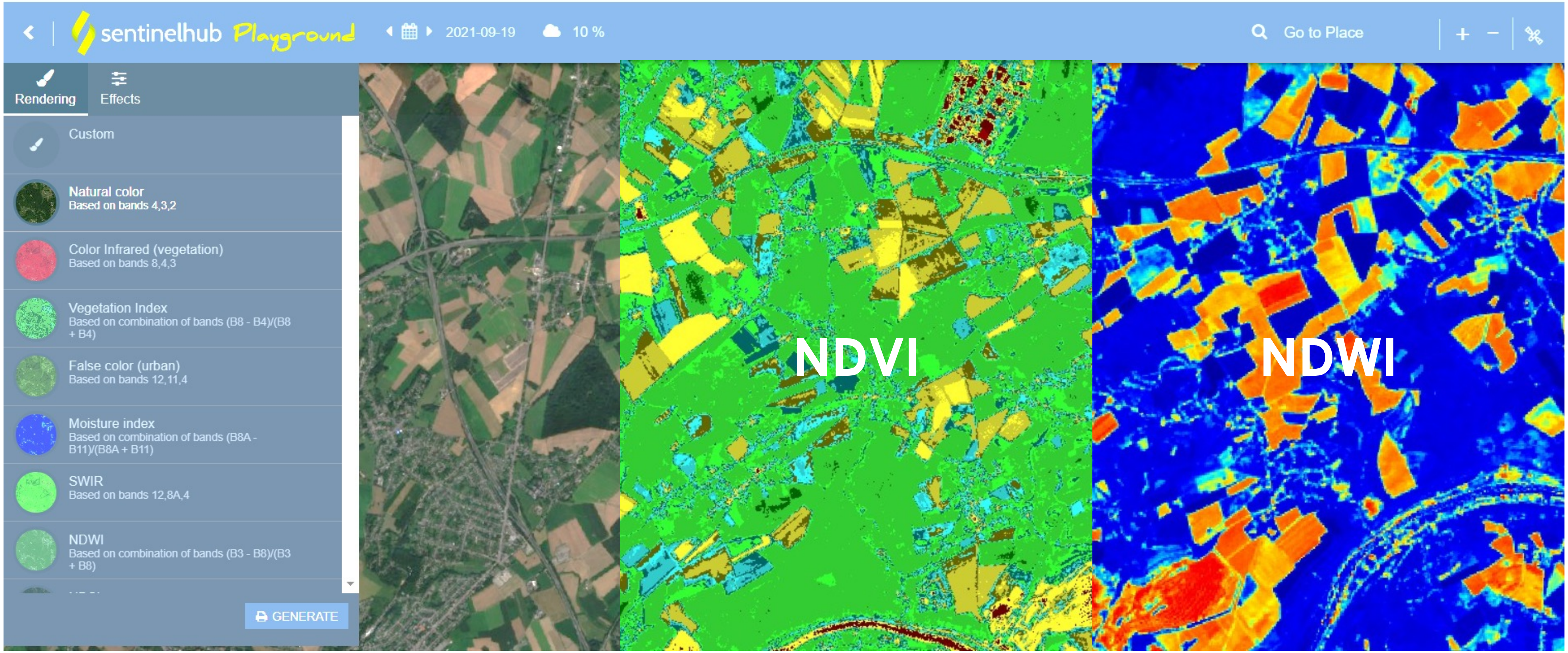
- **Red Edge Position (REP):** Specific wavelength where the change in reflectance is at its maxima (maximum slope) in the 680–780 nm region. REP moves to longer wavelengths with increasing chlorophyll content.

Table 7.3. Chlorophyll indices.

Name	Abbreviation	Index calculation	Parameter	Reference
Simple chlorophyll index (high sensitivity)	R675	R_{675}	Chlorophyll	Jacquemoud and Baret, 1990
Simple chlorophyll index (low sensitivity)	R550	R_{550}	Chlorophyll	Jacquemoud and Baret, 1990
Wavelength of the red edge	λ_{re}	The maximum slope in the reflectance spectra between the RED and NIR regions.	Chlorophyll and N status	Filella *et al.*, 1995
Amplitude in the 1st derivative of the reflectance spectra	dR_{re}	The maximum amplitude in the 1st derivative of the reflectance spectra.	Chlorophyll and N status	Filella *et al.*, 1995
Sum of the amplitudes (680–780 nm) in the 1st derivative of the reflectance spectra	$\sum dR_{680-780}$	Sum of the amplitudes between 680 and 780nm in the 1st derivative of the reflectance spectra.	Chlorophyll and N status	Filella *et al.*, 1995
Normalized difference red edge	NDRE	$(R_{790} - R_{720}) / (R_{790} + R_{720})$	Chlorophyll and N status	Barnes *et al.*, 2000; Rodriguez *et al.*, 2006
Normalized phaeophytinization index	NPQI	$(R_{415} - R_{435}) / (R_{415} + R_{435})$	Chlorophyll degredation	Peñuelas *et al.*, 1995b
Canopy chlorophyll content index	CCCI	Calibrated index using NDRE as function of NDVI.	Chlorophyll and N status	Barnes *et al.*, 2000; Fitzgerald *et al.*, 2006; Rodriguez *et al.*, 2006
Modified spectral ratio	MSR	$(R_{750} - R_{445}) / (R_{705} - R_{445})$	Chlorophyll concentration	Sims and Gamon, 2003
Pigment simple ratio	PSR	R_{430} / R_{680}	Carotenoid to chlorophyll ratio	Peñuelas *et al.*, 1993
Normalized difference pigment index	NDPI	$(R_{680} - R_{430}) / (R_{680} + R_{430})$	Carotenoid to chlorophyll ratio	Peñuelas *et al.*, 1993
Structural independent pigment index	SIPI	$(R_{800} - R_{435}) / (R_{415} + R_{435})$	Carotenoid to chlorophyll ratio	Peñuelas *et al.*, 1995a
Photochemical reflectance index	PRI	$(R_{531} - R_{570}) / (R_{531} + R_{570})$	Radiation use efficiency	Peñuelas *et al.*, 1995a

(Reynolds et al., 2012)

Spectral Indices – Sentinel-2 Playground to Visualize Various Spectral Indices



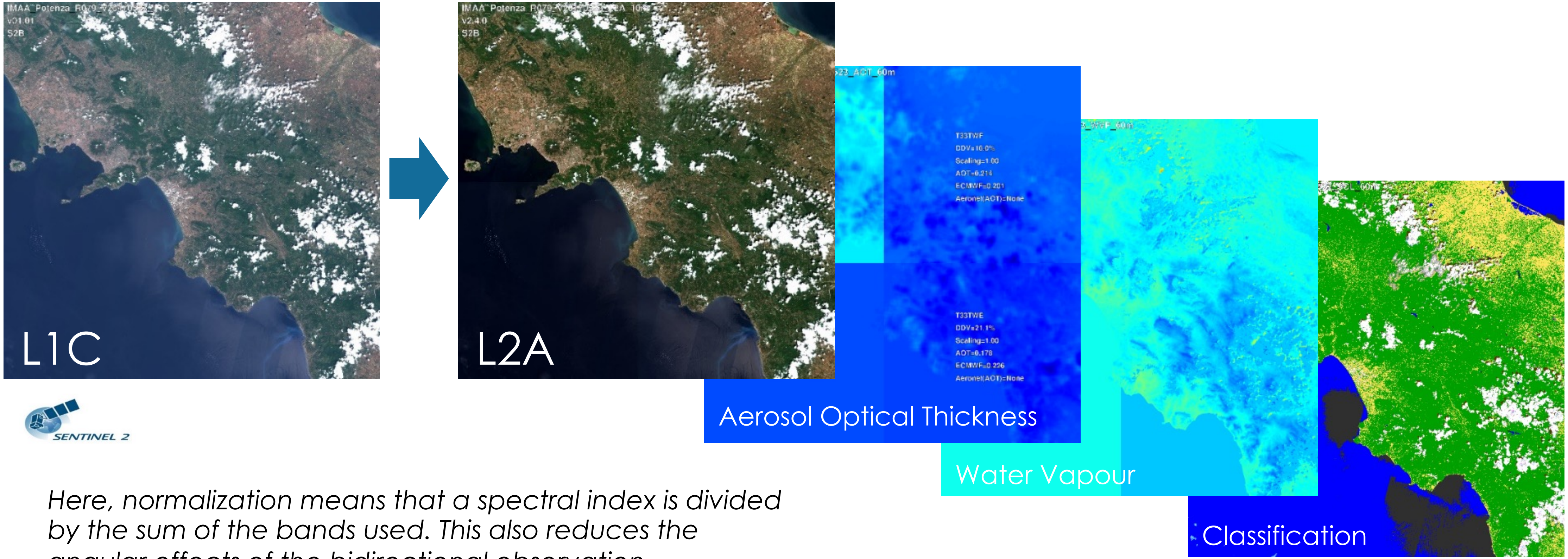
https://apps.sentinel-hub.com/sentinel-playground/

Spectral Indices – Temporal Profile Affected by Atmospheric Perturbations

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

Spectral Indices – Derived Only from Cloud-Free Surface Reflectance (L2A)

The normalized spectral indices minimize the signal noise and the residual atmospheric perturbations but must always be computed from the L2A surface reflectance imagery after masking clouds and cloud shadows and applying atmospheric correction (for aerosols, water vapour, ozone).



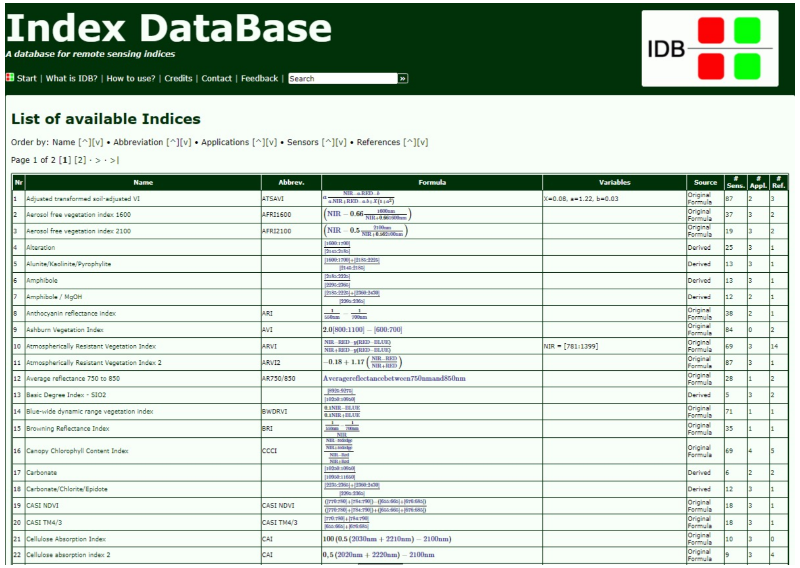
Here, normalization means that a spectral index is divided by the sum of the bands used. This also reduces the angular effects of the bidirectional observation.

Used for the cloud and cloud shadow mask and in the atmospheric correction algorithm.

Spectral Indices – Spectral Bands Vary According to Each Sensor

The spectral signature and the derived spectral indices can be sensitive to many vegetation variables of interest depending on the wavelength and the bandwidth recorded by the satellite sensor.

The **Index Database**, for instance, provides the formula for 300+ Indices for most satellite instruments.



Index DataBase

A database for remote sensing indices

Start | What is IDB? | How to use? | Credits | Contact | Feedback | Search

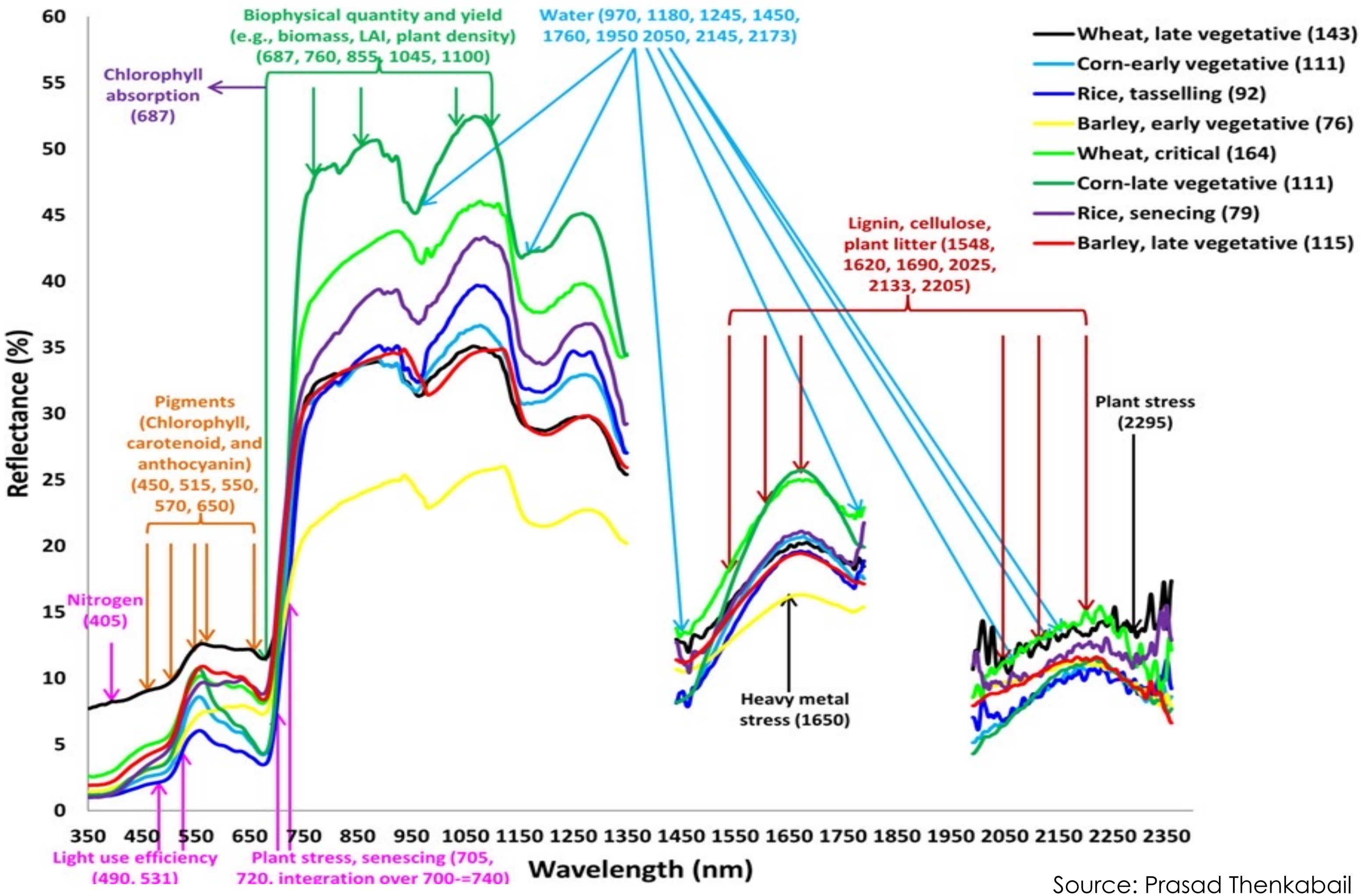
IDB

List of available Indices

Order by: Name [^][v] • Abbreviation [^][v] • Applications [^][v] • Sensors [^][v] • References [^][v]

Page 1 of 2 [1] [2] · > · >|

Nr	Name	Abbrev.	Formula	Variables	Source	# Sens.	# Appl.	# Ref.
1	Adjusted transformed soil-adjusted VI	ATSAVI	$a\frac{NIR-a \cdot RED-b}{a \cdot NIR+RED-a \cdot b+X(1+a^2)}$	X=0.08, a=1.22, b=0.03	Original Formula	87	2	3
2	Aerosol free vegetation index 1600	AFRI1600	$\left(NIR-0.66\frac{1600nm}{NIR+0.66 1600nm}\right)$		Original Formula	37	3	2
3	Aerosol free vegetation index 2100	AFRI2100	$\left(NIR-0.5\frac{2100nm}{NIR+0.5 2100nm}\right)$		Original Formula	19	3	2
4	Alteration		$\frac{[1600:1700]}{[2145:2185]}$		Derived	25	3	1
5	Alunite/Kaolinite/Pyrophylite		$\frac{[1600:1700]+[2185:2225]}{[2145:2185]}$		Derived	13	3	1
6	Amphibole		$\frac{[2185:2225]}{[2295:2365]}$		Derived	13	3	1
7	Amphibole / MgOH		$\frac{[2185:2225]+[2360:2430]}{[2295:2365]}$		Derived	12	2	1
8	Anthocyanin reflectance index	ARI	$\frac{1}{550nm}-\frac{1}{700nm}$		Original Formula	38	2	1
9	Ashburn Vegetation Index	AVI	$2.0[800:1100]-[600:700]$		Original Formula	84	0	2
10	Atmospherically Resistant Vegetation Index	ARVI	$\frac{NIR-RED-y(RED-BLUE)}{NIR+RED-y(RED-BLUE)}$	NIR = [781:1399]	Original Formula	69	3	14
11	Atmospherically Resistant Vegetation Index 2	ARVI2	$-0.18+1.17\left(\frac{NIR-RED}{NIR+RED}\right)$		Original Formula	87	3	1
12	Average reflectance 750 to 850	AR750/850	Averagereflectancebetween750nmand850nm		Original Formula	28	1	2
13	Basic Degree Index - SIO2		$\frac{[8925:9275]}{[10250:10950]}$		Derived	5	3	2
14	Blue-wide dynamic range vegetation index	BWDRVI	$\frac{0.1NIR-BLUE}{0.1NIR+BLUE}$		Original Formula	71	1	1
15	Browning Reflectance Index	BRI	$\frac{\frac{1}{550nm}-\frac{1}{700nm}}{NIR}$		Original Formula	35	1	1
16	Canopy Chlorophyll Content Index	CCCI	$\frac{\frac{NIR-rededge}{NIR+rededge}}{\frac{NIR-Red}{NIR+Red}}$		Original Formula	69	4	5
17	Carbonate		$\frac{[10250:10950]}{[10950:11650]}$		Derived	6	2	2
18	Carbonate/Chlorite/Epidote		$\frac{[2235:2365]+[2360:2430]}{[2295:2365]}$		Derived	12	3	1
19	CASI NDVI	CASI NDVI	$\frac{([770:780]+[784:790])-([655:665]+[676:685])}{([770:780]+[784:790])+([655:665]+[676:685])}$		Original Formula	18	3	1
20	CASI TM4/3	CASI TM4/3	$\frac{[770:780]+[784:790]}{[655:665]+[676:685]}$		Original Formula	18	3	1
21	Cellulose Absorption Index	CAI	$100\,(0.5\,(2030nm+2210nm)-2100nm)$		Original Formula	10	3	0
22	Cellulose absorption index 2	CAI	$0,5\,(2020nm+2220nm)-2100nm$		Original Formula	9	3	4



Source: Prasad Thenkabail

Section 2.1: Biophysical Variable Estimation for Agricultural Applications

Biophysical variables are plant traits or characteristics of interest, which can be measured on the ground and possibly estimated by remote sensing at various scales depending on the sensor's spatial resolution (at leaf, plant, canopy, and landscape level).

Crop Traits

Crop processes	LAI	FAPAR	FCOVER	Albedo	Chlorophyll	Water-content	SLA	soil brightness	Temperature
Photosynthesis	+++	+++			+++		++		
Evapotranspiration	++	+++	+++	++		++			+++
Respiration	++								
Nitrogen	+++				+++				
Phenology	+++	++	++						
Lodging									
Impact of pests	+++								
Soil permanent charac.								+++	
Residues									

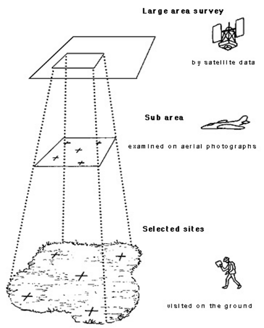
(Baret, 2016)

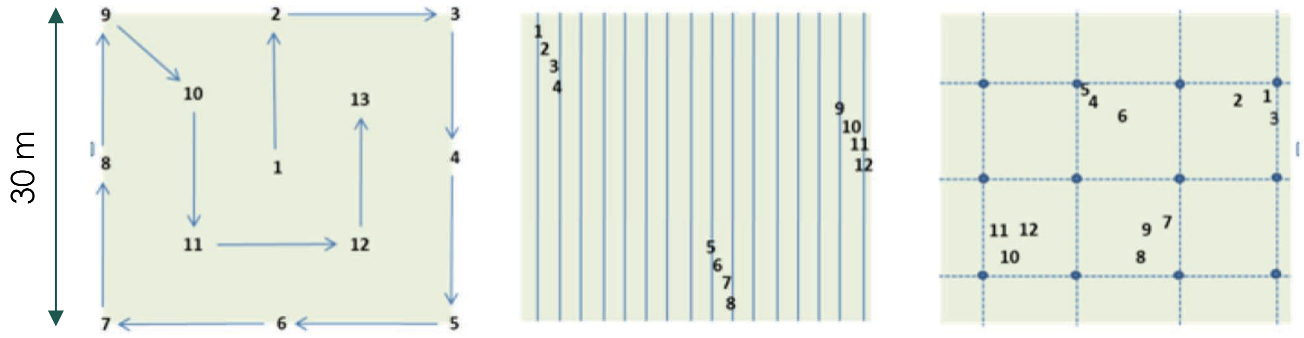
Biophysical Variables – Ground Measurements as Reference

Ground measurements are designed as **reference observations for calibration and/or validation**.

Elementary Sampling Unit (ESU): Described by ground measurements representative of an area corresponding to a single pixel or a small cluster of pixels (typically 3x3 pixels) precisely georeferenced.

Sampling protocol within an ESU: Estimates the average value within the ESU given that the ground measurement footprint is generally much smaller than the size of an ESU.





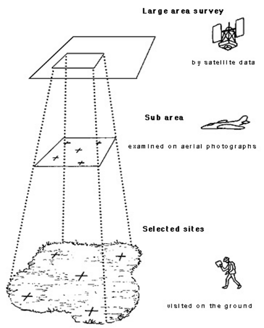
Typical ESU sampling for random (left), row (center) or regularly planted vegetation (right).

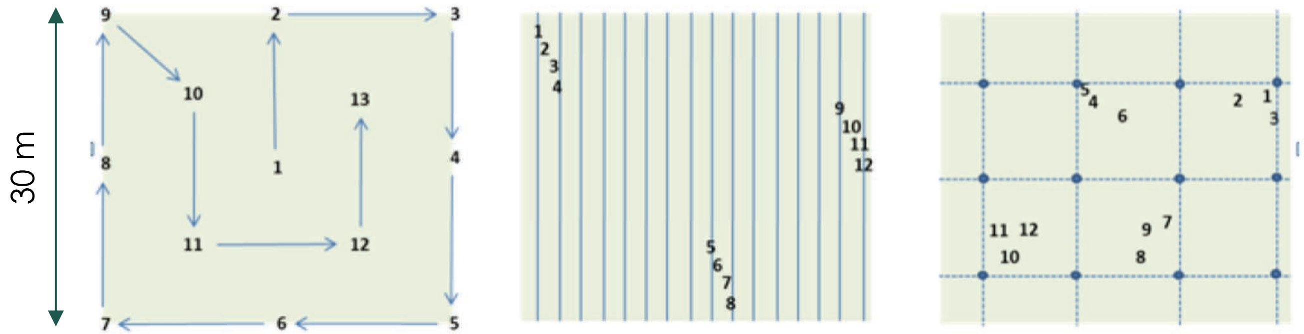
Numbers refer to the location of individual measurements.

Biophysical Variables – Ground Measurements as Reference

Critical choices for the ESUs:

- **Number:** Calibration and validation datasets ideally exceed 30 ESU
- **Location:** At a reasonable distance (i.e., 1 or 2 pixels) from the border of a different land cover
- **Timing:** The closest to the satellite acquisition day and at an appropriate time in the diurnal cycle
- **Homogeneity:** For a good ESU representation from a limited number of ground measurements per ESU
- **Diversity:** Set of ESUs covering the full range of ground measurement values observed in the area
- **Size:** The Point Spread Function should be considered to match the ESU with the corresponding footprint of the in-orbit sensor.





Typical ESU sampling for random (left), row (center) or regularly planted vegetation (right).

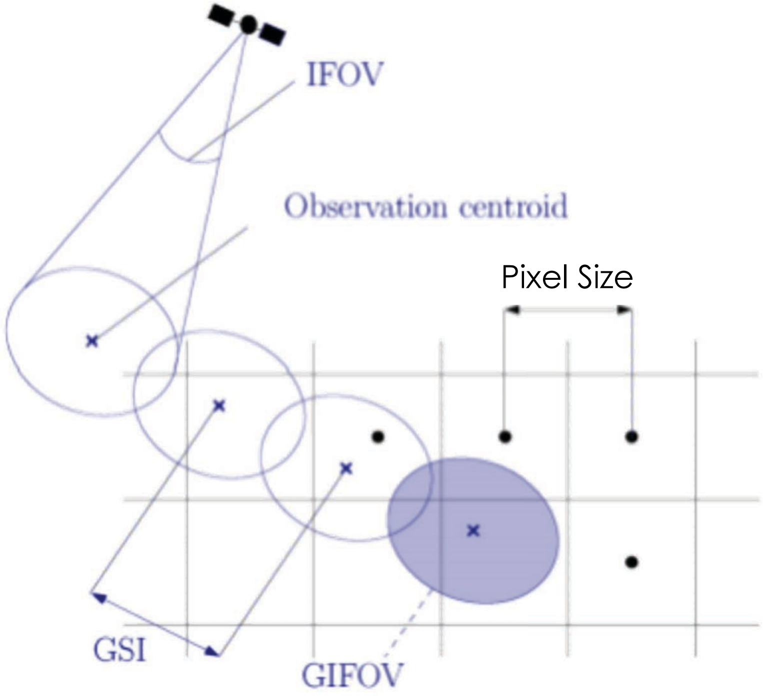
Numbers refer to the location of individual measurements.

Biophysical Variables – Satellite Footprint Measurement

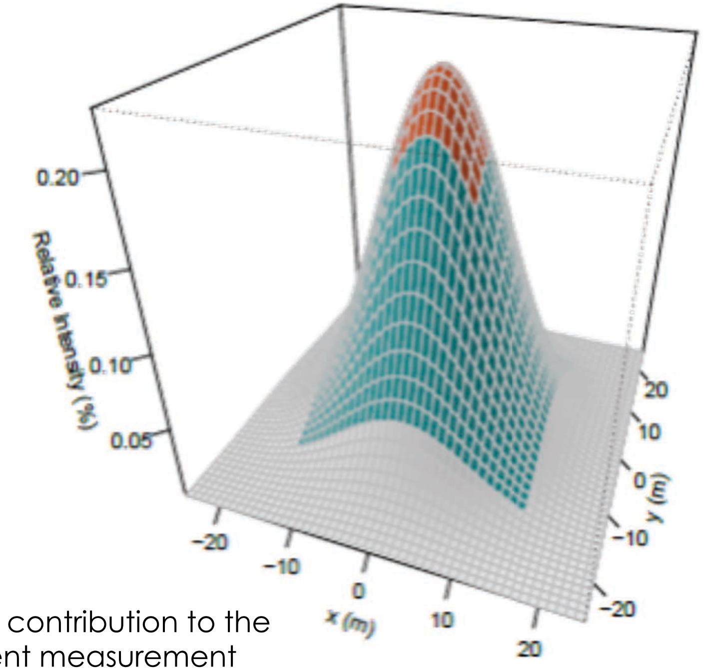
In-orbit instrument observation footprint ≠ pixel size.

- Instantaneous Field of View (IFOV)
- Ground IFOV (Ground-projected IFOV varying across track and enhanced by the Earth's curvature)
- Ground Sampling Interval (GSI)

Point Spread Function (PSF) describing the response of an imaging system to a point object



(Waldner, Duveiller and Defourny, 2018)



Relative contribution to the instrument measurement
Red : GIFOV area
Red + Blue: effective area contributing to the radiance measurement

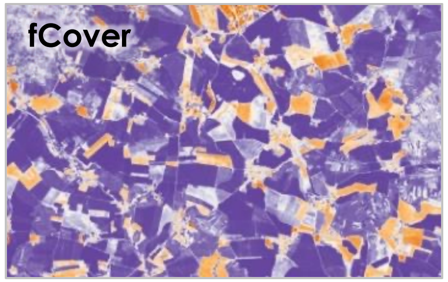
(Radoux et al., 2016)

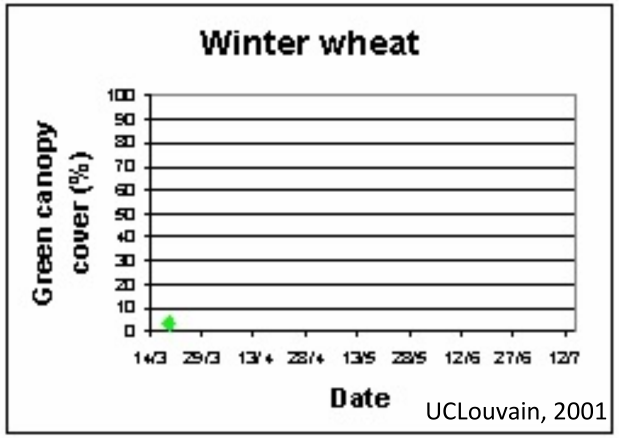
Biophysical Variables – fCover

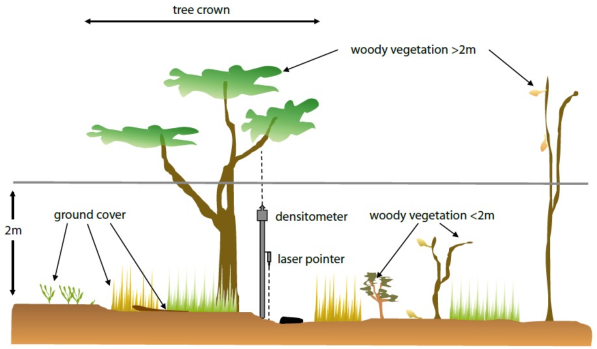
Cover Fraction (fCover): Green cover fraction as seen from the nadir direction.

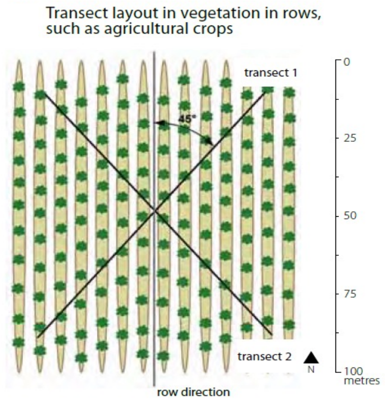
- A canopy structural variable, which is dimensionless
- Independent of the geometry of illumination unlike FAPAR
- Very sensitive to low cover fraction
- Saturation at 100% is reached before full plant development

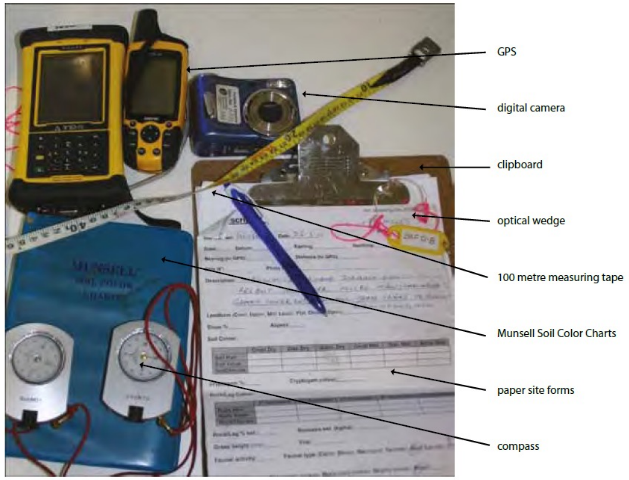
fCover measurement by LiDAR or vertical photograph











Source: Field measurement of fractional ground cover, Australia 2011

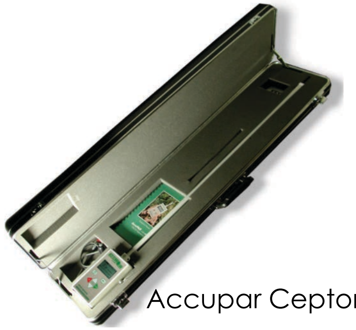
Biophysical Variables – fAPAR

Biomass $= \int_{time} PAR_i . fAPAR(time) . \varepsilon_b$

ε_b=Light Use Efficiency (LUE)

Fraction of Absorbed Photosynthetically Active Radiation (fAPAR)

- Balance between incident and transmitted PAR (400-700 nm) through the canopy
- A non-dimensional value ranging from 0 to almost 1 for full green vegetation
- Used as a descriptor of photosynthesis and evapotranspiration processes
- Depends also on the illumination conditions (sun angular position and the relative contributions of the direct and diffuse illumination - black-sky or white sky)



Accupar Ceptometer

Measurements :

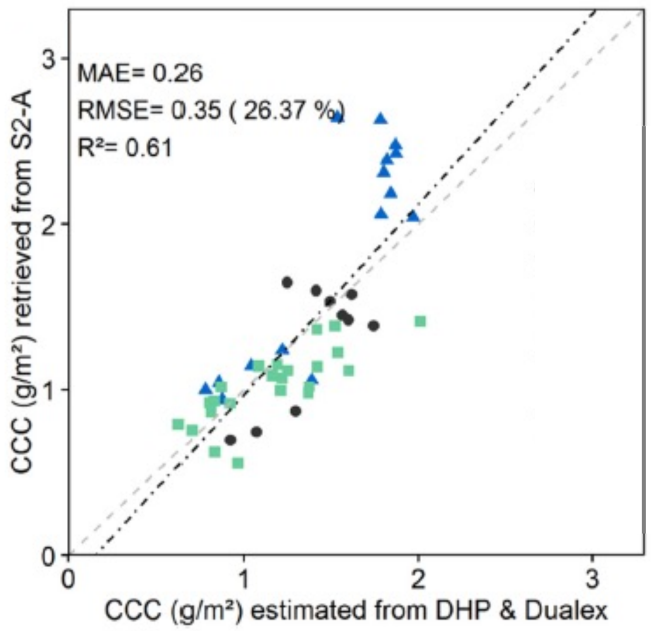
- To compute the PAR balance, you need a permanent setup with continuous measurements, covering the illumination variability over days and/or seasons.
- Estimated from measurement of PAR transmitted at the bottom of the canopy (the so-called ceptometers)

Biophysical Variables – Canopy Chlorophyll Content (CCC)

CCC is the **total amount of chlorophyll a and b pigments** in a contiguous group of plants per unit ground area (in g/m²).

- Closely related to plant nitrogen content (fertilization)
- Reflectance at 675 nm is very sensitive to changes in chlorophyll content, but only for low CCC values.
- Lower chlorophyll absorption at 550 nm, sensitive to a greater range of CCC, not easily saturated but less sensitive to chlorophyll changes

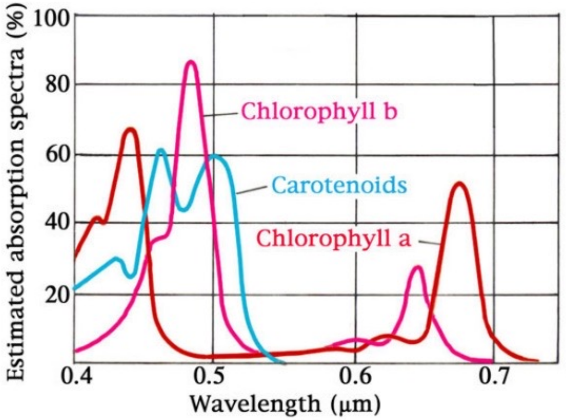
CCC ground measurement using a handheld single-leaf meter that measures chlorophyll using light transmittance at 650 nm and 940 nm (e.g., using SPAD or Dualex instrument)



(Delloye et al., RSE2018)

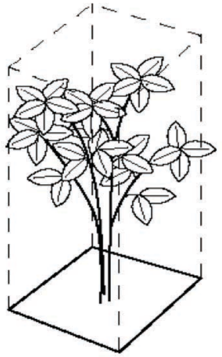
Chloroplast

Pigment Optical Spectrum



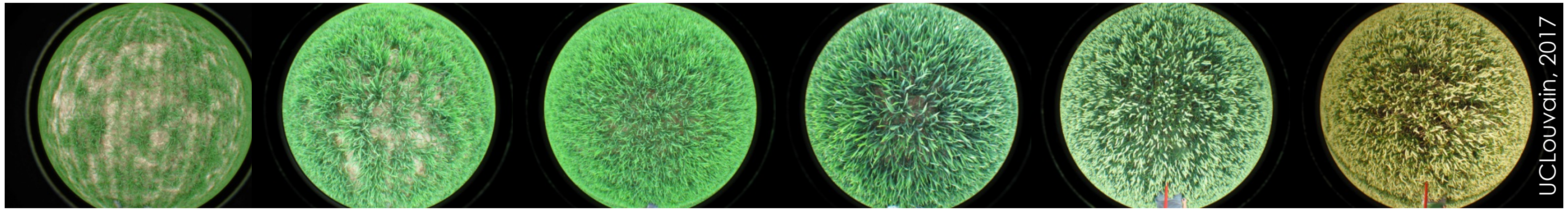
Biophysical Variables – Leaf Area Index (LAI)

More precisely **Green Area Index (GAI)**



LAI-2200

- **True GAI**: Half the developed area of green elements per unit horizontal ground area (destructive measurements)
- **Effective GAI**: The value retrieved from green fraction (gap fraction) measurements based on turbid medium assumption (DHP, LAI2200)



Ground GAI measurement obtained from Digital Hemispherical Photography (DHP) using Can-Eye Software

- **Apparent GAI**: The value retrieved from remote sensing observations that depends on the assumptions associated to the estimation algorithm (e.g., leaf orientation, leaf clumping)

Section 2.2: Calibration of Biophysical Variable Retrieval Models and Performance Assessment

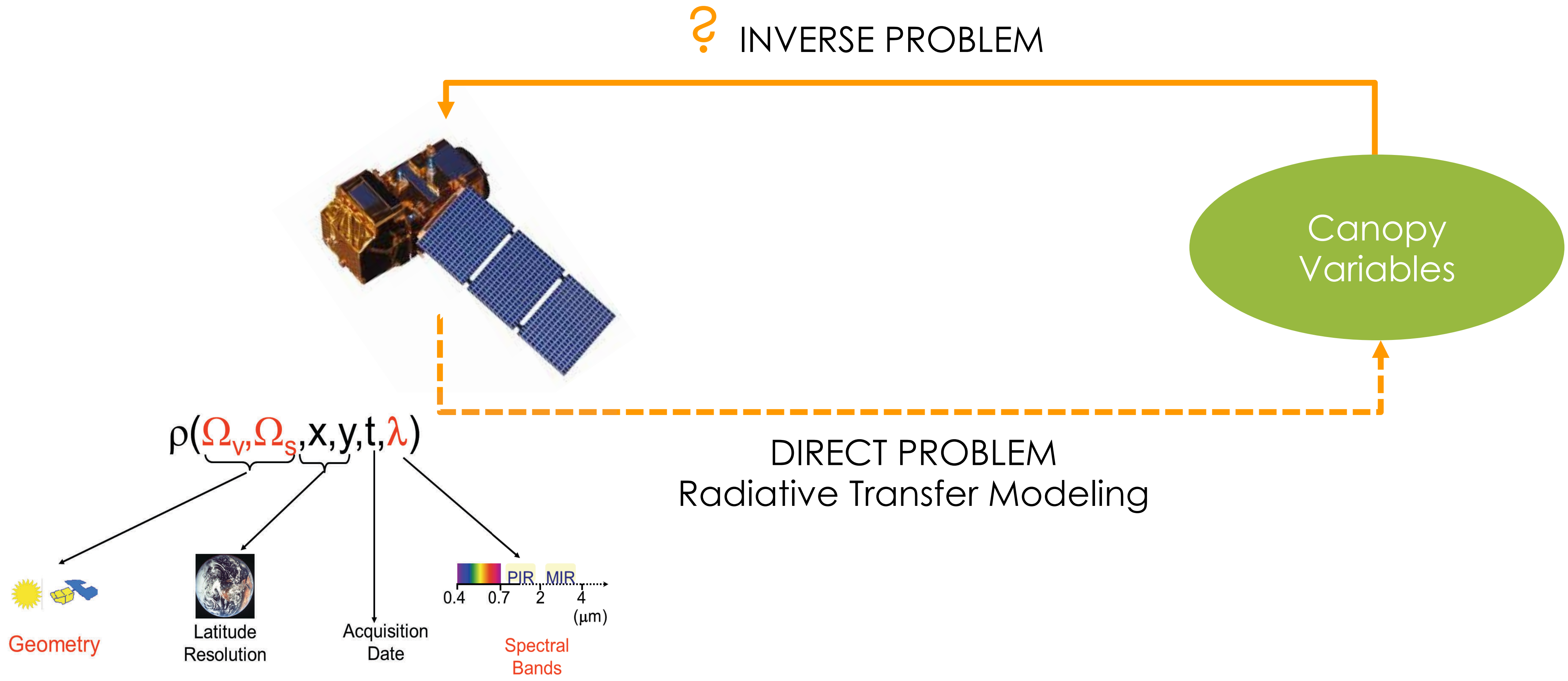


Illustration from Weiss – ESA Training 2019

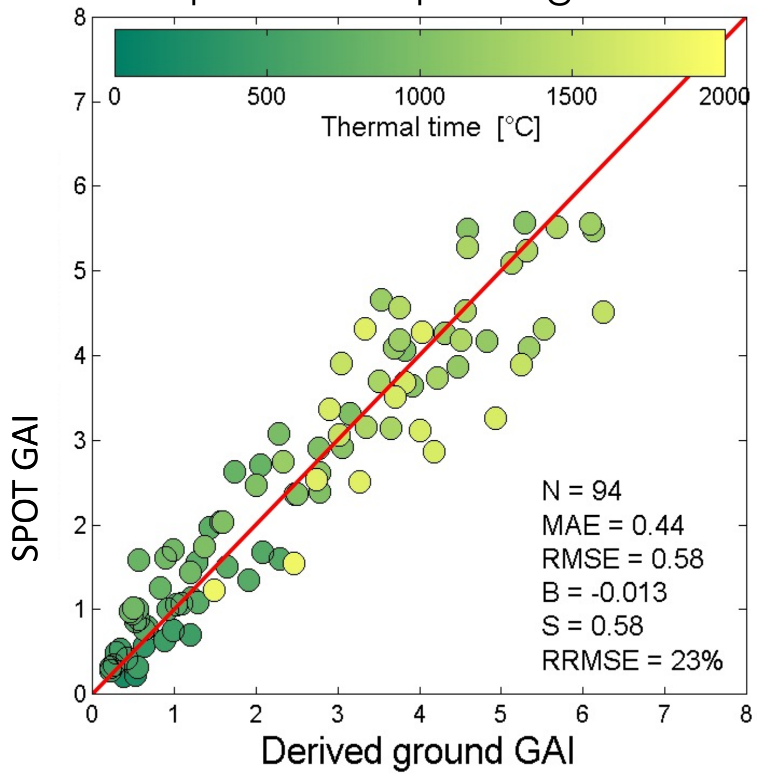
Biophysical Variable Retrieval - Empirical Models

Empirical models using statistical regression or machine learning relationships

- **Calibration** between indices or spectral reflectance values and the corresponding reference values (typically from ground measurements)
- **Validation** using an independent dataset to estimate the prediction error of the model

Empirical Models	**vs.**	**Physically-Based Models**
Empirical models that are locally calibrated are valid for the area and conditions corresponding to the dataset calibration		Physically-based models are transposable to other areas and conditions because they are designed to be generic

Stepwise Multiple Regression



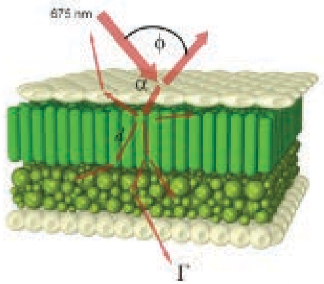
MAE: Mean Absolute Error
RRMSE: Relative Root Mean Squared Error

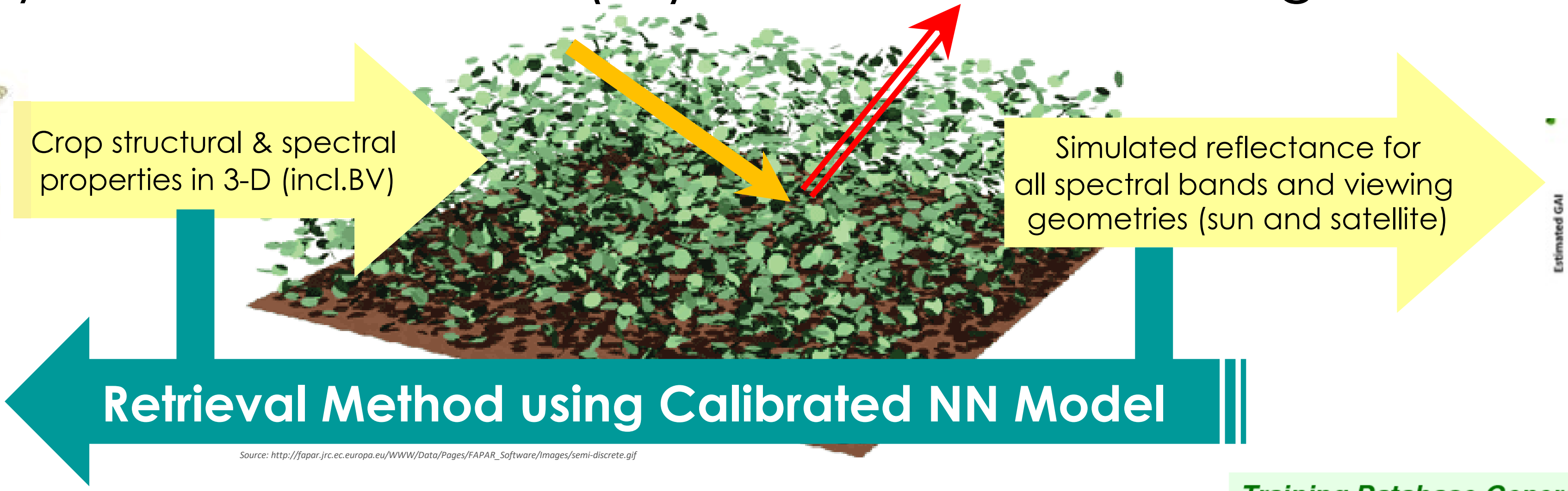
(Duveiller et al. RSE 2011)

Biophysical Variable Retrieval – Physically-Based Models

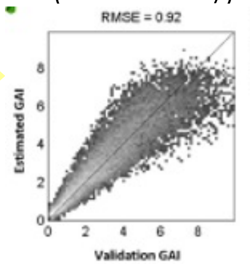
GAI retrieval by Radiative Transfer (RT) model inversion using Neural Network

PROSPECT RT model at leaf level

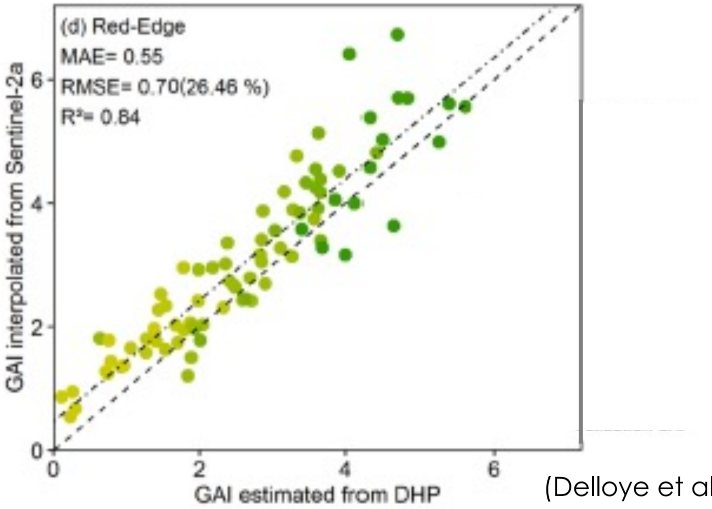




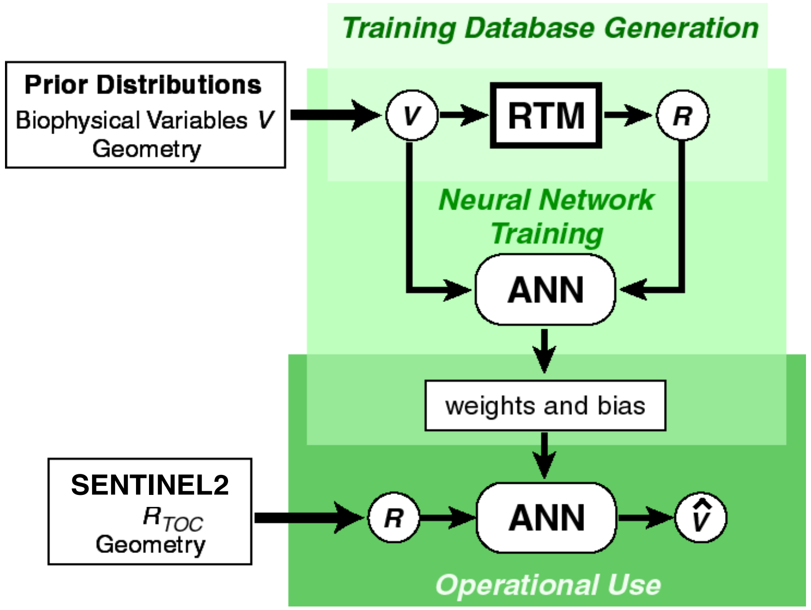
Simulated Performances (Model Only)



Actual performances of model estimation (validation from ground measurements)



(Delloye et al., RSE 2018)

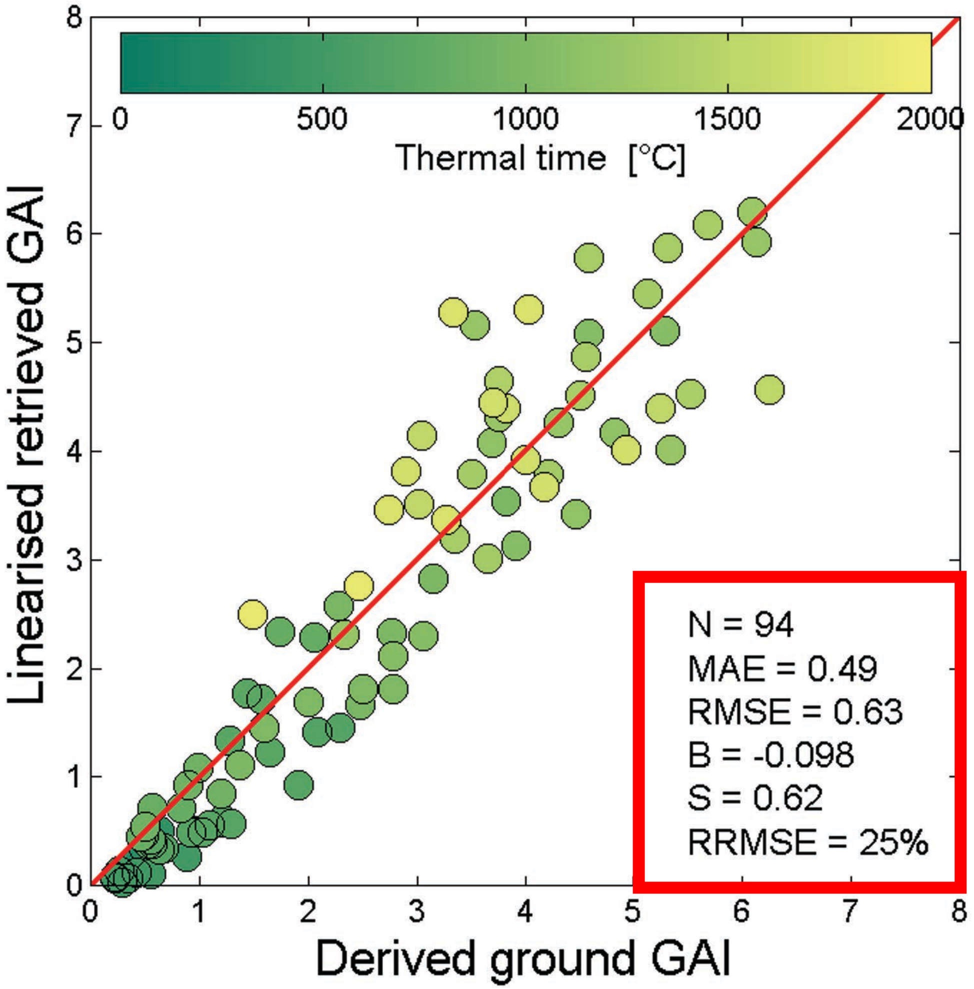


BV-net (Weiss, 2019)

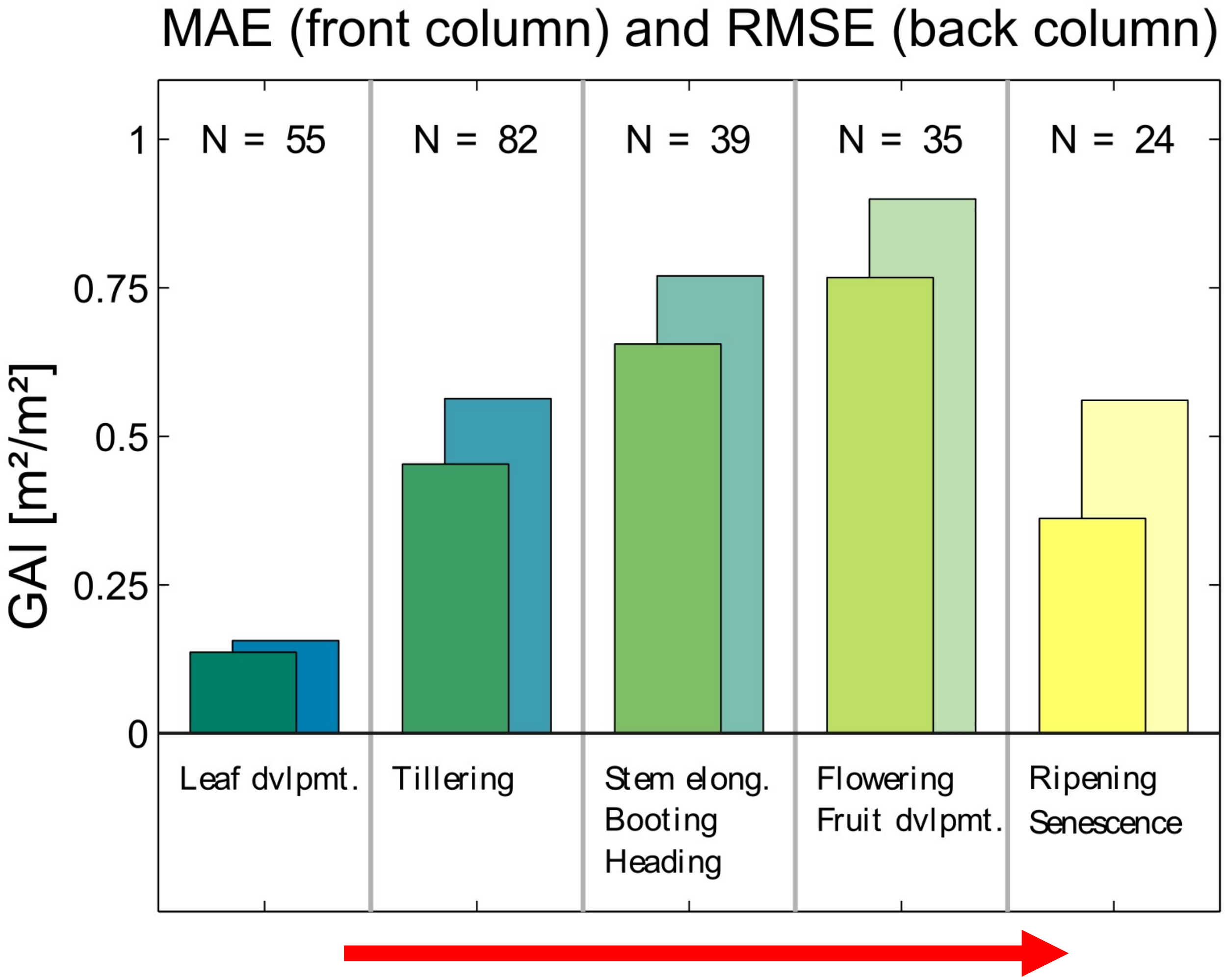
sen4cap common agricultural policy

Biophysical Variable Retrieval – Performance Analysis

Validation of LAI Retrieved using NN&RTM



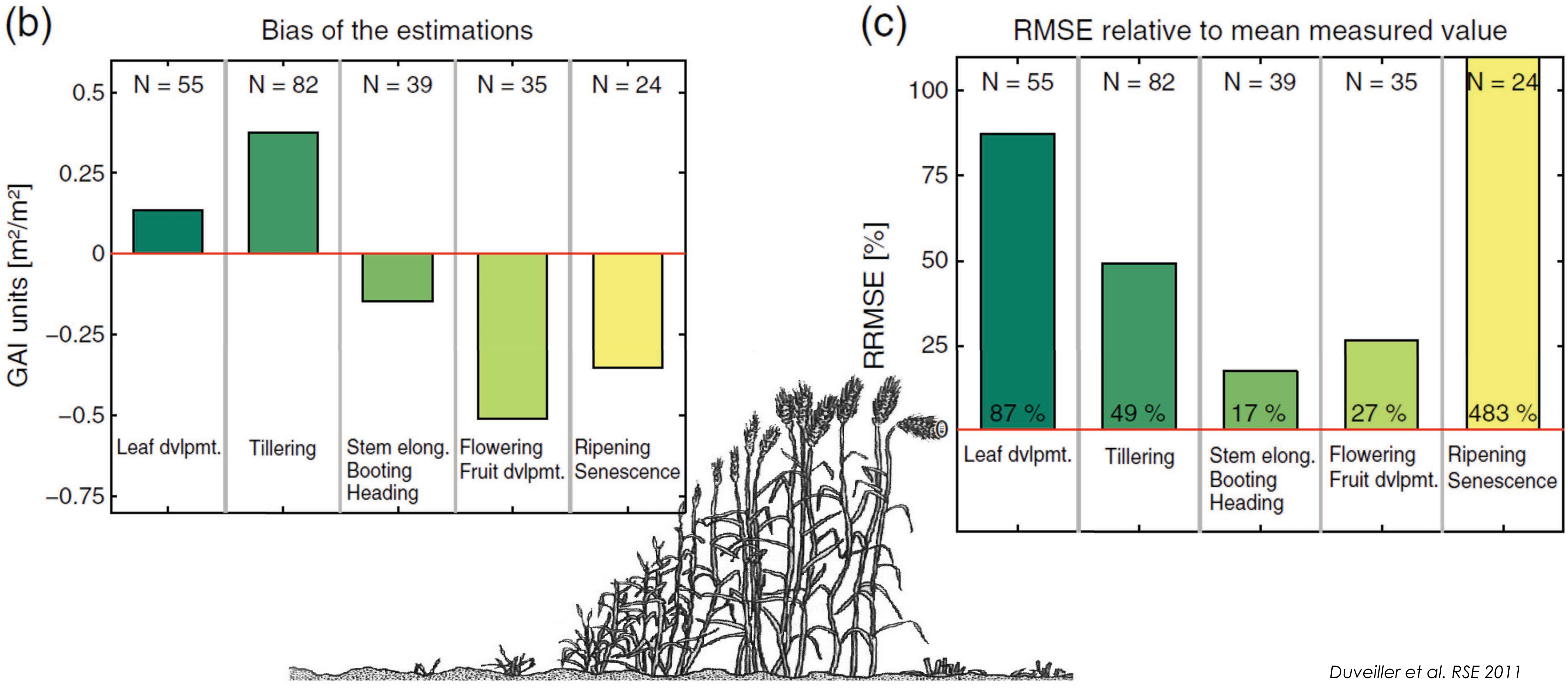
LAI Error According to the Development Stage



Duveiller et al. RSE 2011

Biophysical Variable Retrieval – Performance Analysis

Bias and Relative RMSE of retrieved LAI according to the development stage



Duveiller et al. RSE 2011

Table of Contents

Section 3: Phenometrics to Identify the Distribution and Timing of a Given Crop

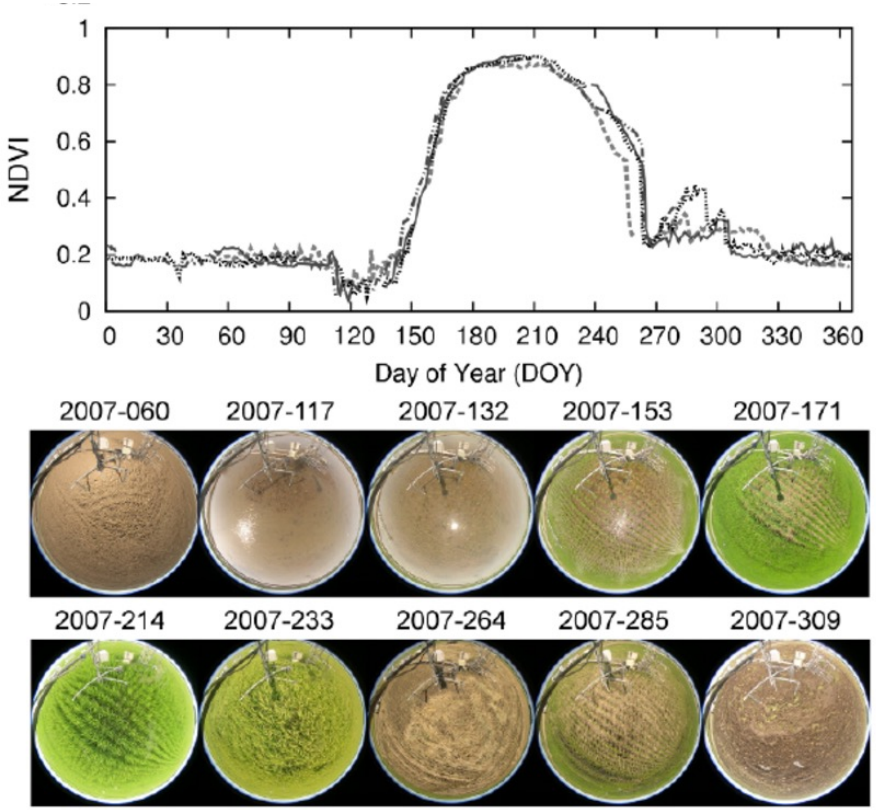
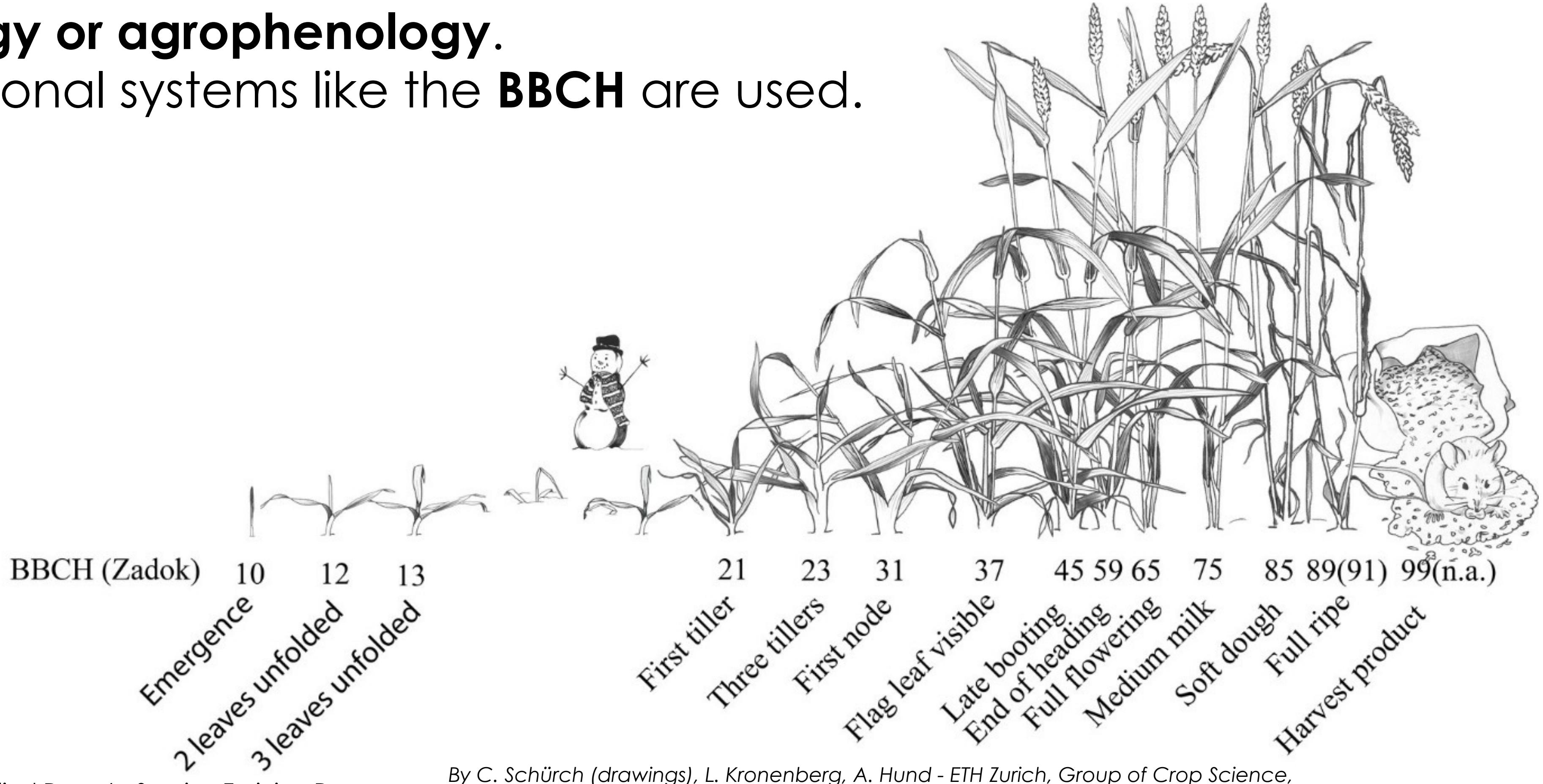


Illustration from Bochetti – ESA Training 2019

Phenology and Phenometrics

- Plant **phenology** deals with the definition of the **development stages** of plants and the recording of **dates** in which these stages occur in different environments.
- If the plants under observation are cultivated, we are in the field of **agricultural phenology or agrophenology**.
- Conventional systems like the **BBCH** are used.

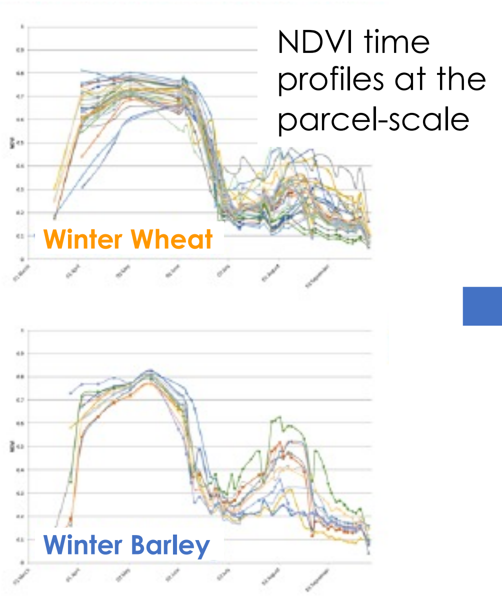


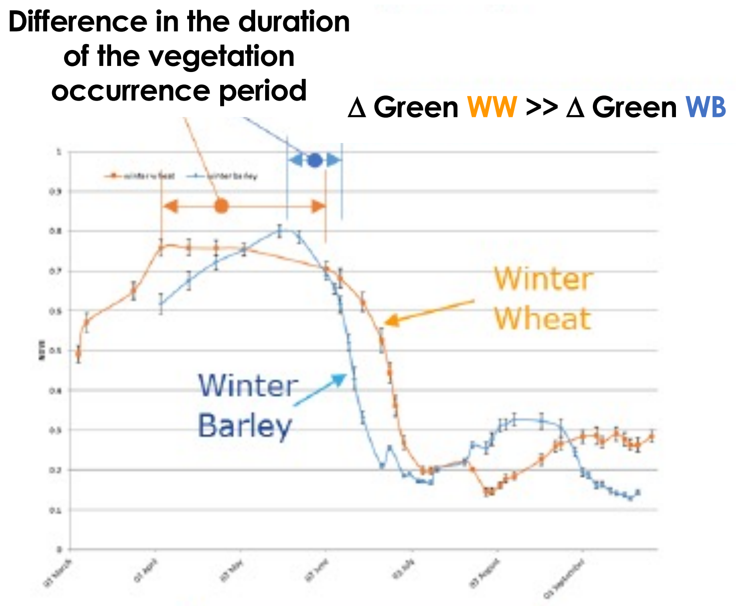
By C. Schürch (drawings), L. Kronenberg, A. Hund - ETH Zurich, Group of Crop Science, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=70621817

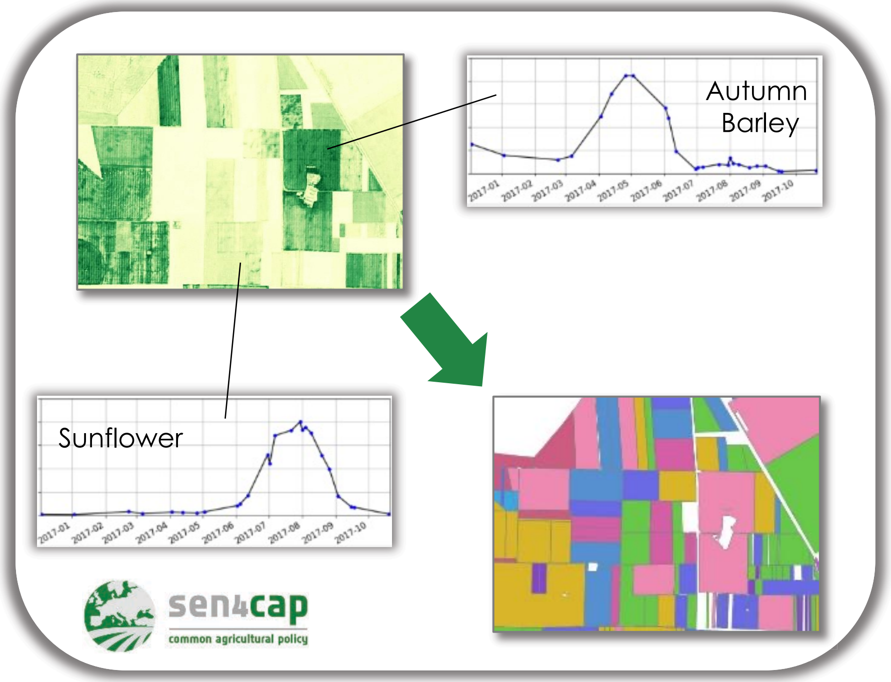
Monitoring Phenology Allows for Characterizing Crop Types and Monitoring Crop Growth

- Identify the distribution and timing of a given crop - where and when it is grown
- **Time series analysis** to study the multi-temporal signal of spectral indices/ biophysical variables

1) Full time series analysis







JRC Technical Reports, DS/CDP/2018/18

Monitoring Phenology Allows for Characterizing Crop Types and Monitoring Crop Growth

2) Extraction of crop-specific temporal metrics related to crop phenology

1	2	3	4	5
Maximum Red (average of 3 max.)	**Max. Positive Slope**	**Maximum NDVI** (average of 3 max.)	**Max. Negative Slope**	**Minimum NDVI** (average of 3 max.)
Bare soil at sowing preparation	Fastest growth of vegetation	Maximum green biomass	Fast reduction of vegetation	Harvested crop or non green residues

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

Sen2-Agri

Example: Extracting the Start of Season (SoS) Phenometry

Comparison of extraction of $\mathbf{SOS_{20}}$ and $\mathbf{SOS_{inflection}}$ from the fitted curve of EVI2

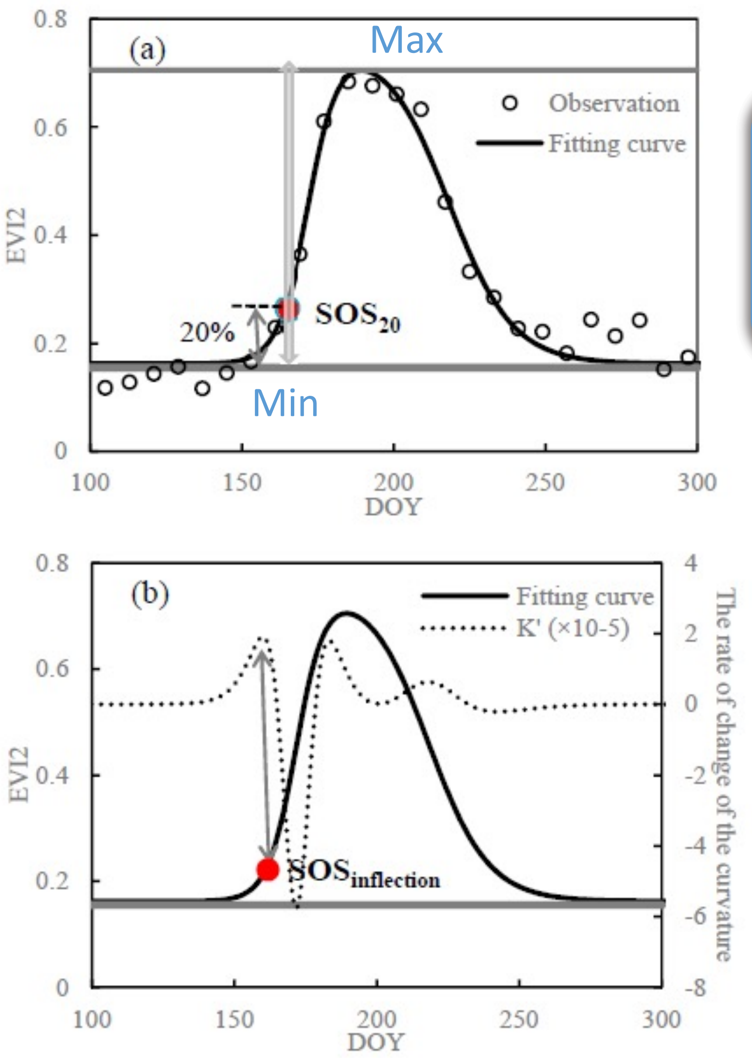
- **Local Threshold Criteria**: Identification of **specific condition of VI/BV values** in relation to the curve

  e.g., SOS = Date when VIs reach a threshold level

  - Absolute (expert-based)
  - Relative (e.g., about 10–20% of the seasonal maximum amplitude)

- **Curve Analysis**: Changes in the derivative to identify inflection points

  e.g., SOS = Inflection point corresponding to the onset of rapid vegetation growth



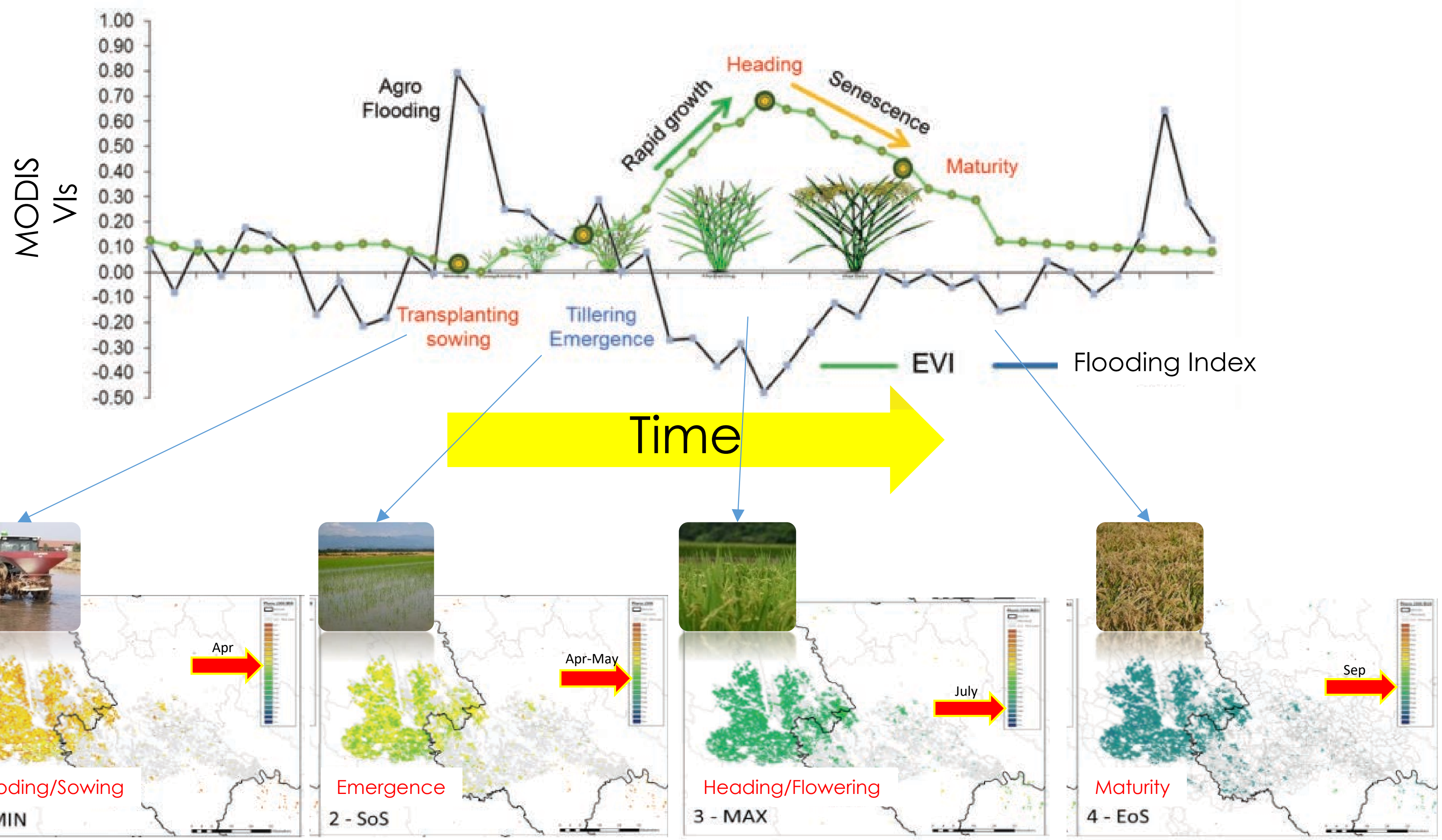
Local thresholds according to relative threshold (> curve min, max values)

(first) Max value of the first-order derivative of the curvature of the fitted curve (K')

Dong et al. 2019 in Bochetti – ESA Training 2019

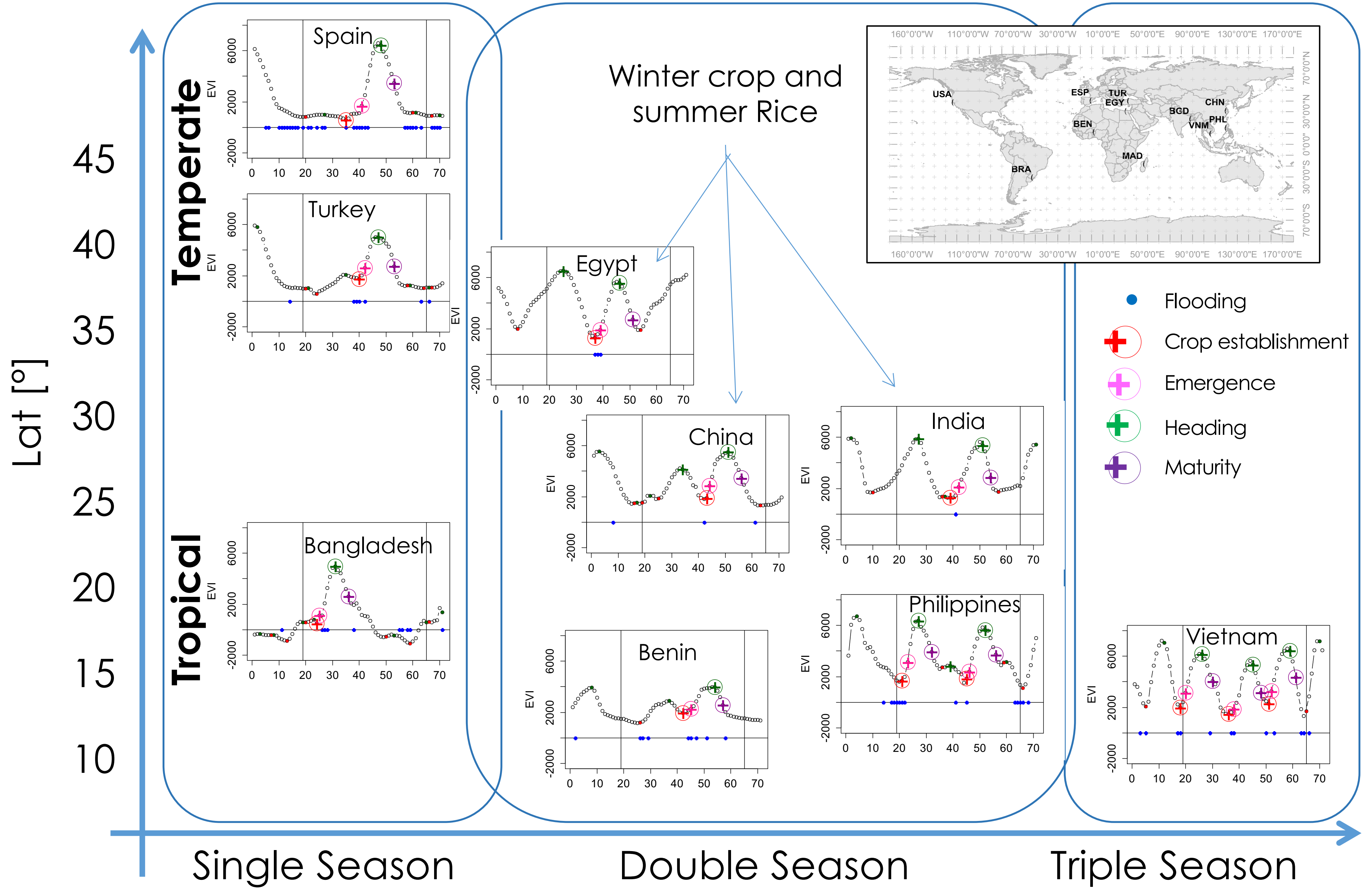
Regional Level Application 1: MODIS Based Dynamic Cropland Calendars: An Example for Rice

Phenorice Concept



Boschetti et al. 2017

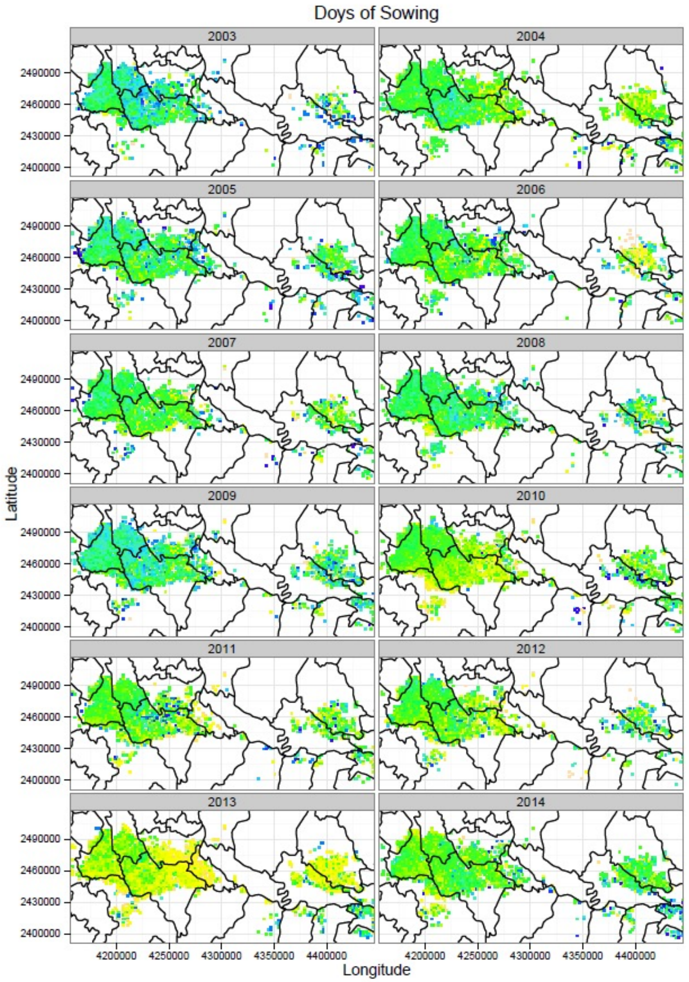
NEEDS A TITLE

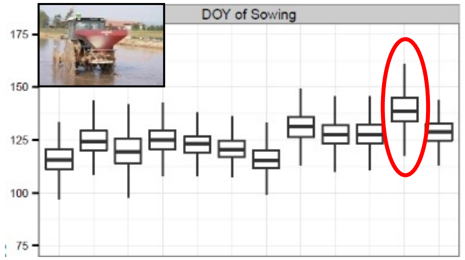


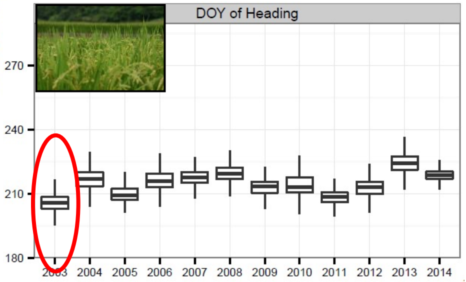
PhenoRice Output: From “Static Crop Calendar” to Seasonal Dynamics: Example in Italy

- **Retrospective analysis** with MODIS data can be used for regional studies and crop model forcing.

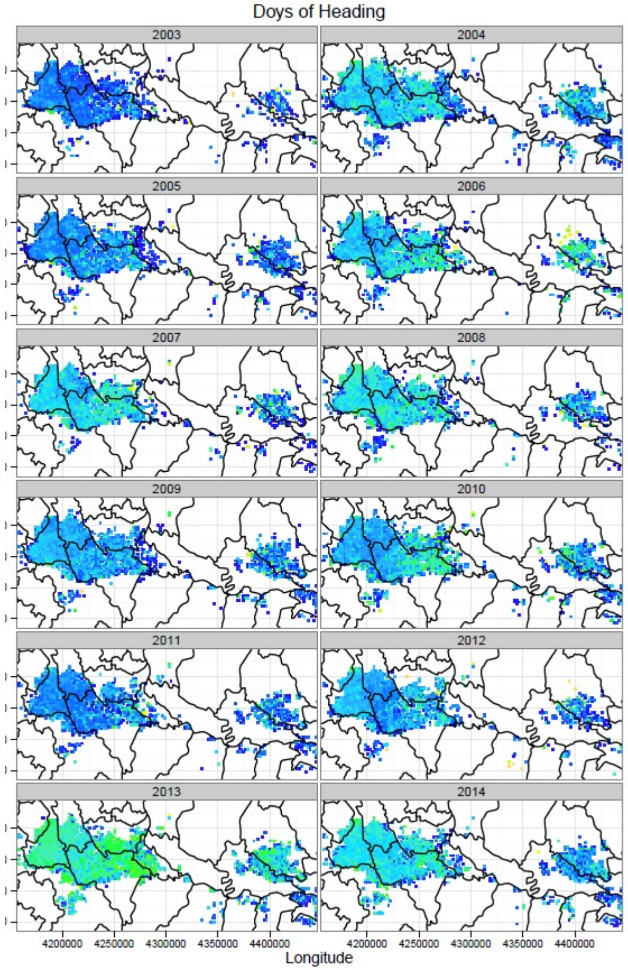
- **Seasonal retrieval** provides NRT information for operational crop monitoring systems (MARS).







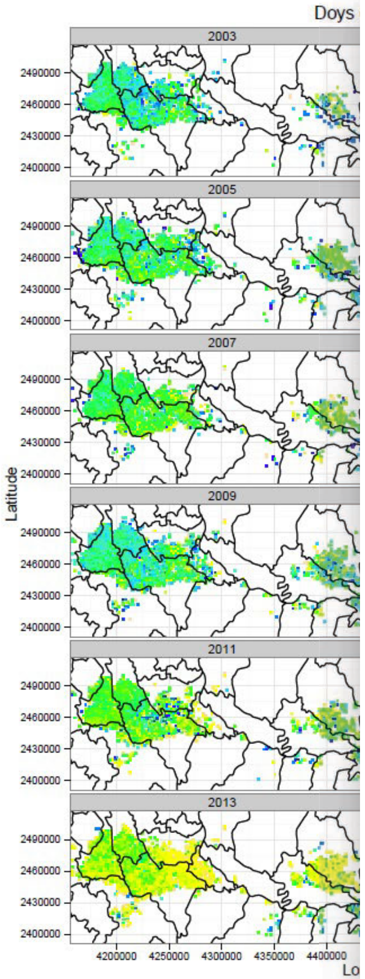
ERMES
AN EARTH OBSERVATION MODEL BASED RICE INFORMATION SERVICE
SEVENTH FRAMEWORK PROGRAMME

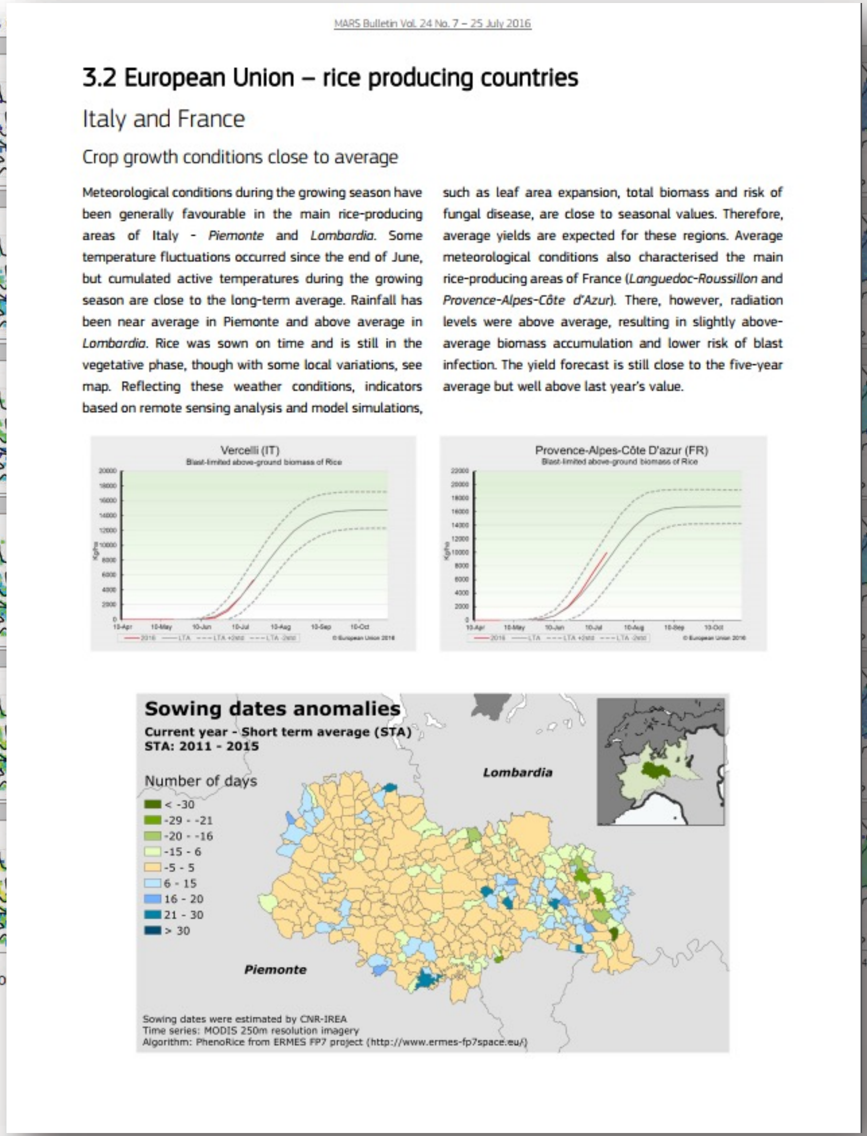


PhenoRice Output: From "Static Crop Calendar" to Seasonal Dynamics: Example in Italy

- **Retrospective analysis** with MODIS data can be used for regional studies and crop model forcing.

- **Seasonal retrieval** provides NRT information for operational crop monitoring systems (MARS).





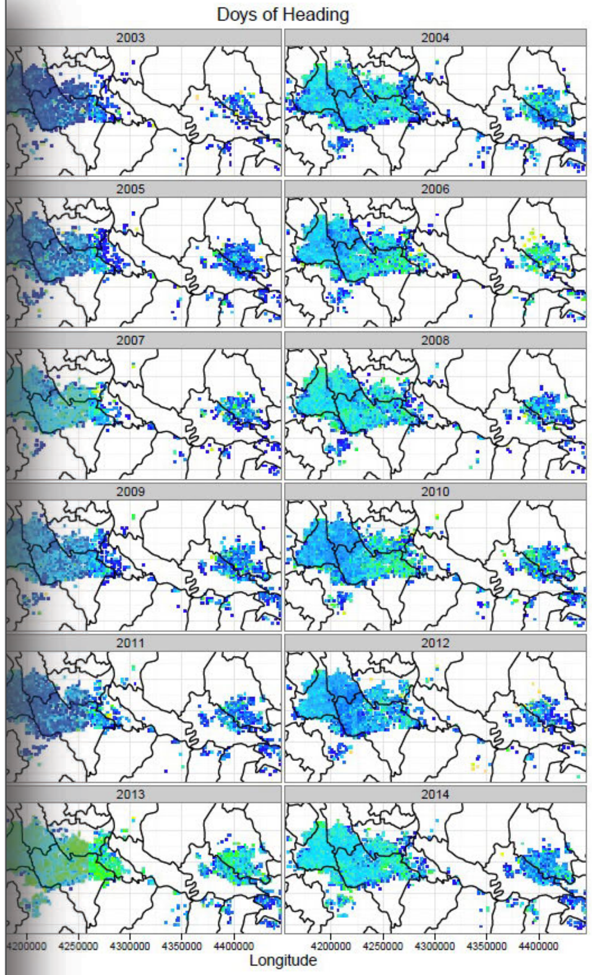
MARS Bulletin Vol. 24 No. 7 – 25 July 2016

3.2 European Union – rice producing countries

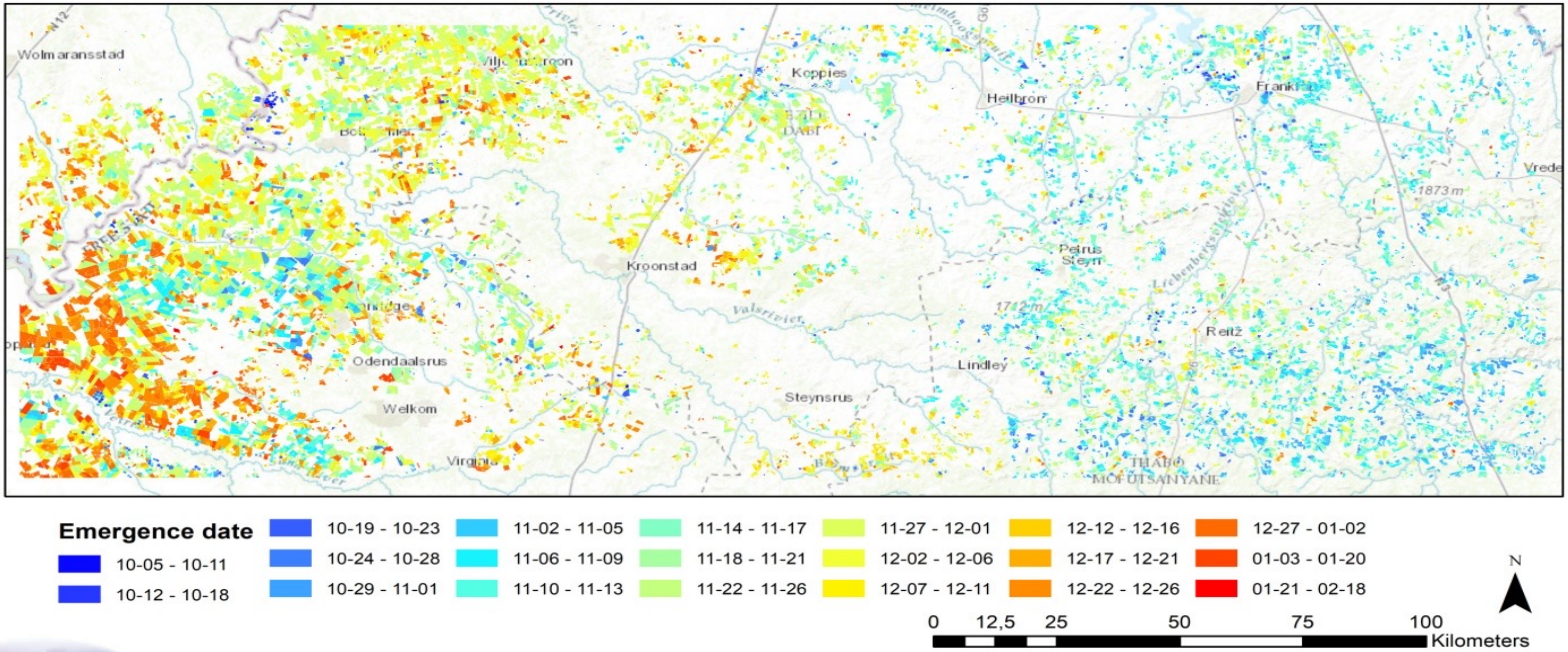
Italy and France

Crop growth conditions close to average

Meteorological conditions during the growing season have been generally favourable in the main rice-producing areas of Italy - *Piemonte* and *Lombardia*. Some temperature fluctuations occurred since the end of June, but cumulated active temperatures during the growing season are close to the long-term average. Rainfall has been near average in Piemonte and above average in *Lombardia*. Rice was sown on time and is still in the vegetative phase, though with some local variations, see map. Reflecting these weather conditions, indicators based on remote sensing analysis and model simulations, such as leaf area expansion, total biomass and risk of fungal disease, are close to seasonal values. Therefore, average yields are expected for these regions. Average meteorological conditions also characterised the main rice-producing areas of France (*Languedoc-Roussillon* and *Provence-Alpes-Côte d'Azur*). There, however, radiation levels were above average, resulting in slightly above-average biomass accumulation and lower risk of blast infection. The yield forecast is still close to the five-year average but well above last year's value.



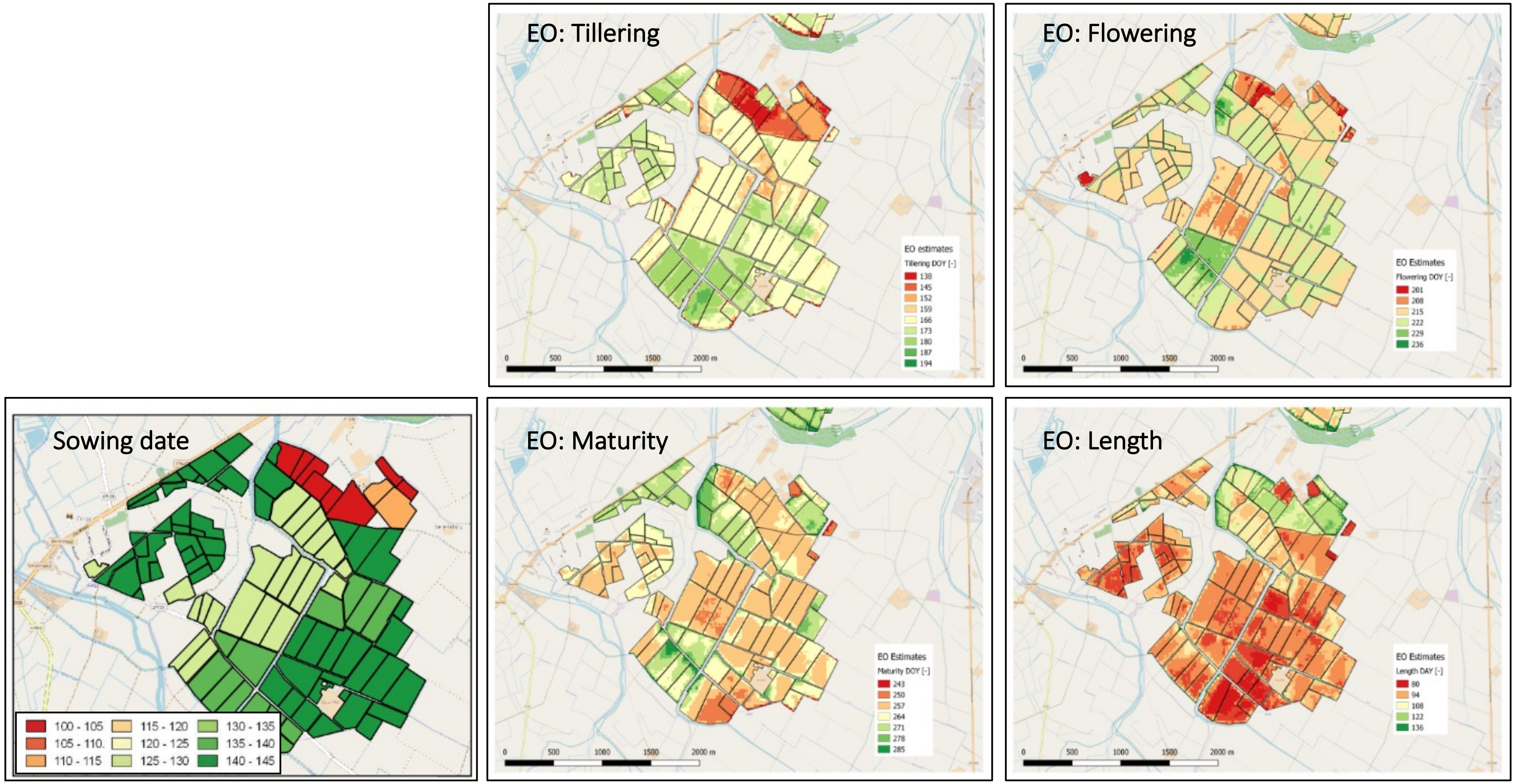
Regional Level Application 2: Maize Emergence Date Map at the Field Level: An Example in Free State, South Africa



H2020 ECoLaSS project- UCLouvain

Farm and Field Level Application: Phenometrics as a Diagnostic "Tool" for Identifying Rice Variety Groups

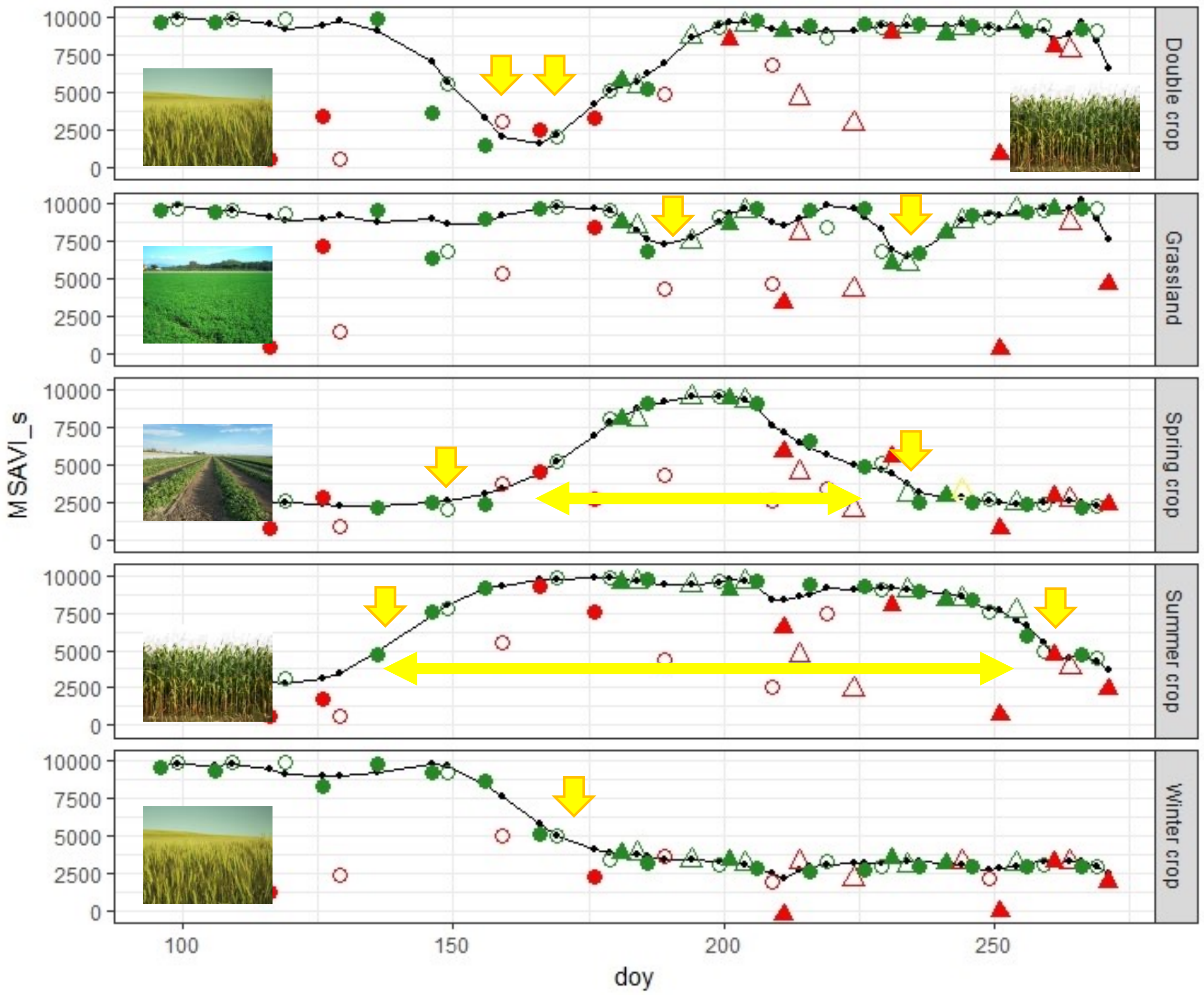
Mapping of phenological development at field-level, thanks to Sentinel-2 10 m resolution

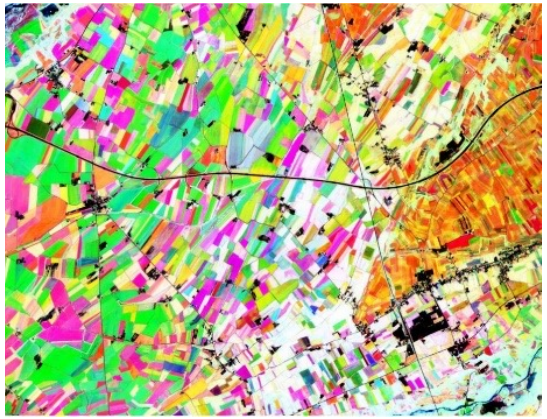


Possible link with rice varieties

Bochetti – ESA Training 2019

Section 4: Monitoring Agricultural Practices





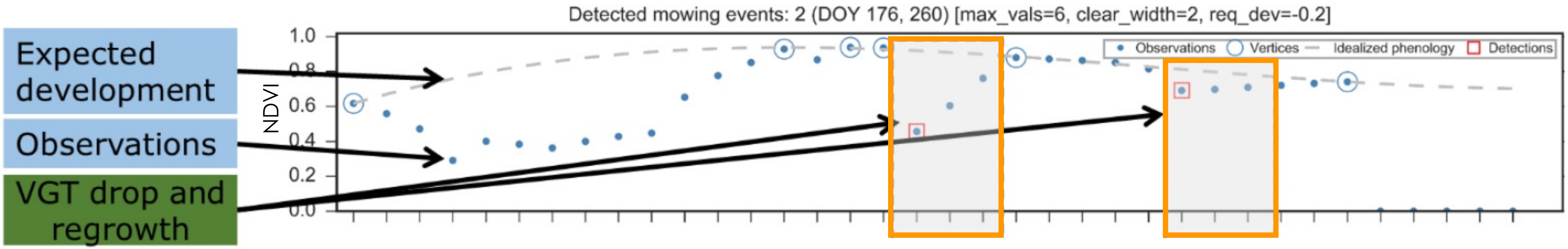
RGB MSAVI
R = Mar.
G = Jun.
B = Aug.

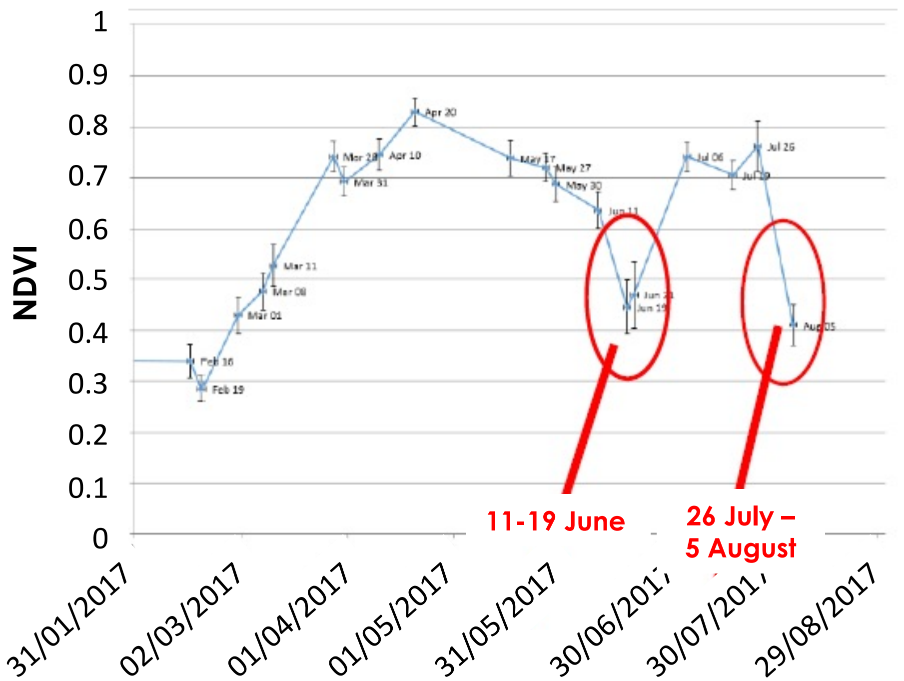
Sensor and Orbit
- S2A_108
- S2A_65
- S2B_108
- S2B_65

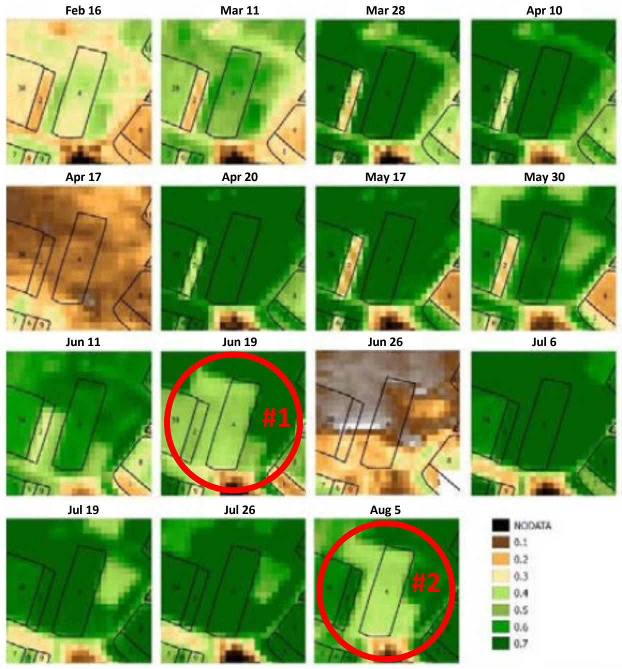
Data quality level
- Bad
- Good
- Medium

Bochetti – ESA Training 2019

Detection of Mowing Events on Permanent Grassland



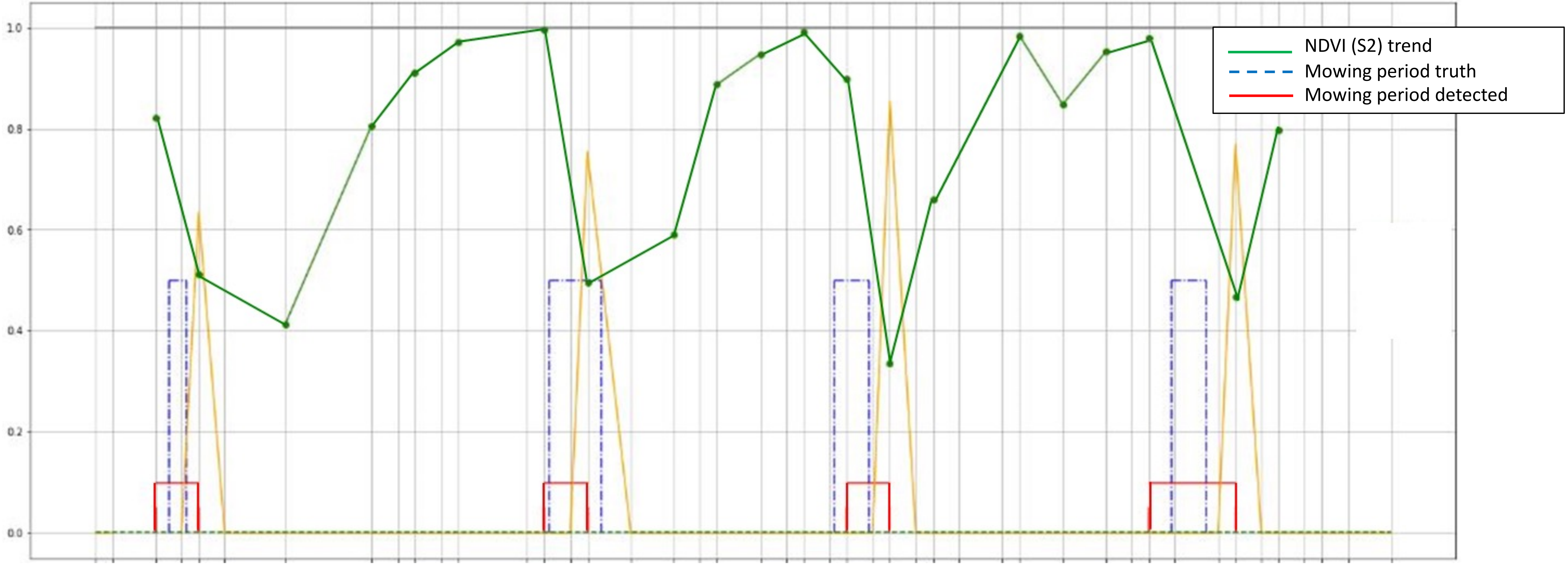




NDVI Time Series

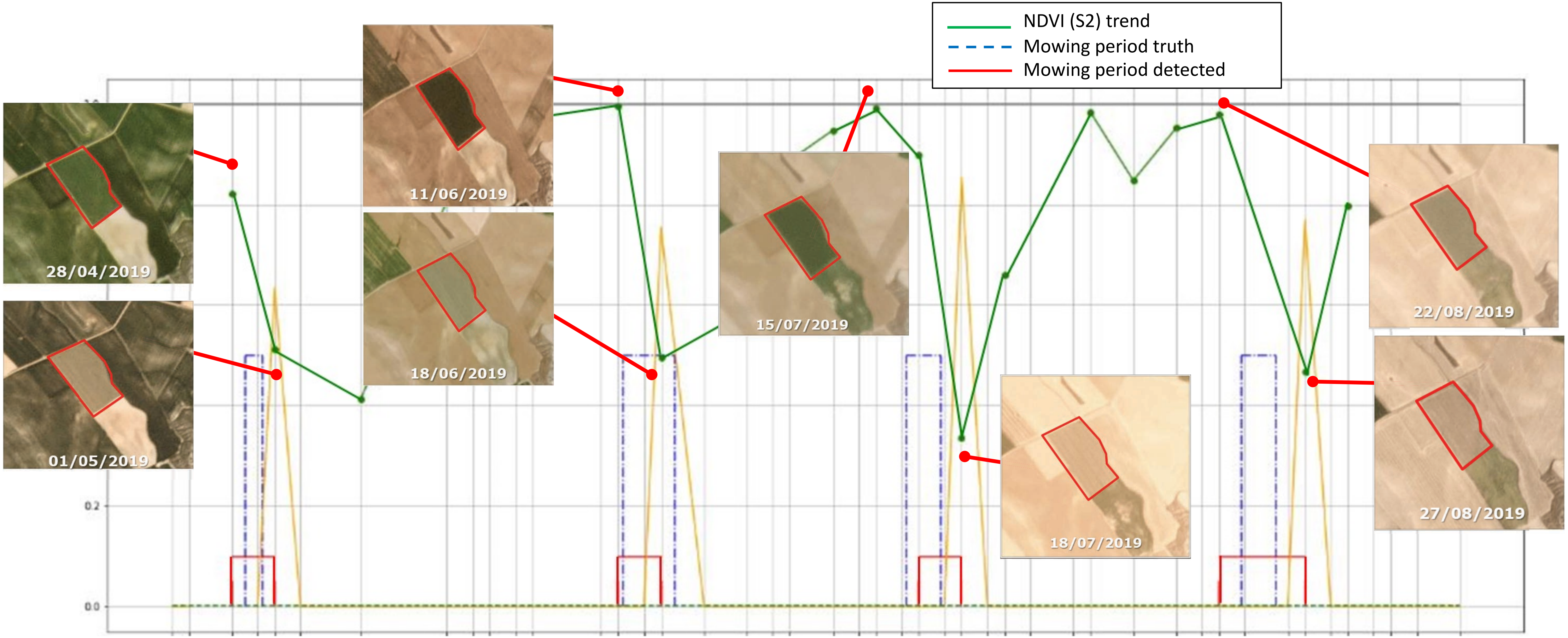
JRC Technical Reports, DS/CDP/2018/18 & DS/CDP/2017/03 revising R2014/809

Mowing Detection Example in Spain - Castilla y Leon



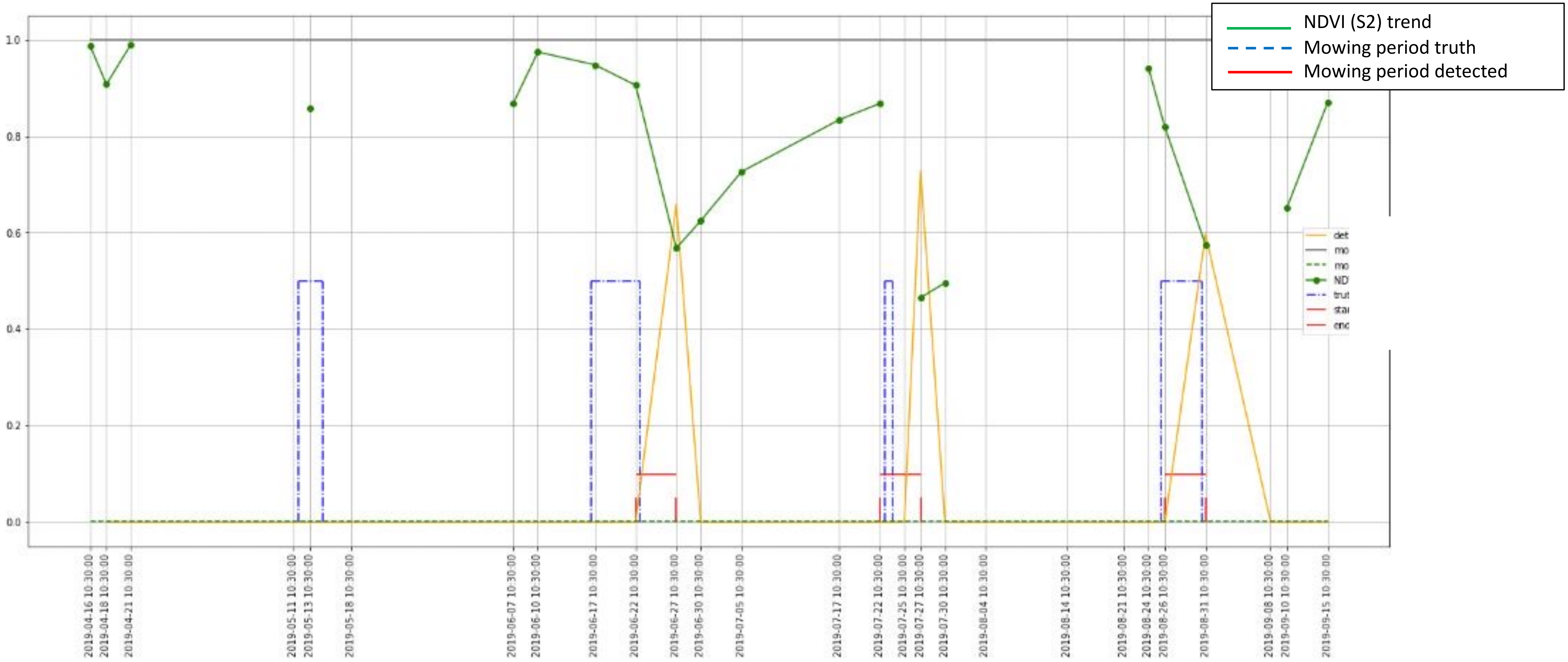
NDVI time series & mowing detection on a selected parcel

Mowing Detection Example in Spain - Castilla y Leon



NDVI time series & mowing detection on a selected parcel

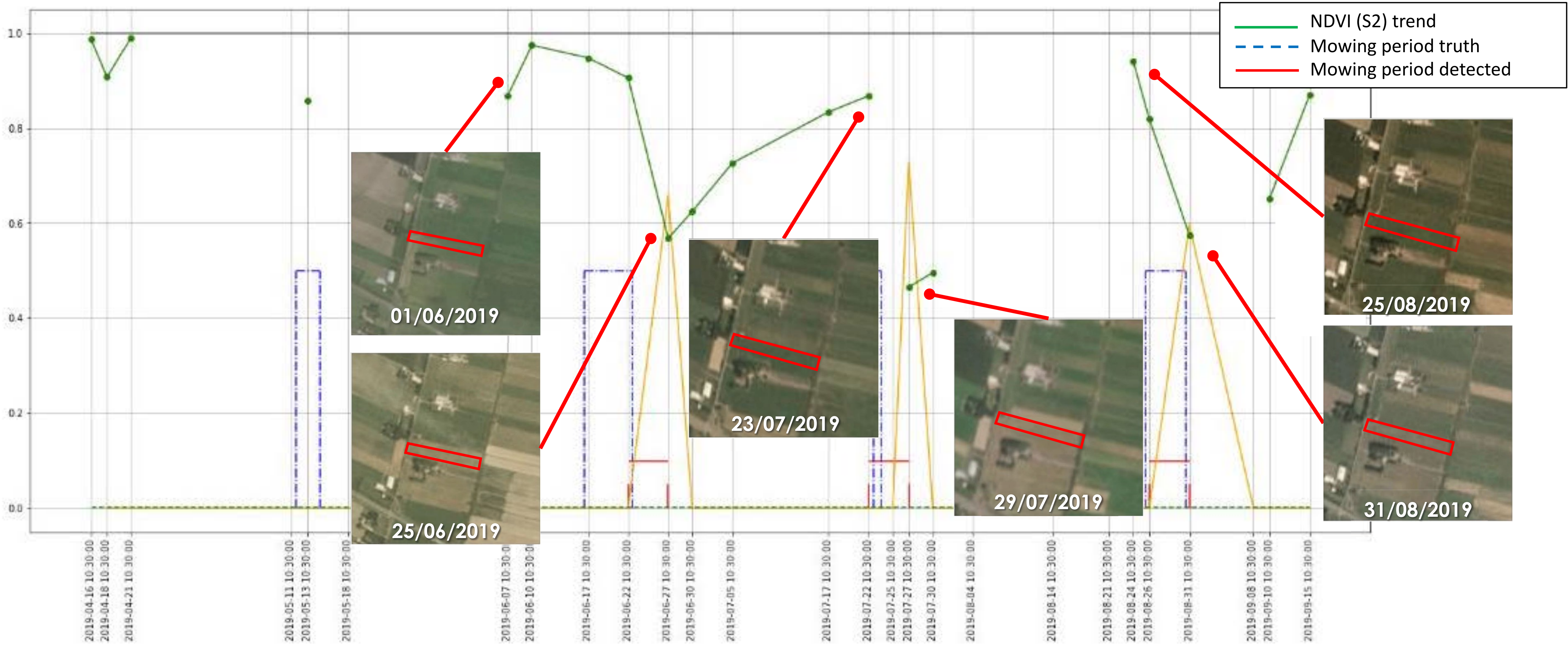
Mowing Detection Example in the Netherlands



NDVI time series & mowing detection on a selected parcel

sen4cap common agricultural policy
UCL Université catholique de Louvain
SINERGISE
gisat
e-geos AN ASI / TELESPAZIO COMPANY
CS ROMÂNIA

Mowing Detection Example in the Netherlands



NDVI time series & mowing detection on a selected parcel

Mowing Detection Example in the Netherlands
Agricultural Practices from SAR Metrics

Sentinel-1 SAR coherence time series & mowing detection on a selected parcel

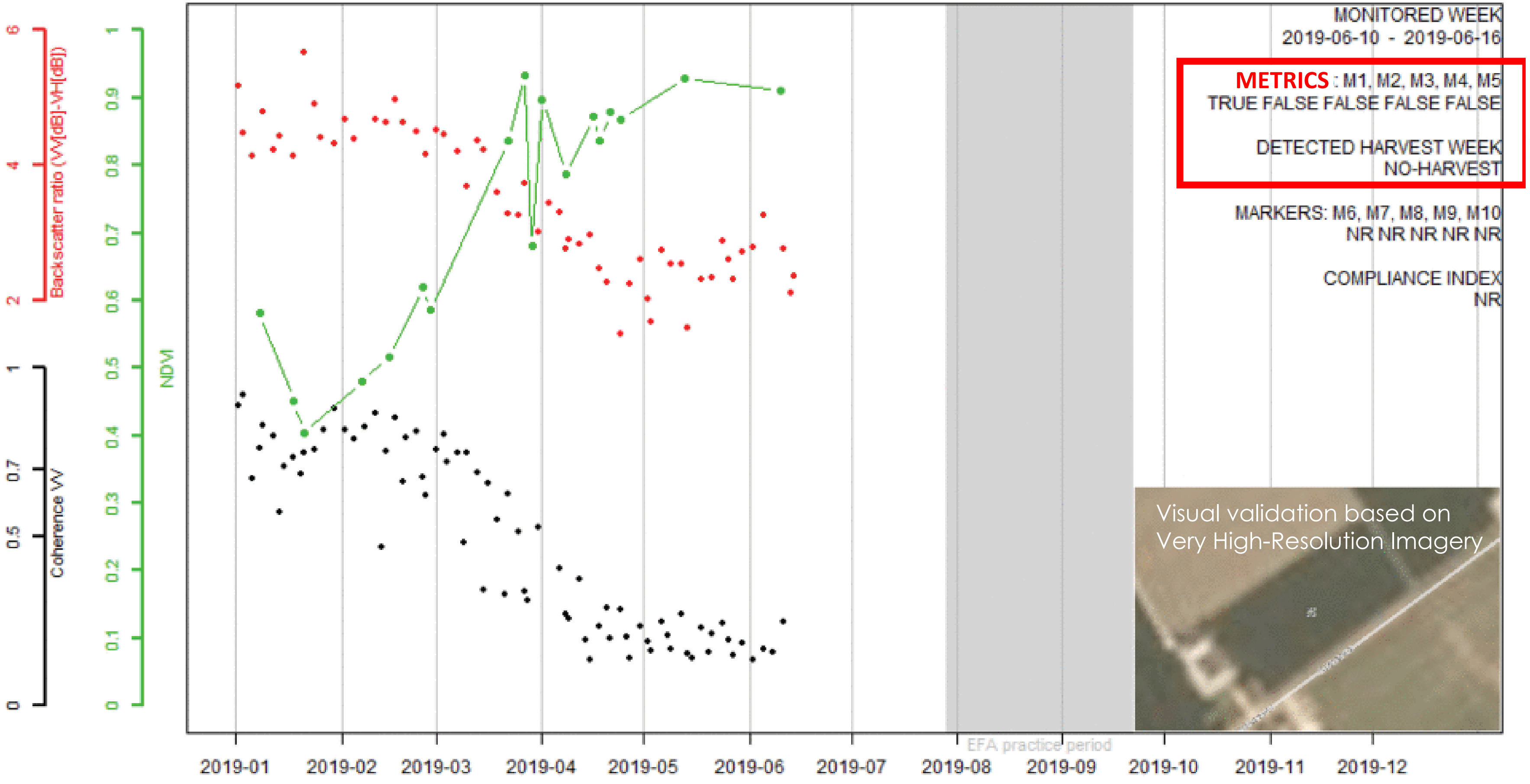
Mowing Detection Example in the Netherlands
Agricultural Practices from SAR Metrics

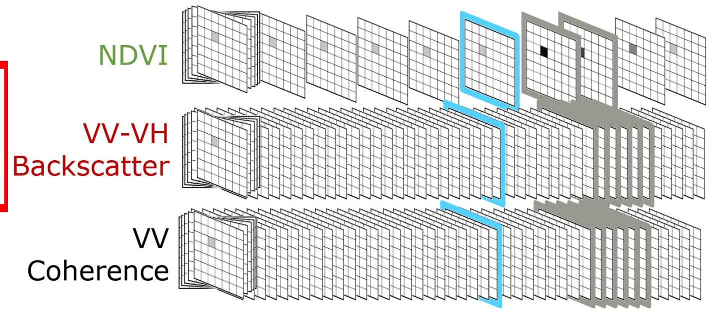
Sentinel-1 SAR coherence time series & mowing detection on a selected parcel

sen4cap common agricultural policy · UCL Université catholique de Louvain · SINERGISE · gisat · e-geos · CS ROMÂNIA

Harvest Date Detection Based on Five Metrics Computed from Three Parallel Time Series Images

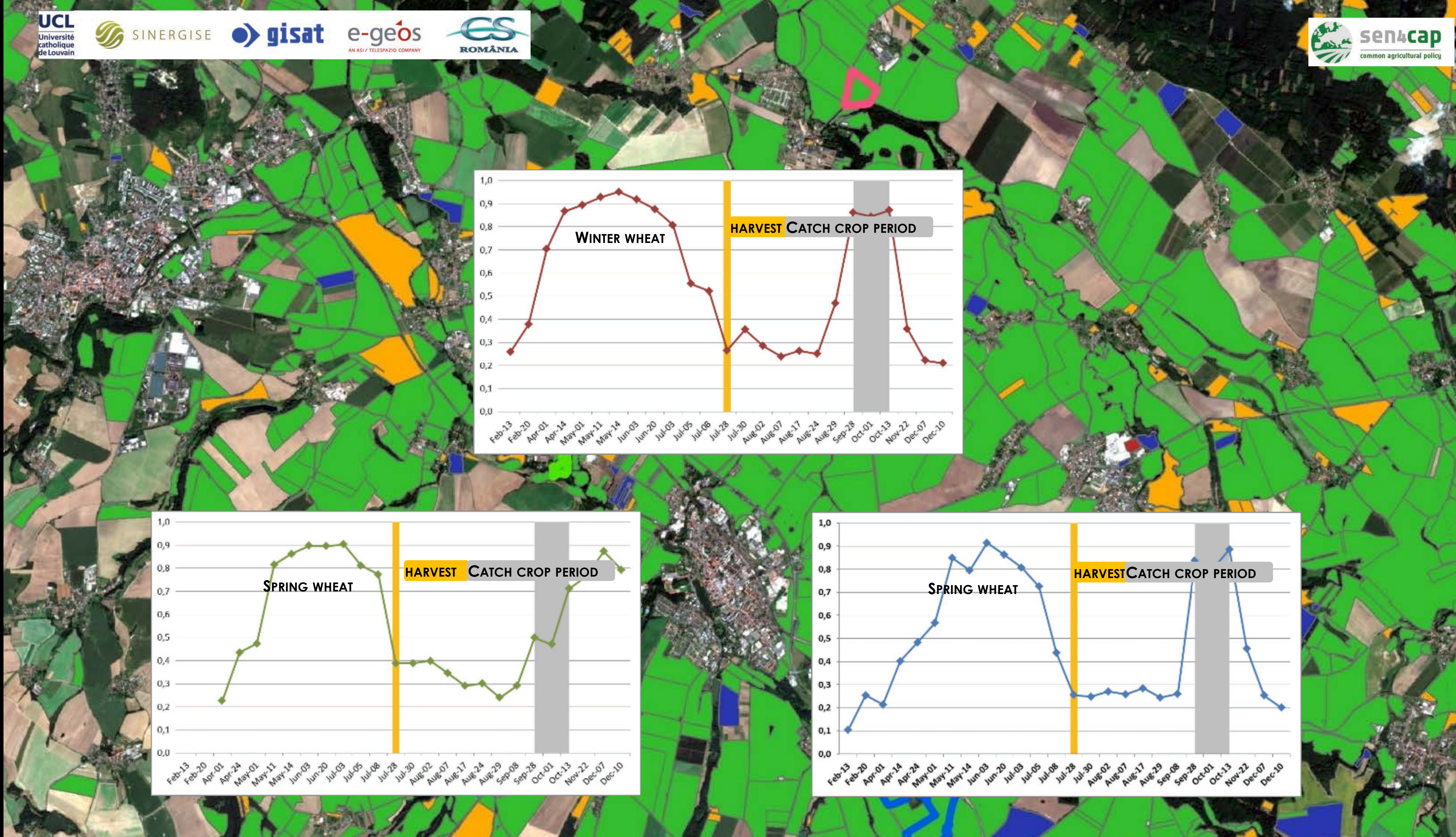
Harvest and Cover Crop Monitoring





Harvest detected between 29 July and 4 August.

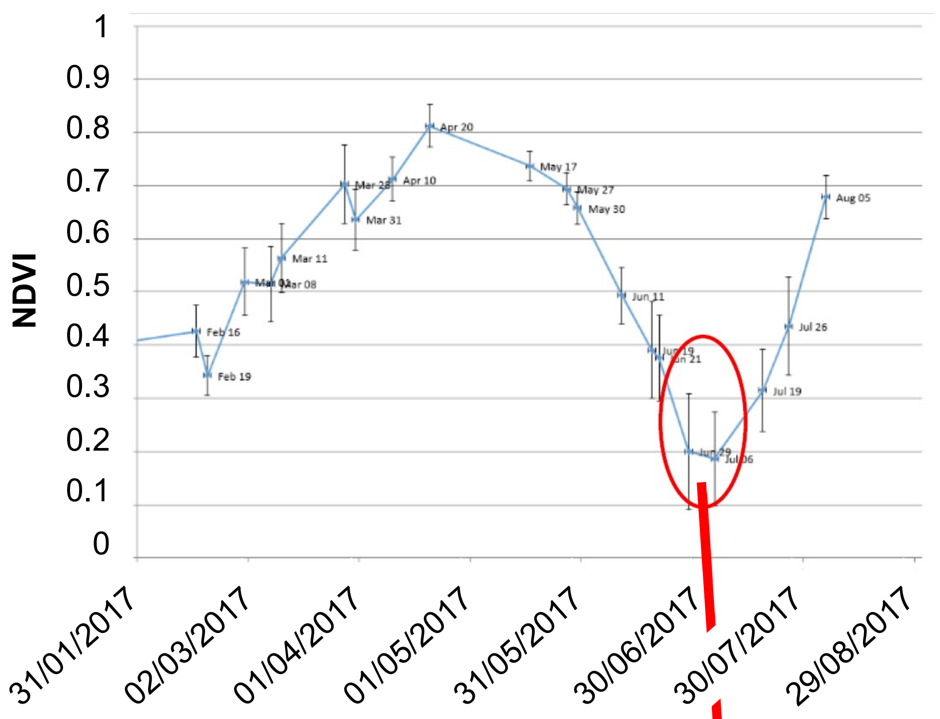
Cover crop in place during the mandatory period and not harvested before its end.


UCL Université catholique de Louvain
SINERGISE
gisat
e-geos
AN ASI / TELESPAZIO COMPANY
CS ROMÂNIA
sen4cap
common agricultural policy
Winter wheat
harvest
Catch crop period
1,0
0,9
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0,0
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

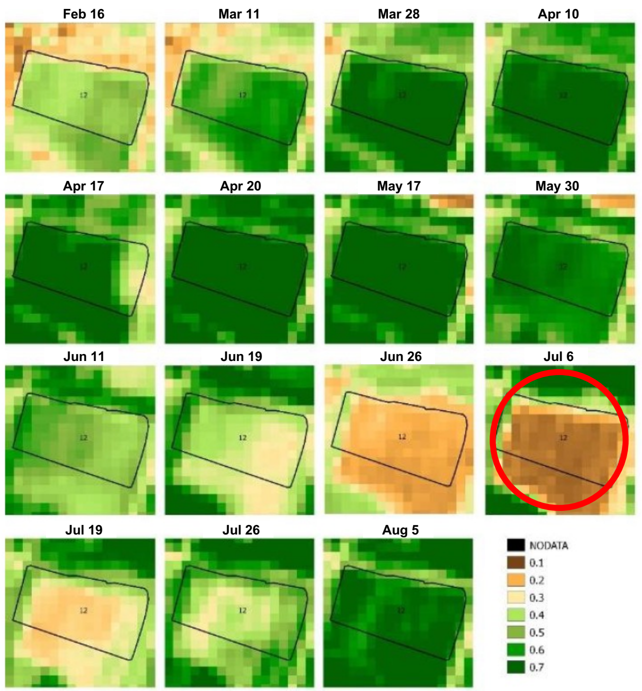
Detection of Ploughing/Tillage Events

NDVI Time Series on a Selected Parcel of Cereals

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



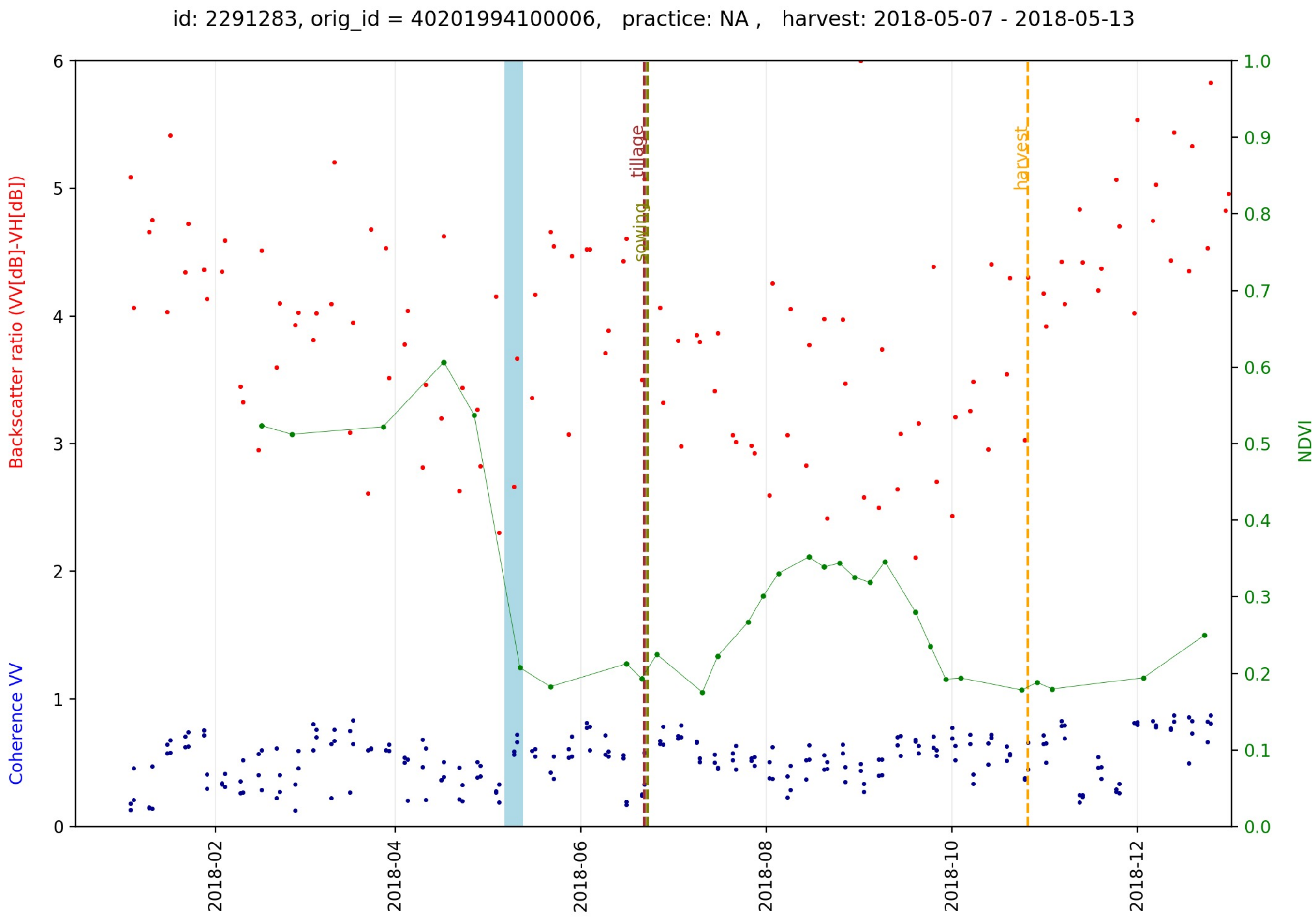
Ploughing immediately after the harvest



NDVI Time Series

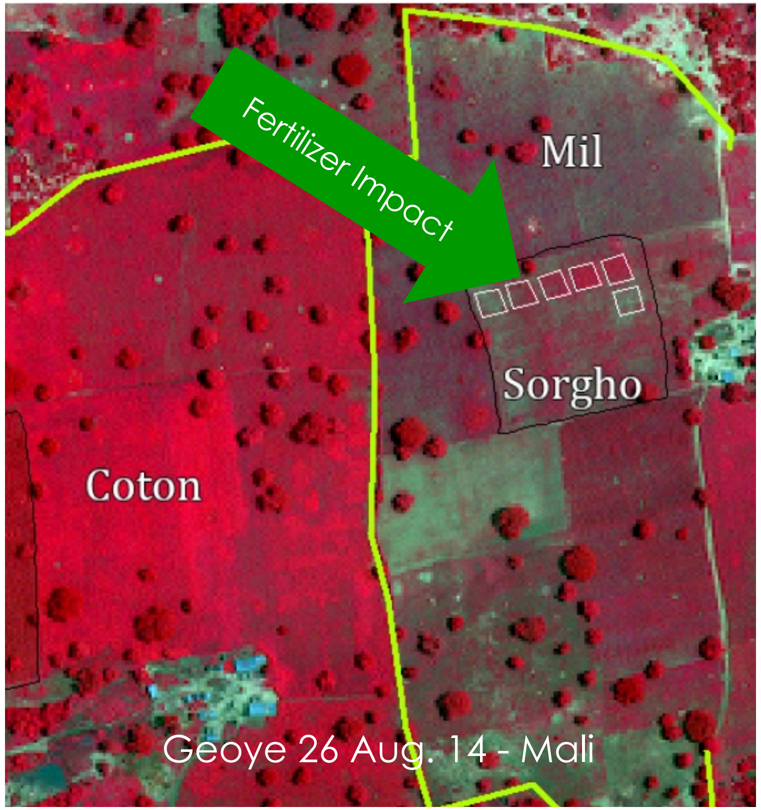
Tillage Detection from Optical NDVI/LAI and SAR Backscatter/Coherence Time Series

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.

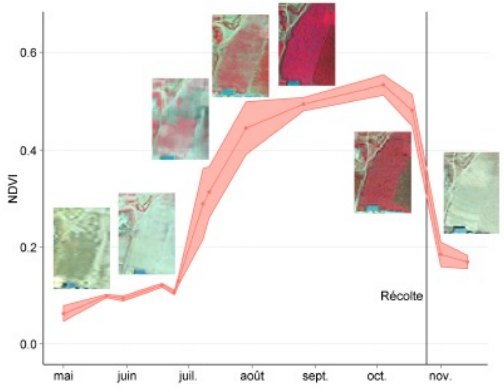


Monitoring Agricultural Practices in Smallholder Farming Systems with 1(0) m Time Series – Fertilization in Mali

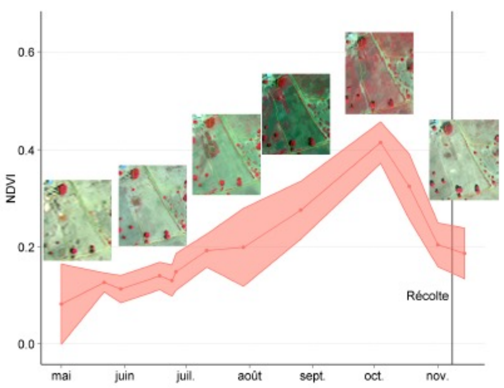
Exploiting (deca)metric time series to capture crop development signals including spatial field heterogeneity (sorghum for 3 different fields)



2-m resolution time series captured large field heterogeneity

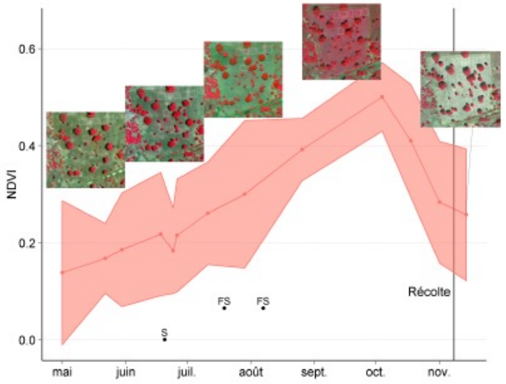


a) Parcel close to the village, homogeneous and early cropping



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

SORGHUM FIELDS



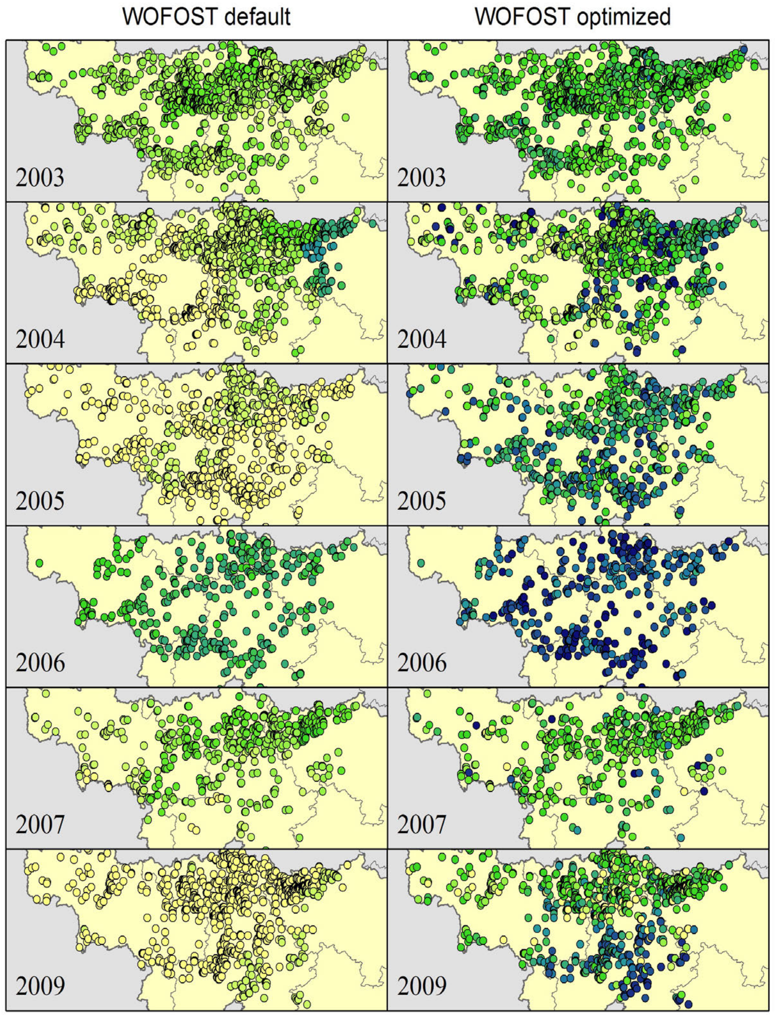
c) Parcel close to plateau, catching-up, for production (S = sowing, FS = Fertilization of STARS plots)

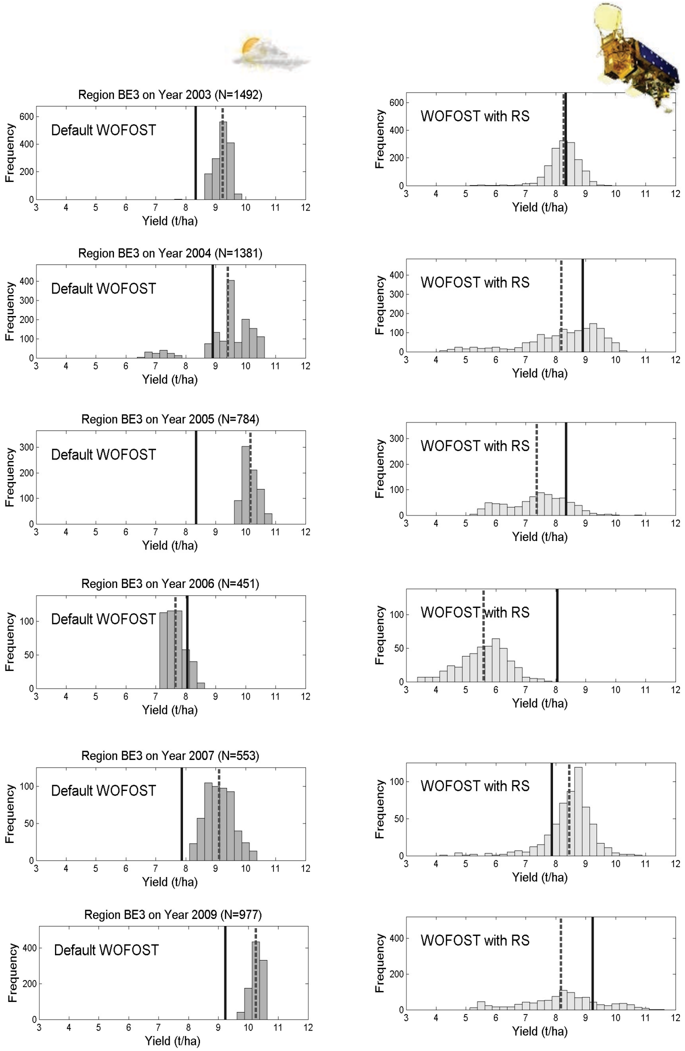
Gates Fundation – STARS Project
Blaes et al., 2016

Section 5: Biophysical Variables Supporting Yield Estimation

Yield Estimations

- < 5.0 t/ha
- 5.0 - 5.5 t/ha
- 5.5 - 6.0 t/ha
- 6.0 - 6.5.0 t/ha
- 6.5 - 7.0 t/ha
- 7.0 - 7.5 t/ha
- 7.5 - 8.0 t/ha
- 8.0 - 8.5 t/ha
- 8.5 - 8.5 t/ha
- 9.0 - 9.5 t/ha
- 9.5 - 10.0 t/ha
- > 10. t/ha





(Duveiller et al., 2010)

State of the Art

- EO-based yield estimation approaches at high resolution are mostly under development.
  - The use of EO technology currently remains limited to coarse spatial resolution data (> 250 m) and inability to capture a crop-specific signal in most regions of the world.
  - EO biophysical variables to assess crop condition and crop condition anomalies - e.g.: https://cropmonitor.org/

- Copernicus operational HR Sentinel mission is changing the game. New opportunities and also new challenges.

- Main Methods:
  - **Empirical regression using simple VI/BV-based yield predictors**
  - Semi-empirical Monteith-based models (plant modelling and light use efficiency concept)
  - Mechanistic crop model and data assimilation

Empirical Relation Using Simple VI/BV - Based Yield Predictors

Since the early 1980s – VI or LAI have been used as seasonal biomass proxies to estimate crop yield

Tucker et al. 1980 reported that the **NDVI for a five-week period** (stem elongation to anthesis) explained ~64% of wheat yield variation. Pinter et al. 1981 **summed the NDVI** for wheat and barley (heading to full senescence) explaining about 88% of the yield.

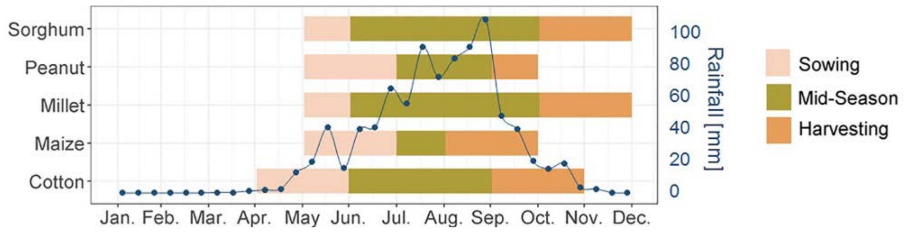
In recent years, thanks to the availability of satellite data, many applications have been developed using empirical relationships between yields and various VI's/BV's.

Becker-Reshef et al. (2010) used the **maximum NDVI from MODIS** and built a generalized regression model for forecasting winter wheat yields. Franch et al. (2015) further improved this approach by **adjusting NDVI before the peak date using growing degree day** (GDD) information for earlier prediction.

Burke and Lobell (2017) and Lambert et al. (2018) demonstrated the added-value of **(very) high resolution imagery** for smallholder agriculture by linking field data with the **green chlorophyll vegetation index** or the **maximum LAI.**

Despite the local validity and limited applicability to different areas or years, these methods are **simple and effective** if ground survey samples are representative and accurate.

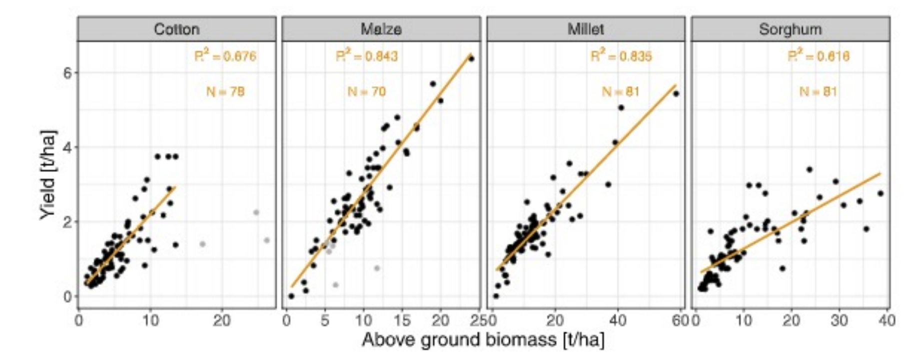
Empirical Regression Relating VIs/BVs with Yield
An Example Linking Yield and Max (LAI) in Mali

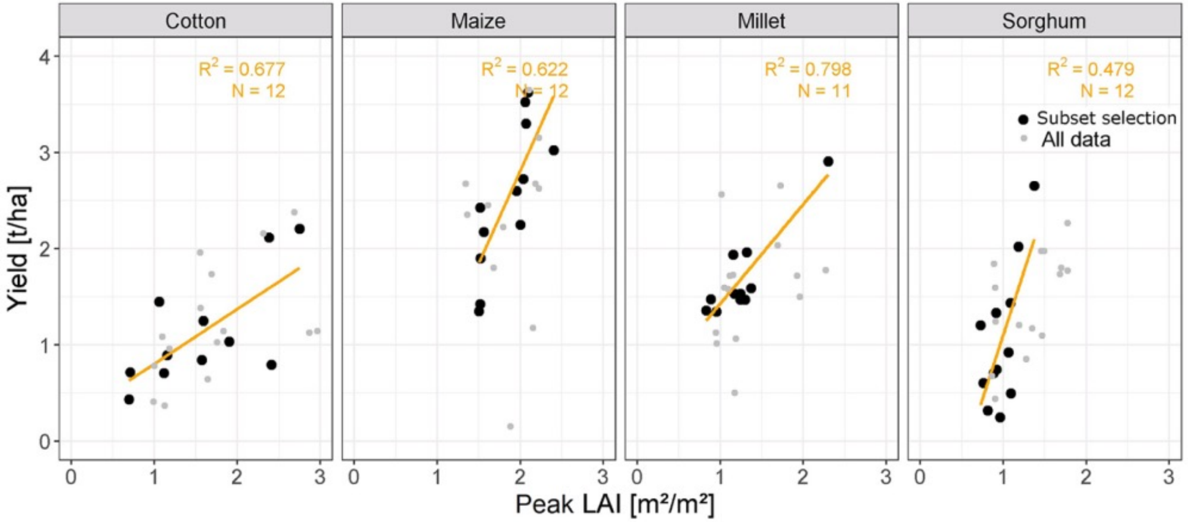


Lambert et al., 2018

Crop specific yield linear regressions between max (LAI) and yield calibrated on a homogeneous subset of field data (black dots)

Ground Data: Yield is strongly linked with Above Ground Biomass (high R^2 for crop-specific linear regressions)





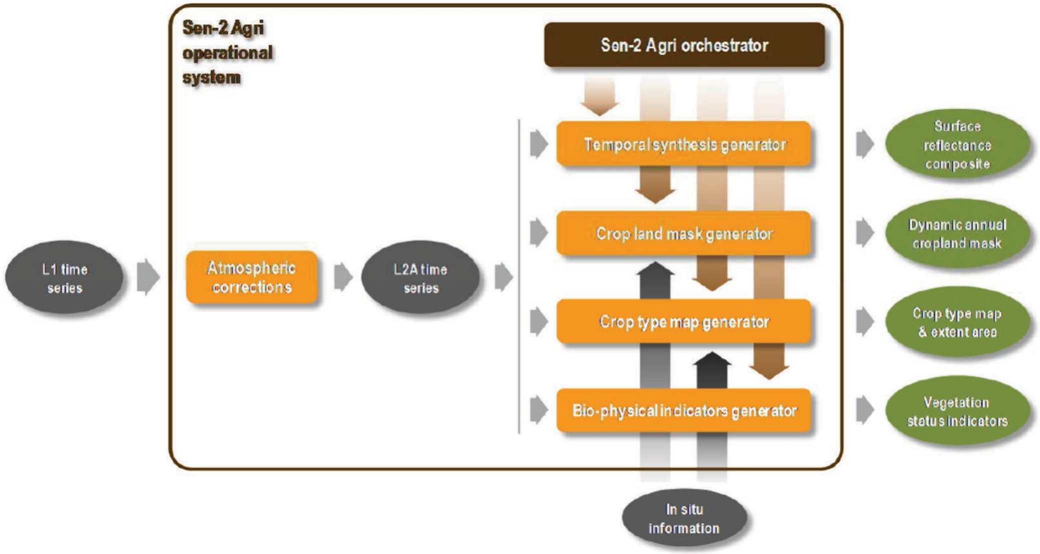
EO data – and more specifically, biophysical variables – can be used to do more than assess crop conditions. They can be a **reliable yield proxy** because we are working at high spatial resolution, and thus we can be **crop-specific**.

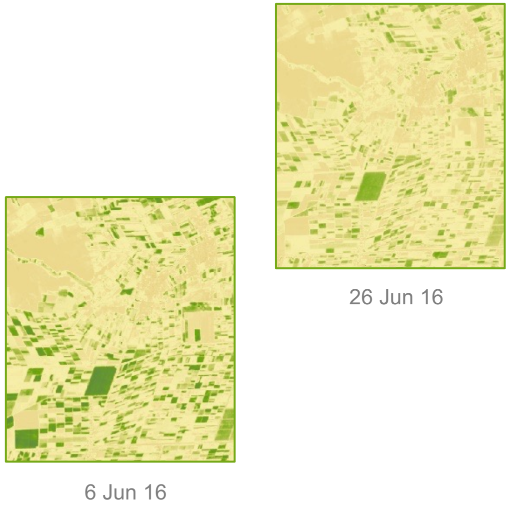
Section 6: Open-Source Toolboxes: ESA Sen2-Agri/Sen4CAP/Sen4Stat

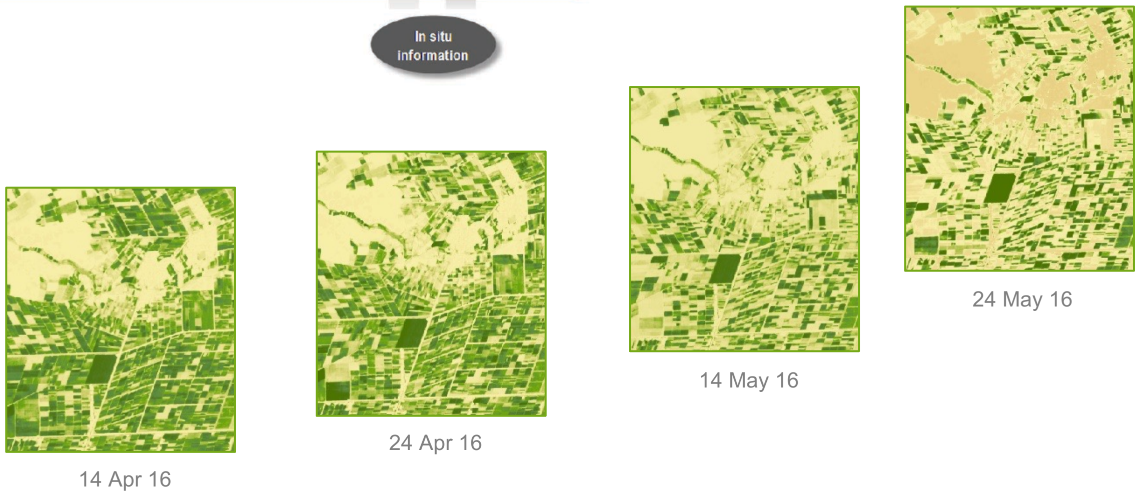
Sen2-Agri
Sentinel-2 for Agriculture

sen4cap
common agricultural policy

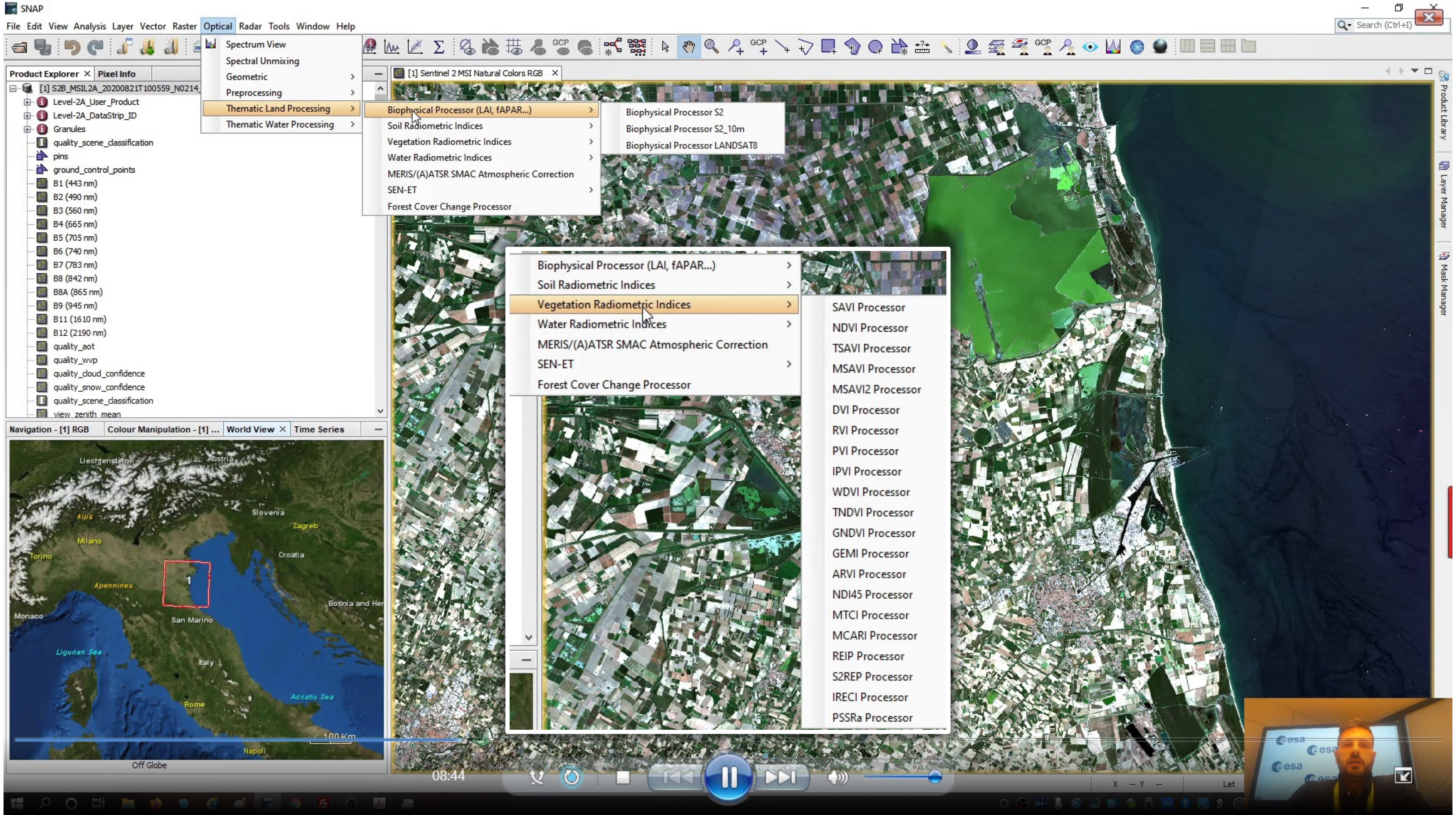
Sen4Stat
Sentinels for Agricultural Statistics



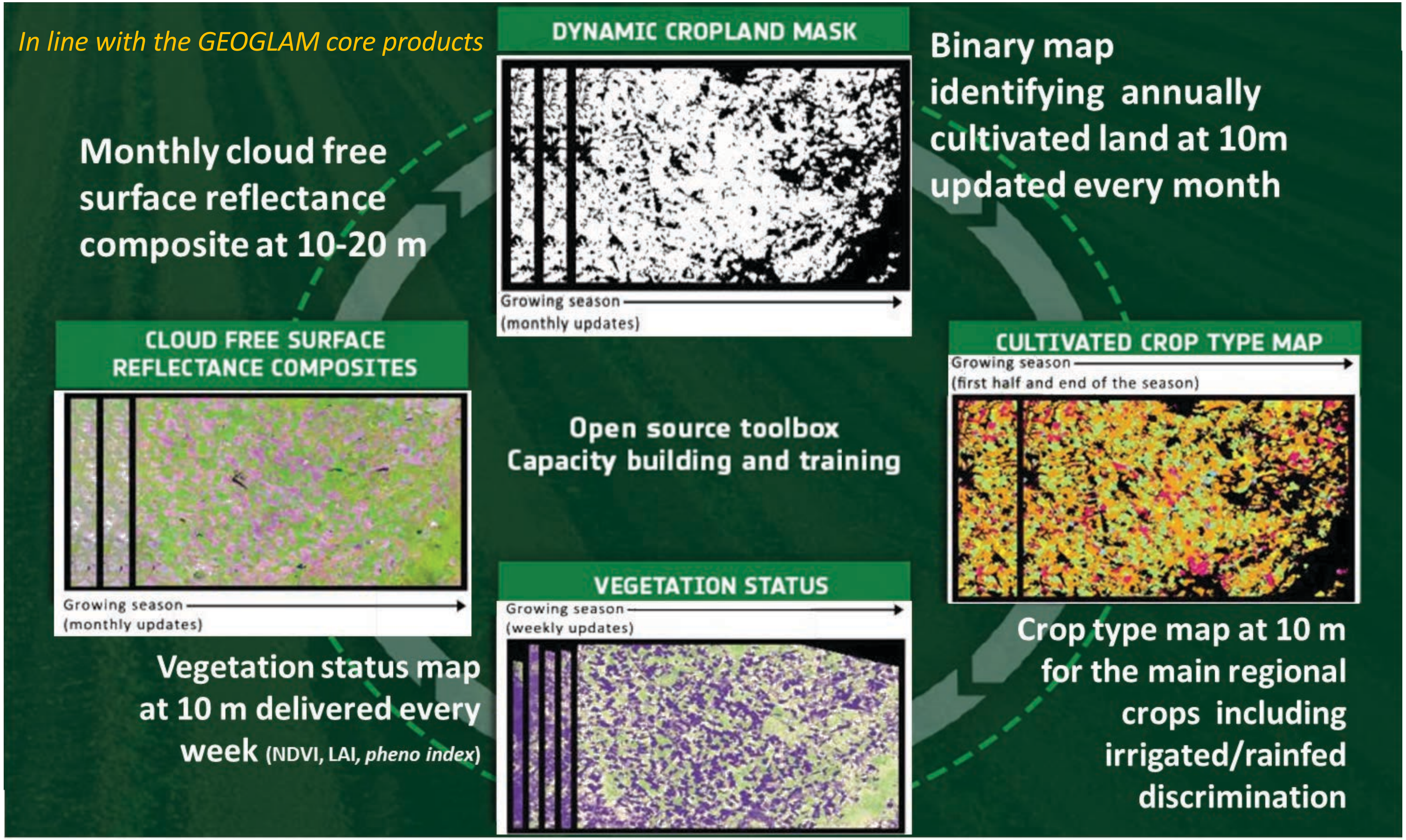




Spectral Indices & Biophysical Variables Calculated with SNAP
See From Session 2

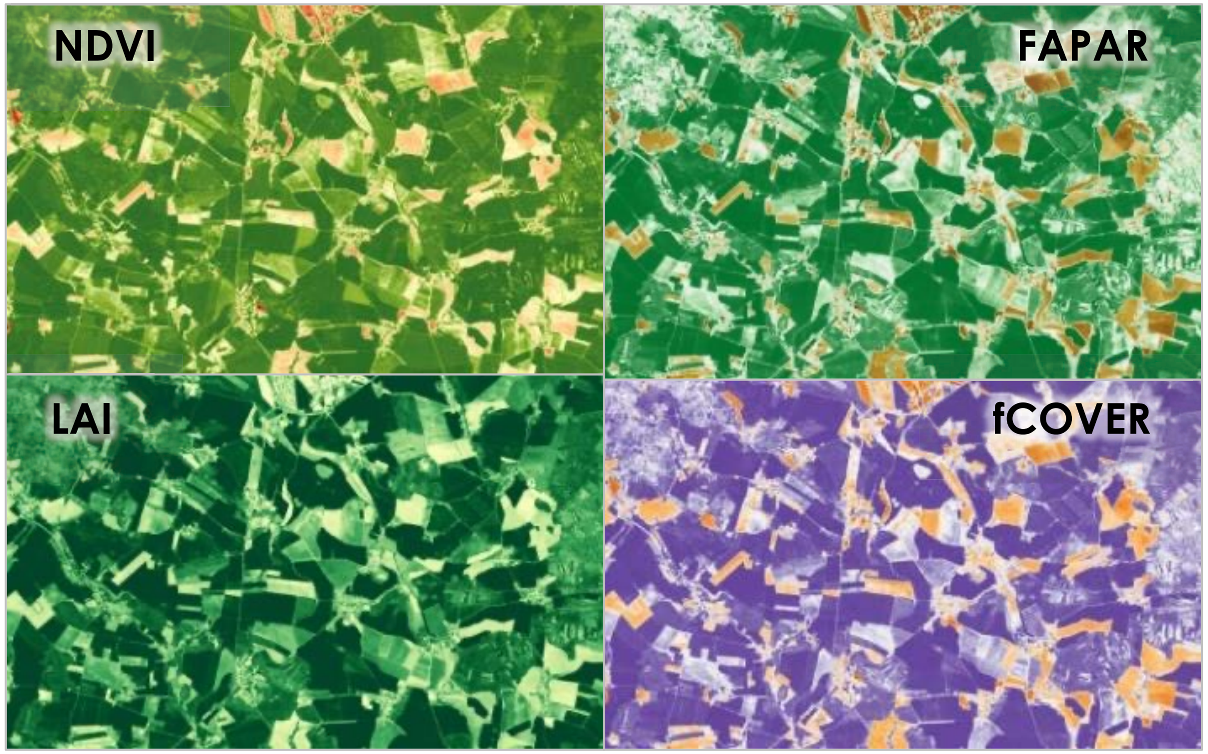


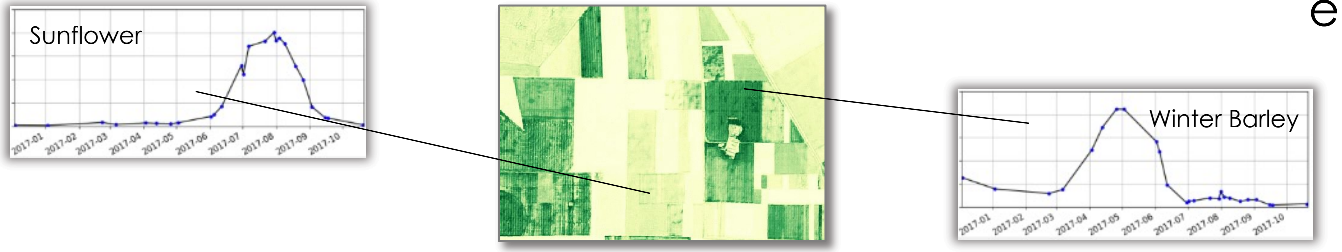
Sen2-Agri Top Priority: Automatic Delivery of 4 Agricultural Products Throughout the Season Using S2 & L8 Images



Sen2-Agri

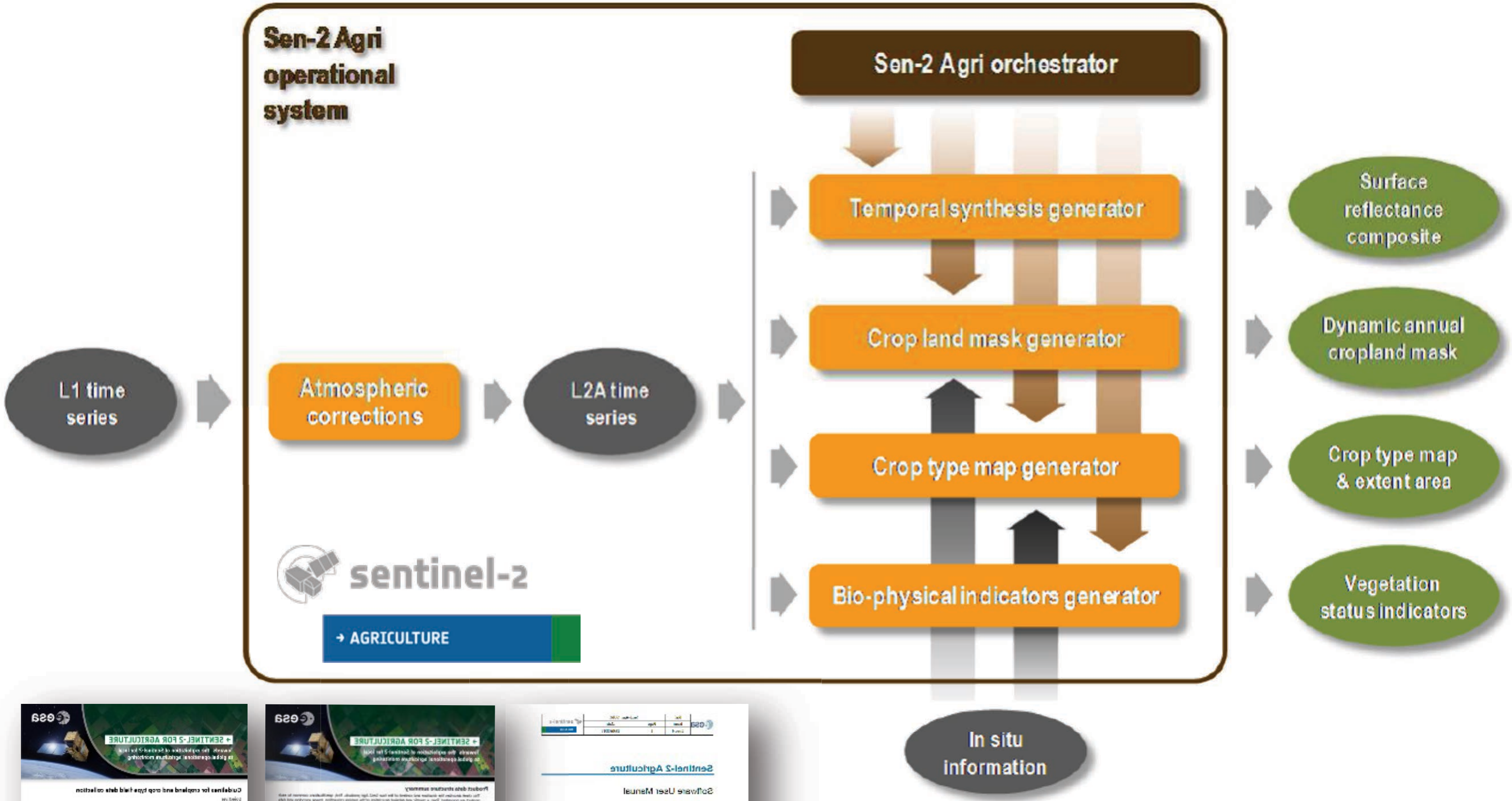
Vegetation Status Map at 10 m: 4 Variables to Describe the Crop Growing Cycle

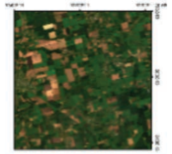




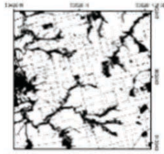
- **NDVI (Normalized Difference Vegetation Index):** The most popular indicator for monitoring vegetation; already widely used in operational applications
- **LAI (Leaf Area Index):** The size of the interface that is used for the exchange of energy and mass between the canopy and the atmosphere
- **FCover (fraction of Vegetation Cover):** Fraction of the ground covered by green vegetation
- **FAPAR: (fraction of Absorbed Photosynthetically Active Radiation)** by the green and living elements of the canopy

Sen2-Agri System: An Open-Source System Demonstrated at Full Scale in NRT or Off-Line, Running Locally or in the Cloud

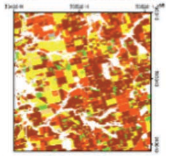




Monthly cloud free surface reflectance composite at 10-20 m



Cropland mask at 10m updated every month



Crop type map at 10 m for the main regional crops

Vegetation status map at 10 m delivered every week (NDVI, LAI, *fCover*, *fAPAR*)

Documented and downloadable at http://www.esa-sen2agri.org/resources/software/

UCLouvain CESBIO CS ROMÂNIA Sen2-Agri

Sen2-Agri System: Simple Parameterization for Field Data Collection

Before the Monitoring Period	Monitoring Period

System Initialization

Start of the Season → **End of the Season**

Sen2-Agri System: Main Parameters Settings

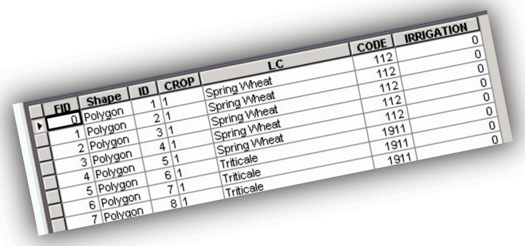
Area of Interest	Shapefile to be uploaded
Monitoring Period	Start and end dates to be defined
S2 or S2 + L8	To be selected
Other Parameters	…

Mali Stratification (PIRT)

Agro-ecological strata in Ukraine

Sen2-Agri System: Field Campaigns

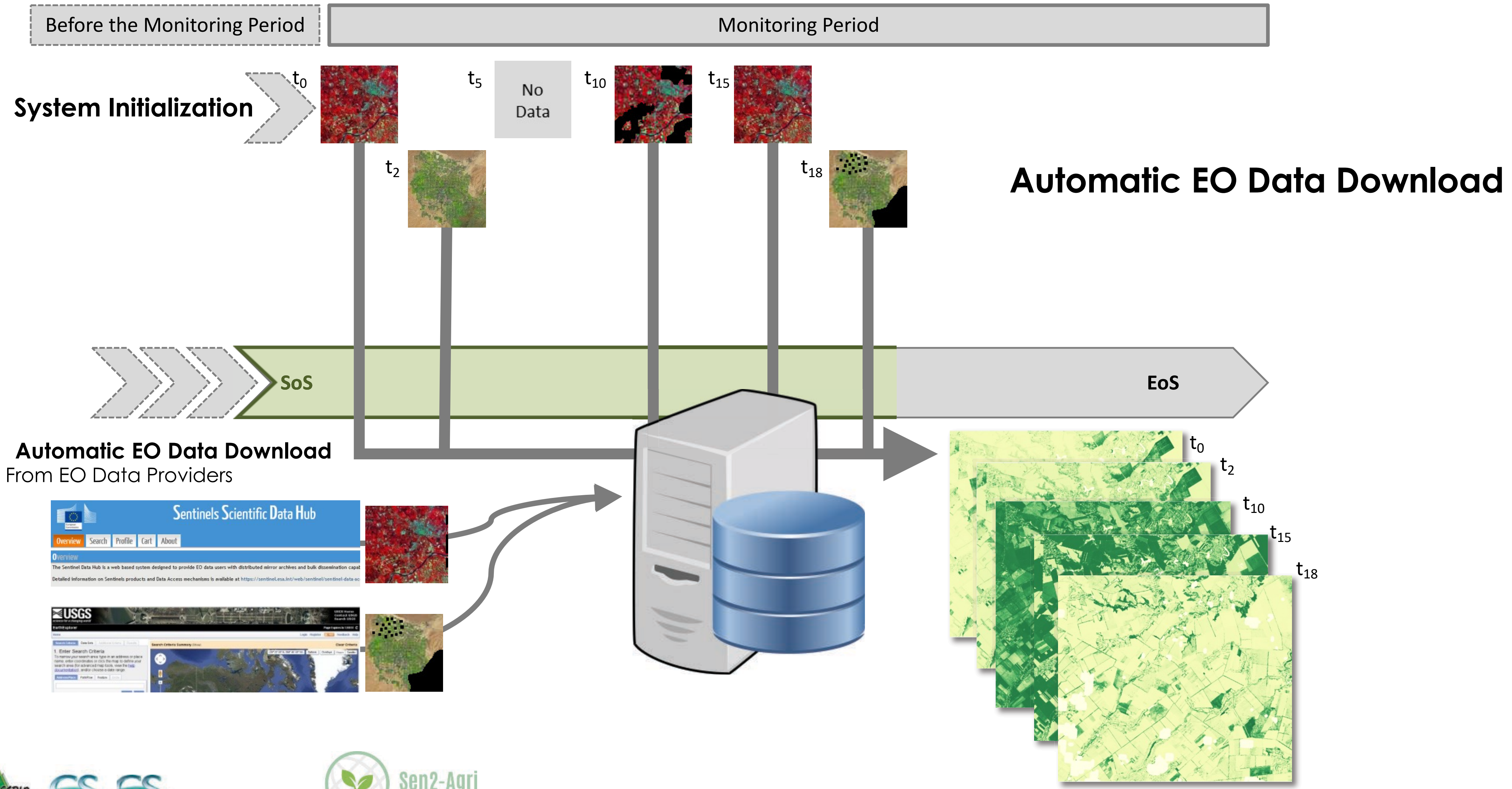
Sampling Design	Stratification and Sampling
Field Visit	In situ data collection – early survey
	In situ data collection – mid-season survey
Data Upload	Field data quality control and formatting



FID	Shape	ID	CROP	LC	CODE	IRRIGATION
0	Polygon	1	1	Spring Wheat	112	0
1	Polygon	2	1	Spring Wheat	112	0
2	Polygon	3	1	Spring Wheat	112	0
3	Polygon	4	1	Spring Wheat	112	0
4	Polygon	5	1	Spring Wheat	112	0
5	Polygon	6	1	Triticale	1911	0
6	Polygon	7	1	Triticale	1911	0
7	Polygon	8	1	Triticale	1911	0

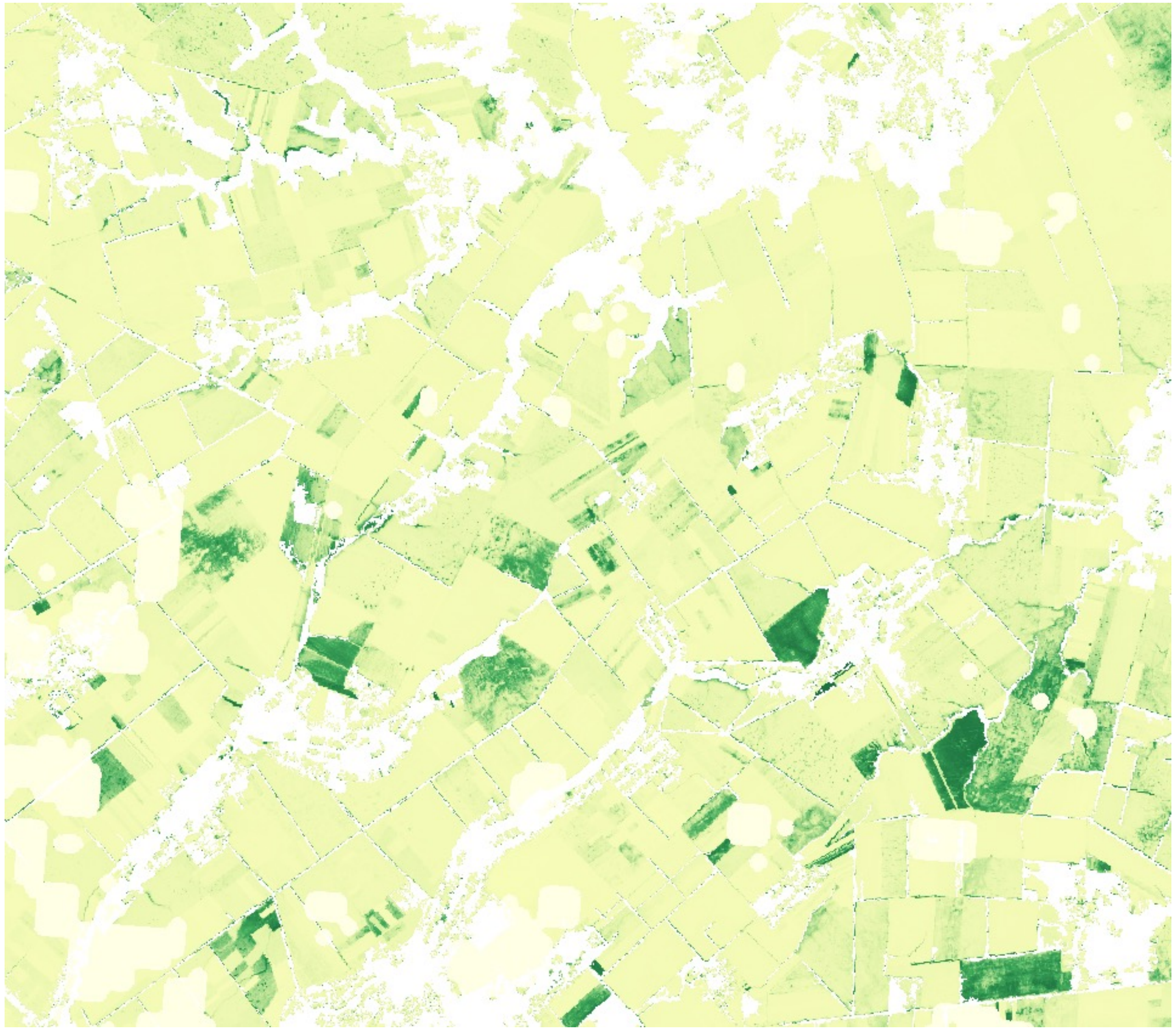
UCLouvain CESBIO CS ROMÂNIA Sen2-Agri

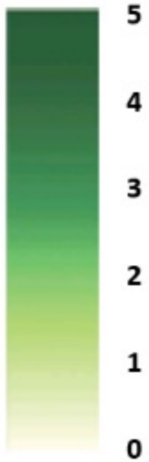
System Operation for Crop Growth Monitoring in NRT



Large Scale - Nationwide - Cropland Monitoring
LAI Time Series at Pixel Scale (10 m) - Ukraine

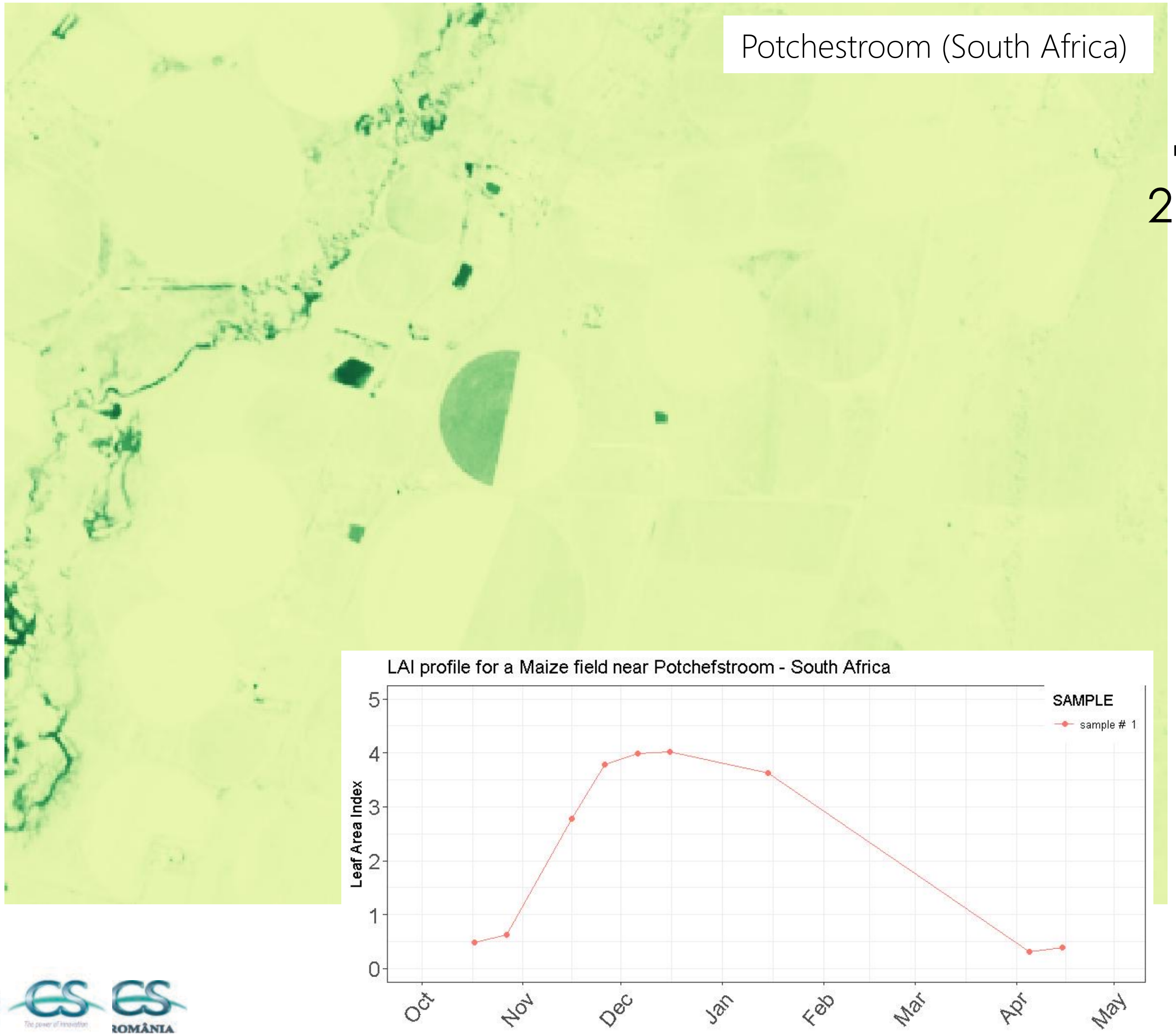
18 Feb. 16
18 Apr. 16
28 Apr. 16
17 Jun. 16
17 July 16
08 Sep. 16

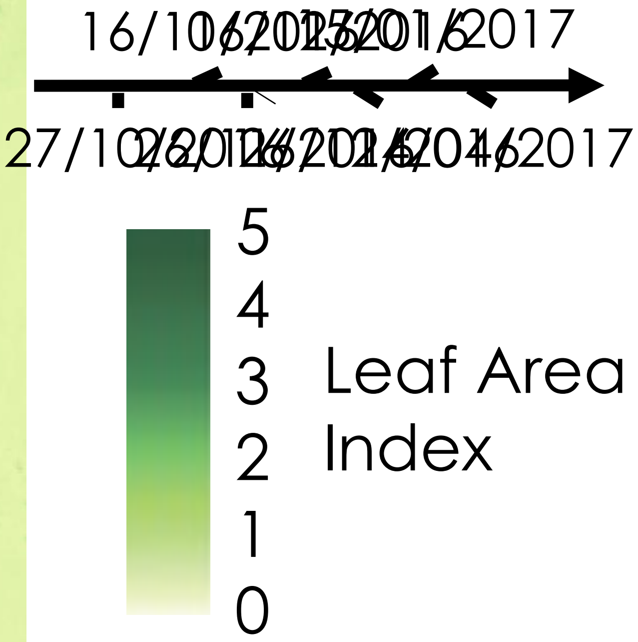




Leaf Area Index Values

Large Scale - Nationwide - Cropland Monitoring
LAI Time Series at Pixel Scale (10 m) - South Africa





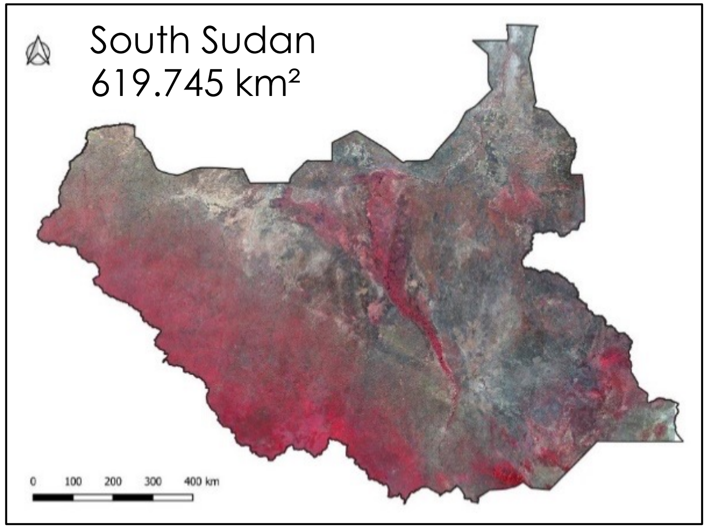
Large Scale - Nationwide – Crop-Specific Monitoring
LAI Time Series at Pixel Scale (10 m) - Mali

ICRISAT
INTERNATIONAL CROPS RESEARCH INSTITUTE FOR THE SEMI-ARID TROPICS

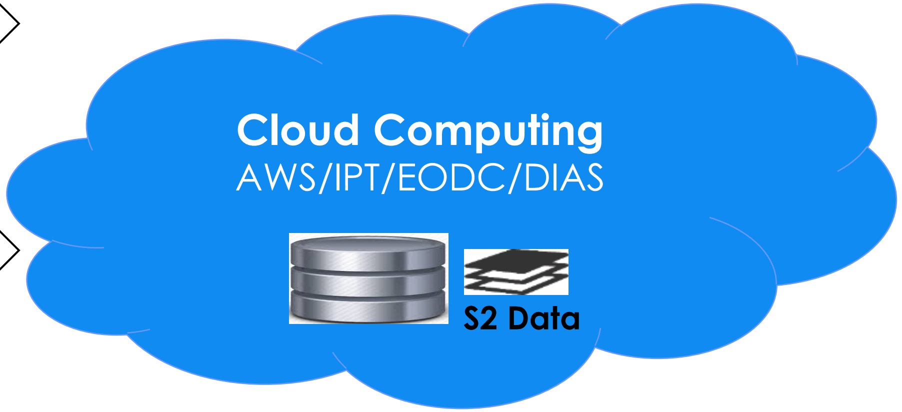
Sen2-Agri

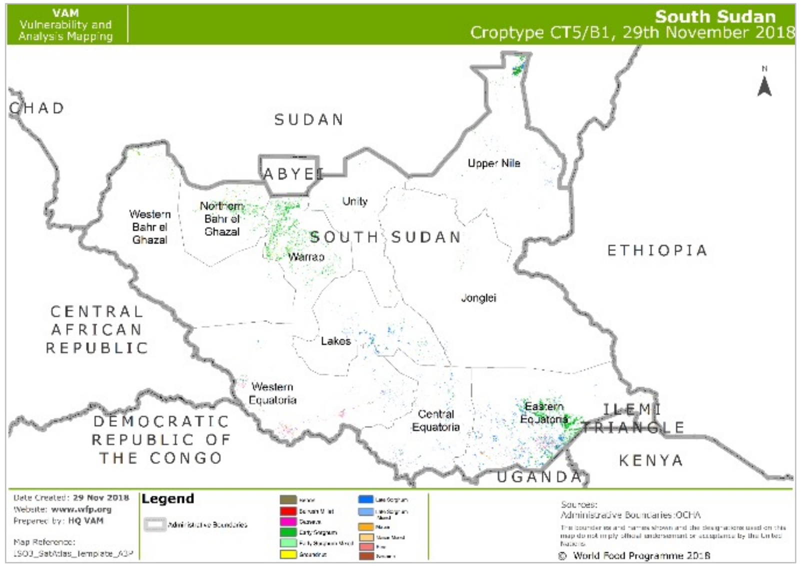
Sen2Agri System Implemented on Commercial Cloud Infrastructure for Operational NRT Services

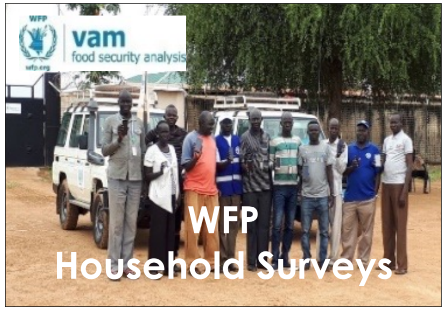
Open-Source



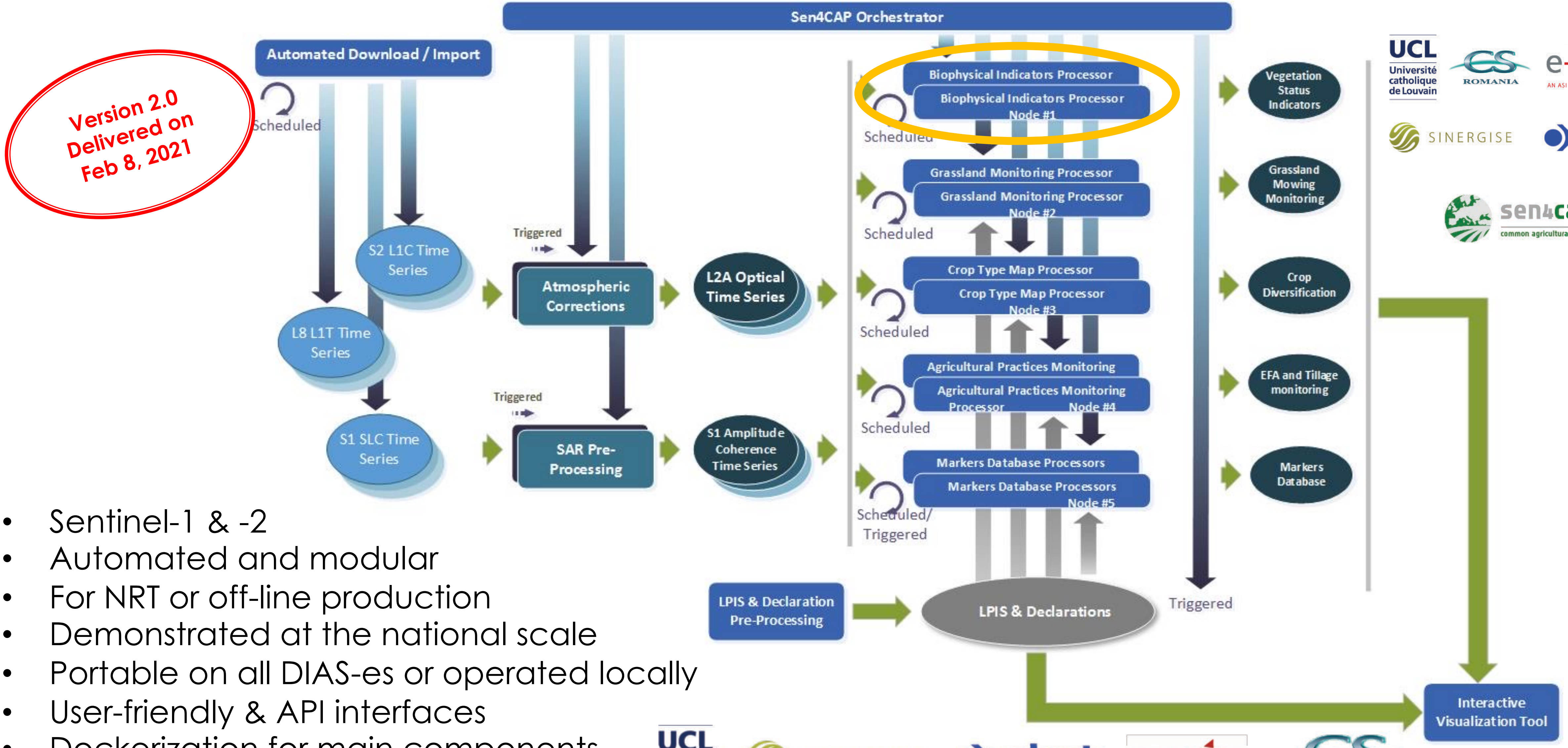
In Situ
Data with GeoODK





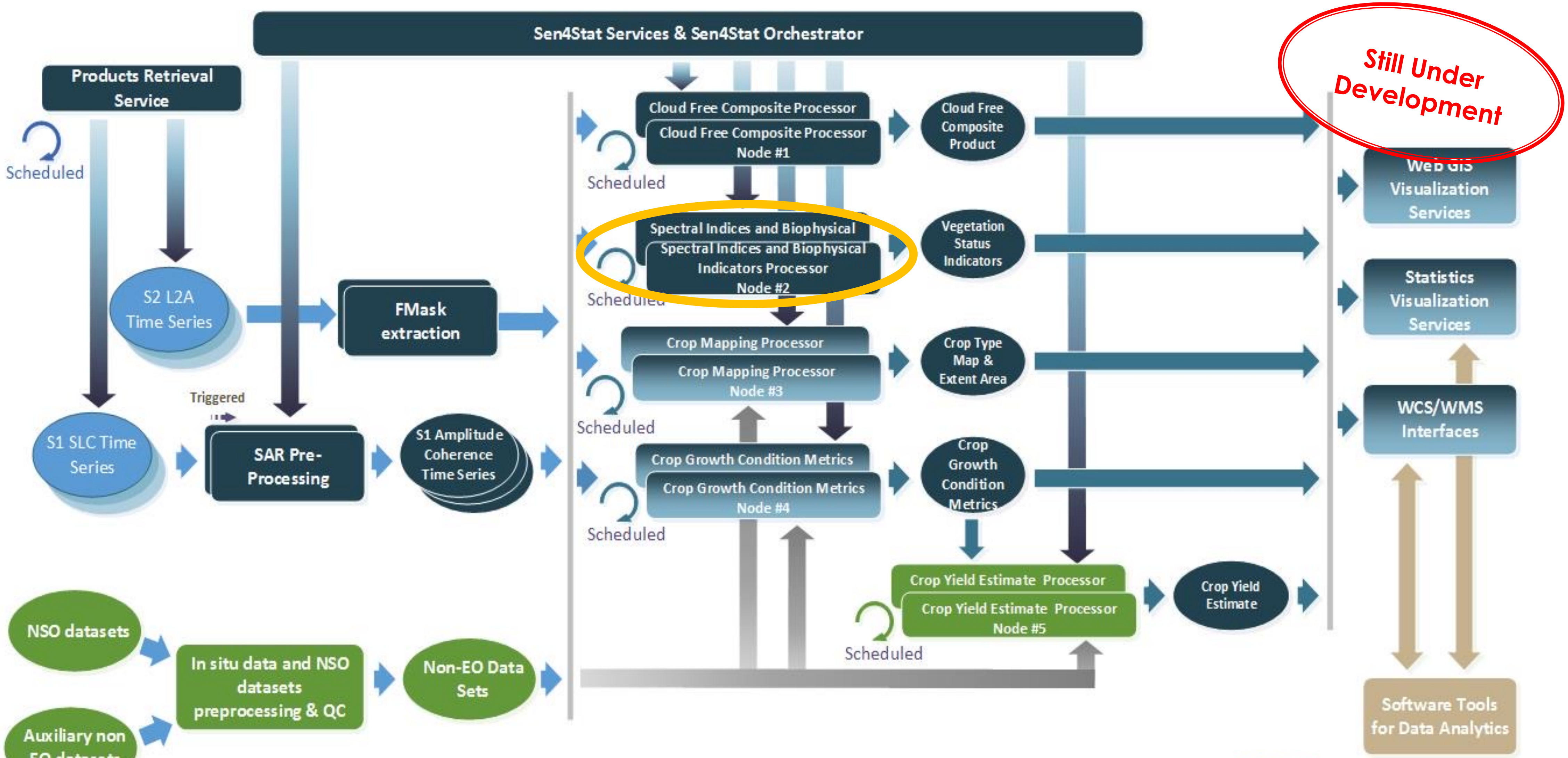


Sen4CAP – An Open-Source System, Object-Based and Combining Sentinel-1 and Sentinel-2



- Sentinel-1 & -2
- Automated and modular
- For NRT or off-line production
- Demonstrated at the national scale
- Portable on all DIAS-es or operated locally
- User-friendly & API interfaces
- Dockerization for main components

Sen4Stat – Building on Sen2-Agri and Sen4CAP
Pixel-Based, Sentinel-1 and Sentinel-2, In Situ Data QC Module



Sen4Stat UCLouvain CS ROMANIA CLS

Questions?

- Please enter your questions in the Q&A box. We will answer them in the order they were received.
- We will post the Q&A to the training website following the conclusion of the webinar.

Contacts

- Trainers:
  - Pr. Pierre Defourny: Pierre.Defourny@uclouvain.be
  - Dr. Sophie Bontemps: Sophie.Bontemps@uclouvain.be
- Training Webpage:

  https://appliedsciences.nasa.gov/join-mission/training/english/arset-agricultural-crop-classification-synthetic-aperture-radar-and
- ESA's Toolboxes for Agriculture:
  - Sen2-Agri: http://www.esa-sen2agri.org/
  - Sen4CAP: http://esa-sen4cap.org/
  - Sen4Stat: https://www.esa-sen4stat.org/

Main references

- Blaes, Xavier ; Chomé, Guillaume ; Lambert, Marie-Julie ; Traoré, Pierre Sibiry ; Schut, Antonius G.T. ; Defourny, Pierre, 2016. Quantifying Fertilizer Application Response Variability with VHR Satellite NDVI Time Series in a Rainfed Smallholder Cropping System of Mali. In: Remote Sensing, Vol. 8, p. 531
- Boschetti et al 2018 Testing Multi-Sensors Time Series of Lai Estimates to Monitor Rice Phenology: Preliminary Results. IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium. DOI: 10.1109/IGARSS.2018.8518494
- Boschetti et al. 2017 PhenoRice: A method for automatic extraction of spatio-temporal information on rice crops using satellite data time series. Remote Sensing of Environment. Volume 194, 1 June 2017, Pages 347–365 https://doi.org/10.1016/j.rse.2017.03.029Boschetti 2018
- Cai et al. 2017 "Performance of Smoothing Methods for Reconstructing NDVI Time-Series and Estimating Vegetation Phenology from MODIS Data. *Remote Sens*,9, https://doi.org/10.3390/rs9121271
- Defourny, Pierre ; Bontemps, Sophie et al., 2019. Near real-time agriculture monitoring at national scale at parcel resolution: Performance assessment of the Sen2-Agri automated system in various cropping systems around the world. In: Remote Sensing of Environment, Vol. 221, p. 551-568 (2019).
- Delloye, Cindy ; Weiss, Marie ; Defourny, Pierre, 2018. Retrieval of the canopy chlorophyll content from Sentinel-2 spectral bands to estimate nitrogen uptake in intensive winter wheat cropping systems. In: Remote Sensing of Environment, Vol. 216, p. 245-261 (2018).
- Duveiller G., De Wit, A. , Kouadio, L. , Djaby, B. , Curnel, Y. , Tychon, B. & Defourny, P. (2010). Exploring the potential of crop specific green area index time series to improve yield estimation at regional scale. Proceedings in: RAQRS'III - Recent advances in quantitative remote sensing, Torrent, Spain, 27 September - 1 October 2010, 6 pp
- Lambert et al. 2018, Estimating smallholder crops production at village level from Sentinel-2 time series in Mali's cotton belt. Remote Sensing of Environment, 216(2), pp. 647-657, https://doi.org/10.1016/j.rse.2018.06.036
- Radoux, Julien ; Chomé, Guillaume ; Jacques, Damien Christophe ; Waldner, François ; Bellemans, Nicolas ; Matton, Nicolas ; Lamarche, Céline ; d'Andrimont, Raphaël ; Defourny, Pierre, 2016. *Sentinel-2's Potential for Sub-Pixel Landscape Feature Detection*. In: *Remote Sensing*, Vol. 8, no.6, p. 488

Thank You!