Agriculture monitoring & retrievals

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ESA–MOST China Dragon 4 Cooperation

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中欧科技合作“龙计划”第四期 2019年陆地遥感高级培训班

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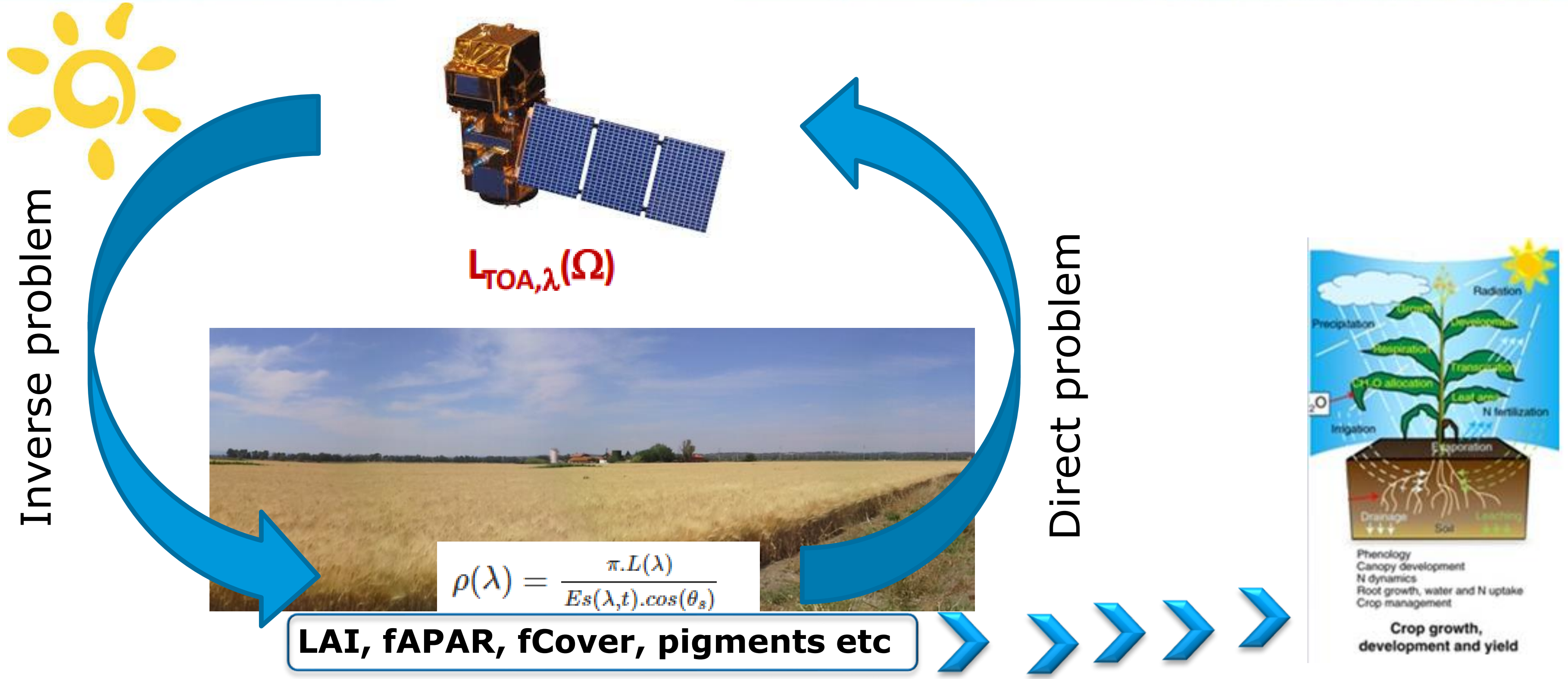
培训时间:2019 年11月18日-23日 主办方:重庆大学

Outline

1. Agriculture as combination of soil & vegetation components
2. Crop biophysical variables retrieval with optical RS
3. Soil parameters retrieval with optical RS
4. Sampling procedures for ground measurements
5. Agronomical variables



Inverse problem
Direct problem
$L_{TOA,\lambda}(\Omega)$
$\rho(\lambda) = \frac{\pi.L(\lambda)}{Es(\lambda,t).cos(\theta_s)}$
LAI, fAPAR, fCover, pigments etc
Radiation
Precipitation
Irrigation
N fertilization
Soil
Phenology
Canopy development
N dynamics
Root growth, water and N uptake
Crop management
Crop growth,
development and yield

Overview of the crop/plants' diversity that can be derived by EO

Taxonomic diversity	Structural diversity	Functional diversity
• Biochemical & biophysical • Physiological & functional • Structural	• Physiognomic & morphological • Phenology & senescence • Stress	• Phenotypical • Aggregated

EO related traits

A.Lausch et al. Ecological Indicators 70 (2016)

Taxonomical Spectral Traits

Biochemical & biophysical ST

- Chlorophyll a,b
- α,β Carotene
- Xanthophyll
- Protein
- Nitrogen
- Phosporus
- Lignin
- Cellulose
- Oil
- Plant water
- Wax
- Starch
- Sugar
- Carbon

Physiologic & functional ST

- Photosynthesis
- Photosynthesic pathway
- Carbonsequentiation
- Stomata conductivity
- Respiration
- Evapotranspiration
- Nitrogen fixation capapcity
- Litter decomosability
- Leaf absorbance
- Leaf conductance
- Leaf persistence
- Nutrient retention

Structural ST

Composition & Configuration
- Area, density, size, shape
- Fragmentation
- Spatial distribution
- Patterns
- Homogeneity / Heterogeneity
- Abundance
- Diversity
- Neighbourhood relationships
- Connectivity
- Complexity
- Extent
- 2D / 3D architecture & layering
- Leaf Area Index (LAI)

Structural

Physiognomic & morphological ST

- Leaf size, form, type
- Leaf anatomy
- Leaf angle
- Leaf cuticula thickness
- Leaf mechanical restistance
- Leaf dray matter content (LDMC)
- Specific leaf area (SLA)
- Leaf mass per area (LMA)
- Leaf corbon content (LCC)
- Leaf nitrogen content (LNC)
- Leaf phosporus content (LPC)
- Leaf pigment content
- Leaf water content

Phenology & senescence ST

- Leaf phenology type
- Flowering phenology
- Plant phenology
- Land surface phenology

Functional

Phenotypical ST

- Plant growth form
- Plant age structure
- Plant height
- Plant crown size
- Plant life span (longevity)
- Plant life form
- Plant flammability
- Plant surface roughness
- Blossom types
- Pollination mode
- Basis colors of flowers
- UV reflection of flowers

Aggregated ST

- Net primary productivity (NPP)
- Fraction of Photosynthetically Active Radiation (fAPAR)
- Biomass

"Agriculture and Food security" domain

Soil components

EO Products	Description	Unit	EO product maturity level	Notes
CLAY	Percentage of clay in the first 30 cm of soil	%	medium	limited to mechanically prepared bare ground
SILT	Percentage of silt in the first 30 cm of soil	%	medium	
SAND	Percentage of sand in the first 30 cm of soil	%	medium	
SOC	Percentage of organic carbon in the first 30 cm of soil	%	low	

Vegetation components

EO Products	Description	Unit	EO product maturity level	Notes
LAI	Leaf Area Index	-	high	limited to herbaceous crops
Cab	Chlorophyll a and b Content of in leaves per unit of area	mg cm^{-2}	high	
FPAR	Fraction of photosynthetically active radiation absorbed by vegetation cover	-	high	

Variables of interest for agriculture

Agricultural components

EO Products	Description	Unit	EO product maturity level	Notes
YLD	Crop production	t ha^{-1}	low	limited to a cereal crop to be defined
QN	Content of nitrogen in the aboveground biomass	%	low	
GN	Nitrogen content in grain	%	low	
Nres	nitrate nitrogen (NO3-N-) in the soil at the end of crop cycle	kg ha^{-1}	low	

Require models assimilation for biophysical products (e.g. LAI, fAPAR, fCover, Albedo etc.) and their dynamics

Biophysical Variables of interest for agricultural user community

Survey of the user needs to highlight the most relevant RS layers in terms of:

- relevance for the Copernicus Information needs;
- algorithms readiness;
- EO data availability

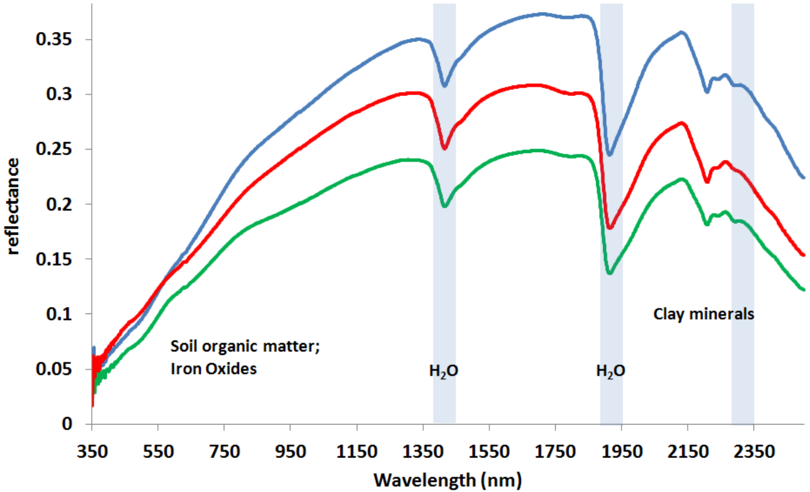
Thematic Area	Id	Layer name	Score	Potential retrieval algorithms
Assessment of biophysical and biochemical variables related to the crops and of agronomic interest	AGR-01	Leaf Area Index	77.8	Hybrid methods based on ANN/LUT or other machine learning algorithms e.g. GPR (Gaussian Process methods applied to vegetation canopy reflectance models (e.g. PROSAIL).
	AGR-02	Leaf Pigments: Chlorofill a+b	77.8	Narrow-band vegetation indices; Hybrid methods based on ANN/LUT or other machine learning algorithms e.g. GPR methods applied to vegetation canopy reflectance models (e.g. PROSAIL).
Top Soil Properties	AGR-08	Soil texture	72.2	Chemometrics modelling; spectral analysis; multivariate statistics (e.g., PLSR models); ANN.
Assessment of biophysical and biochemical variables related to the crops and of agronomic interest	AGR-11	Canopy water content	66.7	Narrow-band vegetation indices; Hybrid methods based on ANN/LUT or other machine learning algorithms e.g. GPR methods applied to vegetation canopy reflectance models (e.g. PROSAIL).
	AGR-03	Leaf Pigments: Carotenoids	61.2	Narrow-band vegetation indices.
Top Soil Properties	AGR-09	Soil organic carbon content	61.2	Chemometrics modelling; spectral analysis; spectral indexes, multivariate statistics (e.g. PLSR models)
Assessment of biophysical and biochemical variables related to the crops and of agronomic interest	AGR-12	Leaf mass / area	50.0	Narrow-band vegetation indices; Hybrid methods based on ANN/LUT or other machine learning algorithms e.g. GPR methods applied to vegetation canopy reflectance models (e.g. PROSAIL).

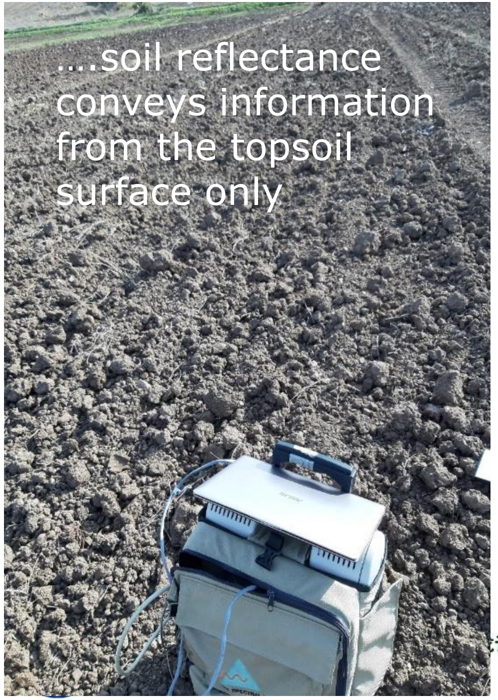
Agricultural soils

Tillage operations in agricultural fields make topsoil (0-30cm) properties, such as texture (clay, silt and sand) and soil organic content (SOC), measurable from the surface.

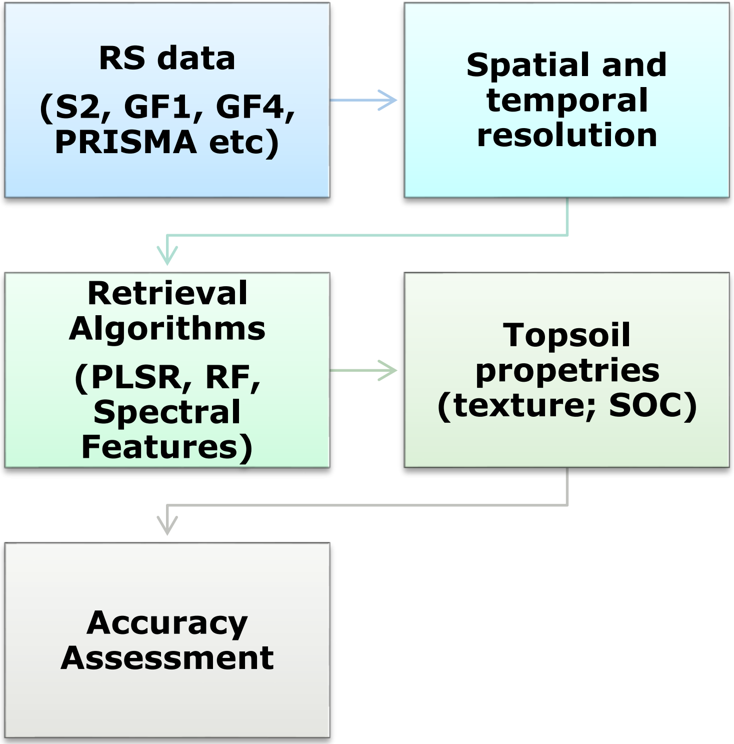
The 0.4-2.5μm spectral region has shown the capability to retrieve topsoil properties, so reducing the costs of collecting and analyzing soil samples, with great application potential, especially in the context of precision agriculture.

Soil chromophores





Agricultural soils



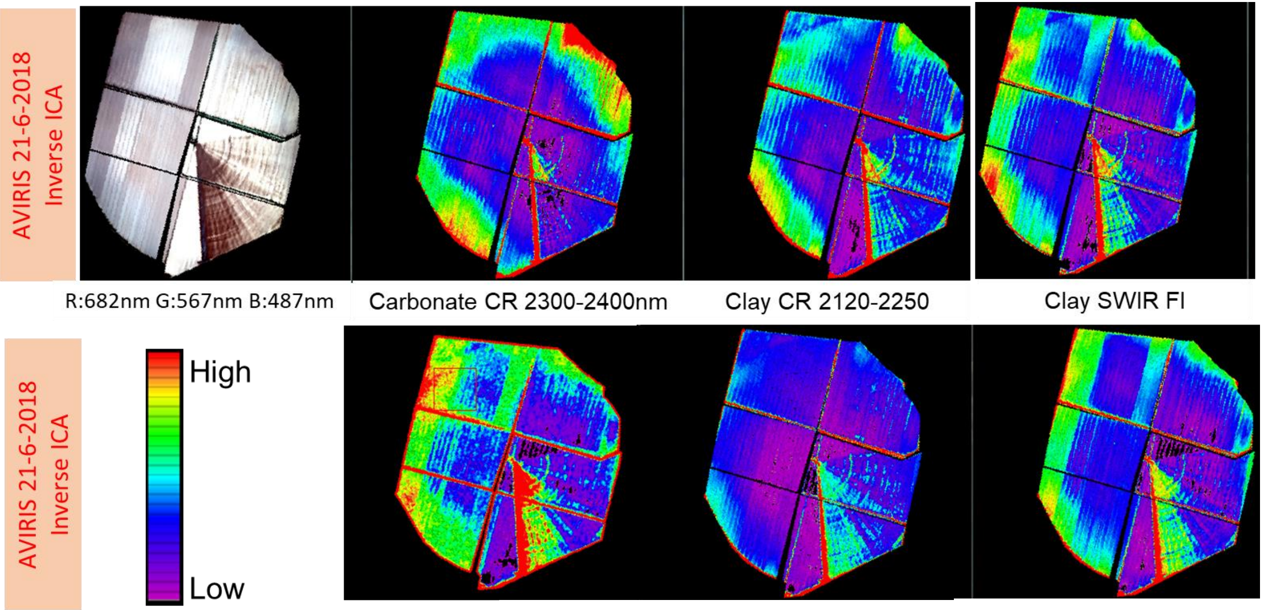
Chemometrics and multivariate calibrations are used to obtain models that relate soil properties to spectral variables, such as:

- multiple linear regression (**MLR**),
- stepwise multiple linear regression (**SMLR**), principal components regression (**PCR**),
- partial least-squares regression (**PLSR**), Random Forests (**RF**)
- Support vector machines (**SVM**)

(Stenberg et al., 2010; Terra et al., 2015).

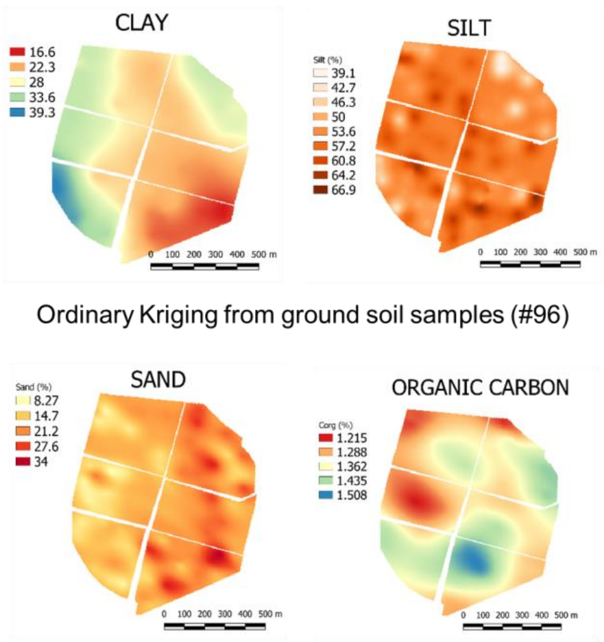
Agricultural soils

http://worldsoils2019.esa.int/



R:682nm G:567nm B:487nm | Carbonate CR 2300-2400nm | Clay CR 2120-2250 | Clay SWIR FI

Clay SWIR FI | (gaussian model) | SOC 400-600 nm

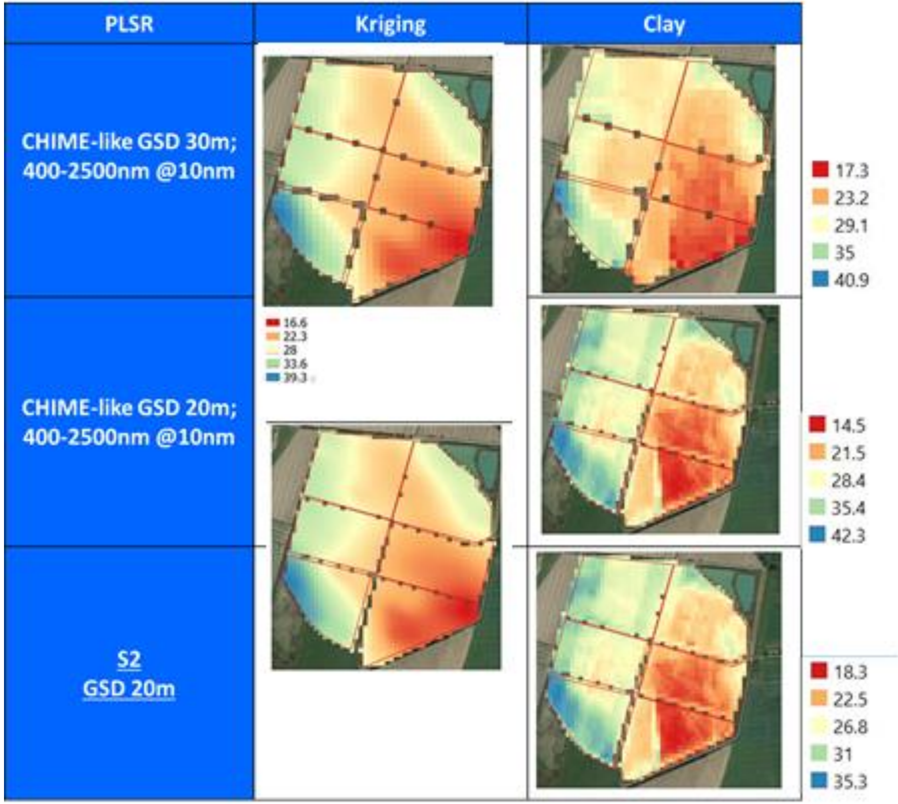


Ordinary Kriging from ground soil samples (#96)

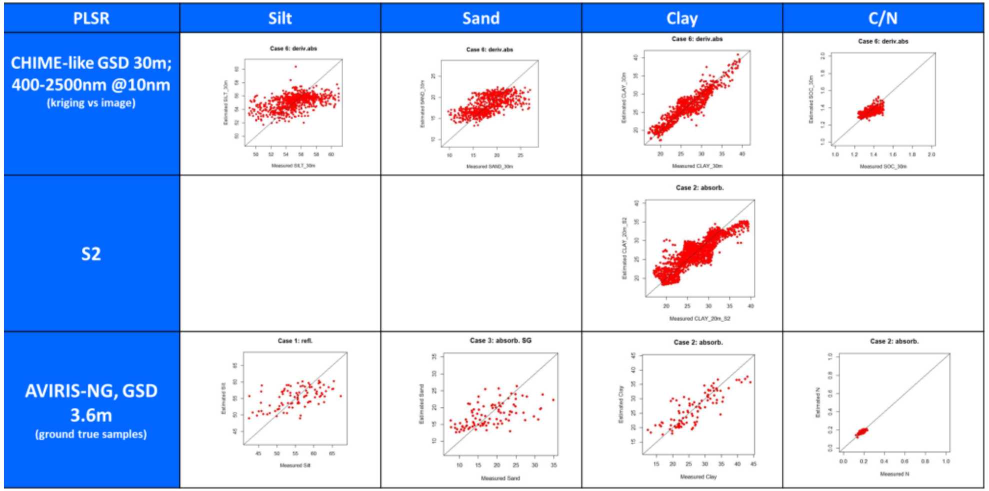
Soil properties have been spatialized by applying block kriging on the field data.

Agricultural soils

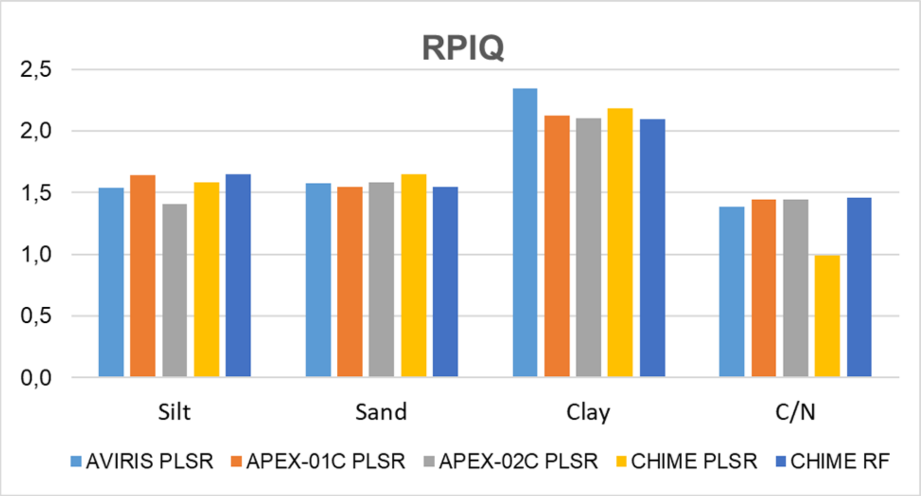
http://worldsoils2019.esa.int/

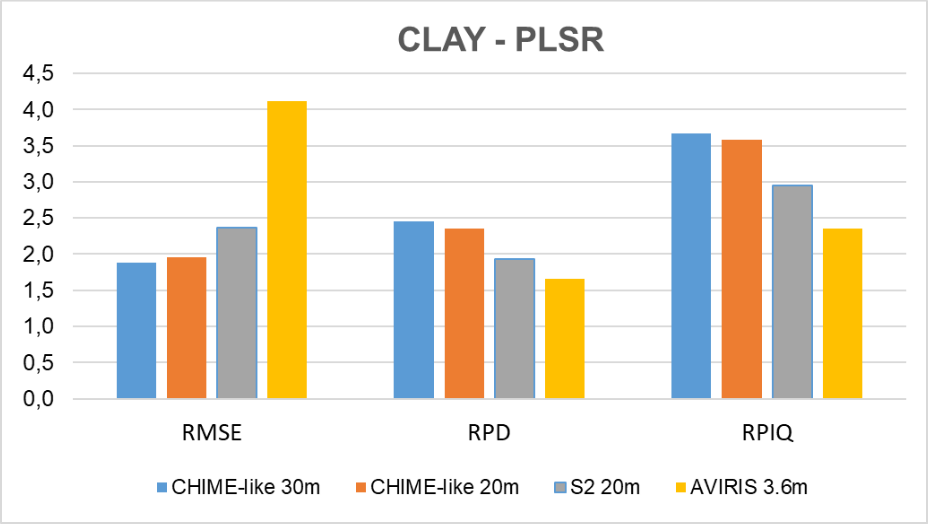


Grosseto (IT) experiments, 2018



Grosseto (IT) experiments, 2018

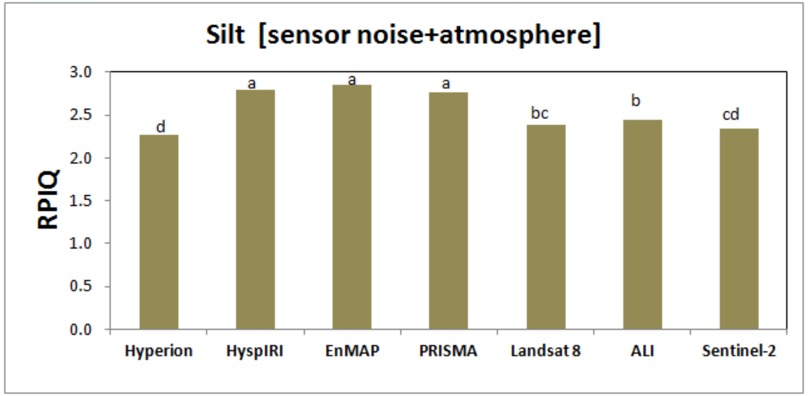


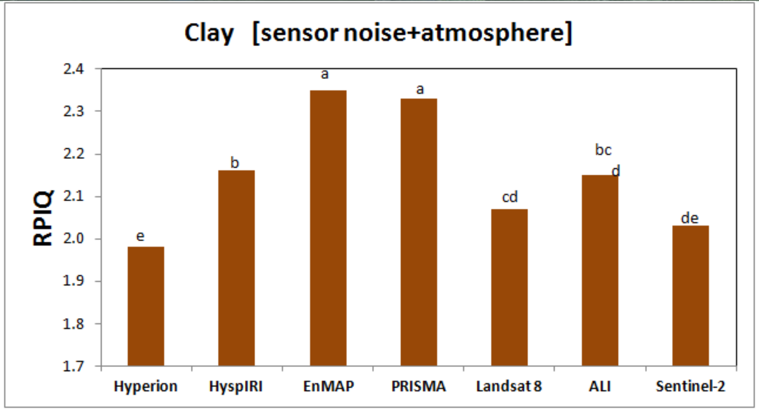


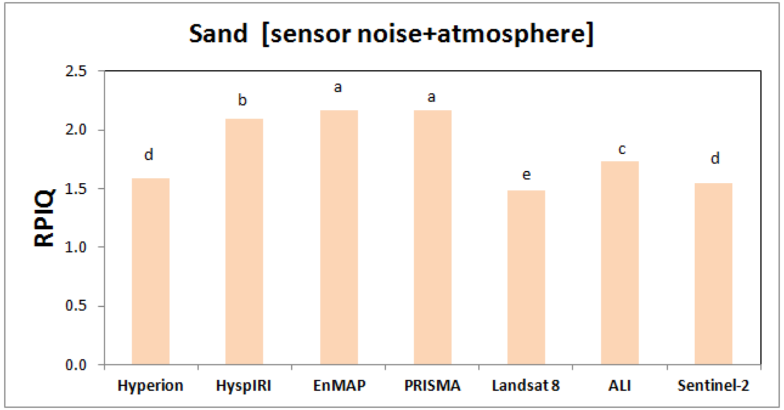
The RPIQ values depict a non optimal prediction of the considered soil variables. High RPIQ values were obtained only for clay. Similar low prediction performances are identified for airborne data (APEX and AVIRIS) for the other soil properties.

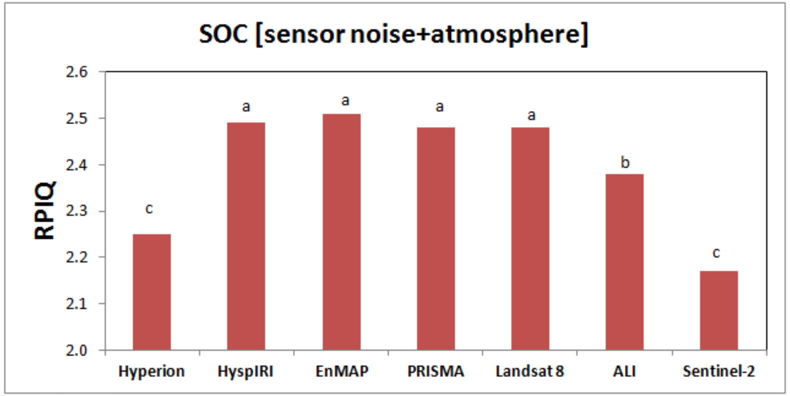
http://worldsoils2019.esa.int/

Agricultural soils



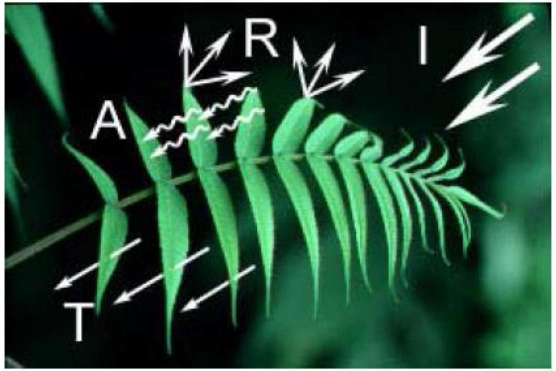






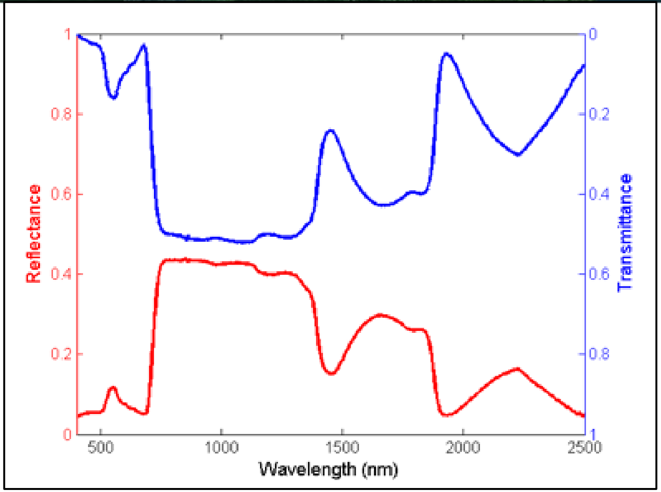
Castaldi, F., Palombo, A., Santini, F., Pascucci, S., Pignatti, S., Casa, R.., 2016. Evaluation of the potential of the current and forthcoming multispectral and hyperspectral imagers to estimate soil texture and organic carbon. Remote Sensing of Environment, 179, 54-65.

Leaf light interception

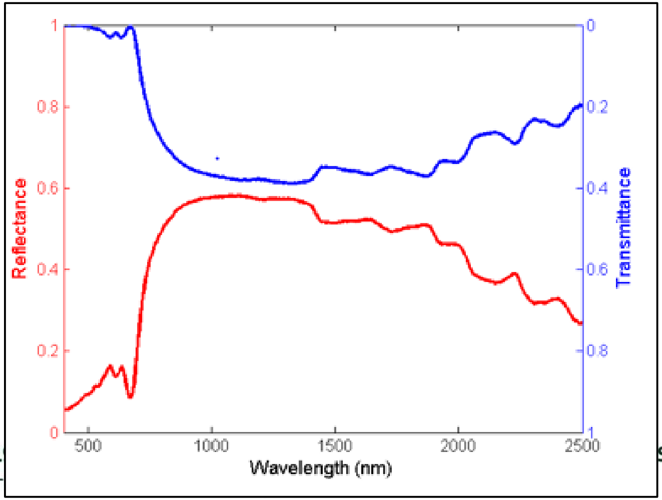


Source: Plants in Action, published by the Australian Society of Plant Scientists, http://plantsinaction.science.uq.edu.au/edition1/

The sum of the reflectance R, transmittance T, and absorptance A, equals one



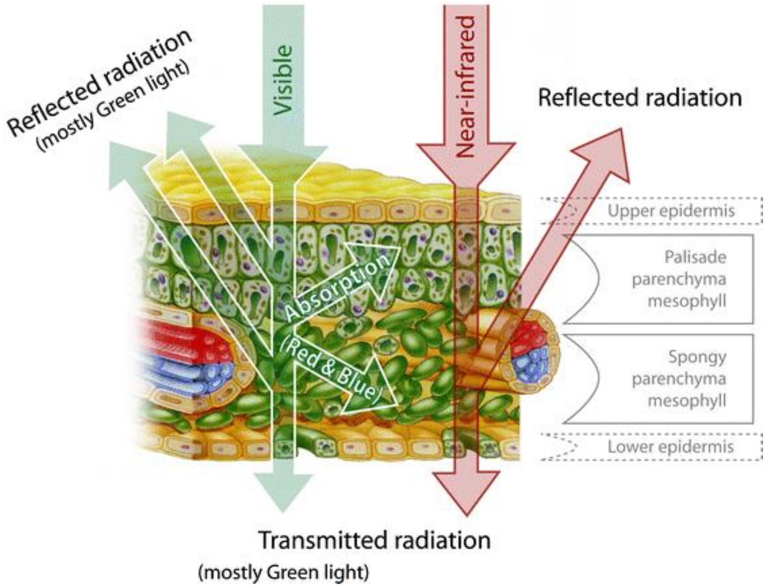
Vegetation spectral propenttp://photobiology.info/Jacq_Ustin.htmlrties



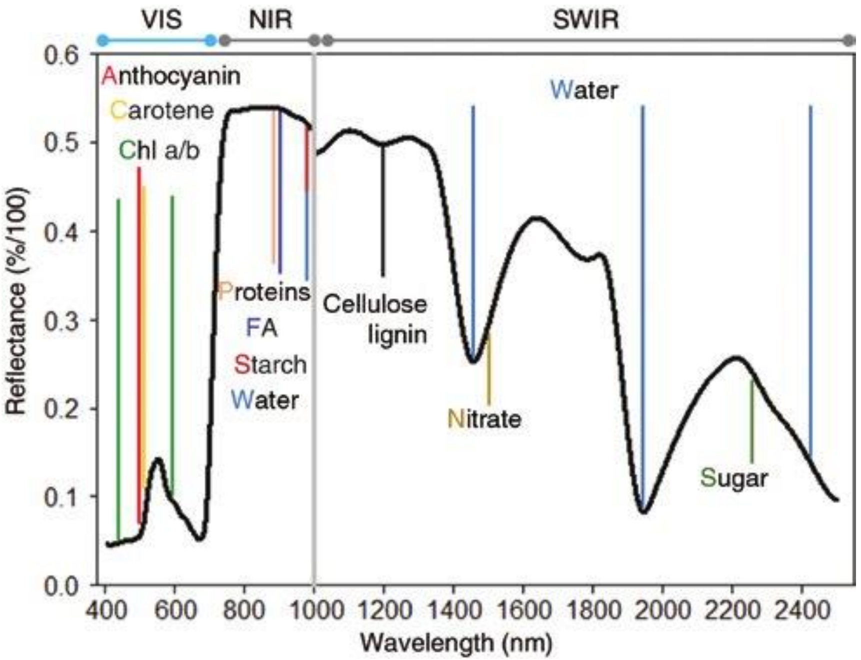
The reflectance can be split into two terms: a fraction, that is reflected at the leaf surface and a fraction that is caused by multiple scattering within the leaf tissues

Leafs energy capture, pigments

https://link.springer.com/article/10.1007/s10816-011-9104-5

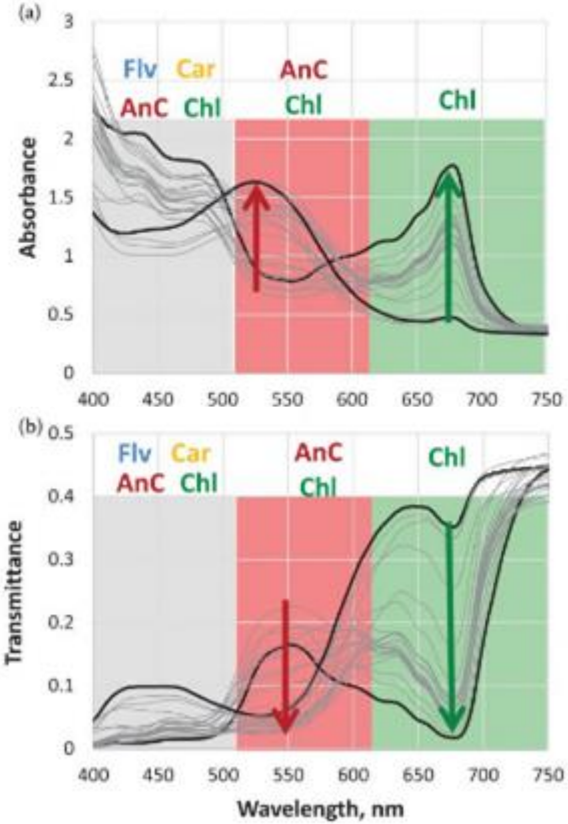


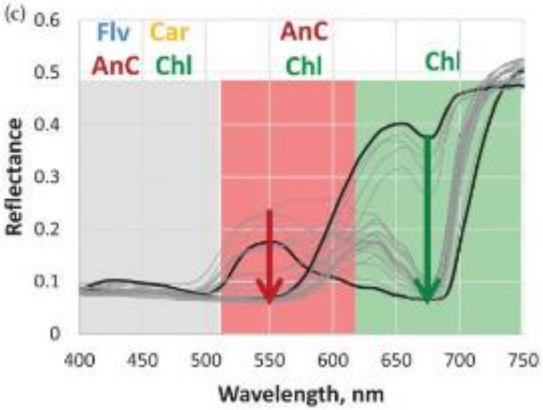
Structure of a plant leaf and its interaction with incident visible and NIR radiation



Kuska, M. Tet al. 2018https://doi.org/10.1515/pac-2018-0102

Leafs energy capture: pigments





Leaves with widely varying pigment contents and composition.

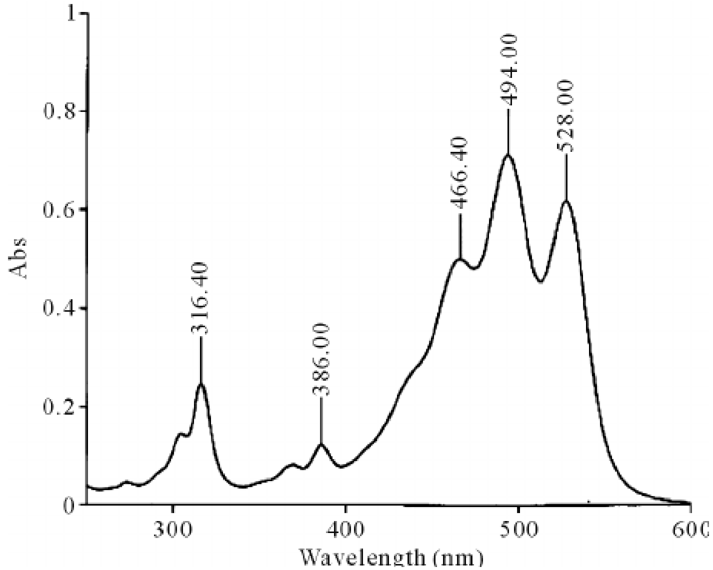
- green shaded area is controlled by Chlorophyll;
- red shaded area: Anthocyanins and Chl;
- grey shaded area: jointly by Chl, Carotenoids, AnC and Flavonoids

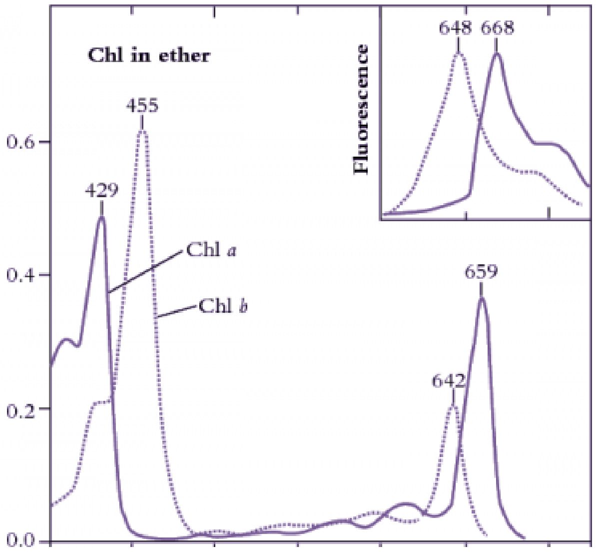
Thenkabail, P.S., Lyon, J.G., & Huete, A.R. (2018). Hyperspectral Indices and Image Classifications for Agriculture and Vegetation.

Leafs energy capture, pigments

Absorption spectrum of caronetoids and chlorophill a-b

Cahoon, L. B., 2012. DOI: 10.4236/as.2012.360985





RTM

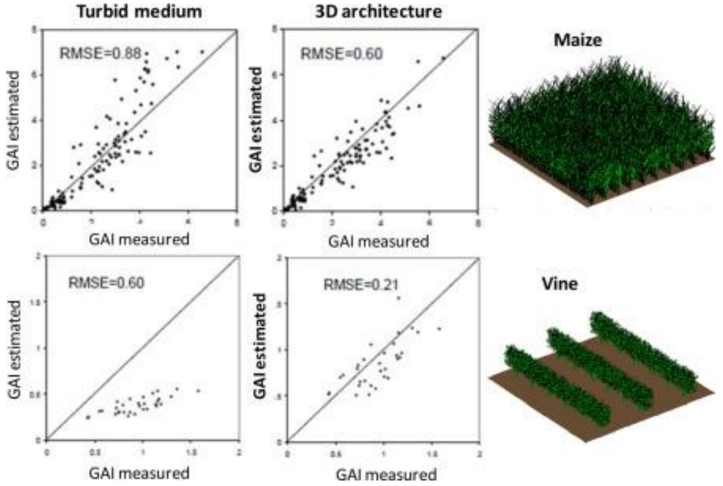
Radiative transfer models of leaf biophysical processes have been used to directly estimate biochemical composition and structural characteristics.

RTM is used to study spectral transmission or signature of plants, light reflected or emitted from plant and amount of energy absorbed.

There are two main categories of RTMs:

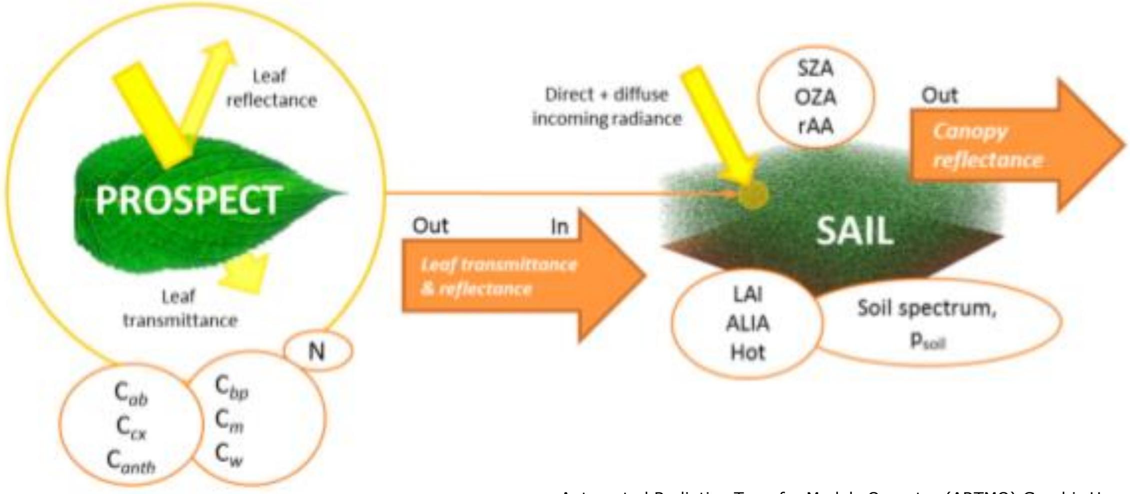
- Homogeneous Models

- Heterogeneous Models



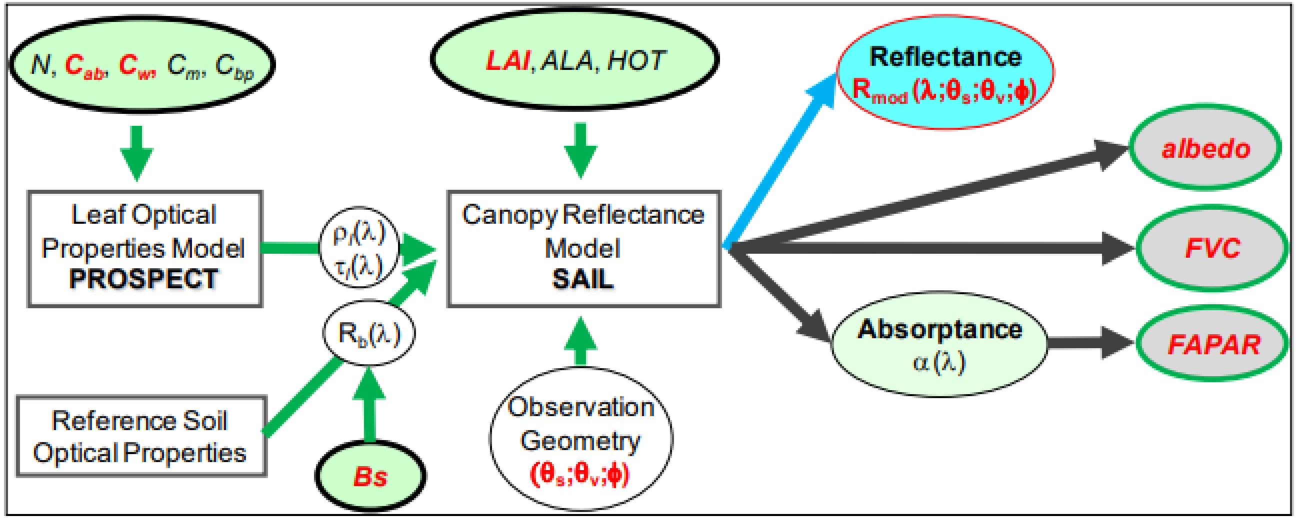
PROSAIL Model: PROSPECT + SAIL

- PROSPECT: determine leaf reflectance and transmittance signatures in the optical domain;
- SAIL: canopy reflectance models.



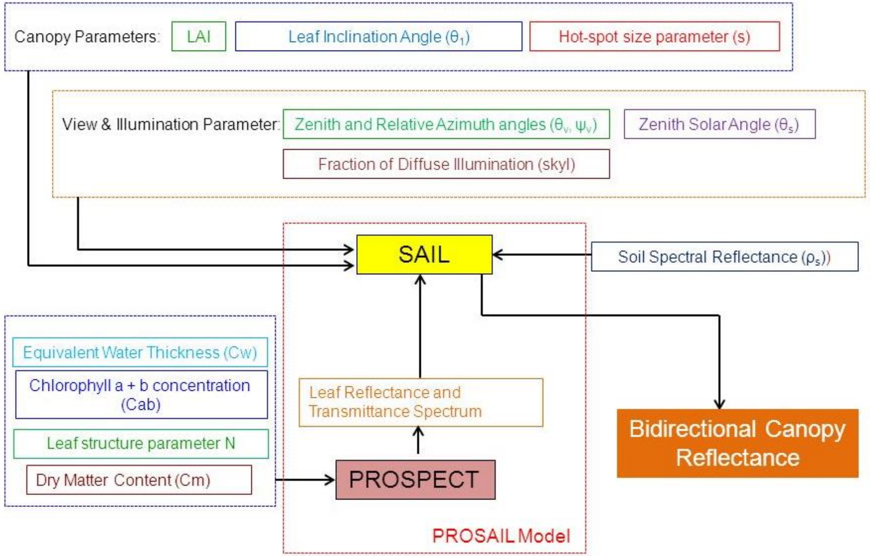
Automated Radiative Transfer Models Operator (ARTMO) Graphic User Interface (GUI) http://artmotoolbox.com

S2ToolBox



https://step.esa.int/docs/extra/ATBD_S2ToolBox_L2B_V1.1.pdf

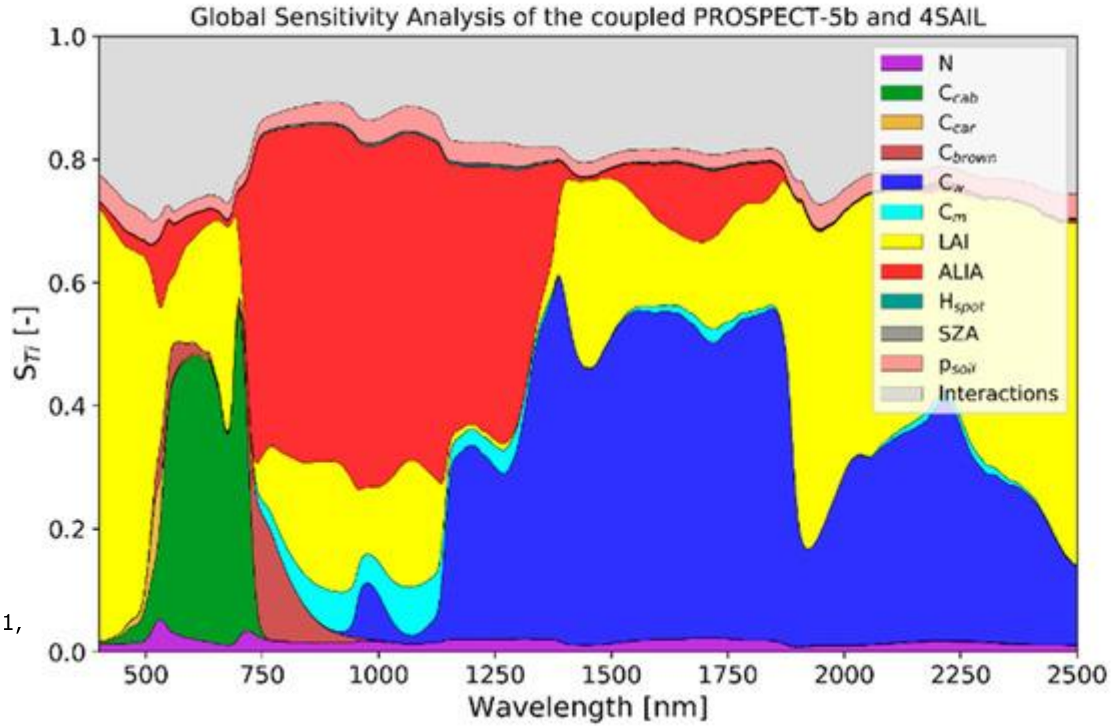
RTM: PROSAIL



1. Chlorophyll a + b concentration **Cab** [µg/cm2]
2. Equivalent Water Thickness **Cw** [g/cm2]
3. Dry Matter Content **Cm** [mg/cm2]
4. Leaf length / Leaf height **hSpot** [m/m]
5. Carotenoid content, **Car** [µg/cm2]
6. Brown pigment content **Cbrown** [-]
7. Structural Coefficient **N** [-]
8. Leaf Area Index **LAI** [m2/m2]
9. Average leaf angle **Angl** [°];
10. Soil Soil brightness factor **psoil** [-];
11. Diffuse/direct radiation **Skyl** [-]
12. Solar zenith angle between sun position and with respect to zenith **tts** [°]
13. Observer zenith angle between observer (sensor) position and with respect to zenith. **tto** [°]
14. Relative azimuth angle between sun - sensor position with respect to North. **psi**[°]

Sensitivity Analysis

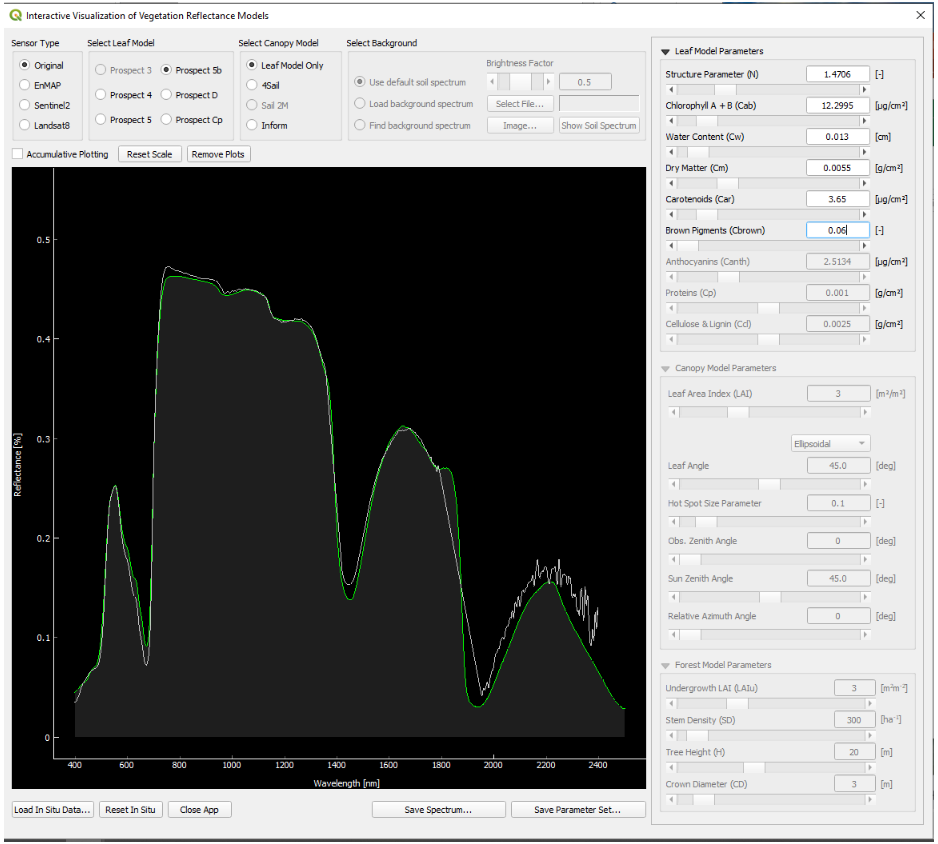
Global Sensitivity Analysis of the coupled ROSPECT-5b and 4SAIL models

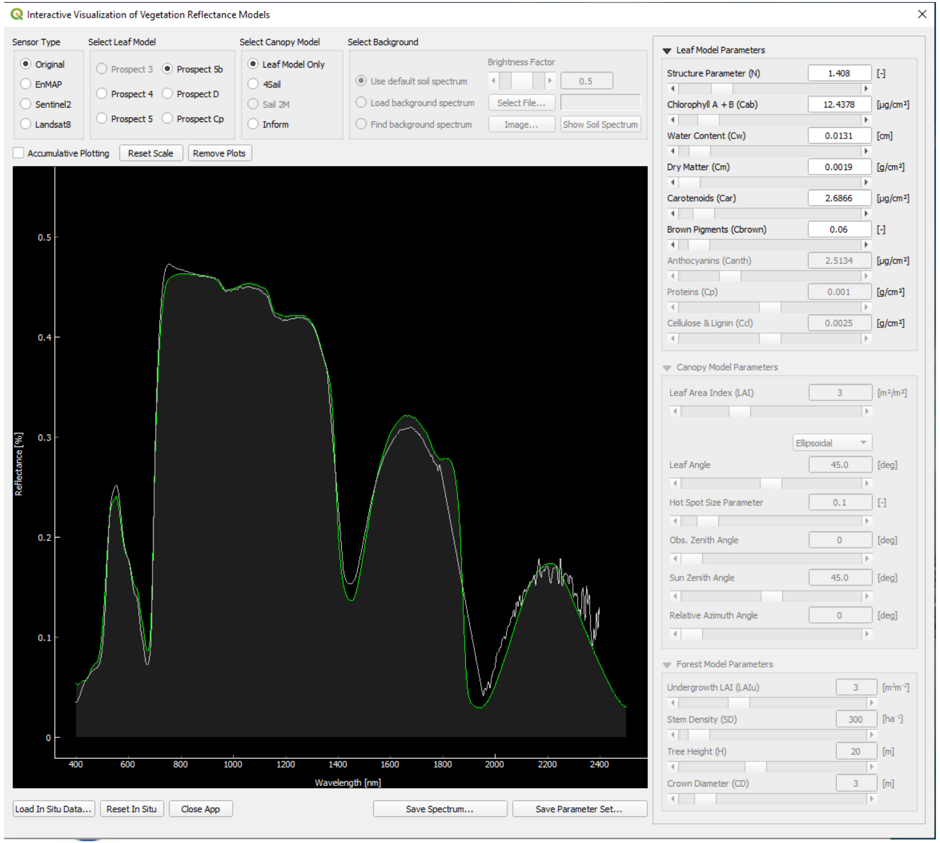


Dammer M. Remote Sens. 2019, 11, 1150; doi:10.3390/rs11101150

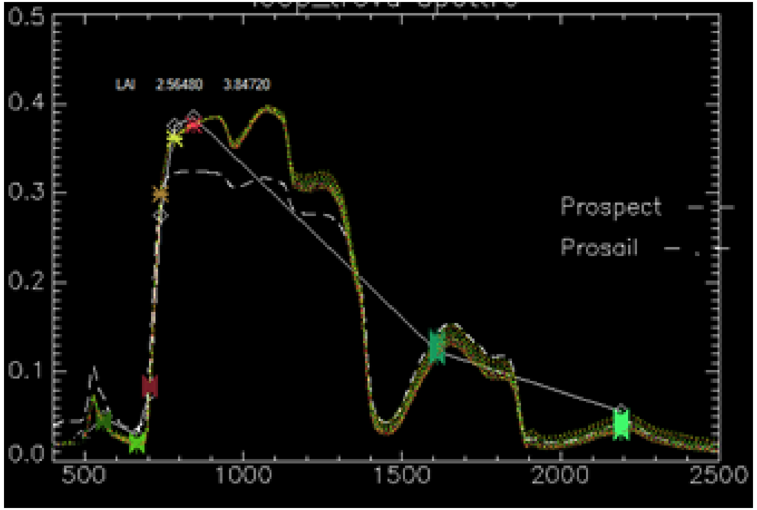
Interactive Visualization of Vegetation Reflectance Models (IVVRM) tool

https://enmap-box-lmu-vegetation-apps.readthedocs.io/en/latest/

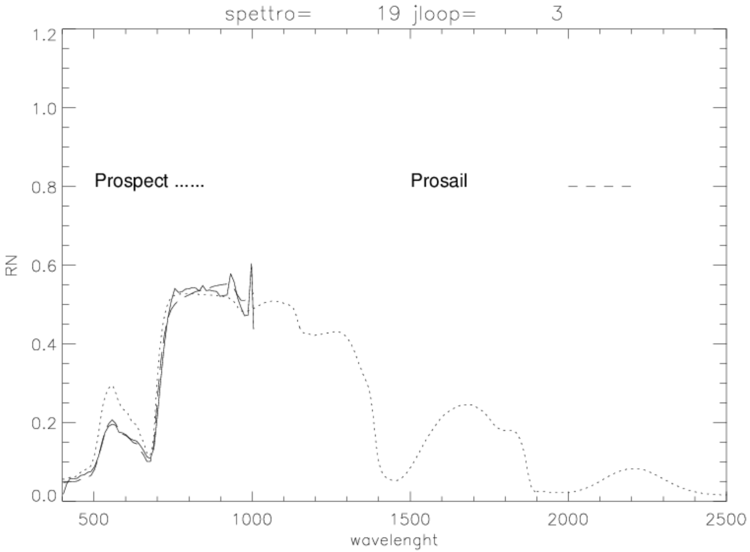




Vegetation Reflectance Models IDL tool



S2 reflectance inverted with the IDL code



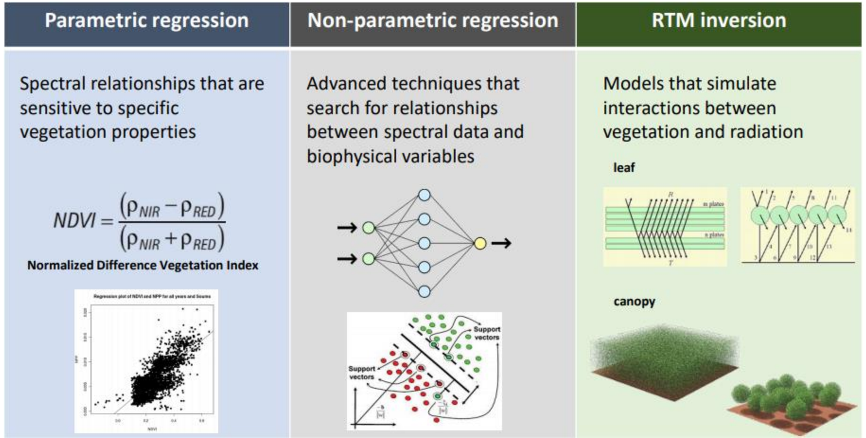
VNIR Hyperspectral on drone

Retrieval of vegetation biophysical variables

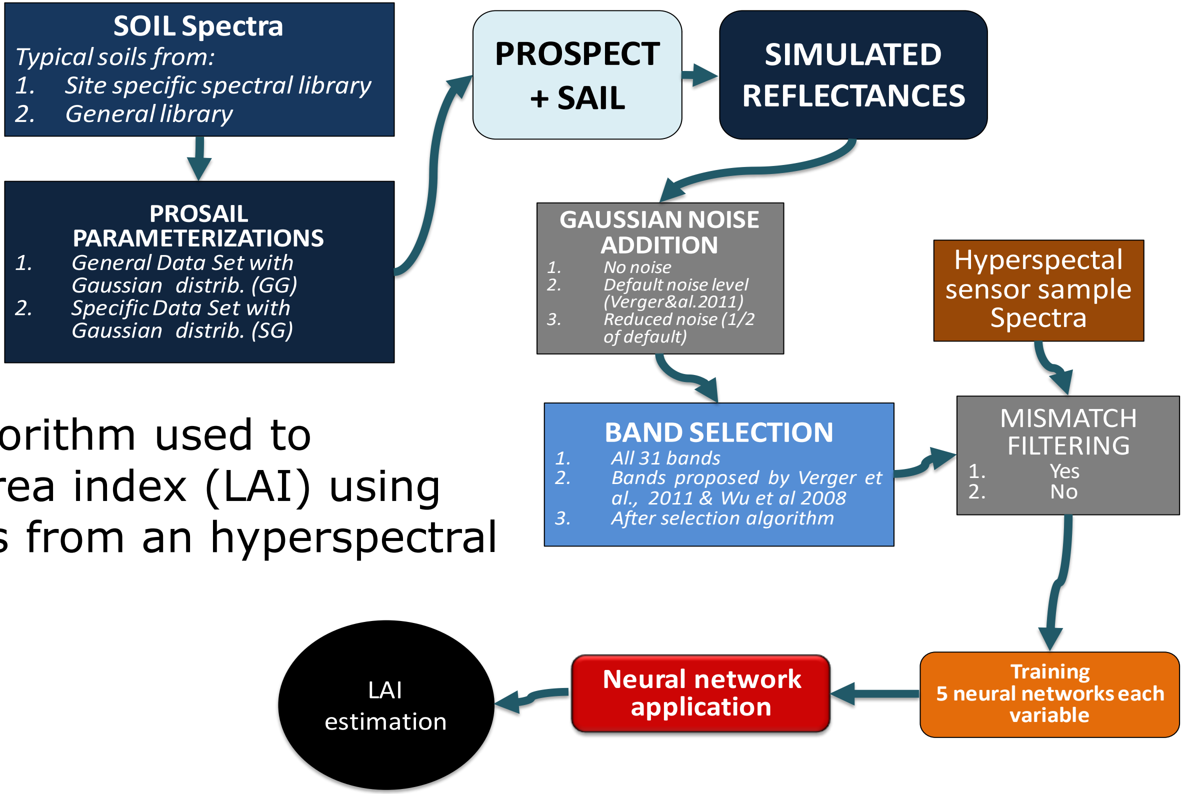
Vegetation variables was retrieved by using different approaches:

- statistical i.e. build expressions (fitting techniques) to relate spectral bands to specific biophysical parameter. They can be parametric or not parametric

- based on the inversion of RTM, i.e. numerical optimization and LUT based inversion. Various regularization strategies are implemented to optimize the inversion, including:
  i) the use of prior knowledge to restrict input variables variability;
  ii) the use of different cost functions;
  iii) the use of multiple best solutions of the inversion instead of the single best solution.

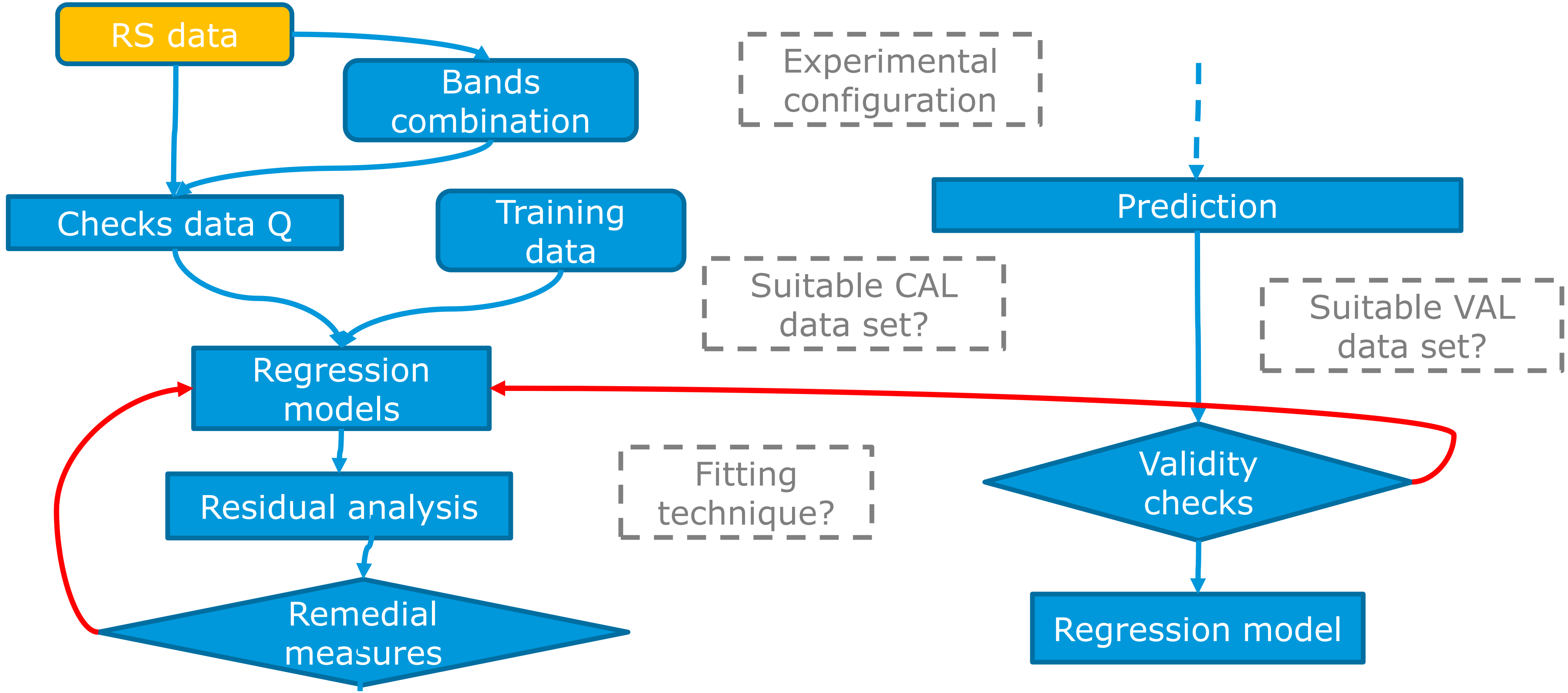


NN applied to PROSAIL



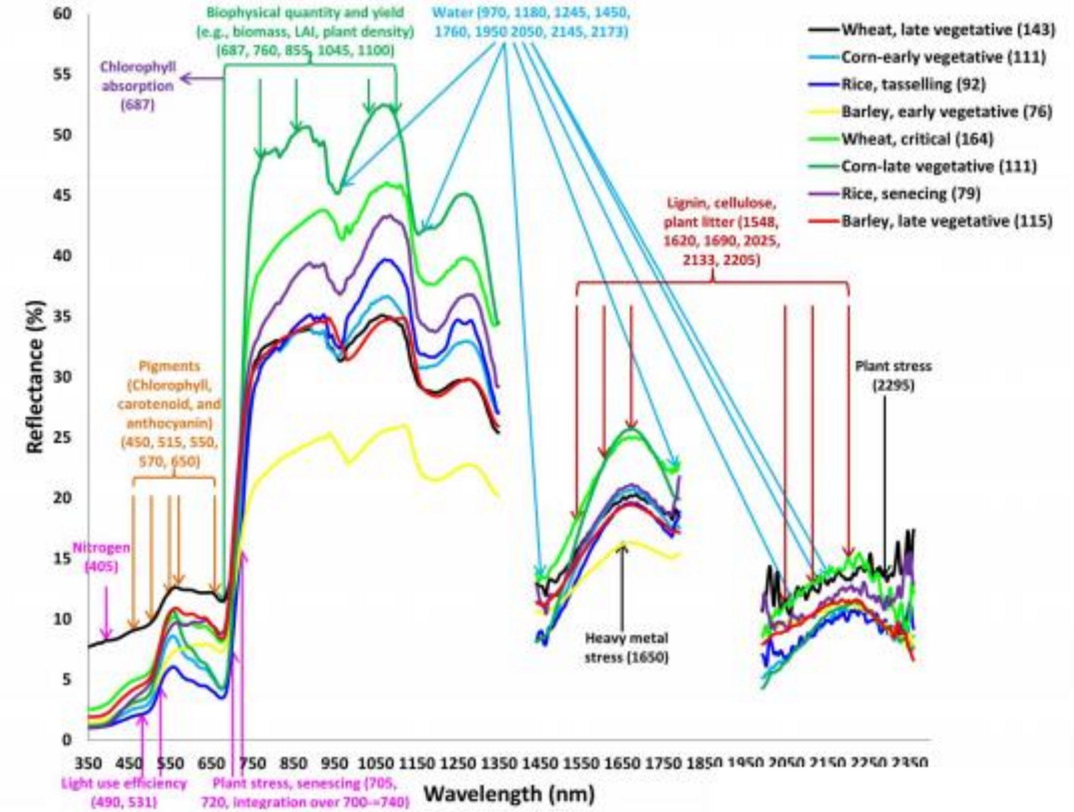
Neural Network algorithm used to estimate the leaf area index (LAI) using canopy reflectances from an hyperspectral satellite sensor

Empirical relationship



Crop spectrum

https://prd-wret.s3-us-west-2.amazonaws.com/assets/palladium/production/s3fs-public/atoms/files/A7-hyperspectral-UND-thenkabail-3c.pdf



Dependent variables

Reflectances or vegetation index or other optical related variables.
For a selection of possible vegetation index: https://www.indexdatabase.de/

Nr.	Name	Abbrev.	General Formula	Specific Formula	Calculated
1	Atmospherically Resistant Vegetation Index	ARVI	$\frac{NIR-RED-y(RED-BLUE)}{NIR+RED-y(RED-BLUE)}$	$\frac{9-5-y(5-1)}{9+5-y(5-1)}$	Automatic
2	Atmospherically Resistant Vegetation Index 2	ARVI2	$-0.18+1.17\left(\frac{NIR-RED}{NIR+RED}\right)$	$-0.18+1.17\left(\frac{9-5}{9+5}\right)$	Automatic
3	Canopy Chlorophyll Content Index	CCCI	$\frac{\frac{NIR-rededge}{NIR+rededge}}{\frac{NIR-Red}{NIR+Red}}$	$\frac{\frac{9-5}{9+5}}{\frac{9-Red}{9+Red}}$	Automatic
4	Chlorophyll Absorption Ratio Index	CARI	$\left(\frac{700nm}{670nm}\right)\frac{\sqrt{(a\cdot670+670nm+b)^2}}{(a^2+1)^{0.5}}$	$\left(\frac{5}{4}\right)\frac{\sqrt{\left(\frac{5-3}{150}\cdot670+4+\left(3-\left(\frac{5-3}{150}\cdot550\right)\right)\right)^2}}{\left(\frac{5-3}{150^2}+1\right)^{0.5}}$	Automatic
5	Chlorophyll Absorption Ratio Index 2	CARI2	$\left(\frac{\lvert(a\cdot670+670+b)\rvert}{(a^2+1)^{0.5}}\right)\left(\frac{700}{670}\right)$	$\left(\frac{\left\lvert\left(\frac{5-3}{150}\cdot4+4+3-(a\cdot3)\right)\right\rvert}{(a^2+1)^{0.5}}\right)\left(\frac{5}{4}\right)$	Automatic
6	Chlorophyll Green	Chlgreen	$\left(\frac{760:800}{540:560}\right)^{(-1)}$	$\left(\frac{7}{3}\right)^{(-1)}$	Automatic
7	Chlorophyll Red-Edge	Chlred-edge	$\left(\frac{760:800}{690:720}\right)^{(-1)}$	$\left(\frac{7}{5}\right)^{(-1)}$	Automatic
8	Chlorophyll vegetation index	CVI	$NIR\frac{RED}{GREEN^2}$	$9\frac{5}{3^2}$	Automatic
9	Green leaf index	GLI	$\frac{2GREEN-RED-BLUE}{2GREEN+RED+BLUE}$	$\frac{23-5-1}{23+5+1}$	Automatic
10	Leaf Chlorophyll Index	LCI	$\frac{850-710}{850+680}$	$\frac{8-5}{8+4}$	Automatic
11	MCARI/MTVI2	MCARI/MTVI2	$\frac{((700nm-670nm)-0.2(700nm-550nm))\left(\frac{700nm}{670nm}\right)}{\left(1.5\frac{1.2(800nm-550nm)-2.5(670nm-550nm)}{\sqrt{(2800nm+1)^2-(6800nm-5\sqrt{670nm})-0.5}}\right)}$	$\frac{((5-4)-0.2(5-3))\left(\frac{5}{4}\right)}{\left(1.5\frac{1.2(8-3)-2.5(4-3)}{\sqrt{(28+1)^2-(68-5\sqrt{4})-0.5}}\right)}$	Automatic
12	Normalized Difference 800/680 Pigment specific normalised difference A2, Lichtenthaler indices 1, NDVIhyper	ND800/680	$\frac{800nm-680nm}{800nm+680nm}$	$\frac{8-4}{8+4}$	Automatic
13	Normalized Difference NIR/Red Normalized Difference Vegetation Index, Calibrated NDVI - CDVI	NDVI	$\frac{NIR-RED}{NIR+RED}$	$\frac{8-4}{8+4}$	Automatic
14	Normalized Difference Vegetation Index 690-710	NDVI690-710	$\frac{NIR-690:710}{NIR+690:710}$	$\frac{9-5}{9+5}$	Automatic

Fitting Techniques

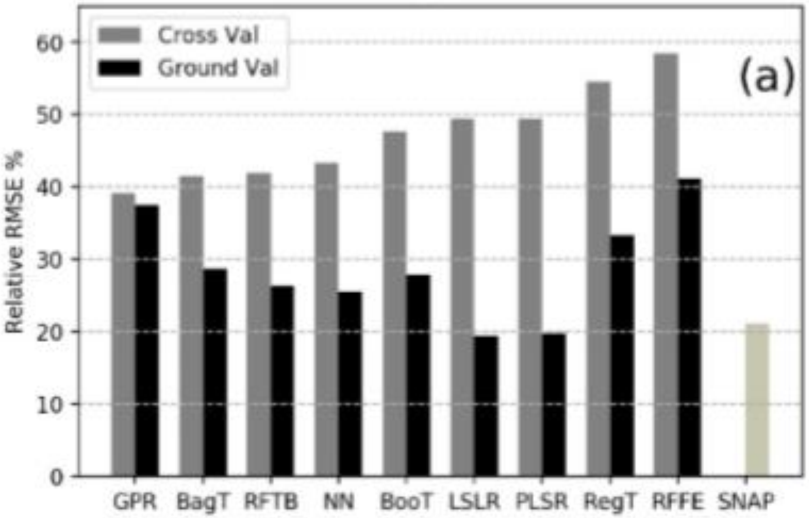
- Are very fast when determined
- Training could be time demanding when using large data set
- Accuracy is strictly dependent by the training set
- Normally refers to a single variable of interest

Simple regression: is a statistical tool for quantifying the relationship between just one independent variable and one dependent variable based on observations

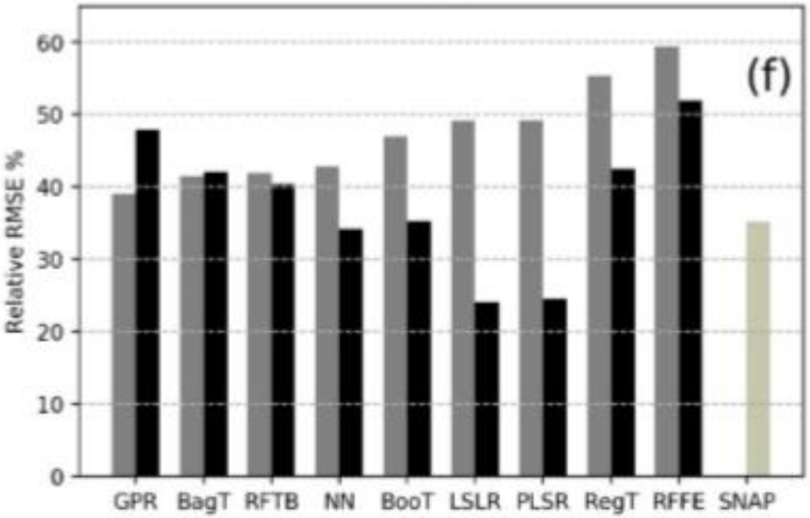
Machine learning: is more complex and can be based based on the value of one or multiple predictor variables (x).

Fitting Techniques

Maccarese (IT) LAI



Shunyi (China) LAI



Machine Learning perform better; decreased Performances on ground dataset

GPR: Gaussian Process Regression	RFTB: Random Forest Tree Bagger	BooT: boosting trees	PLSR: partial least square regression	RFFE: random forest fit ensemble
BagT: Bagging Trees	NN: Neural Network	LSR: least squares linear regression	RegT: regression trees	SNAP

Biophysical Variables vs crop processes

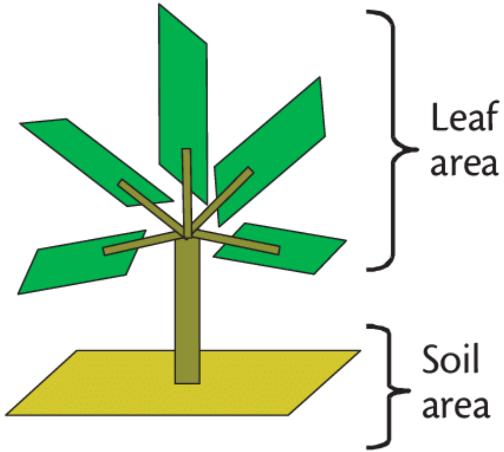
Crop processes	LAI	FAPAR	FCOVER	Albedo	Chlorophyll	Water-content	SLA	Soil brightness	Temperature
Photosynthesis	+++	+++			+++		++		
Evapotranspiration	++	+++	+++	++		++			+++
Respiration	++								
Nitrogen	+++				+++				
Phenology	+++	++	++						
Lodging									
Impact of pests	+++								
Soil permanent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

F. Baret web resources

Leaf area Index (LAI) definition

LAI is defined as half the developed area of photosynthetically active elements of the vegetation per unit horizontal ground area [m2/m2].

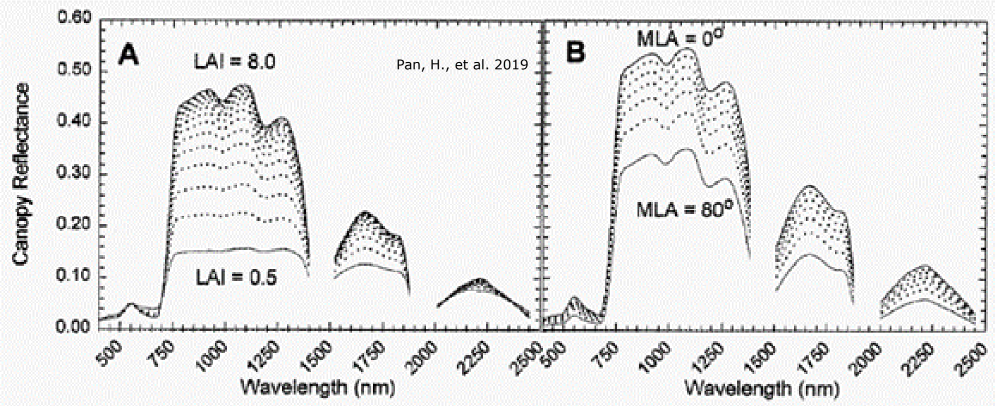
- Is an intrinsic canopy primary variable that should not depend on observation conditions.
- LAI practically, quantifies the thickness of the vegetation cover.
- LAI is strongly non-linearly related to reflectance
- LAI is mainly corresponding to the green elements: the correct term to be used would be GAI (Green Area Index)

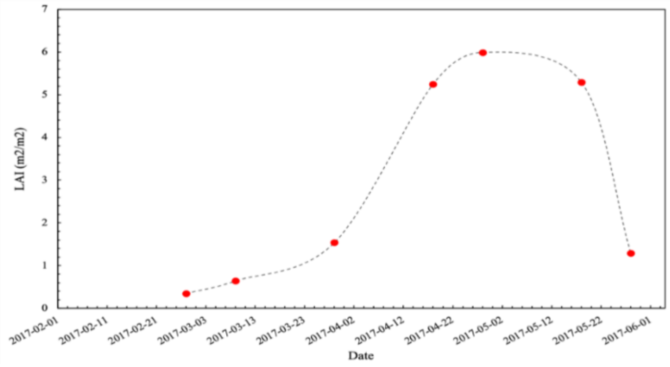


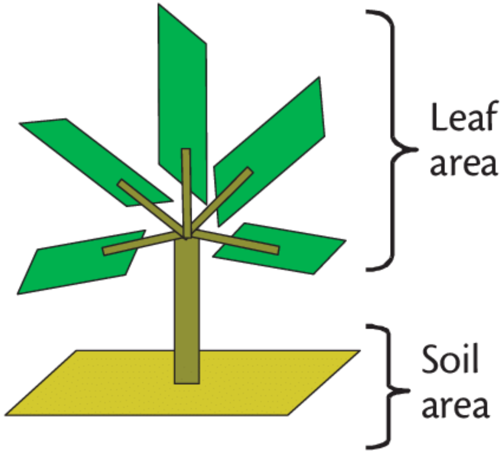
$$LAI = \frac{\text{Leaf area}}{\text{Soil area}}$$

Barrett-Lennard, 2003

Leaf area Index (LAI)





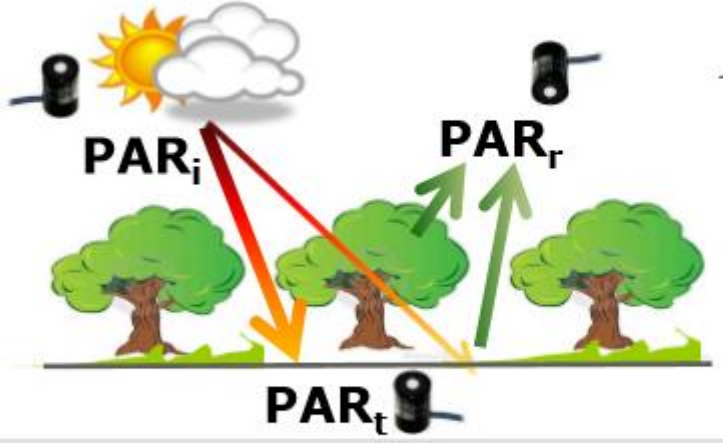


Barrett-Lennard, 2003

$$\text{LAI} = \frac{\text{Leaf area}}{\text{Soil area}}$$

fAPAR definition

- FAPAR is defined as the fraction of photosynthetically active radiation (PAR) absorbed by a vegetation canopy. PAR is the solar radiation reaching the canopy in the 0.4–0.7 μm wavelength region.
- Ground-based estimates of FAPAR require the simultaneous measurement of PAR above and below the canopy.
- FAPAR is a key variable in the assessment of vegetation productivity and yield estimates.
- Fraction of absorbed photosynthetically active radiation (FAPAR) (400-700nm) is one of the main trait used in the production efficiency models.



fAPAR definition

$APAR = PAR_{inc} - PAR_{out} - PAR_{trasm} + PAR_{soil}$ quantity absorbed by the veg.

incoming PAR (PAR_{inc}), reflected by canopy and soil (PAR_{out}), transmitted through the canopy (PAR_{transm}); reflected by the soil (PAR_{soil})

FAPAR=APAR/PARinc

$FAPAR = [(PAR_{inc} - PAR_{out}) - (PAR_{trasm} - PAR_{soil})] / PAR_{inc}$; norm. between 0-1

fAPARgreen=fAPAR×(LAIgreen/LAItotal)

A common approach is the use of vegetation indices (VI), combinating visible and near-infrared reflectance

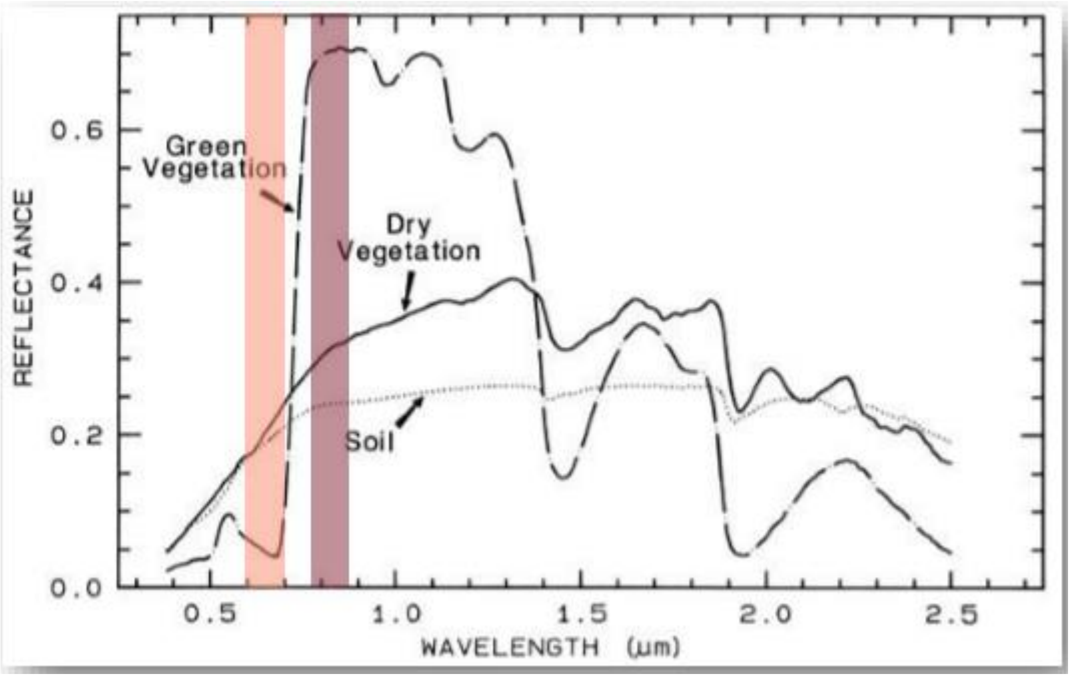
Measuring vegetation status by VIs

Vegetation indices

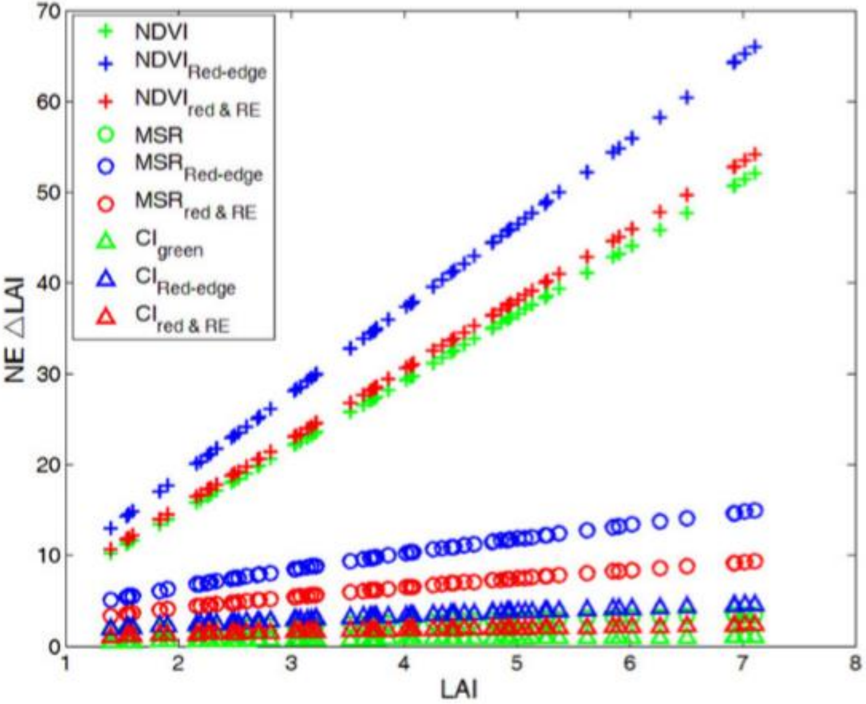
Vegetation indices are designed to maximize sensitivity to the vegetation characteristics while minimizing confounding factors such as soil background reflectance, directional, or atmospheric effects.

Indices exploit specific spectral properties of vegetation

Are potentially illimited



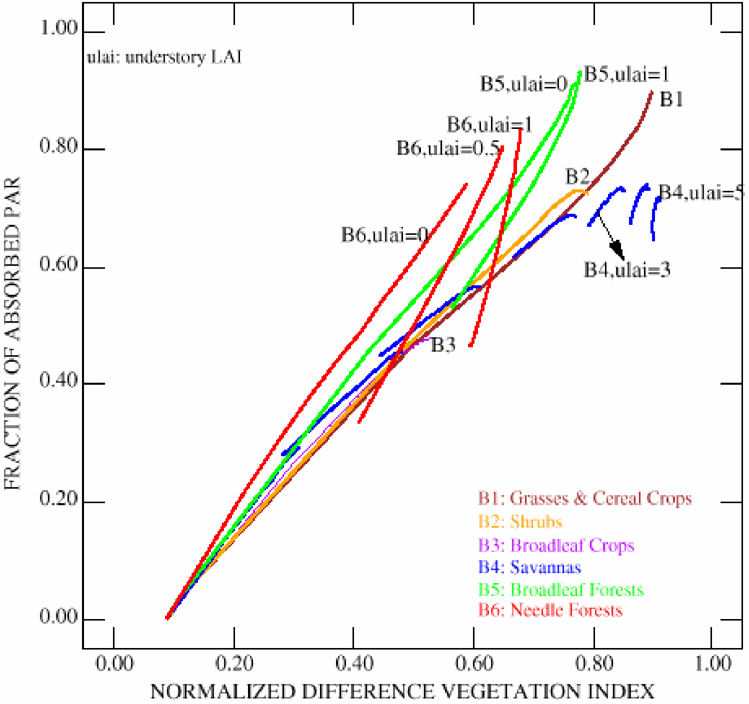
Leaf area Index (LAI)



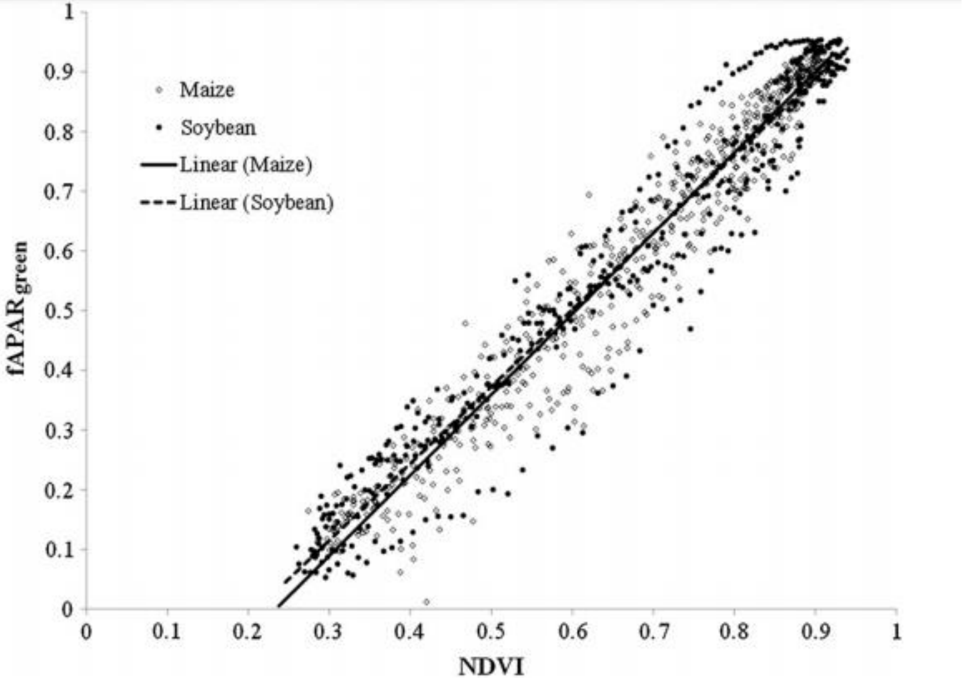
Index	Description	Formula	Reference
	Existing indices		
NDVI	NDVI	$\frac{\rho_{NIR}-\rho_{red}}{\rho_{NIR}+\rho_{red}}$	[15]
$\text{NDVI}_{\text{Red-edge}}$	Red-edge NDVI	$\frac{\rho_{NIR}-\rho_{RE}}{\rho_{NIR}+\rho_{RE}}$	[41]
MSR	MSR index	$\frac{\rho_{NIR}/\rho_{red}-1}{\sqrt{\rho_{NIR}/\rho_{red}+1}}$	[38]
$\text{MSR}_{\text{Red-edge}}$	Red-edge MSR index	$\frac{\rho_{NIR}/\rho_{RE}-1}{\sqrt{\rho_{NIR}/\rho_{RE}+1}}$	[34]
CI_{green}	Green CI	$\frac{\rho_{NIR}}{\rho_{green}}-1$	[42]
$\text{CI}_{\text{Red-edge}}$	Red-edge CI	$\frac{\rho_{NIR}}{\rho_{RE}}-1$	[43]
	Improved indices		
$\text{NDVI}_{\text{red\& RE}}$	Red and red-edge NDVI	$\frac{\rho_{NIR}-(a^*\rho_{red}+(1-a)^*\rho_{RE})}{\rho_{NIR}+(a^*\rho_{red}+(1-a)^*\rho_{RE})}$	–
$\text{MSR}_{\text{red\& RE}}$	Red and red-edge MSR index	$\frac{\rho_{NIR}/(a^*\rho_{red}+(1-a)^*\rho_{RE})-1}{\sqrt{\rho_{NIR}/(a^*\rho_{red}+(1-a)^*\rho_{RE})+1}}$	–
$\text{CI}_{\text{red\& RE}}$	Red and red-edge modified CI	$\frac{\rho_{NIR}}{a^*\rho_{red}+(1-a)^*\rho_{RE}}-1$	–

Xie, Q., Dash, et al. (2018 IEEE Journal of selected topics in applied earth observations and remote sensing, 11(5), 1482-1493.

http://www2.geog.ucl.ac.uk/~plewis/climate/lai.html



Gitelson et al., RSE 147, 2014)



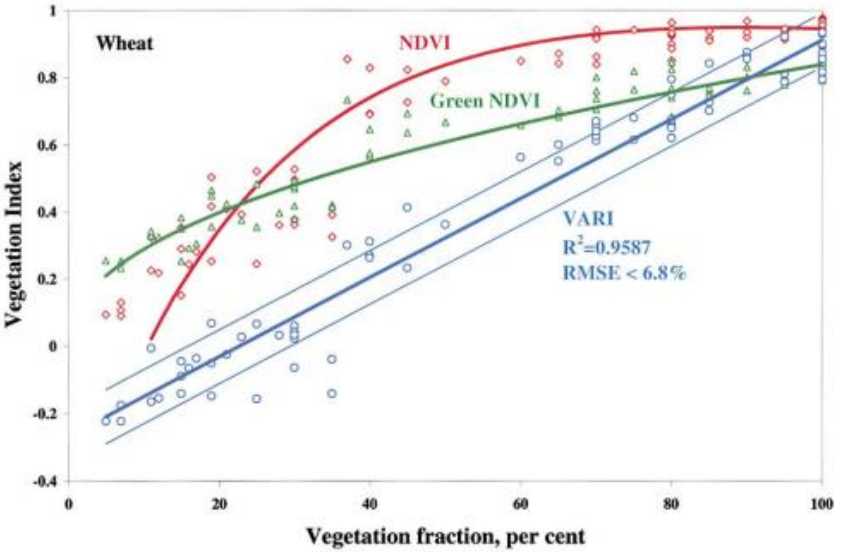
The MODIS-retrieved fAPARgreen/NDVI relationships for maize (2001-18) and soybean (sparce years) in vegetative stage

Empirical Transfer Functions

Vegetation indices, based on spectral behavior of vegetation, are widely used for monitoring, analyzing, and mapping temporal and spatial variations of some biophysical parameters.

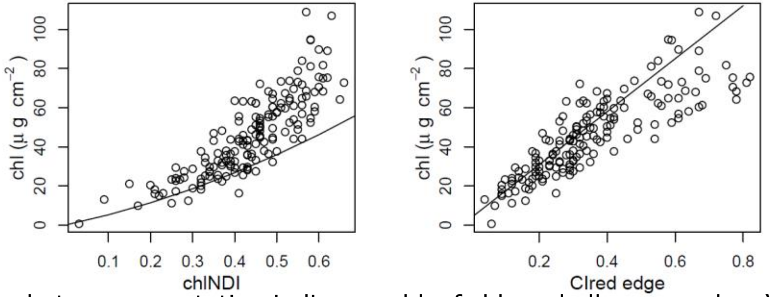
They require an accurate calibration and validation base on ground measurements.

A.A. Gitelson et al. / Remote Sensing of Environment 80 (2002) 76–87

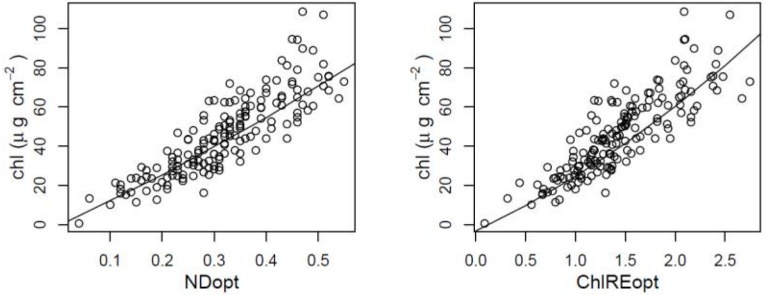


Estimation of leaf chlorophyll

Indice	Formulazione
Chlorophyll Normalized Difference Index	$ChlNDI = \frac{(R_{750} - R_{705})}{(R_{750} + R_{705})}$
Green NDVI	$GreenNDVI = \frac{(R_{780-890} - R_{500-590})}{(R_{780-890} + R_{500-590})}$
Red Edge Chlorophyll Index	$CI_{red\_edge} = \frac{R_{avg(770-800)}}{R_{avg(720-730)}} - 1$
Modified Simple Ratio	$mSR = \frac{(R_{728} - R_{434})}{(R_{720} - R_{434})}$
Modified Normalized Difference	$mND = \frac{(R_{728} - R_{720})}{(R_{728} + R_{720} - 2R_{434})}$
Chlorophyll vegetation index (CVI)	$CVI = \frac{(R_{610-680} \cdot R_{780-890})}{(R_{610-680})^2}$
Chlorophyll Red Edge Optimized Index	$Chl_{RE\_opt} = \left(\frac{1}{R_{avg(680-730)}} - \frac{1}{R_{avg(780-800)}}\right) \times R_{avg(755-780)}$
Normalized Difference Optimized Index	$ND_{opt} = \frac{(R_{780} - R_{712})}{(R_{780} + R_{712})}$



Relationships between vegetation indices and leaf chlorophyll proposed as 'general purpose' predictive models in the literature.
ChlNDI: Richardson et al. 2002; CIred_edge: Ciganda et al. 2009; NDopt: Féret et al. 2011; ChlRE_opt: Féret et al. 2011



Casa, R., Castaldi, F., Pascucci, S., Pignatti, S., 2014. Chlorophyll estimation in field crops: an assessment of handheld leaf meters and spectral reflectance measurements. Journal of Agricultural Science, 153, 876-890.

Estimation of leaf chlorophyll from hyperspectral remote sensing

Table 7. *Results of the calibration models for the reflectance indices and the PLSR on the experimental dataset of Table 1. The coefficients correspond to the relationship chlorophyll = a + b × index for the linear model and chlorophyll = a + b × index + c × index² for the quadratic model. Significance of the coefficients is reported*

Index	Equation	a	b	c	R^2	RMSE ($\mu g/cm^2$)	RPD	RRMSE (proportion)
ChlNDI	Linear	−19·1 ($P<0·01$)	149·90 ($P<0·01$)		0·70	11·18	1·83	0·244
	Quadratic	5·79 (ns)	13·79 (ns)	169·36 ($P<0·01$)	0·73	10·73	1·91	0·234
CI_{red_edge}	Linear	12·15 ($P<0·01$)	95·96 ($P<0·01$)		0·72	10·95	1·87	0·239
	Quadratic	−0·86 ($P<0·01$)	174·88 ($P<0·01$)	−94·65 ($P<0·01$)	0·75	10·39	1·97	0·227

Table 8. *Results of the calibration models for the reflectance indices and the PLSR on the synthetic dataset simulated by PROSPECT. The coefficients correspond to the relationship chlorophyll = a + b × index for the linear model and chlorophyll = a + b × index + c × index² for the quadratic model*

Index	Equation	a	b	c	R^2	RMSE ($\mu g/cm^2$)	RPD	RRMSE (proportion)
CI_{red_edge}	Linear	20·2	80·0		0·64	2·98	1·63	0·059
	Quadratic	1·3	180·6	−131·9	0·64	2·94	1·65	0·059
$ChlRE_{opt}$	Linear	9·8	23·6		0·63	3·00	1·62	0·060
	Quadratic	−2·8	38·4	−4·3	0·63	3·00	1·62	0·060

Casa, R., Castaldi, F., Pascucci, S., Pignatti, S., 2014. Chlorophyll estimation in field crops: an assessment of handheld leaf meters and spectral reflectance measurements. Journal of Agricultural Science, 153, 876-890.

VIs in SNAP

The following table summarizes the radiometric indices provided with the toolbox:

Name	Purpose/Classification	Short Description
NDVI	Normalized Difference Vegetation Index	The well-known classical vegetation index. The NDVI composes a measurement for the photosynthetic activity and is strongly in correlation with density and vitality of the vegetation
DVI	Difference Vegetation Index	This index is sensitive to the amount of vegetation
RVI	Ratio Vegetation Index	The simplest ratio-based index, it is also called the Simple Ratio (SR). It indicates the amount of vegetation. It also reduces the effects of atmosphere and topography
PVI	Perpendicular Vegetation Index	This index could be considered a generalization of the DVI, which allows for soil lines of different slopes.
IPVI	Infrared Percentage Vegetation Index	This index is functionally equivalent to NDVI and RVI, but it only ranges in value from 0.0 - 1.0
WDVI	Weighted Difference Vegetation Index	WDVI is a mathematically simpler version of PVI, but it has an unrestricted range
TNDVI	Transformed Normalized Difference Vegetation Index	TNDVI algorithm indicates a relation between the amount of green biomass that is found in a pixel
GNDVI	Green Normalized Difference Vegetation Index	GNDVI is more sensible than NDVI to identify different concentration rates of chlorophyll, which is highly correlated at nitrogen.
GEMI	Global Environmental Monitoring Index	Was developed to eliminate the need for a detailed atmospheric correction by constructing a stock atmospheric correction for the vegetation index
ARVI	Atmospherically Resistant Vegetation Index	This index takes advantage of the different scattering responses from the blue and red band to retrieve information regarding the atmosphere opacity
NDI45	Normalized Difference Index	This index algorithm is more linear, with less saturation at higher values than the NDVI.
MTCI	Meris Terrestrial Chlorophyll Index	This index was developed for estimating chlorophyll content from MERIS (Medium Resolution Imaging Spectrometer) data
MCARI	Modified Chlorophyll Absorption Ratio Index	This index was developed to be responsive to both leaf chlorophyll concentrations and ground reflectance.
REIP	Red-Edge Inflection Point index	This index was developed for applications in biomass and nitrogen (N) uptake measurment/management in heterogeneous fields.
S2REP	The Sentinel-2 Red-Edge Position index	This index is based on linear interpolation as presented by Guyot and Baret (1988). The reflectance at the inflexion point is estimated and in turn, the REP is retrieved through interpolation of S-2 band 5 and 6 which are positioned on the RE slope.
IRECI	Inverted Red-Edge Chlorophyll Index	This index algorithm incorporates the reflectance in four bands to estimate canopy chlorophyll content
PSSRa	Pigment Specific Simple Ratio (chlorophyll) index.	This index was developed to investigate the potential of a range of spectral approaches for quantifying pigments at the scale of the whole plant canopy.

SAVI	Soil Adjusted Vegetation Index	This index attempts to be a hybrid between the ratio-based indices and the perpendicular indices
TSAVI	Transformed Soil Adjusted Vegetation Index	This index assumes that the soil line has arbitrary slope and intercept, and it makes use of these values to adjust the vegetation index
MSAVI	Modified Soil Adjusted Vegetation Index	The basic idea of MSAVI was to provide a variable correction factor L. The correction factor used is based on the product of NDVI and WDVI
MSAVI2	The second Modified Soil Adjusted Vegetation Index	Basically, it is used an iterative process and substitute 1 - MSAVI(n-1) as the L factor in MSAVI(n). They then inductively solve the iteration where MSAVI(n) = MSAVI(n-1)
BI	Brightness Index	This index is representing the average of the brightness of a satellite image
BI2	The second Brightness Index	This index is representing the average of the brightness of a satellite image. The result looks like a panchromatique image with the same resolution of the original image.
RI	Redness Index	The Redness Index algorithm was developed to identify soil colour variations
CI	Colour Index	The Colour Index algorithm was developed to differentiate soils in the field
NDWI	Normalized Difference Water Index	This index is a measure of liquid water molecules in vegetation canopies that interacted with the incoming solar radiation.
NDWI2	The second Normalized Difference Water Index	This index was developed to detect surface waters in wetland environments and to allow for the measurement of surface water extent.
MNDWI	Modified Normalized Difference Water Index	This index was developed to enhance open water features, while efficiently suppressing and even removing built-up land noise as well as vegetation and soil noise.
NDPI	Normalized Difference Pond Index	The NDPI algorithm makes it possible not only to distinguish small ponds and water bodies (down to 0.01 ha), but also to differentiate vegetation inside ponds from that in their surroundings
NDTI	Normalized Difference Turbidity Index	This index was developed to allow for the measurement of water turbidity.

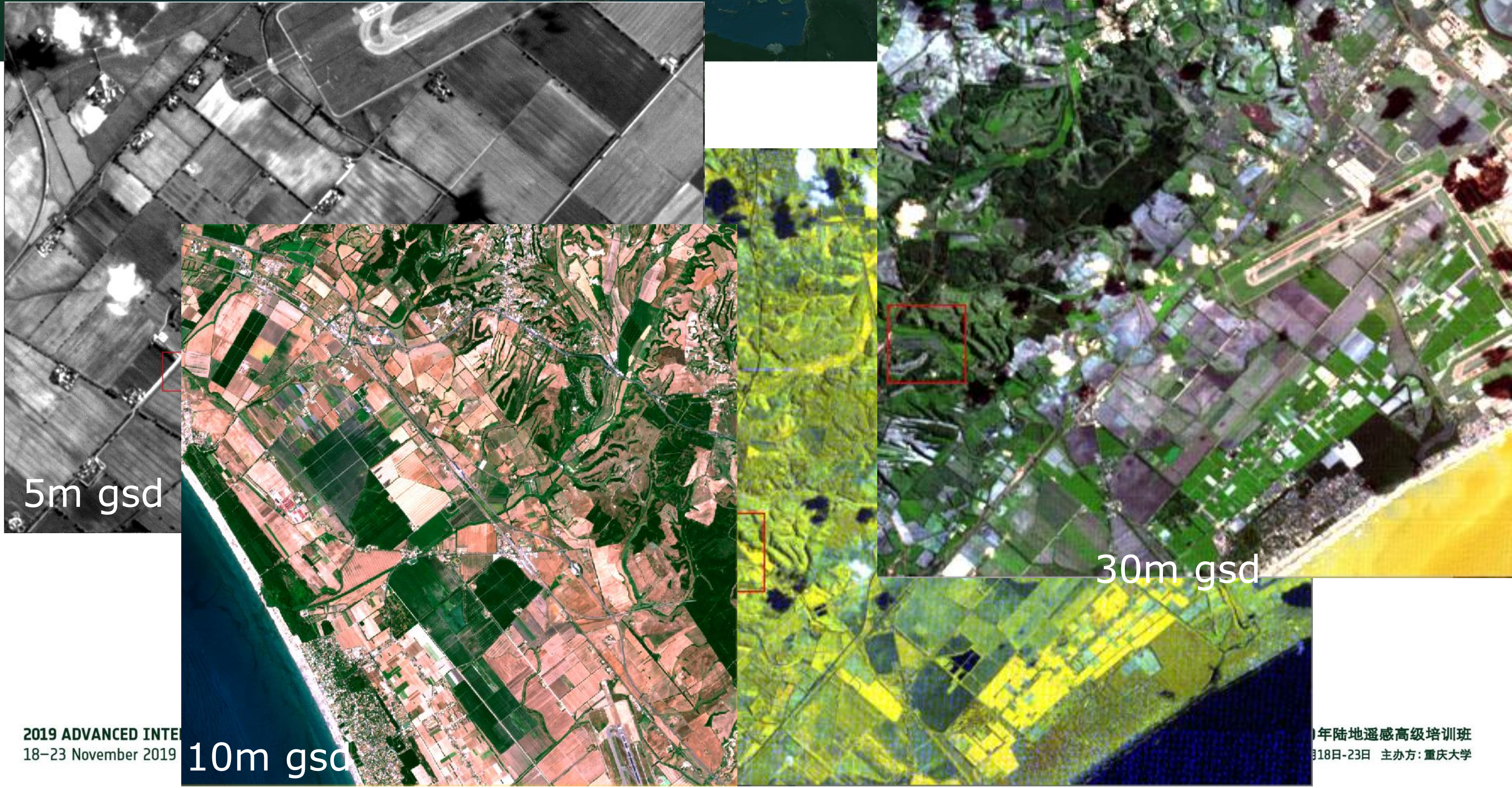
Accuracy metrics

Statistical metrics for accuracy/error assessment of the parameters retrieval

- Bias $Bias = \frac{\sum_{i=1}^{n} y_i - \hat{y}_i}{n}$
- Relative Bias $rBias = \frac{Bias}{\frac{\sum_{i=1}^{n} \hat{y}_i}{n}} * 100$
- Coefficient of determination $R^2 = \left(\frac{cov(y,\hat{y})}{\sigma_y \sigma_{\hat{y}}}\right)^2 = \left(\frac{\sum_{i=1}^{n}(y_i - \mu_y)(\hat{y}_i - \mu_{\hat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i - \mu_y)^2}\sqrt{\sum_{i=1}^{n}(\hat{y}_i - \mu_{\hat{y}})^2}}\right)^2$
- Root mean square error $RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}$
- Relative RMSE rRMSE $\frac{RMSE}{\frac{\sum_{i=1}^{n} \hat{y}_i}{n}} * 100$
- Mean Absolute Error $MAE = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n}$
- Ratio of performance to deviation $RPD = \frac{\sigma_y}{RMSE}$
- Ratio of performance to interquartile range $RPIQ = \frac{IQ_y}{RMSE}$

y are the observed variables, y ̂ are the estimated variables, n is the number of observations, σ and IQ are the standard deviation and the interquartile range, respectively

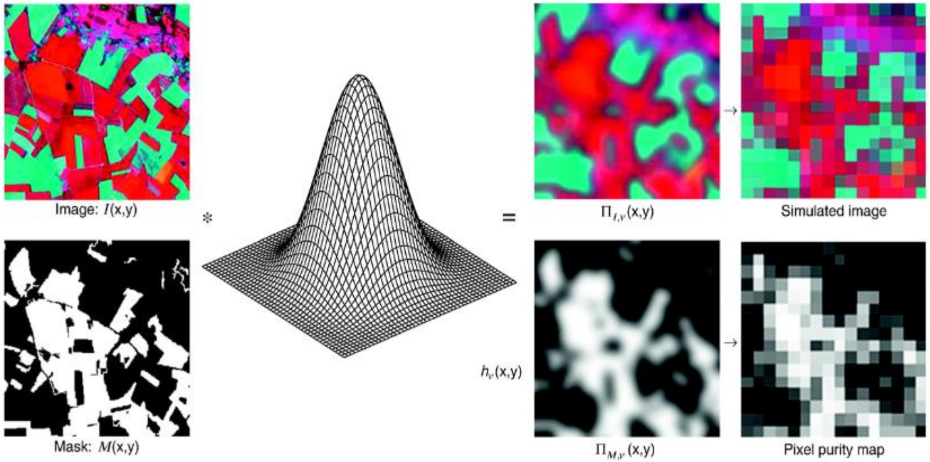
Spatial sampling vs GSD

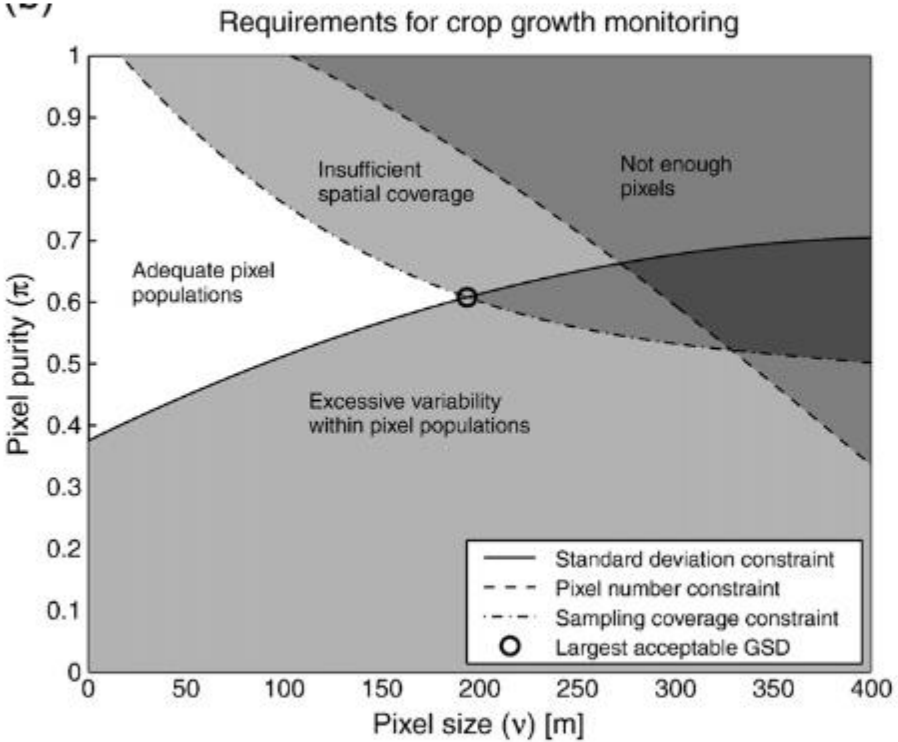



[1] Sentinel 2 MSI Natural Colors RGB
[2] RGB

Sampling strategies

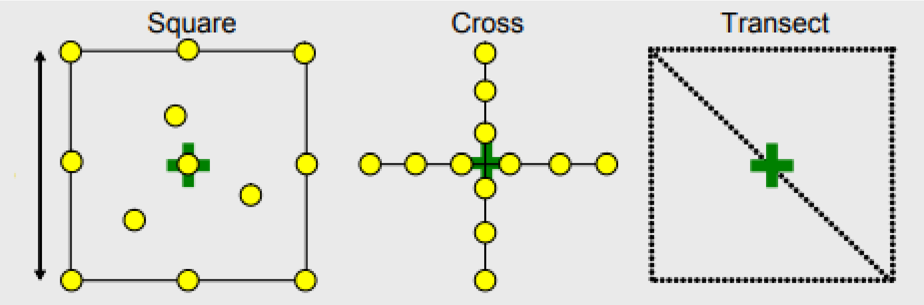
Duveiller at al., 2010 RSE

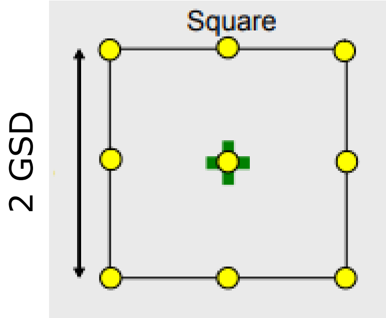




Theoretical boundaries in the pixel size–pixel purity space used to define the requirements for pixel crop growing

ESU





http://w3.avignon.inra.fr/valeri/documents/VALERI-RSESubmitted.pdf

ESU applied to the S2 Maccarese test site

ESU

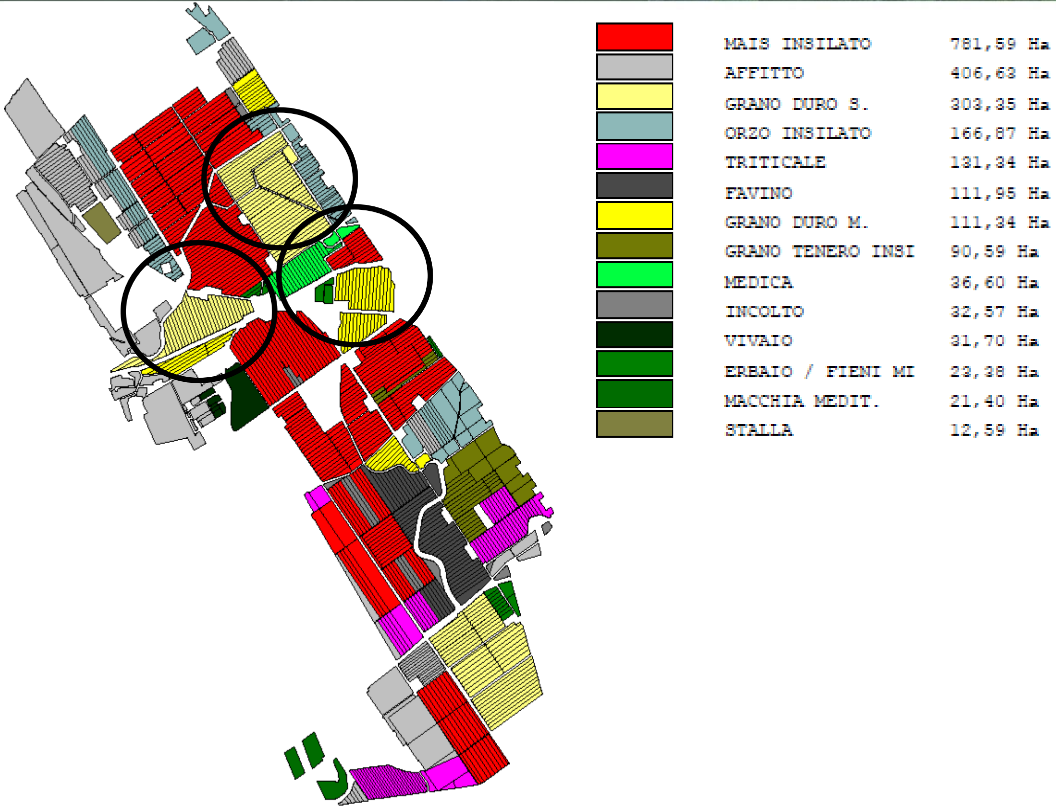
campaigns carried out during the durum crop season from February to April 2018 (S2)

31-gen; LAI, Chl
16-feb; LAI, Chl , biomass
06-apr; LAI, Chl
20-apr; LAI, CHL, biomass

In situ data collection: field campaign in Italy (Maccarese 2018)

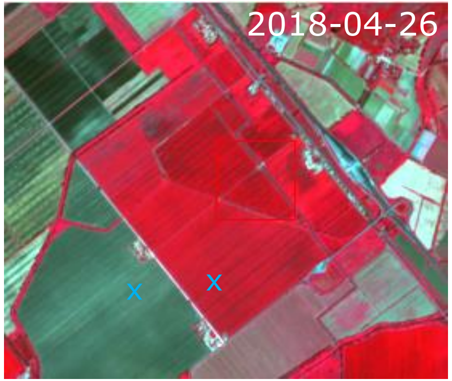
Study area is the Maccarese farm located in Central Italy, which is the second largest Italian private farm with about 3500 ha of agricultural fields (typically 10 ha or larger) was selected as study area.

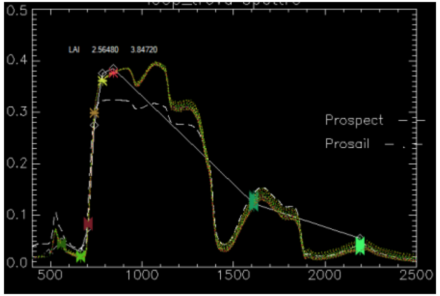
The farm is equipped with VRT and yield maps machinery.

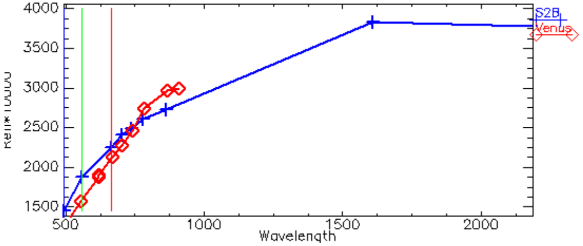


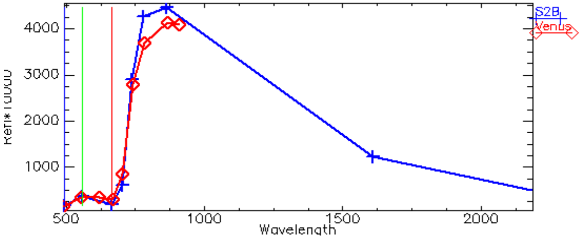
Venus / S-2 reflectances

S-2

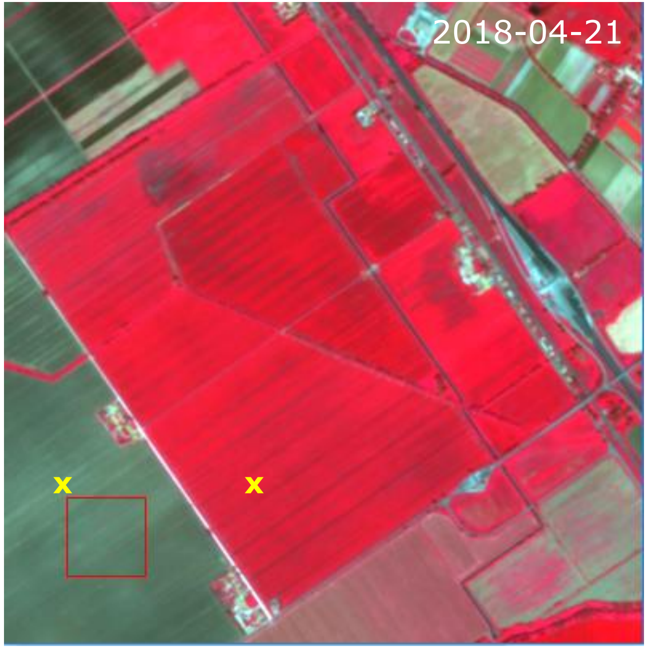




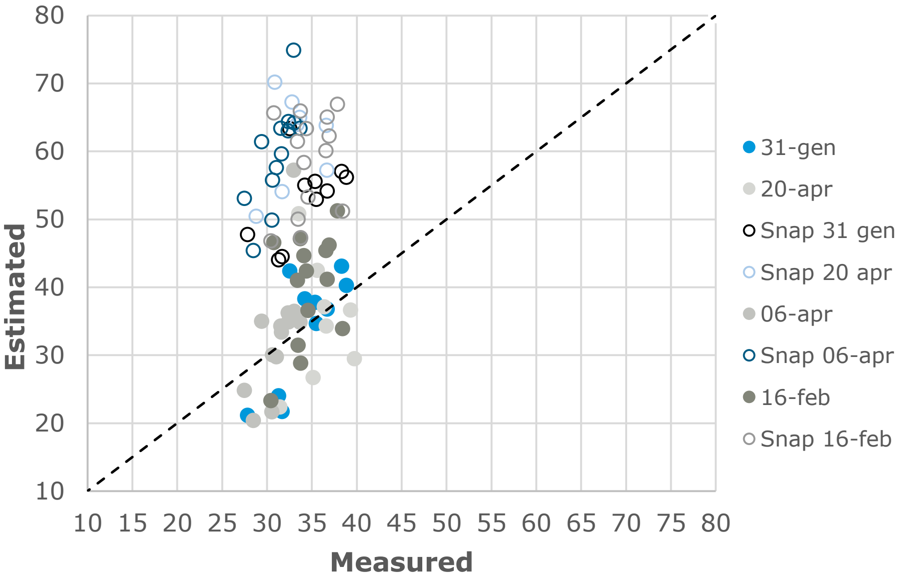


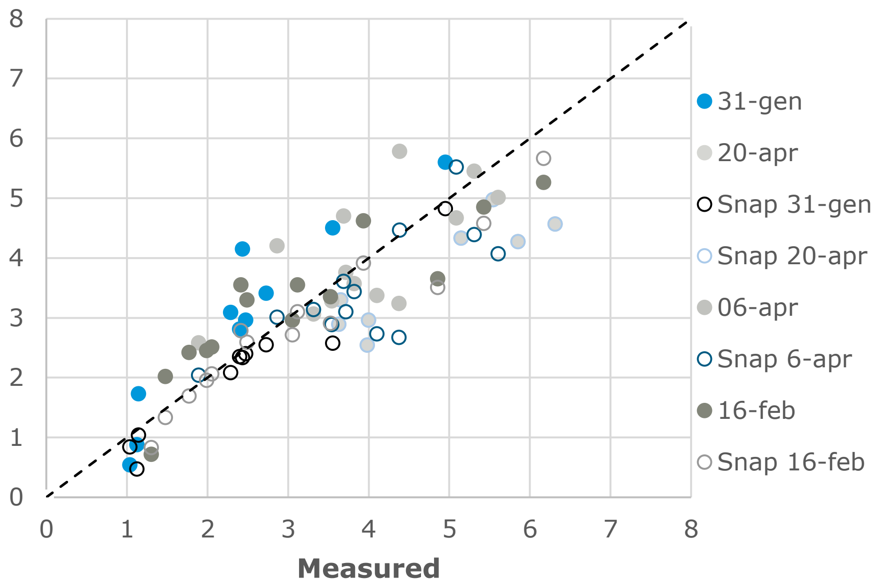


Venus



RS Validation using field campaign data in Italy (Maccarese 2018)





Chl SNAP R^2 = -0,14; RMSE = 25,91

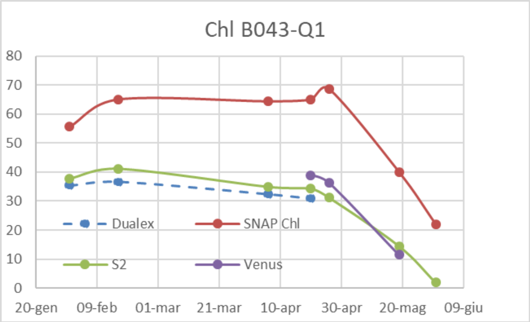
Chl R^2 = 0,27; RMSE =8,06

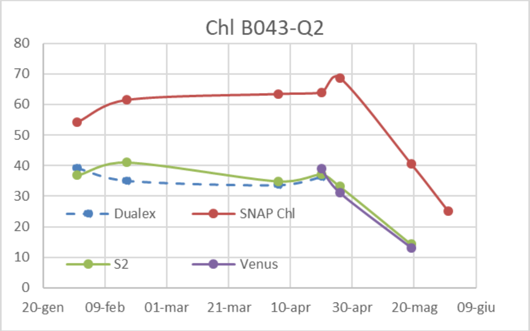
LAI SNAP R^2 = 0,85; RMSE = 0,74

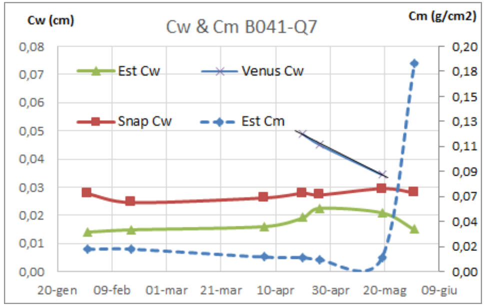
LAI R^2 = 0,71; RMSE = 0,77

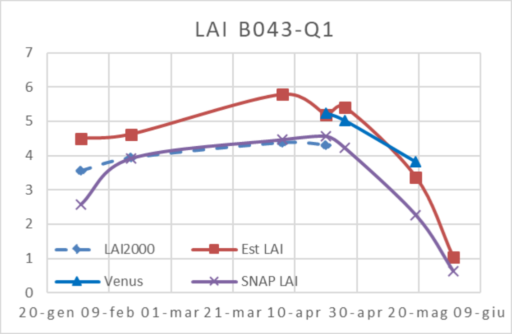
RS Validation using field campaign data in Italy (Maccarese 2018)

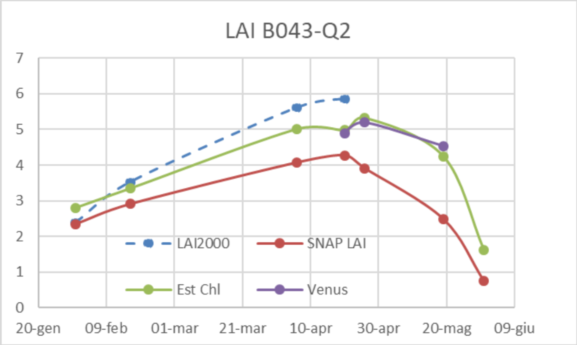
S2 & Venus vs time

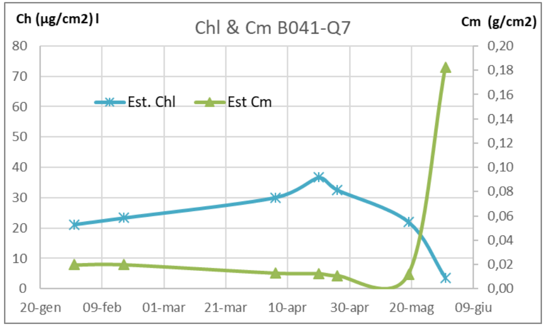








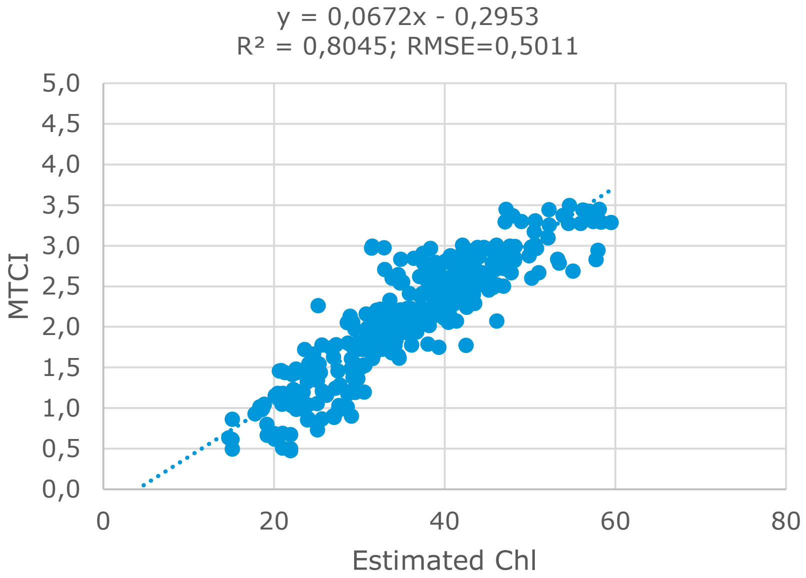




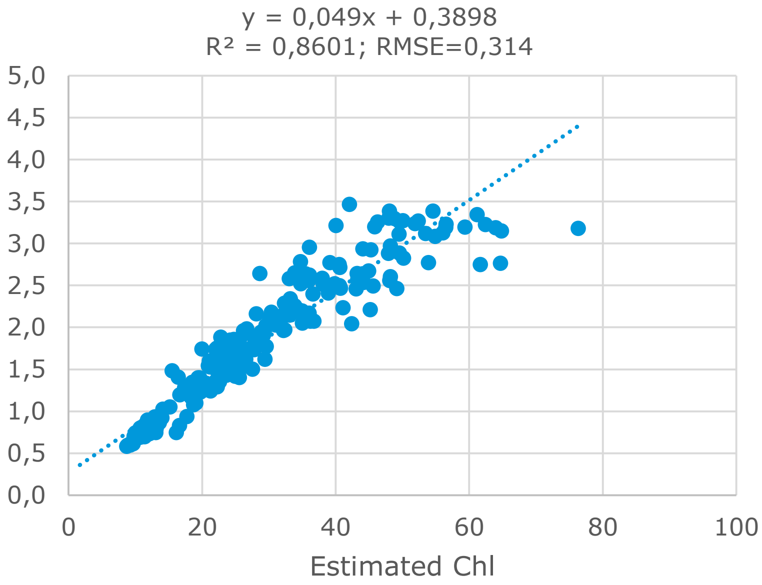
S2/Venµs MTCI vs Chl

S2 Jan. to May

(740-665)/(740+665)



(742-620)/(742+620)



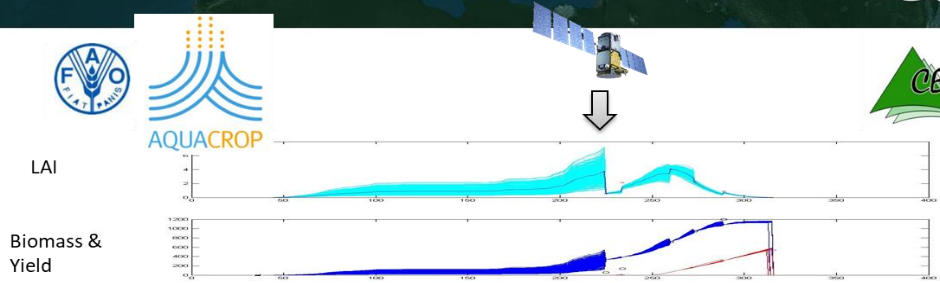
Venµs Apr. to May

Assimilation of RS data into crop models:

example of LAI, Biomass and Yield in China

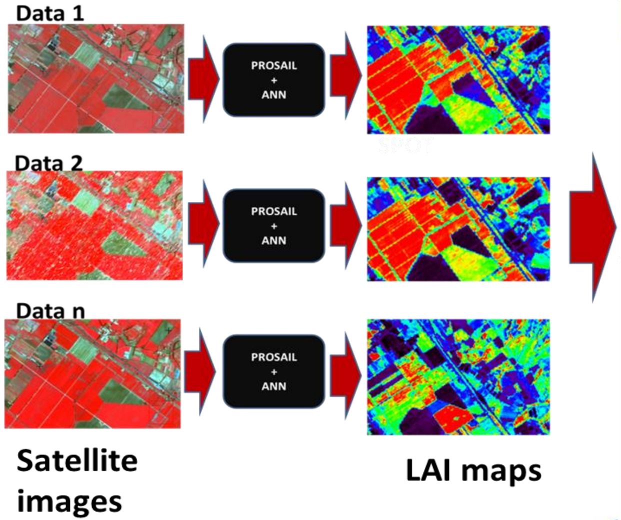
Analysis about:

- LAI
- Biomass
- Height
- Yield
- Soil Moisture
- Soil Roughness

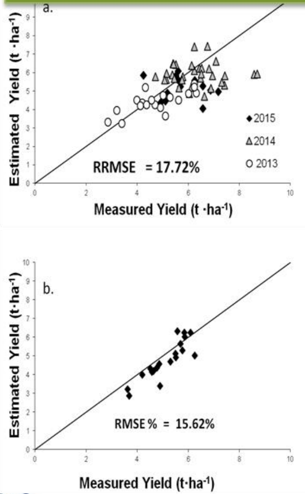


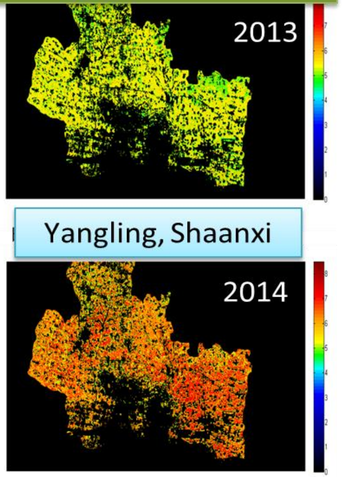
SAFY

Example of LAI, Biomass and Yield simulation with EnKF assimilation for SAFY
(7 Oct 2008, Xiaotangshan field experiments)



Wheat yield estimation





Yangling, Shaanxi

RS variables assimilation in crop models

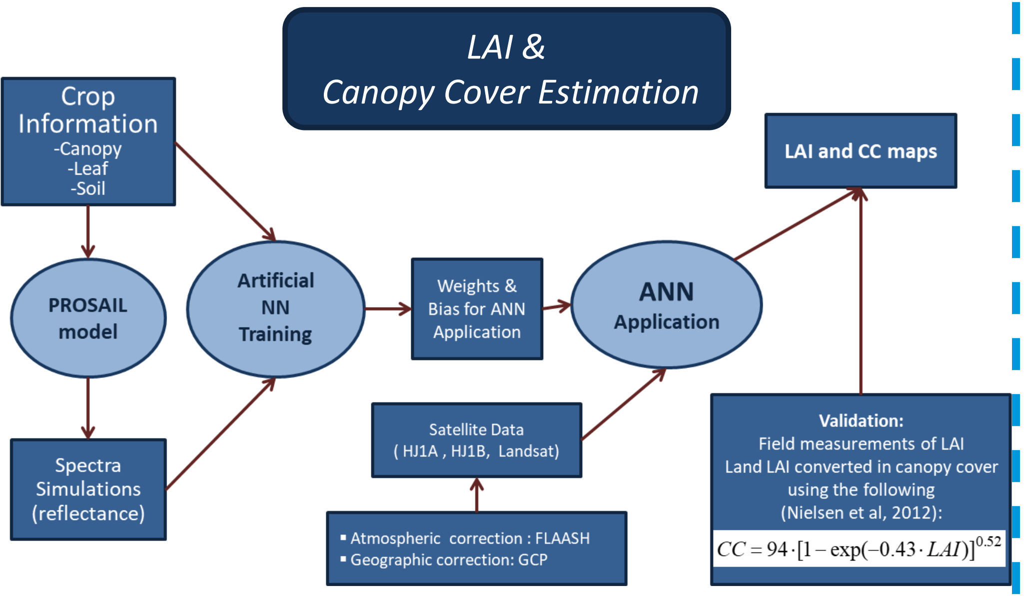
Yangling, Shaanxi, (China)

Xiaotanshang, Beijing (China)

Type	Date	Measurements
Field Data	30/3/2013	High, density, SPAD, TDR, LAI , Fresh and dry Biomass
Field Data	27/4 2013	High, density, SPAD, TDR, LAI , Fresh and dry Biomass
Field Data	1/6/2013	TDR, Yield
Climate	2013	Precipitacion, Average wind speed, Temperature (min, MAX, average), sunshine duration
HJ1B	05/03/2013	multispectral
HJ1B	20/03/2013	multispectral
HJ1B	28/03/2013	multispectral
HJ1A	30/03/2013	multispectral
Landsat 8	03/04/2013	multispectral
HJ1A	07/04/2013	multispecral
HJ1A	26/04/2013	multipectral
HJ1A	11/05/2013	multispectral

Type	Notes
Climate	Precipitation, Average wind speed, Temperature (min, max, average), Sunshine duration
Sowing Date	27 Sep, 7Oct, 20 Oct 2008 25 Sep, 5 Oct, 15 Oct 2009 25 Sep, 5 Oct, 15 Oct 2010
Yield measurement	Grain yield was measured following maturation from samples obtained from a 1.5 m 2 area in each plot, with three replications for each treatment.
Field Management	List of different management, required only by Aquacrop model
Biomass	Biomass was determined from a 0.25 m^2 area by randomly cutting four representative plants from each plot . All plant samples were oven dried at 70°C to a constant weight, and final dry weight recorded.
Canpy Cover	Canopy Cover was eximated as function of LAI (Hsiao et al.) . The LAI-2000 Plant Canopy Analyzer (LI-COR Inc.,Lincoln, NE, USA) was used in measuring for determination of LAI.
Irrigation	Day of irrigation, amount of irrigated water (in mm)
Soil Characteristics	Information s about: Field Capacity, Wilting Point and Saturation

RS variables assimilation in crop models



Crop Models

AQUACROP
(Steduto et al., 2009)

- Water driven crop model
- Main state variables: Canopy Cover and Biomass
- Calibration is not easy because of 100 and more parameters
- Slow to optimize and source code not accessible

SAFY
(Duchemin et al., 2007)

- links the production of total dry phytomass to the of solar radiation (PAR) absorbed by the crop
- Main state variables: LAI and Biomass
- Modified version introduces the water balance according to the equations described in the FAO 56 document
- Reduced number of parameters, easy to use and fast to compute

RS variables assimilation in crop models

Optimization Method on Aquacrop

Solution:
The parameters are re-calibrated using the optimization method wich minimizes the RMSE between measured and estimated CC

Particle Swarm Optimization

Simplex Optimization

Individuation of main Parameter

Calibration of all Parameters

Evaluation of the variation for main parameters

Evaluation of Measurements Error

Simplex Optimization to minimize the MSE:

$$MSE = \sum_{i=1}^{n} \frac{(CC_s(i) - CC_m(i))^2}{n}$$

Yield estimation

Regional Scale Application

Winter Wheat Map:

- 5 images acquired between February and June
- The images were converted into LAI Maps through the PROSAIL-ANN algorithm
- We verified if the LAI temporal series of each pixel matches with the LAI wheat trend

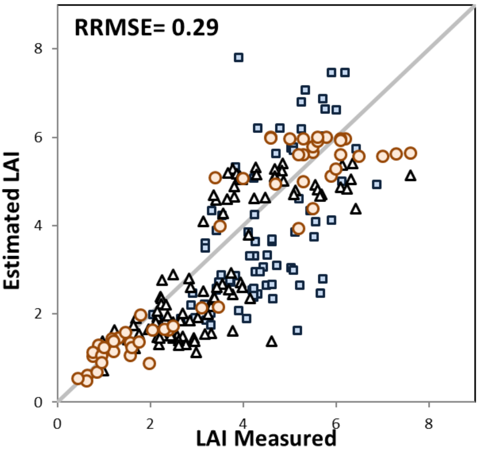
Winter wheat growth cycle in Yangling rural area 2013 and 2014

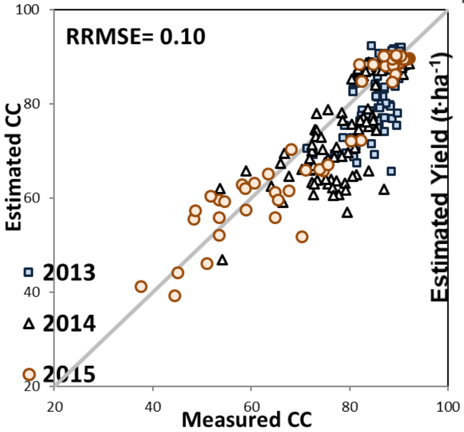
Validation data : Yield/Area provided by the Shaanxi Provincial Bureau of Statistics and the National Bureau of Statistics of the People's Republic of China.

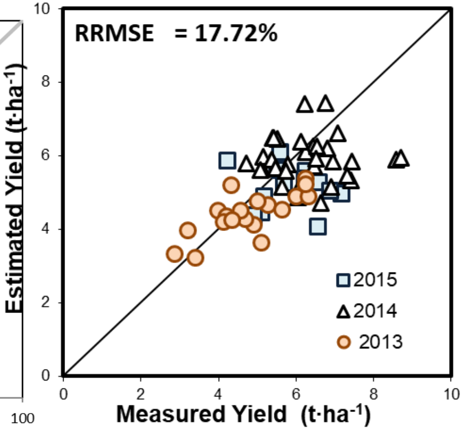
Lai, yield VALIDATION

LAI and Canopy Cover validation

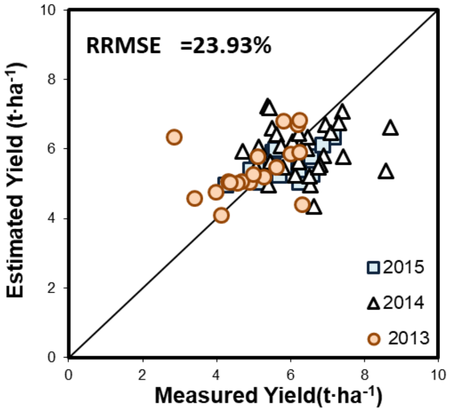
Comparison of two different models







EnKF-SAFY



PSO-Aquacrop

Regional Applicarion results: Yangling Rural Area