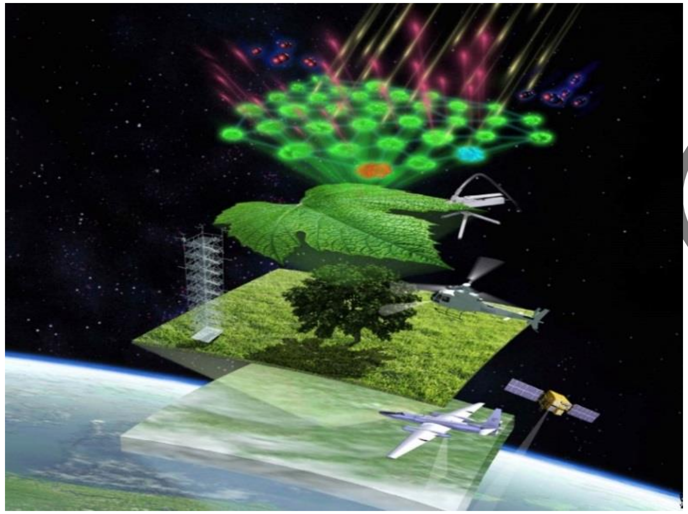
CA17134 - Optical synergies for spatiotemporal SENSing of scalable ECOphysiological traits (SENSECO)

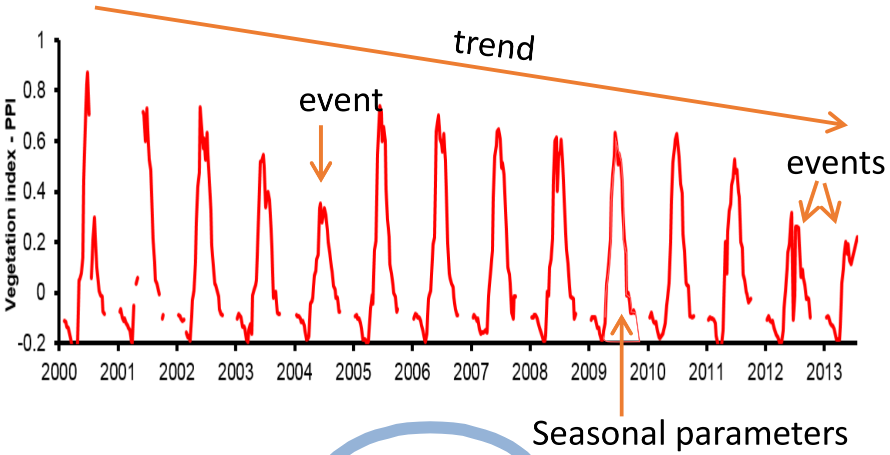
Proposers: J. Verrelst, M. Schlerf, A. Mac Arthur, M. Cendrero-Mateo, S. Van Wittenberghe, H. Aasen, A. Hueni, K. Sakowska, C. van der Tol, L. Kooistra, M. Machwitz, J. Pacheco-Labrador, L. Eklundh and many more

EUROSPEC (2009-13) → OPTIMISE (2014-18) → SENSECO (2018-22)

WG1: Closing the scaling gap



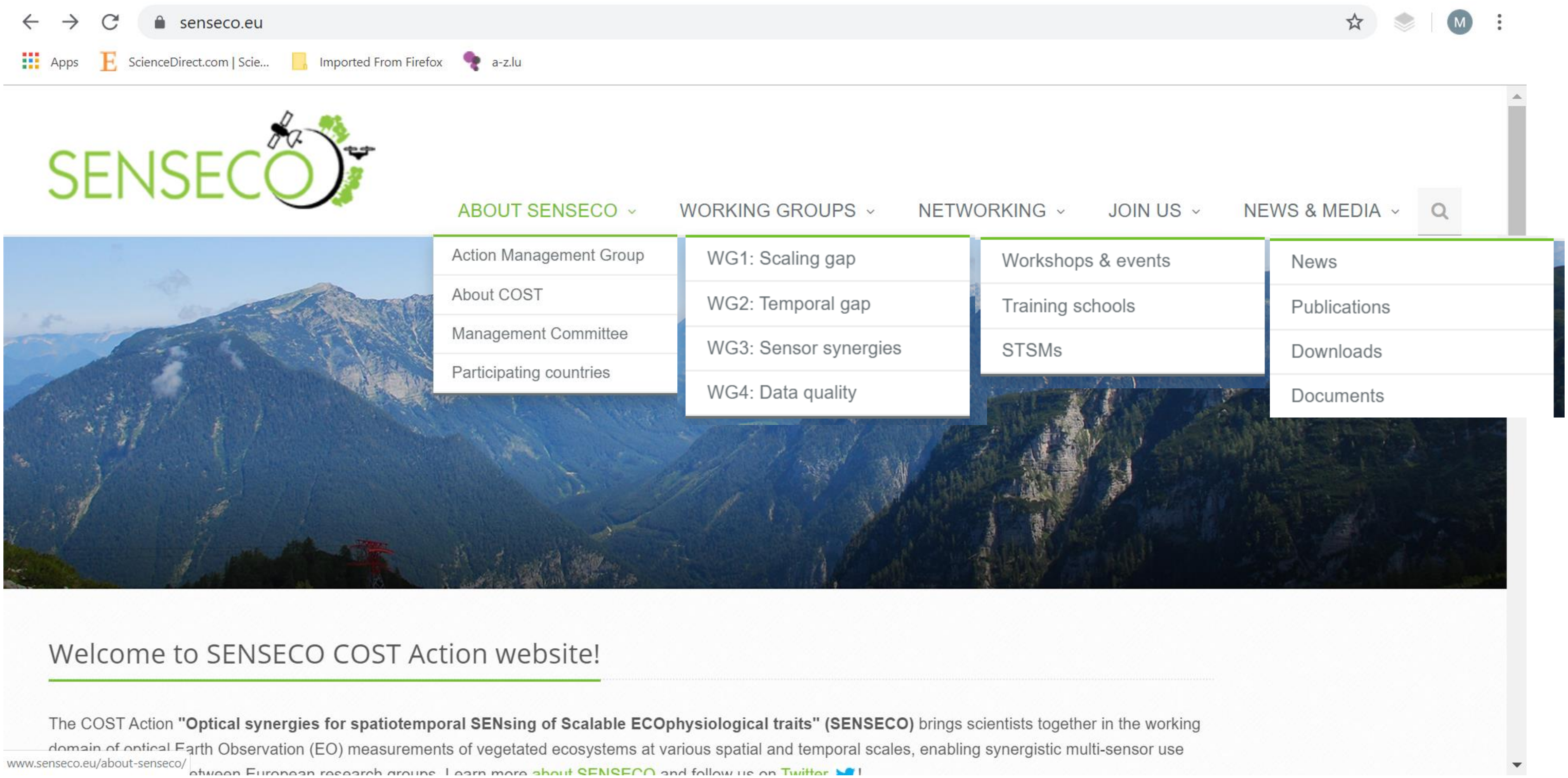
WG2: Closing the temporal gap



WG3: Realizing synergy between passive EO spectral domains

WG 4: Establishing data quality through traceability and uncertainty

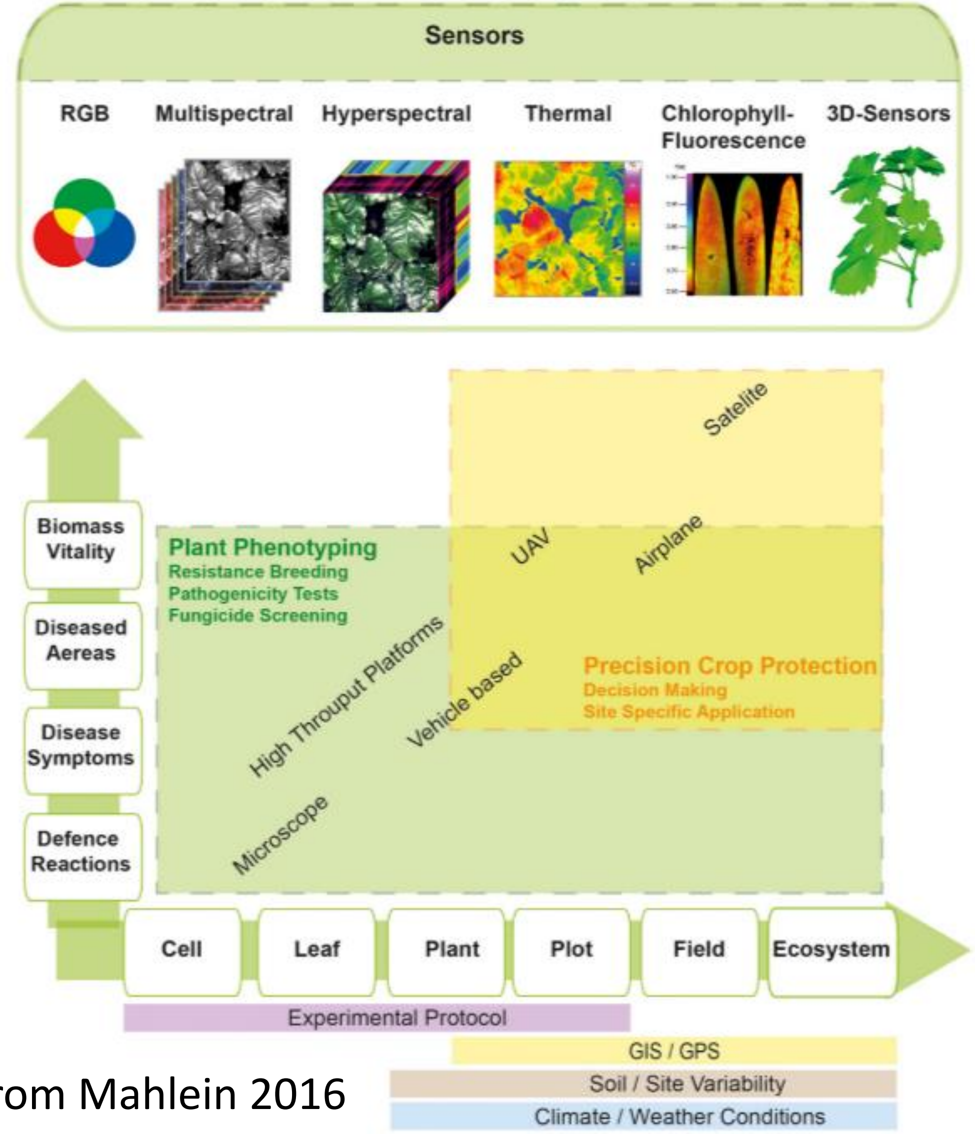
Further information



Remote sensing of vegetation – some claims on selected traits

Martin Schlerf
with input from Katja Berger and the joint SENSECO-WG3 and Phenotyping discussion group

Aim



From Mahlein 2016

While brainstorming on common interests between remote sensing and phenotyping communities, the following question emerged:

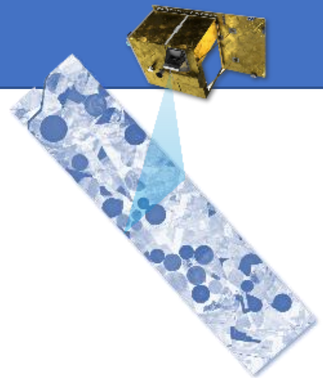
<u>Using RS methods, can we measure physiological variables and processes, for instance biomass, growth, nitrogen, stress? How? Accuracy?</u>

“Modern plant phenotyping relies on a couple of rapidly developing pillars, e.g. non-destructive measurements to be able to follow a trait over time…” (Corrado Costa et al. 2019)

→ Some comments & claims on:

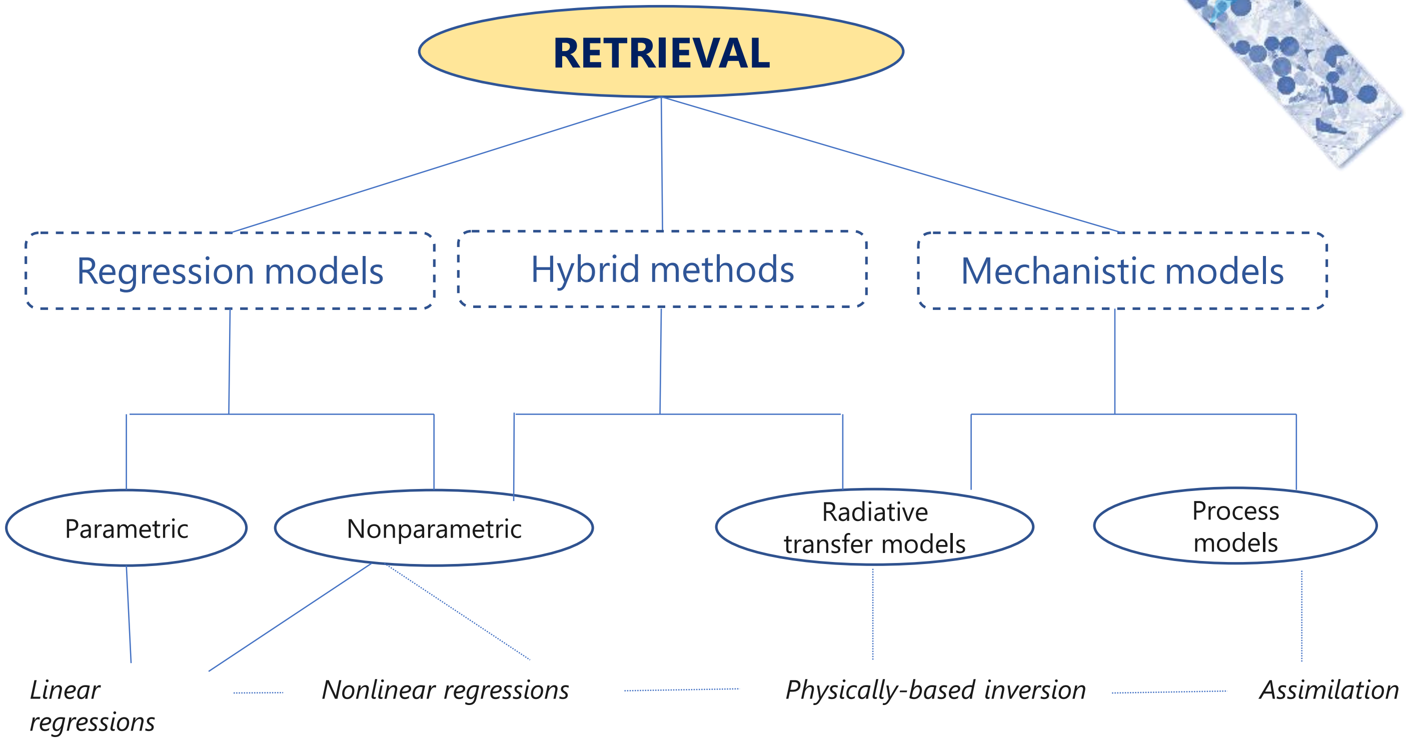
- Nitrogen content
- PRI for LUE
- Other aspects

Available traits and retrieval methods



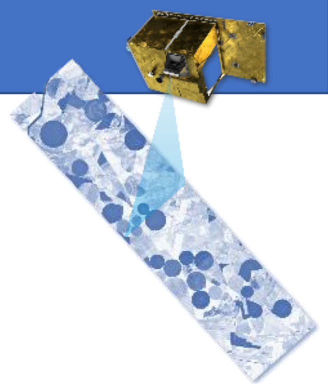
Functional vegetation traits are generally of continuous nature and can be grouped into diverse subgroups (see e.g., Weiss et al., 2020):

- biophysical (e.g. leaf area index, fCover, biomass)
- biochemical (e.g. leaf chlorophyll content, leaf nitrogen content)
- structural (e.g. plant density, leaf inclination)
- biological (e.g. light use efficiency, NPP, yield)
- physiological (e.g. stomatal conductance)
- geophysical (e.g. soil moisture, conductivity)



Adapted from Verrelst et al. (2019a)

Available traits and retrieval methods



Parametric

- Narrowband vegetation indices (NB-VI), using discrete selected bands to formulate simple ratio or normalized difference, e.g. Glenn et al. (2008)
- Spectral positions (red edge inflection point, REIP), e.g. Cho et al. (2008)
- Spectral derivates, e.g., le Maire et al. (2004)
- Spectral integrals, e.g. Pasqualotto et al. (2018)
- Continuum removal, e.g. Malenovsky et al. (2013)
- Wavelet transform, e.g. Blackburn & Ferwerda (2008)

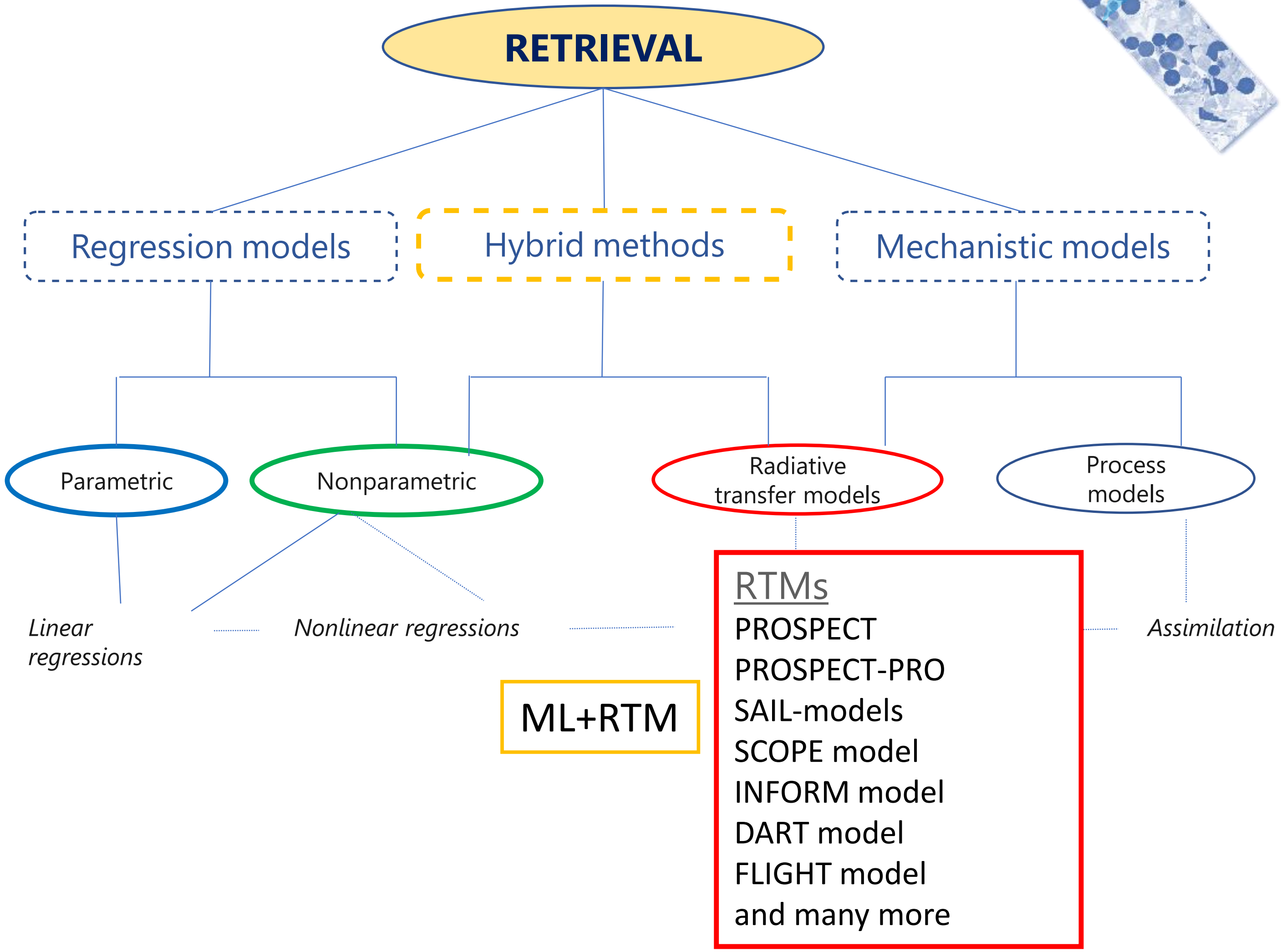
Non parametric linear

- Chemometrics, e.g. PLSR

Non-parametric non-linear (ML)

- Artificial neural networks
- Extreme learning machines
- Decision trees
- Bagging trees
- Boosting trees
- Kernel ridge regression
- Support vector regression
- Relevance vector machine
- Homoscedastic Gaussian process regression
- Variational Heteroscedastic Gaussian process regression

Adapted from Verrelst et al. (2019a)

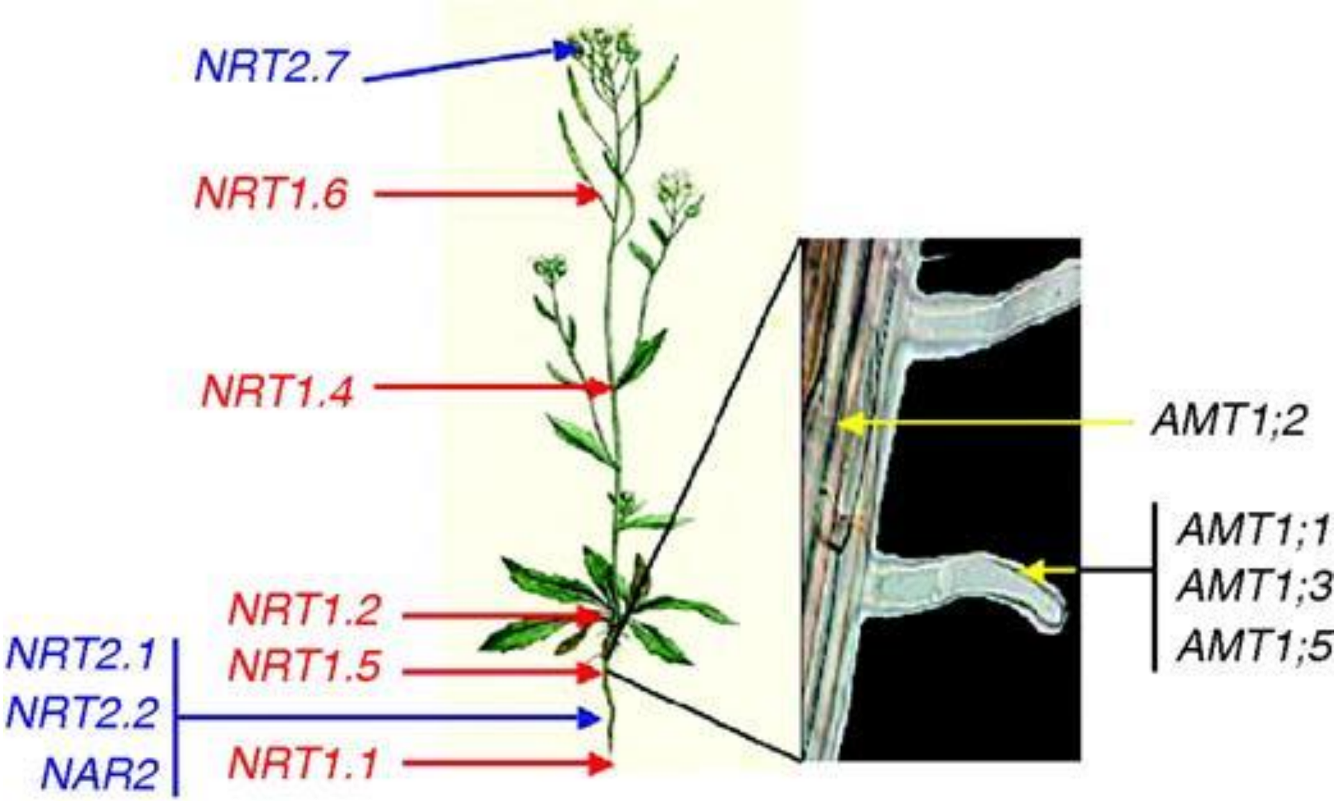


Are RS N quantities relevant to plant scientists?

Level	Variable	Definition	Unit
Leaf	concentration	Mass of N per mass dry matter	%
	content	Mass of N per leaf area	mg / cm2
Canopy	concentration	Mass of N per mass dry matter	%
	content	Mass of N per ground area	g / m2
Plant tissue or whole plant	uptake	a. Dynamic process b. N concentration multiplied by dry matter accumulation	g
Plant to field	nitrogen use efficiency	Output / input (e.g. grain yield per unit of nitrogen available from the soil	unitless

Nitrogen quantities; marked yellow= open to RS

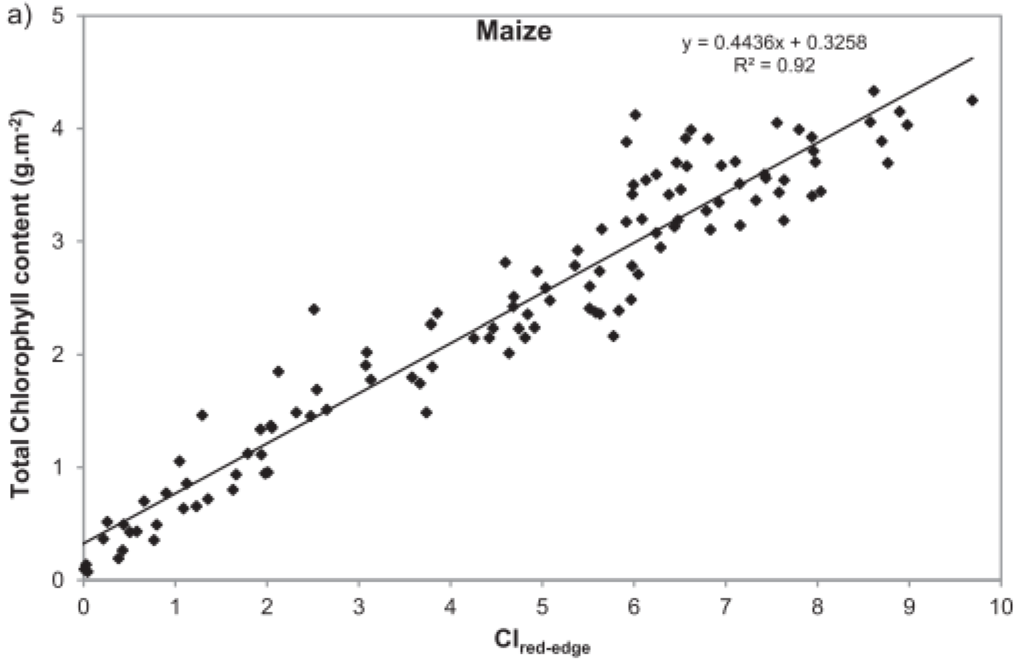
Interest in uptake, assimilation, translocation and, when the plant is ageing, recycling and remobilization



Nitrate uptake occurs at the root level and two nitrate transport systems have been shown to coexist in plants and to act co-ordinately to take up nitrate from the soil solution and distribute it within the whole plant (Masclaux-Daubresse et al 2010)

Indirect N estimation through N-Cab link

- moderately strong correlation between leaf N and Cab exists across different species (r = 0.65 ± 0.15) (Homolova et al. 2013)
- Canopy chlorophyll content can be well retrieved from CIred-edge = R800/R710 − 1)

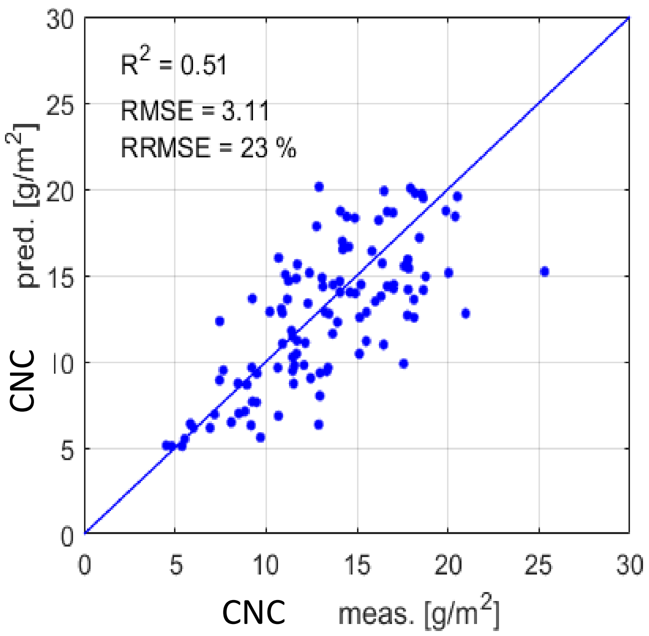


Clevers and Gitelson 2013

Indirect N estimation through LAI-CNC link

R (2017)	LAI	Cab	FM	DM	LNC	CNC	CCC
LAI	**1.00**						
Cab	0.31	**1.00**					
FM	**0.86**	0.34	**1.00**				
DM	0.73	0.38	**0.92**	**1.00**			
LNC	-0.32	-0.08	-0.58	-0.70	**1.00**		
CNC	**0.81**	0.44	**0.84**	**0.81**	**-0.23**	**1.00**	
CCC	**0.90**	0.68	**0.81**	0.74	-0.30	**0.81**	**1.00**

Data from n=181 wheat samples measured in 48 plots over 4 campaigns in 2C
in France and Belgium (Bossung, Schlerf, Machwitz 2021, in prep.)

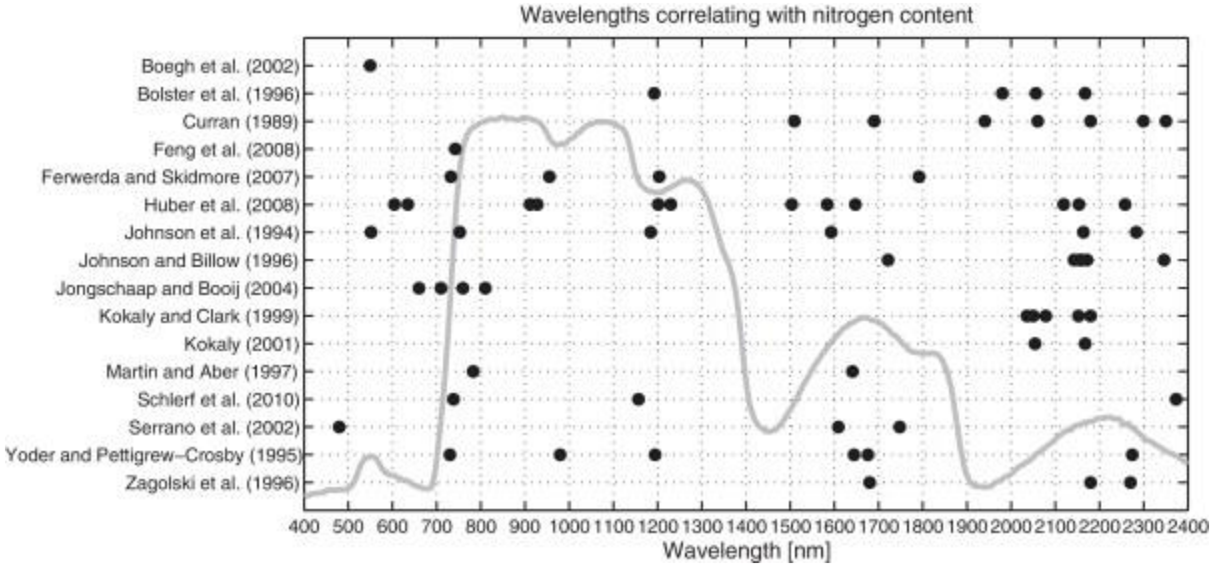


CNC (Can.-N-content) from Sentinel-2

- <u>Claim:</u> If canopy nitrogen content CNC (g/m2) is well linked to biomass (FM) and also to LAI, **and not linked to LNC**, we can use multi-spectral satellite data and common LAI retrieval methods plus empirical LAI-LNC relation to map CNC
- This may be the case on fertilised agricultural fields where LNC is typically at high levels with little spatial variation (But: dilution effect – LNC drops with increasing biomass during growth)

Direct empirical N estimation

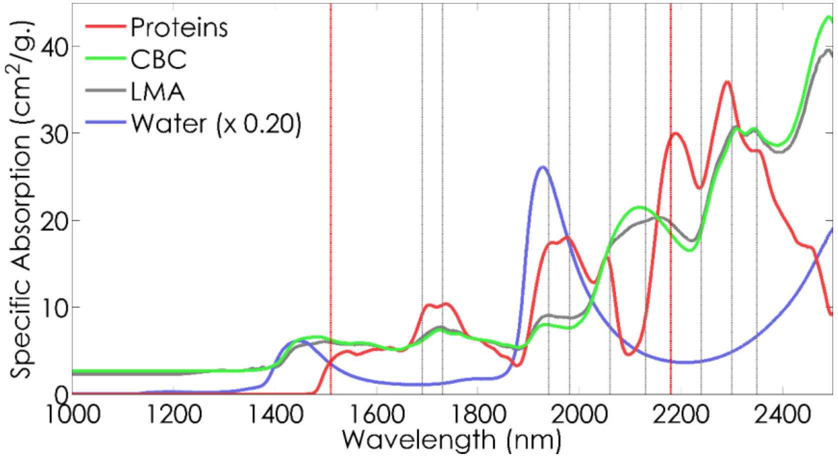
- Direct reflectance – N link, only empirical methods
- 20 studies: R2 = 0.6-0.8, relative RMSE = 10-20% Homolova et al. 2013
- selected wavelength often relate to red edge region and protein absorption features, but vary between studies
- In principle not transferable to other datasets



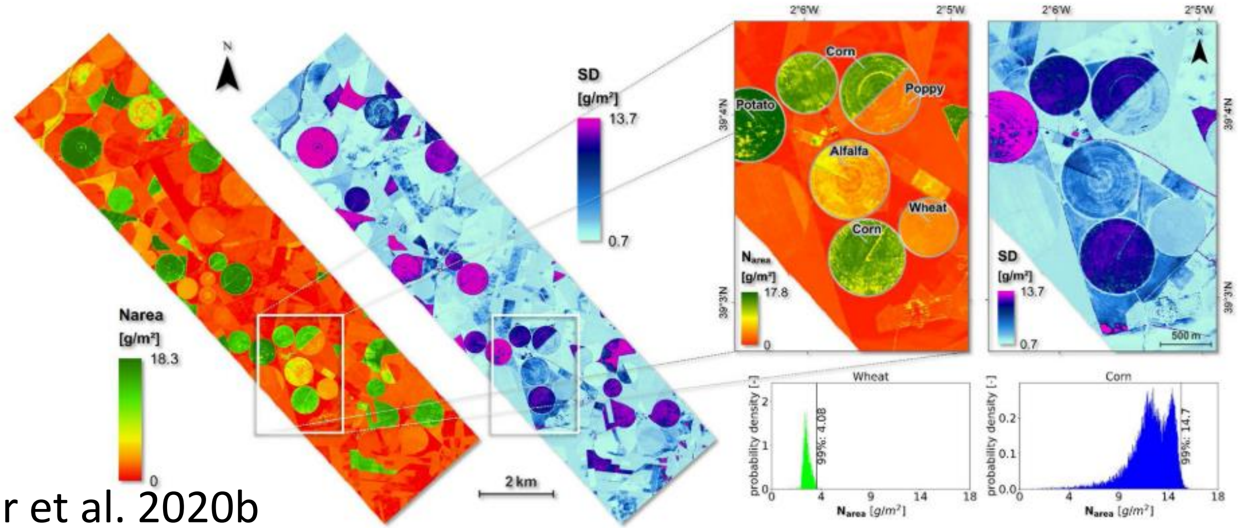
Overview of spectral wavelengths used in scientific literature for estimation of nitrogen concentration and content in green and dry plant leaves (Homolova et al. 2013)

Direct physically-based via protein features

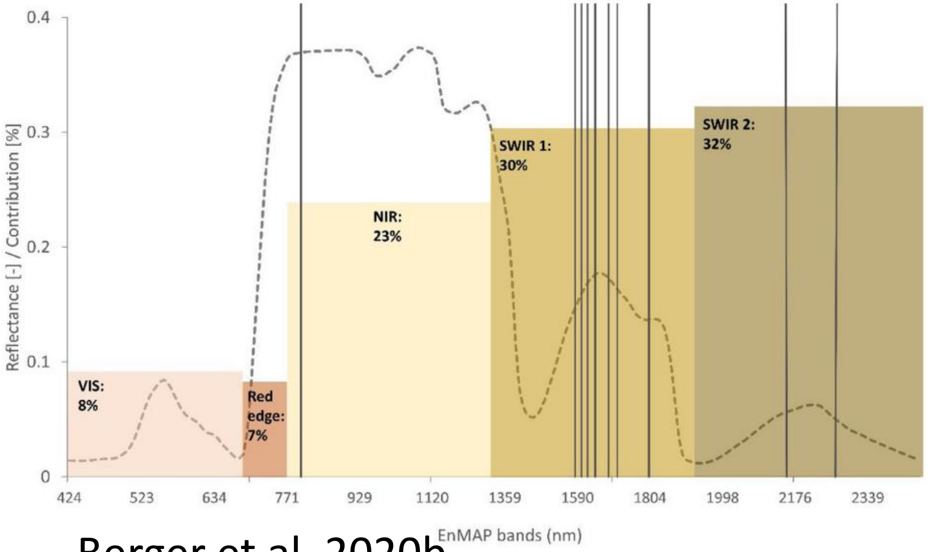
- Earlier attempts to incorporate N into PROSPECT were abandoned due to its strong covariance with other leaf compounds leading to inconsistent results (Jacquemoud et al., 1996).
- The idea has recently been re-vivied by Feret et al. 2020 with the PROSPECT-PRO model
- PROSPECT-PRO was coupled with SAIL to PROSAIL-PRO and the hybrid inversion approach allows to map CNC, uncertainties and the relative contribution of important wavelengths (Berger et al. 2020)
- <u>Claim:</u> The approach could replace the empirical ones and has better generalisation potential; masking effect by leaf water in fresh leaves and confounding effects by cellulose and lignin?



(Féret et al., 2020)



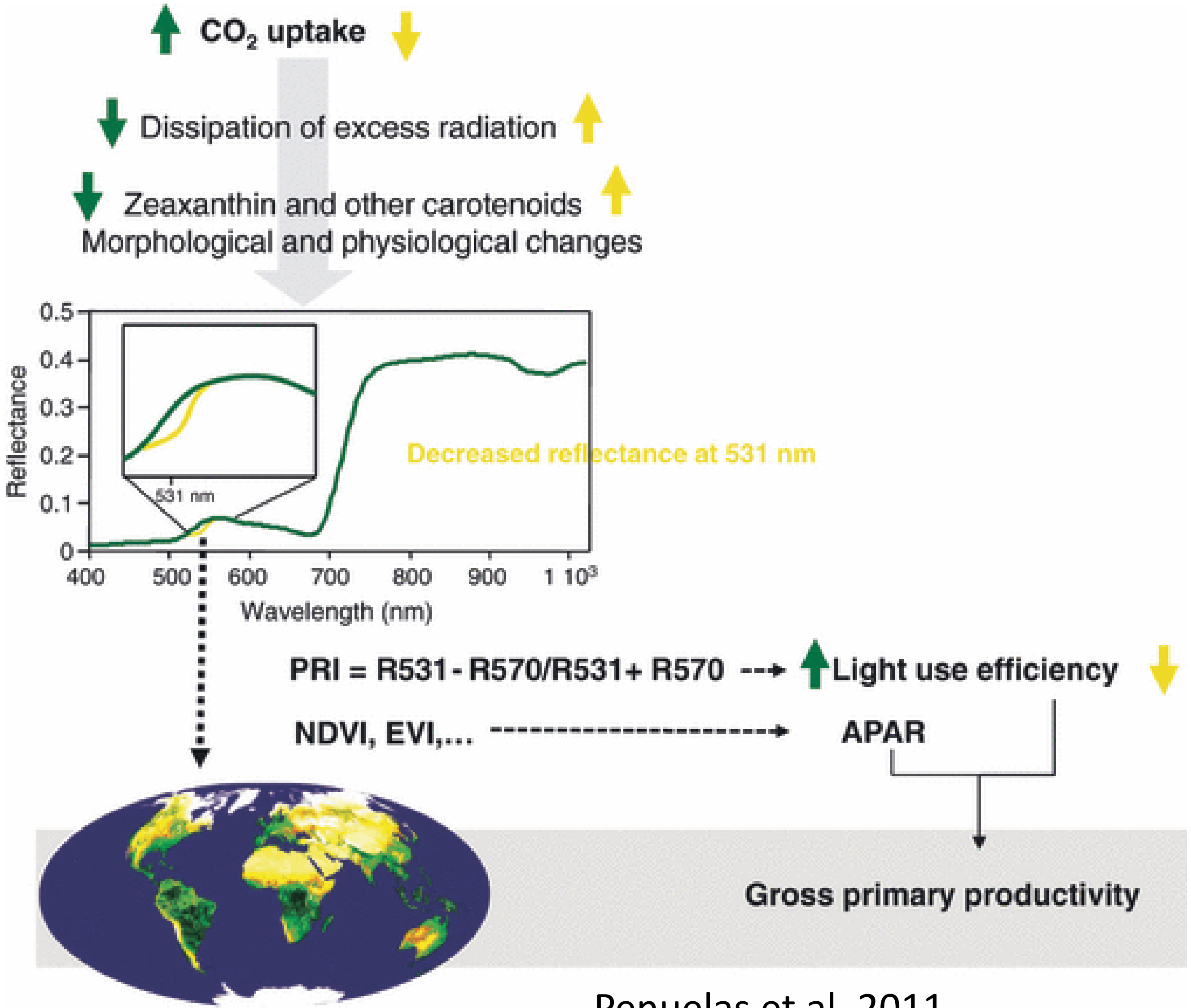
Berger et al. 2020b



Berger et al. 2020b

Photochemical reflectance index (PRI)

Gamon et al. 1990

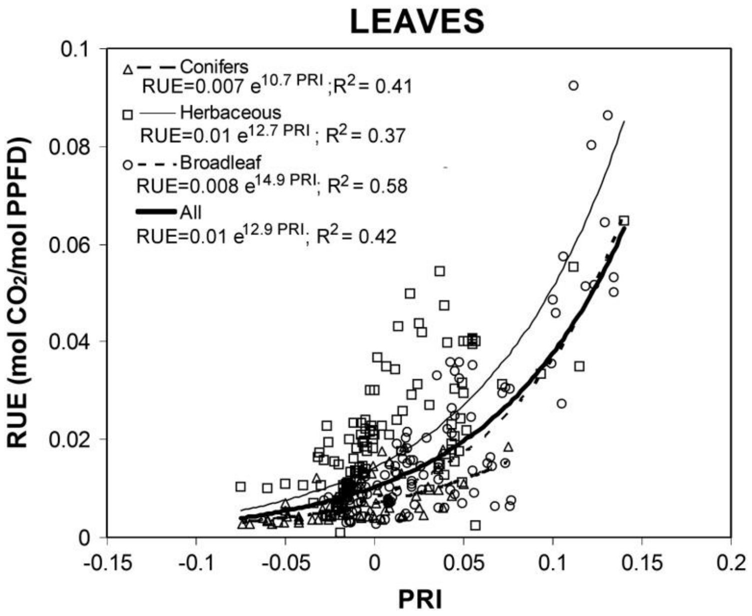


Penuelas et al. 2011

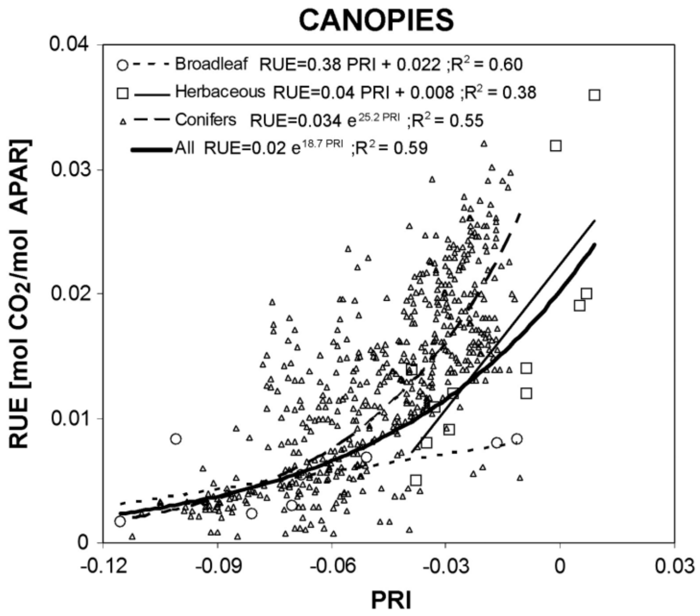
- Requires reflectance at 531 and 570 nm
- Based on slightly differing absorption spectra of **viola-xanthin** (non-stressed) and **zea-xanthin** (stressed) around 531 nm
- 570 nm is insensitive to xanthins change and used as a control
- Details: Under conditions of excess light, when the absorbed PAR can not be processed through photosynthesis, the xantophyll pigment viola-xanthin is de-epoxidized to zea-xanthin; this reaction is readily reversed under limiting light. So the relative concentrations of these xantophyll pigments may be used as an indicator for short term changes in photosynthetic activity.
- PRI has been interpreted as an indicator of LUE and together with an indicator of fAPAR can be used to estimate GPP
- Limitations
  - The relative change in R is very small (~0.5% absolute R)
  - Many confounding effects: LAI changes, leaf movement, sun and viewing angles, soil background and shadows
- But: It also acts as index of the chlorophyll/carotenoid ratios and links to long term changes in PS activities (aging, stress)

PRI-LUE

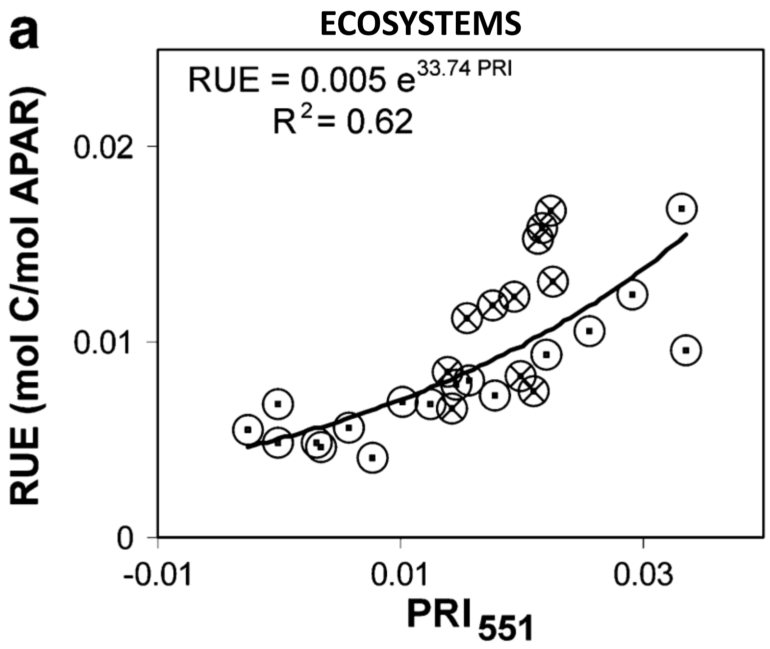
Garbulsky et al. 2011



Relationships between leaf scale photosynthetic RUE (RUE = Net photosynthetic rate/incident PPFD) and PRI for different types of vegetation



Relationships between eddy covariance derived photosynthetic RUE (RUE = GPP/APAR) and PRI for different types of vegetation



RUE calculated from eddy covariance derived GPP and absorbed PAR (RUE = GPP/APAR) and PRI from MODIS data for 2 types of forest

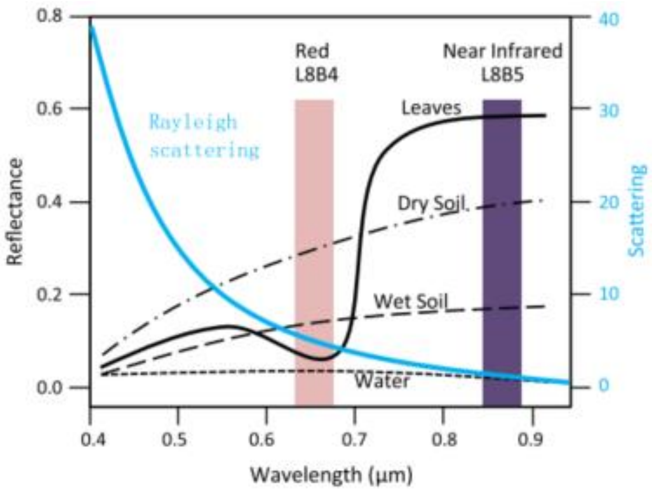
<u>**Claim:**</u> Despite the many potentially confounding factors surprisingly **simple optical RS** methods (e.g., PRI) allow us to explore ecosystem photosynthetic behaviour (e.g. PRI explained 42-67% of the total variance of LUE **at all spatial scales** from leaves to ecosystems), but the use of a **general LUE–PRI relationship** without a proper calibration is still hindered due to methodological differences in the studies, types of vegetation, and other factors (Garbulsky et al. 2011)

Authors stress the need for **standardised protocols** and datasets for a general relationship general LUE–PRI relationship

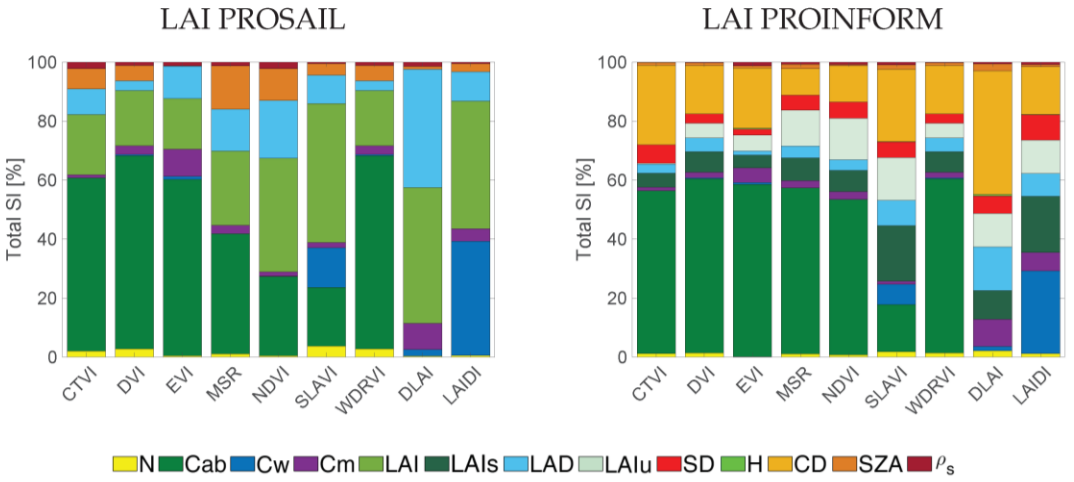
Use of the Normalized Difference Vegetation Index

- now the most popular index used for vegetation assessment (12,618 in the 2010s, Huang et al. 2021)
- UAS boom makes NDVI more popular over time
- NDVI is affected by
  - atmospheric effects (use of reflectance instead of raw data)
  - Is sensor dependent (e.g., the location of the wavebands)
  - its ease for saturation
  - High spatial resolution effect (shadows etc. in drone images)
- NDVI has been known to depend on the
  - fraction of vegetation in a pixel (primary effect)
  - even for full vegetation cover, the NDVI varies with chlorophyll concentration and leaf structure (secondary effect)
  - changing view and illumination angles affect ratios between Red and NIR reflectances (tertiary effect)
- Now GSA offers a quantitative understanding of the confounding effects of for instance NDVI-LAI relation

Claim: NDVI is generally useful if it is obtained with reliable sensors and data processing and after careful checking for plausibility; Data analysts and data providers should educate NDVI users as much as possible (Huang et al. 2021).



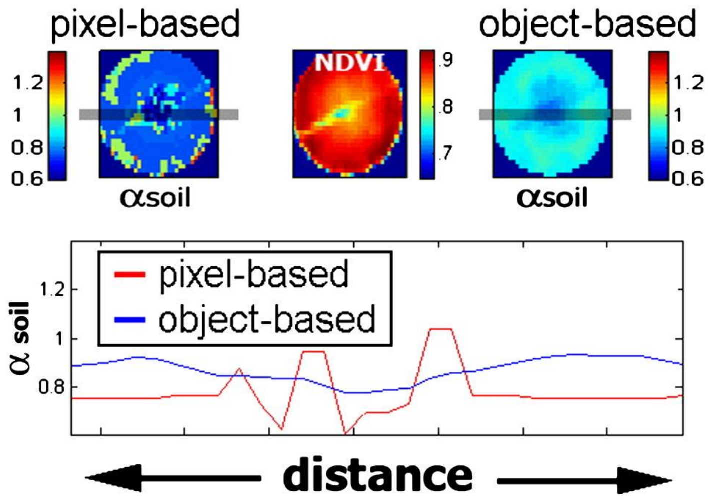
Atmosphere effect on red and NIR bands



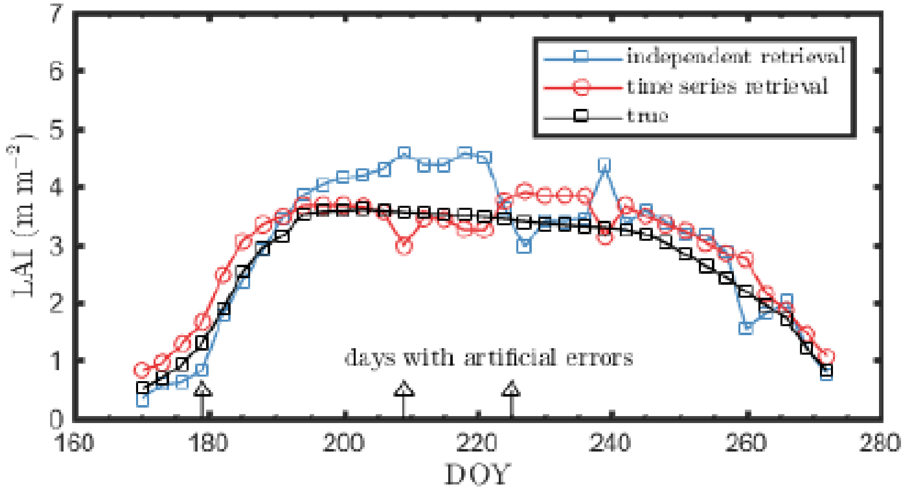
Sensitivity of NDVI and other vegetation indices studied by means of a global sensitivity analysis (Morcillo-Palarés et al., 2019)

Spatial and temporal aspects

- Common problem in inverse modelling: one spectral measurement can lead to multiple solutions of vegetation and soil properties.
- Object-based approach (e.g. Atzberger 2004)
  - takes into account not only the spectral signature of the pixel of interest but also of the neighbouring pixels.
  - Retrieved variables are smoother within an object (e.g. parcel) and more realistic
- Time series retrieval approach (e.g. Yang et al. 2021)
  - Assumes that temporally near attributes are more related than distant ones
  - more robust and smoother time series of LAI than independent retrievals (from individual scenes) and better matching with field measurements
- <u>Claim:</u> RS approaches should exploit more the spatial and temporal aspects of vegetation for reduced uncertainties



From Atzberger and Richter 2012



Kindly provided by Peiqi Yang (from Yang et al. 2021)

Thank you!