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Potato crop nitrogen status monitoring with optical sensors : last decade developments and implementation to contribute to sustainable N-fertilisation management

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Presentation outlines

- **Global context - Background**

- **Reference approach for potato CNS assessment : state of the art and new developments**

- **Evolution of optical sensors types and platforms for potato crop N sensing**

  - Optical sensing for N: concept, sensors and platforms
  - Assessment of potato leaf and canopy Biophysical/Chemical variables (**BVs**) linked to N in potato crop

  - *Transmittance-based sensors*
  - *Chlorophyll fluorescence-based sensors*
  - *Reflectance-based sensors (ground-based, air-borne, space-borne)*

- **Take home message**

Global context for the need of sustainable potato crop N fertilisation management

Issues

Mainly in industrialized agri-food systems, **N overfertilization of the potato crop** is still common practice as a form of insurance against uncertain soil fertility level and low crop N-use efficiency

Consequences:
- Lower fertilizer N use efficiency (NUE)
- High levels of residual N after harvest (soil and haulms)
- Losses in the environment (NO_3 leaching, NH_3 volatilization, N_2O emission)
- Higher N fertilizer cost and reduced profitability for producers

European Green Deal: 20% reduction use of chemical fertilizers as of 2030

Global context for the need of sustainable potato crop N fertilisation management

Solution

- Fertiliser N-recommandation matching expected crop N requirement
  (in space and time)

- In-season monitoring of potato CNS to fine-tune fertilizer N applications to better meet variation in crop N requirements according to cultivars, soil mineral N, climatic conditions, soil properties and crop management

- Robust and easy to operate CNS monitoring methods, as crop fertilizer N requirement is variable among fields, years and within fields

Reference conceptual approach for potato CNS assessment

Crop Nitrogen Status (CNS) assessment based on the Nitrogen Nutrition Index (NNI) concept:

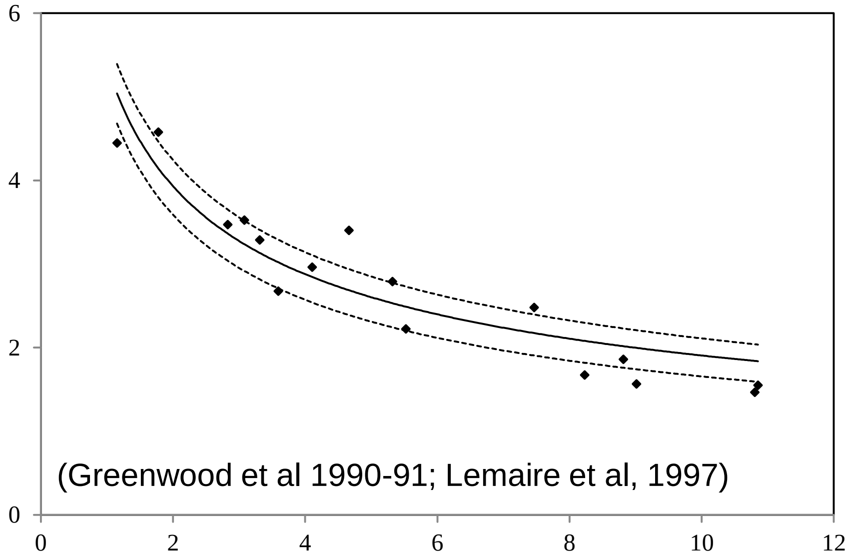
NNI = current N% / critical N%

NNI = 1 optimal N nutrition

NNI > 1 N excess

NNI < 1 N deficiency

Nc % [plant critical N; g N $100g^{-1}$]



W (t DM ha^{-1}) [total dry biomass]

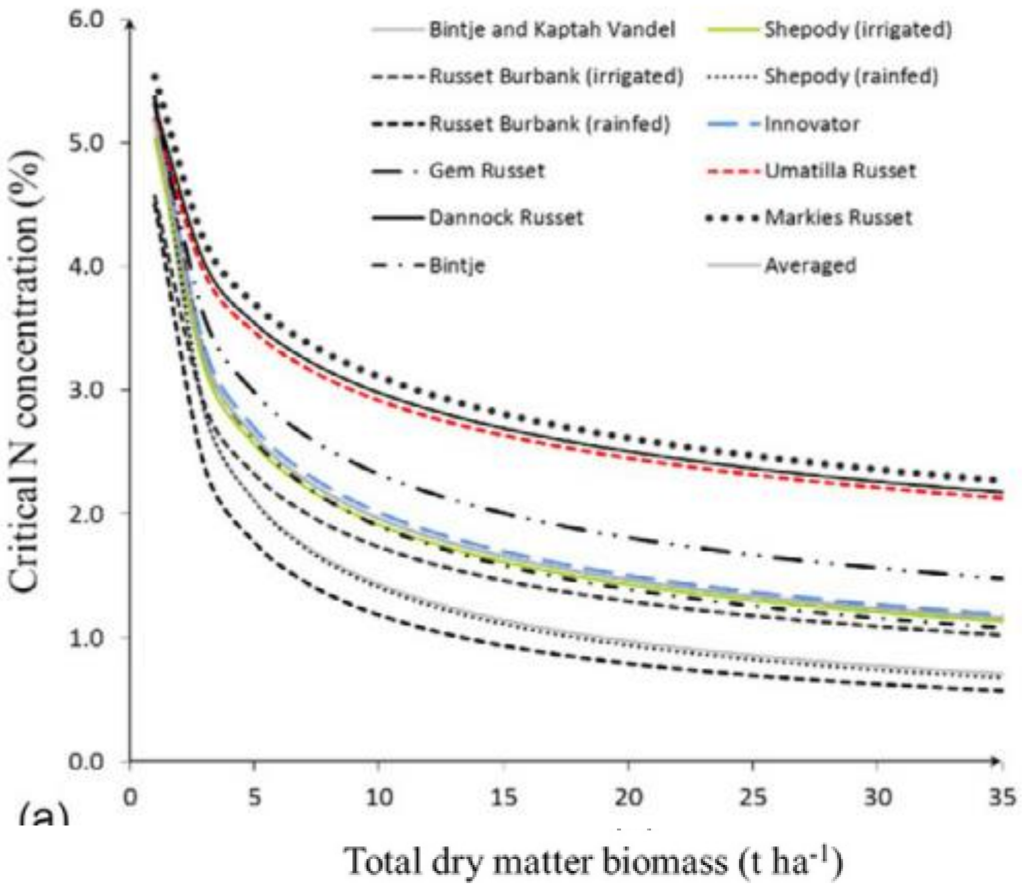
Critical **N**itrogen **D**ilution **C**urve

$$\mathbf{Nc = a\ W^{-b}}$$

a : plant N concentration in units of g N $100g^{-1}$ for W ≤ 1 t ha^{-1}

b : dimensionless ratio between the relative decrease in plant N concentration (%N) and the relative increase in crop growth rate (coefficient of dilution)

11 different CNDCs established for potato to date worldwide



from: Lizana et al. (2021). Chapter 18 - Potato. In: Sadras, V.O., Calderini, D.F. (Eds.), Crop physiology case histories for major crops. Academic Press, pp. 550–587.

CNDCs for potato

Specific CNDCs for different set of cultivars (G) * environment (E) * crop management (M)

“a” varying from 4.50 to 5.53 and “b” from 0.25 to 0.58

Cultivars	**a**	**b**	**Country**	References
Bintje and Kaptah Vandel	**5.21**	**- 0.56**	France	Duchenne et al. (1997)
Shepody (irrigated)	**5.04**	**- 0.42**	Canada	Bélanger et al. (2001)
Russet Burbank (irrigated)	**4.57**	**- 0.42**	Canada	Bélanger et al. (2001)
Shepody (rainfed)	**5.36**	**- 0.58**	Canada	Bélanger et al. (2001)
Russet Burbank (rainfed)	**4.50**	**- 0.58**	Canada	Bélanger et al. (2001)
Innovator	**5.30**	**- 0.42**	Argentina	Giletto and Echeverria (2012)
Gem Russet	**5.32**	**- 0.36**	Argentina	Giletto and Echeverria (2015)
Umatilla Russet	**5.19**	**- 0 25**	Argentina	Giletto and Echeverria (2015)
Dannock Russet	**5.30**	**- 0.25**	Argentina	Giletto and Echeverria (2015)
Markies Russet	**5.53**	**- 0.25**	Argentina	Giletto and Echeverria (2015)
Bintje	**5.37**	**- 0.45**	**Belgium**	**Ben Abdallah et al. (2016)**

CNDCs for potato

<u>Question</u>: Is the variation between CNDCs due to specific effects and interaction of G*E*M combinations on "a" and "b" parameters or rather to sampling and parameters estimation errors ?

Recent studies explored the analyze of uncertainty in fitted potato CNDCs:

- **Makovsky et al. (2020)** Analyzing Uncertainty in Critical Nitrogen Dilution Curves. Eur. J. Agron., 118
- **Soratto et al. (2022)** Establishing a critical nitrogen dilution curve for estimating nitrogen nutrition index of 2 potato crop in tropical environments. Field Crops Research (on line)
- **Fernandez et al. (2022)** Dataset characteristics for the determination of critical nitrogen dilution curves: From past to new guidelines. Eur. J. Agron., 139. (on line)
- **Bohman et al. (2022)** Quantifying critical N dilution curves across G × E × M effects for potato using a partially-pooled Bayesian hierarchical method. Eur. J. Agron. (to be published)

CNDCs for potato

Use of a Bayesian statistical approach to analyse uncertainty in different fitted CNDCs

- **Highlights from these recent studies**

- CNDCs for potato are subject to G x E x M effects
- Variation in %Nc for potato due to tuber initiation timing and tuber bulking rate
- Results support the use of a unique CNDC for estimating the crop N status (NNI) of potato production systems as no evidence of the need for cultivar- or site/year -specific parameters in dedicated larger environment
- Number of used N experiments with at least 3 N rates, sampling times and young-stage biomass sampling are critical for the accuracy of estimation of CNDCs parameters

Evidence for the relevant use of generic CNDCs are suggested for dedicated regional conditions

Limitation in practical use of [Nc], CNDCs, NNI

Very time-consuming and labour intensive procedures in:

(i) **assessing the actual crop mass (W)** with representative sampling areas, weighing fresh mass, sub-sampling to determine dry matter content, oven-drying, weighing, and sample grounding, ***leading to [Nc] through CNDC***

(ii) **assessing actual plant N concentration [N]** by analytical procedures in the laboratory (Kjeldahl digestion, Dumas combustion)

Need for sensitive, specific, accurate and feasible/costless methods enable to deliver quick and reproducible indirect CNS assessment method useful for in-season N fertilization recommendation

Optical sensing to retrieve plant N and biomass

The basic

Changes in Leaf / Canopy N Content (LNC / CNC)

induce variation in BVs variables such as
Leaf Chlorophyll content (LCC)
Leaf Area index (LAI)
Canopy Chlorophyll Content (CCC = LCC*LAI**)**

and consequently induce variation in leaf optical properties

which can be measured as variation
in light **transmittance**, **chlorophyll fluorescence** or **reflectance**
through optical sensors

Available optically-based devices/tools for retrieval BVs LCC, LAI, CCC and related plant [N] and biomass W

Leaf level

Transmittance sensors (leaf clip, contact)

Chlorophyllmeters (SPAD, CCM, …)

Dualex - Chlorophyll

Chlorophyll fluorescence sensors

Dualex- Flavonols (leaf clip)

Multiplex (near remote sensing)

Available optically-based devices/tools for retrieval of BVs LCC, LAI, CCC and related plant [N] and biomass W

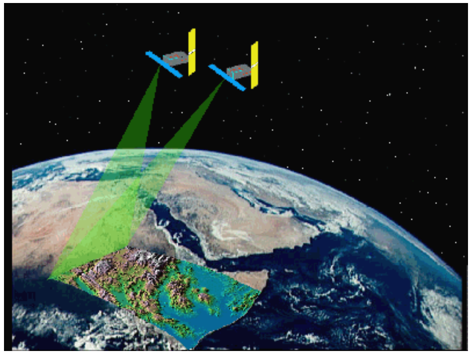
Canopy level

Reflectance sensors (Remote sensing)

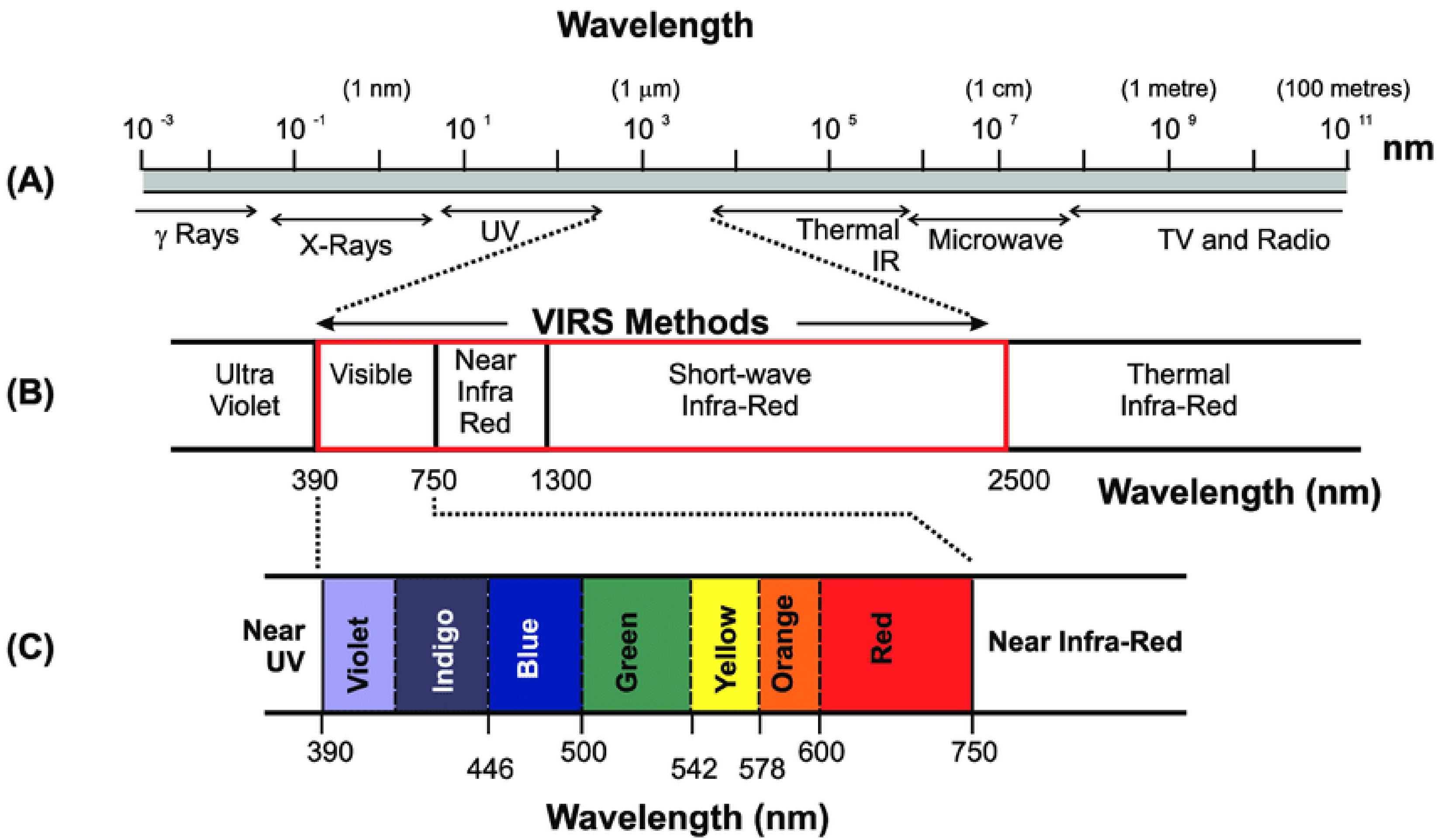
<u>Ground-based</u>
Hand-held radiometer (Cropscan, FieldSpec…)
Tractor or machine-embedded
(N-Sensor, Greenseeker, Crop Circle,...)

<u>Air-borne sensors</u>
UAV- (eBee, octocopter,…)
or Plane-embedded

<u>Space-borne sensors</u>
Satellite-embedded

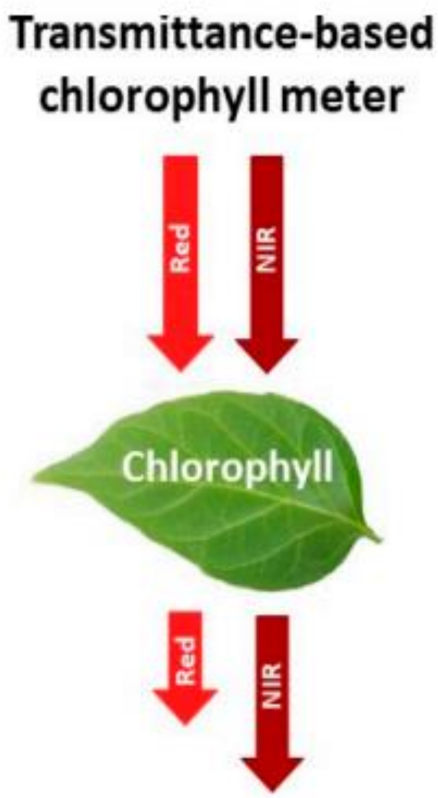


Useful wavelengths of the electromagnetic spectrum for LCC, LAI or N-related BVs assessment are in the VIRS



Transmittance-based sensors

CM SPAD or N tester



2 wavelengths

- Red 650 nm
- NIR 940 nm

Red is absorbed by Chlorophyll

NIR is mainly transmitted

Indirect measurement of LCC

Strong link established (Padilla et al, 2018)

Transmittance-based sensors

Recent developments for the potato CNS assessment

- **Limitations**:
  - **Saturation** measurements at high LCC
  - **Explicit procedure** for readings (at least 30 points per field) but not representative of a field (Goffart et al, 2008)
  - **Effect of numerous confounding factors** on measurements (irradiance, cultivars, locations, sowing dates, growing stage, weather, water status, crop management, irrigation, plant part sampled, diseases), (e.g. Fabiana et al, 2021)
  - **Need of within-field reference areas** (for normalized CM values) and the calculation of NSI to standardize at least partly these confounding effects
  - **NNI better correlated with normalized CM values**
  - **Effect of leaf features on the measurement**: (distribution of chlorophyll in leaves, allocation of N to chlorophyll, …) (Xiong et al. 2015)

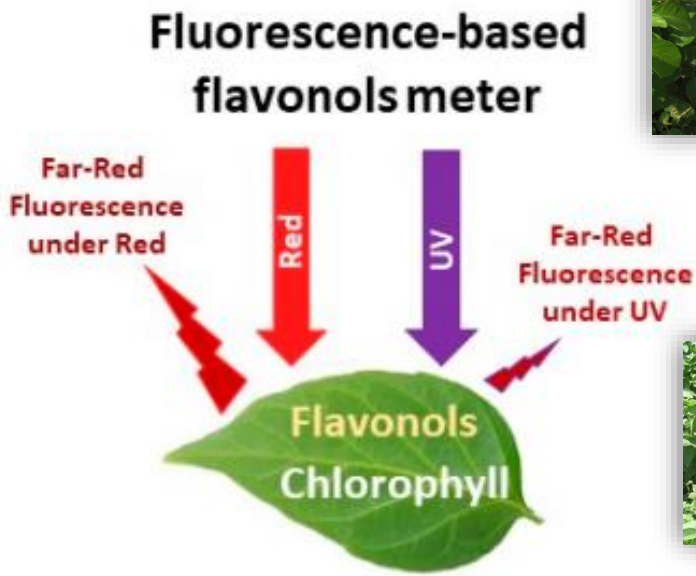
Easy to use, costless, but accuracy to confirm, not specific, poorly sensitive for high LCC

Chlorophyll fluorescence-based sensors

Usual existing devices: Dualex, Multiplex

Concept of epidermal screening effect of chlorophyll fluorescence by leaf phenolic compounds (flavonols)

- 2 wavelengths used
  - Red 650 nm
  - UV 375 nm



Indirect measurement of LCC and Leaf [Flavonols]
In case of N deficiency: LCC decreases and Leaf [Flavonols] increases

Variation in Ratio **ChlF under UV / ChlF under Red**
is used as crop N status indicator (from Tremblay et al 2012, Padilla et al 2018)

Chlorophyll fluorescence-based sensors

Recent developments for the potato CNS assessment

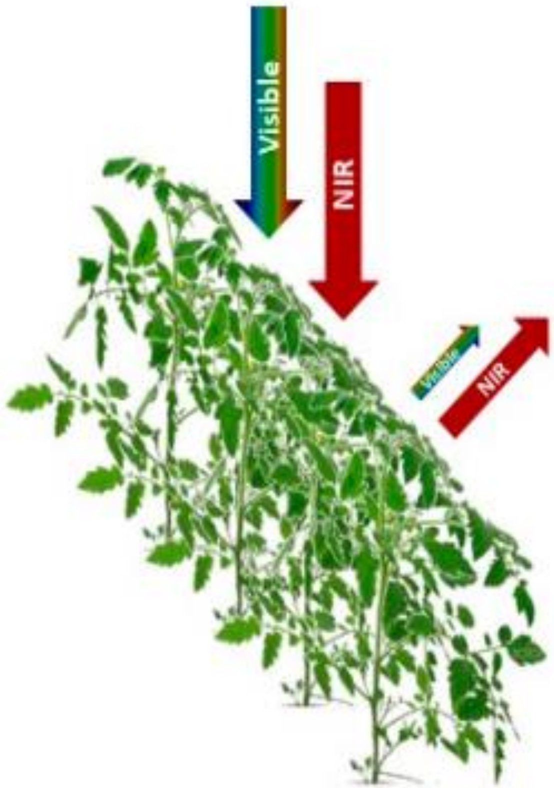
Ben Abdallah et al., 2019 (CRAW, Belgium, Gembloux) . Comparison of optical indicators for potato crop nitrogen status assessment including novel approaches based on leaf fluorescence and flavonoid content. Journal of Plant Nutrition 41(20), 2705-2728 *(from POTFLUO project, 2012-2015)*

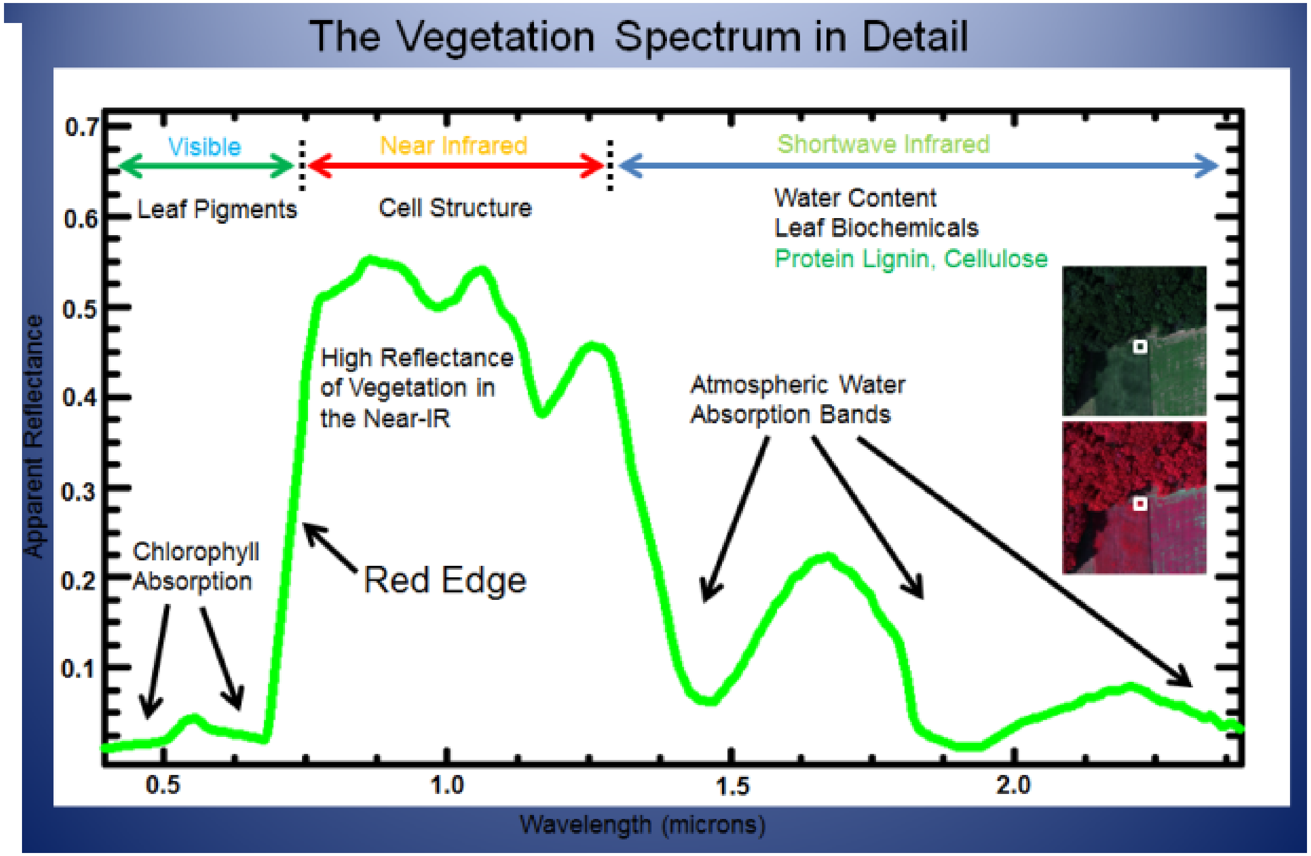
Comparatively to transmittance-based sensors

- **Sensitivity**: increased even for high LCC
- **Earliness in N deficiency detection** : enhanced
- **Specificity**: also low but increased with normalized values
- NNI better correlated with normalized values
- **Accuracy/precision**: increased
- **Feasibility**: experimental, expensive, need also for repeted point measurements, no useful embedded device available , no more commercialized to date

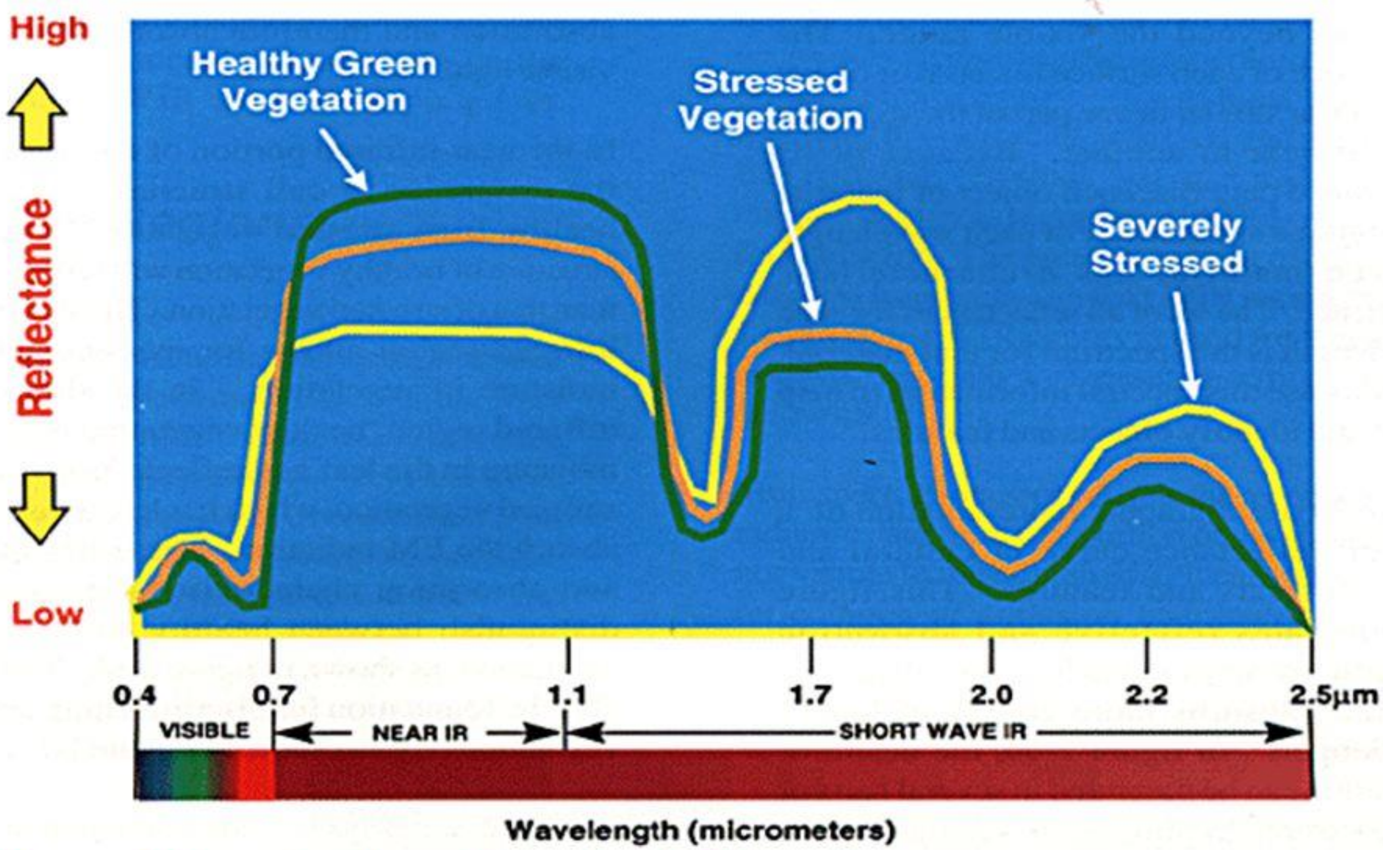
Reflectance-based sensors

<u>Concept</u>:
Measure of a set of specific wavelengths of radiation reflected from crop foliage (canopy)





Plant/canopy N deficiency induces variation in reflectance



Use of Vegetation Spectral Signature

•forest inventories

•healthy vs. stressed vegetation

Reflectance-based sensors

Main advantages (applicable to potato crop)

- Integration of larger canopy area than leaf level sensors.
- Good sensitivity to changes in chlorophyll status, foliage density, biomass

Main limitations (applicable to potato crop)

- Delayed sensitivity accross plant N levels
- Soil background effect (need for specific chlorophyll, biomass or cover fractions)
- Lack of specificity to N deficiency as chlorophyll with confounding factors
- Sensitive to solar irradiance, shade effect, sensor angles related to the measured surface, sensor height/distance to the target canopy

Improvements are expected through methods to retrieve BVs from reflectance measurements

Two main methods with crop reflectance to retrieve BVs (LCC, CCC, LAI, …)

Satellite images

Empirical Vegetation Indices (Vis)

N_{canopy}

Radiative Transfer Model (RTM) inversion

$C_{ab,canopy} \leftrightarrow N_{canopy}$

VIs have been developed as the combination of reflectance in various wavebands and related to various canopy parameters (simple algorithms)

<u>Objective</u>: to enhance the vegetation signal while minimizing the solar irradiance and soil background effects

Xue & Su (2017) Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications, Journal of Sensors (1):1-17

Physically-based approach that describes the transfer and interaction of radiation inside the canopy, <u>based on physical laws</u> and thus providing <u>explicit relation between the biophysical and biochemical variables and the canopy reflectance</u>

More robust and more sensitive to N than VIs but more complex to use

Mostly used RMT: PROSAIL

(Jacquemoud et al. 2009)

Multispectral and hyperspectral bands on sensors are used for reflectance measurements

Optimal hyperspectral narrowbands are recommended in the study of nitrogen and chlorophyll in agricultural crops (Thenkabail, 2011)

Wave band	Waveband centre (nm)	Importance
Blue band	466	Chlorophyll: chlorophyll a and b
	490	Senescing and loss of chlorophyll, ripening, crop yield
Green bands	515	Nitrogen: leaf nitrogen, wetland vegetation studies
	520	Pigment, biomass changes
	525	Vegetation vigour, pigment, nitrogen
	550	Chlorophyll and biomass: total chlorophyll; chlorophyll/carotenoid ratio, vegetation and nutritional and fertility level
	575	Vegetation vigour, pigment, nitrogen
Red bands	675	Chlorophyll absorption maxima: greatest crop-soil contrast is around this band for most crops in growing conditions.
	682	Biophysical quantities and yield and chlorophyll absorption.
Red edge bands	700	Stress and chlorophyll: nitrogen stress, crop stress, crop growth and stage studies
	720	Stress and chlorophyll: nitrogen stress, crop stress, crop growth and stage studies. Red shift for healthy vegetation, blue shift for stressed vegetation.
	740	Nitrogen accumulation: leaf nitrogen an accumulation. Red shift for healthy vegetation, blue shift for stressed vegetation.
SWIR bands	1316	Nitrogen: leaf nitrogen content of crops
	2173	Protein, nitrogen
	2359	Cellulose, protein, nitrogen: sensitive to crop stress, lignin and starch

Mostly used VIs for LCC, CCC, LAI retrieval in potato crop

mainly from Clevers, Kooistra, et al. **2012, 2013, 2016, 2017**

Vegetation Index	Formula	Sensitive to	Reference
NDVI	$(R_{800} – R_{670}) / (R_{800} + R_{670})$	LAI, LCC, CCC	Rouse et al., 1973
WDVI	$R_{870} – (C \times R_{670})$ with $C = (Rsoil_{870}) / (Rsoil_{670})$	LAI	Clevers, 1989
TCARI/ OSAVI	$\dfrac{3[(R_{700} – R_{670}) – 0.2(R_{700} – R_{550}) (R_{700} / R_{670})]}{(1 + 0.16) (R_{800} – R_{670}) / (R_{800} + R_{670} + 0.16)}$	LCC	Haboudane et al., 2002
CVI	$(R_{870}/R_{550}) \times (R_{670}/R_{550})$ or $(R_{870}/R_{550}) / (R_{550}/R_{670})$	LCC	Vincini et al., 2008
$CI_{red\text{-}edge}$	$(R_{780} / R_{705}) – 1$	LCC/CCC	Gitelson et al., 2003
CI_{green}	$(R_{780} / R_{550}) -1$	LCC/CCC	Gitelson et al., 2003
MTCI (hvi)	$(R_{753.75} – R_{708.75}) / (R_{708.75} - R_{681.25})$	LCC	Dash & Curran, 2007

WDVI: Weighted Difference Vegetation Index; **TCARI/OSAVI**:Transformed chlorophyll-adjusted reflectance indice/optimised soil-adjusted vegetation index; **CVI**: Chlorophyll Vegetation Indice; **$CI_{red\text{-}edge}$**: Red edge Chlorophyll Index; **CI_{green}** : Green Chlorophyll Index; **MTCI**: MERIS Terrestrial Chlorophyll Index

Reflectance-based sensors and VIs

Recent developments for the potato CNS assessment

Many others relevant publications have been delivered on the best VIs for the N management of the potato crop

➢ From ground-based sensors

- **van Evert, et al 2012**. Using crop reflectance to determine sidedress N rate in **potato** saves N and maintains yield. Eur. J. Agron. 43, 58–67.
- **Morier et al, 2015**. In-Season Nitrogen Status Assessment and Yield Estimation Using Hyperspectral Vegetation Indices in a **Potato** Crop. Agron. J. 107(4), 1295-1309
- …

➢ From UAV-based and airborne sensors

- **Nigon et al 2015** Hyperspectral aerial imagery for detecting nitrogen stress in two **potato** cultivars. Comput Electron Agric 112:36–46
- **Hunt, et al. 2018** Monitoring Nitrogen Status of **Potatoes** Using Small Unmanned Aerial Vehicles. Precis. Agric. 19, 314–333
- **Yang et al. 2021** Hyperspectral indices optimization algorithms for estimating canopy nitrogen concentration in **potato** (Solanum tuberosum L.) , Int. J. of App. Earth Observation and Geoinformation 102(11):102416
- …

Reflectance-based sensors and VIs

- From satellite-based sensors

June 2015 - March 2017: Launch of ESA New satellites

SENTINEL 2a and 2b

First sensors-based satellite enabling a real field crop monitoring from space

After 30 years of remote sensing with satellites in Europe (SPOT 1 to 7) and 40 years in USA (LANDSAT 1 to 8)

Reflectance-based sensors and VIs

- From satellite-based sensors

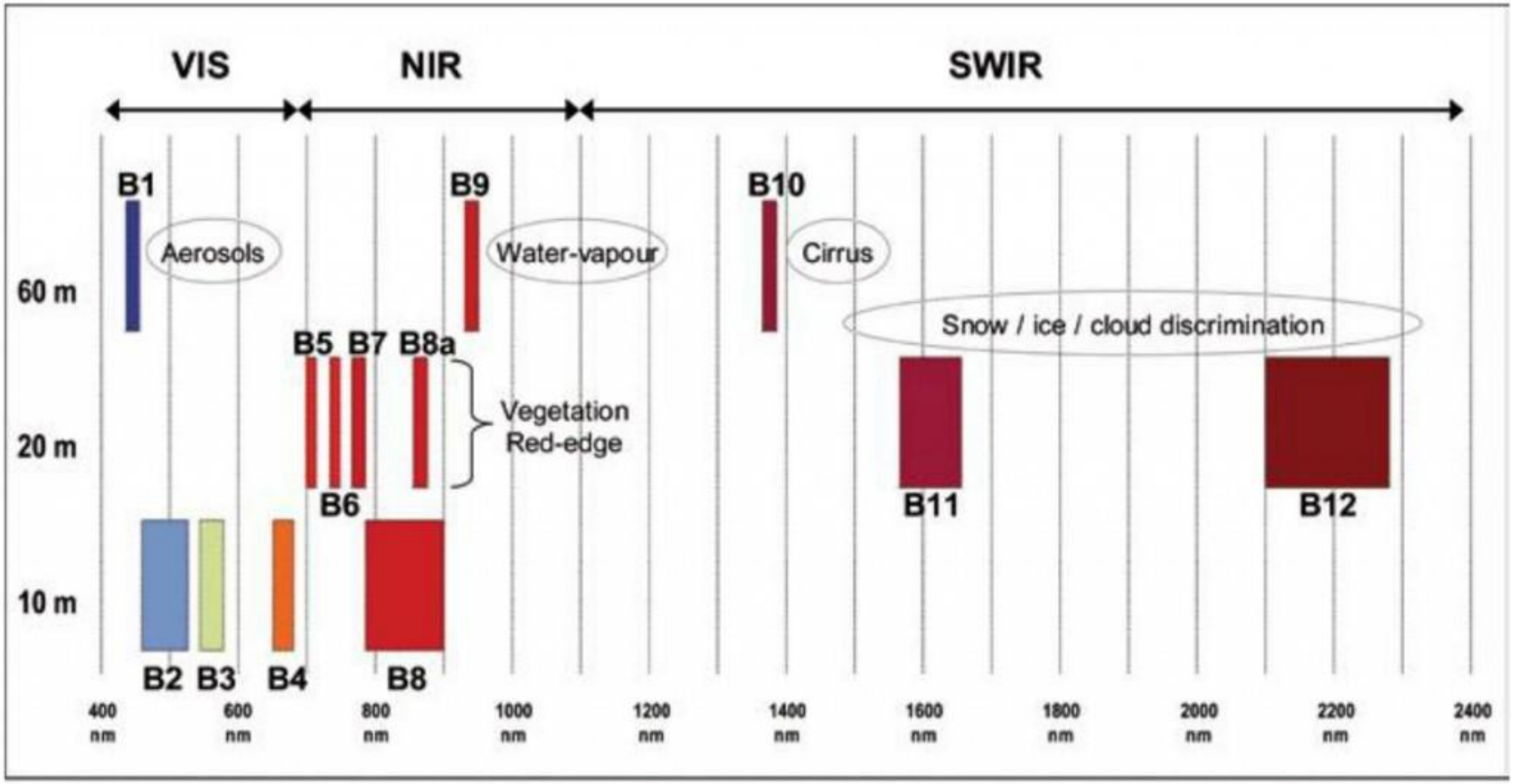
Earth observation at European scale	Currently	From 2015 - 2017 with SENTINEL 2a & 2b
Spatial resolution *(pixels size)*	10 to 300 m	10 to 60 m
Temporal resolution *(revisiting time)*	10 - 25 days	5 days
Image size *(swath)*	60 x 60 km	290 x 290 km
Spectral resolution	5 to 6 wavebands (Visible and NIR)	13 wavebands (Visible, NIR, SWIR)
Costs for image acquisition	2.000 to 4.000 € /image	**Full free access**

Game rules were changing !

Also with the raising up of hyperspectral and constellations of micro- and nano-satellites

Reflectance-based sensors and VIs

- From satellite-based sensors **Sentinel 2a and 2b : spectral resolution**



<u>Expectation</u>: More accurate assessment of BVs such as LCC/CCC, LAI, crop biomass cover percentage (*f*cover), fraction of Absorbed Photosynthetically Active Radiation (*f*APAR)

Reflectance-based sensors and VIs

Recent developments for the potato CNS assessment

Focus on 2 major contributions within the period

From satellite-based sensors (S2)

Clevers J et al (2017)
Using Sentinel-2 data for retrieving LAI , LCC and CCC of a potato crop.
Remote Sensing 9:405.

LAI, LCC and CCC were good estimated with Sentinel-2 bands at 10 m spatial resolution

Biophysical variables (LAI, LCC, CCC) derived from VIs in potato crop

Linear relationships *From Clevers et al. 2017 (S2 for potato crop)*

LAI = (0.1022 * WDVI) + 0.4768 **10m**

$R^2 = 0.809$; RMSEP = 0.36 (equals 10.1% of the mean LAI)

LCC = (-4.5772 * TCARI/OSAVI) + 1.5789 **10m**

$R^2 = 0.696$; RMSEP = 0.062 g m^{-2} (13.0% of the mean LCC)

CCC = (0.843 * $CI_{red\text{-}edge}$) + 0.1797 **20m**

$R^2 = 0,576$; RMSEP = 0.43 g m^{-2} (22.9% of the mean CCC)

CCC = (0.8364 * CI_{green}) - 1.3231 **10m**

R2 = 0,818 ; RMSEP = 0.29 g·m^{-2} (15.3% of the mean CCC)

Reflectance-based sensors and VIs

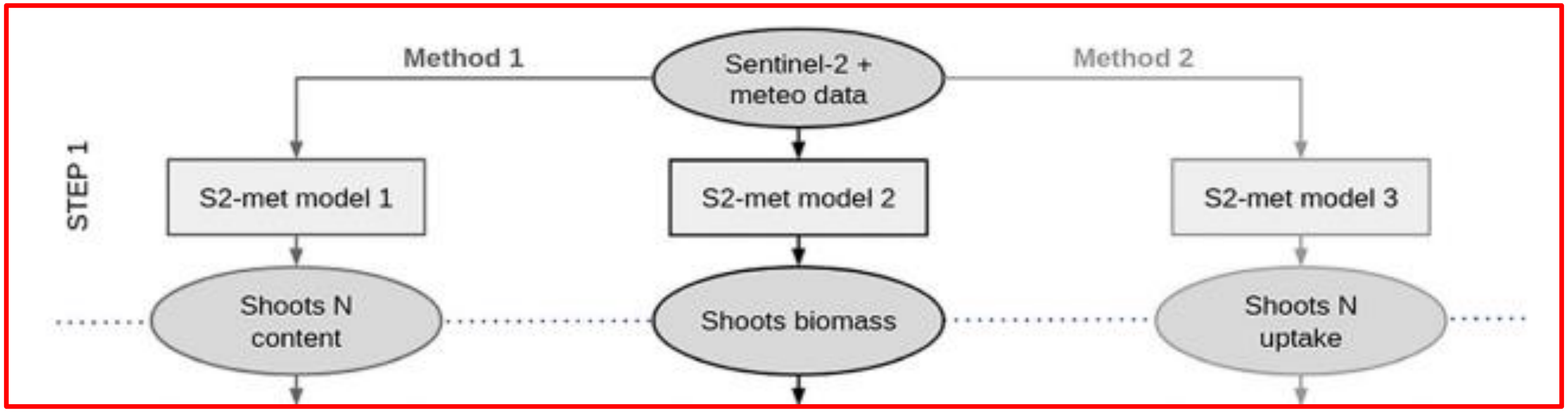
Recent developments for the potato CNS assessment

Focus on 2 major contributions within the period

From satelitte-based sensors (S2)

Goffart D. et al. 2022. Gembloux, Belgium

In-Season Potato Crop Nitrogen Status Assessment from Satellite and Meteorological Data. Potato Research. May 2022 online. (from *BELCAM Project, 2014-2019*)



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Canopy N content (CNC) prediction

Regression models combining WDVI, Fcover, DD, WB

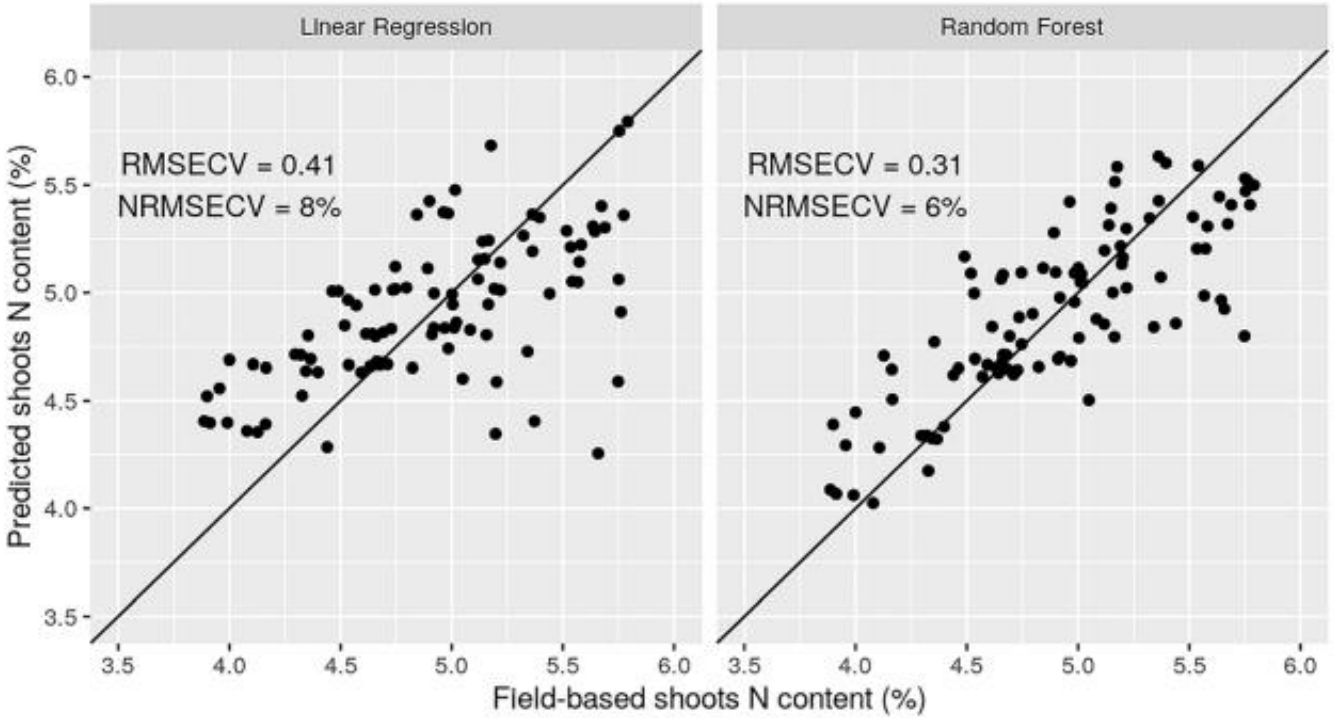


Fig. 10 Shoots N content predictions (cross-validation) of the best multiple linear regression and random forest regression models. Variables integrated in these empirical relationships are respectively DD, WB, FCOVER and WDVI and DD and WB. With the Sentinel-2 data availability, the dataset includes 97 ESUs (including the three cultivars)

Canopy biomass (W) prediction

Regression models combining WDVI, TCARI_OSAVI, $CI_{red\text{-}edge}$, IRECI and DD

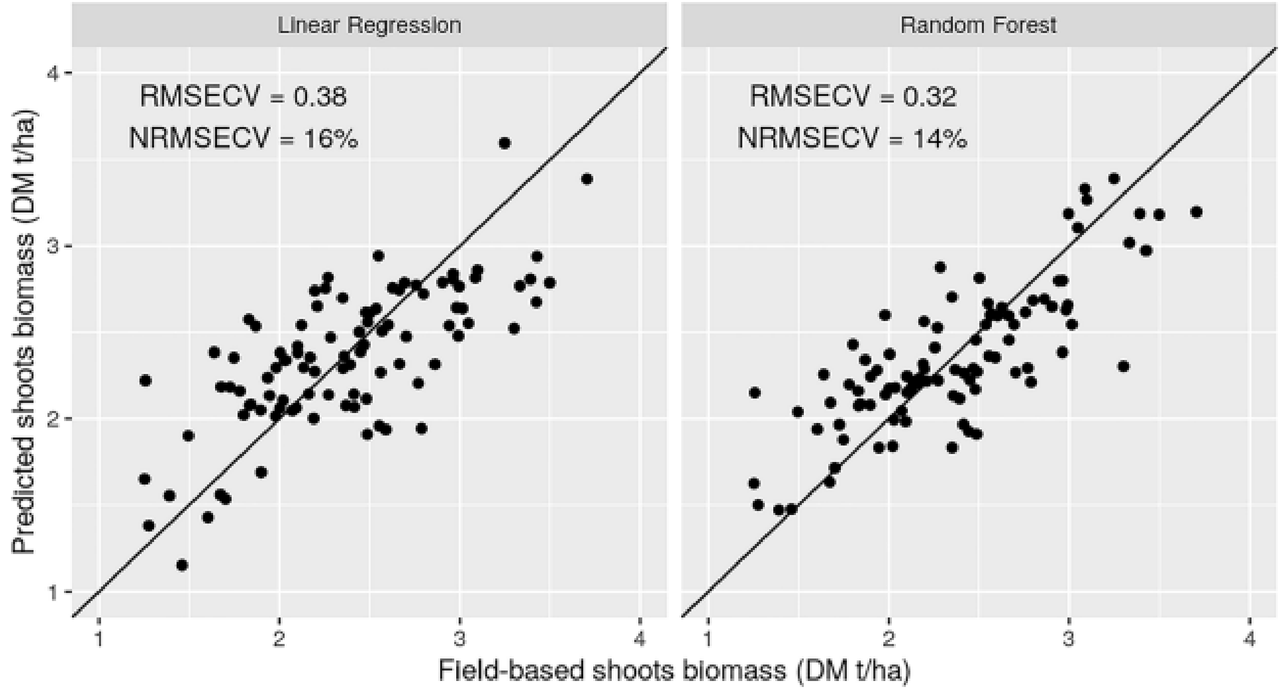


Fig. 9 Shoots biomass predictions (cross-validation) of the bests multiple linear regression and random forest regression models. Variables integrated in these empirical relationships are, respectively, DD, WDVI, TCARI_OSAVI, CIRe and DD and IRECI. With the Sentinel-2 data availability, the dataset includes 97 ESUs (including the three cultivars)

Canopy N uptake prediction

Regression models combining WDVI, TCARI_OSAVI, $CI_{red\text{-}edge}$, SR25 and DD

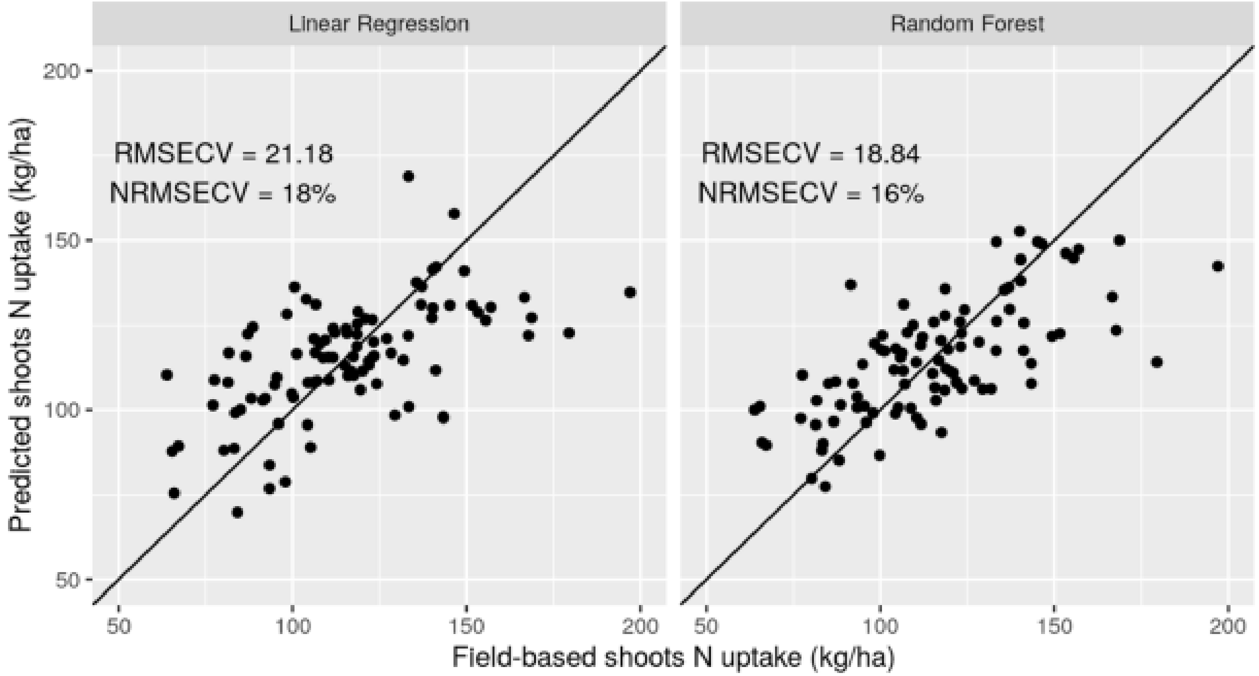
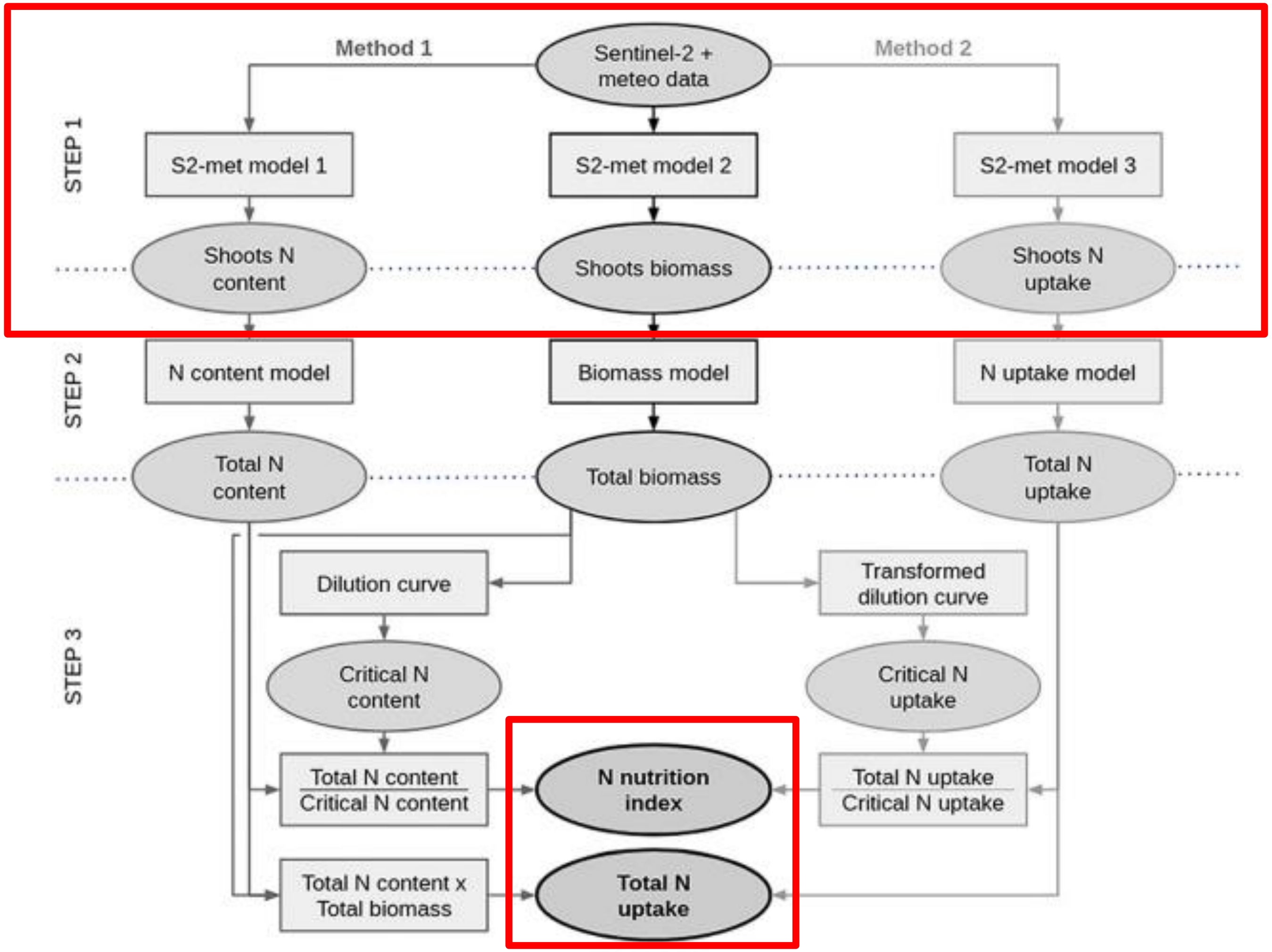


Fig. 11 Shoots N uptake predictions (cross-validation) of the best multiple linear regression and random forest regression models. Variables integrated in these empirical relationships are, respectively, DD, WDVI, TCARI_OSAVI, CIRe, SR25 and DD and WDVI. With the Sentinel-2 data availability, the dataset includes 97 ESUs (including the three cultivars)

SR25:Simple blue and red-edge 1 ratio indice

Workflow for practical assessment of potato CNS using remotely S2-sensed and meteorological data **with NNI and total N uptake as two targeted final products**



Retrieval of BVs using RMT inversion in potato

Advantages and limitations of the approach: illustrations

- **Botha et al 2007**: **Non-destructive estimation of potato LCC from canopy hyperspectral reflectance using the inverted PROSAIL model.** International Journal of Applied Earth Observation and Geoinformation 9(4):360-374

- **Duan et al 2014**: **Inversion of the PROSAIL model to estimate LAI of maize, potato, and sunflower fields from unmanned aerial vehicle hyperspectral data** International Journal of Applied Earth Observation and Geoinformation 26(1):12–20

- **Roosjen et al. 2018**: **Improved estimation of LAI and LCC of a potato crop using multi-angle spectral data – potential of unmanned aerial vehicle imagery (PROSAIL inversion model).** International Journal of Applied Earth Observation and Geoinformation 66, April 2018, 14-26

Accurate method
but non-homogenous canopy architecture, soil background
and need for multi-angular reflectance data
remain cornerstones for the application of PROSAIL RMT inversion solely

Perspectives in methods for retrieval of all kinds of vegetation N-based biophysical and biochemical variables (i.e. CNC, GAI, Canopy N uptake, …)

- **Methods for estimation/prediction of mass-based N (N concentration, N%) and area-based N (N content, Narea) BVs using hyperspectral remote sensing data:**

- ***Last decades***: mainly simple parametric regression algorithms, with such as narrowband VIs

- ***Currently and for the coming years***: increase in the use of machine learning, RTM and hybrid techniques, related to highly increasing and available RS-hyperspectral data from different up-coming new optical sensors and platforms (nano- and micro- satellites)

(1) Parametric regression methods (including VIs, shape indices and spectral transformations)
(2) Linear nonparametric regression methods or chemometrics,
(3) Nonlinear nonparametric regression methods or machine learning regression algorithms
(4) Physically-based or inversion of radiative transfer models (RTMs) using numerical optimization and look-up table or artificial neural network approaches
(5) Hybrid techniques, which combine RTM simulations with machine learning regression methods
(6) Use of alternative data sources (sun-induced fluorescence, SIF)

From Berger et al. 2020 ; Féret et al 2021; Verrehlst et al 2021

- **More attention will also be paid in the near future to plant N bound in proteins and not solely to the correlation of chlorophyll content with nitrogen**

- **Estimation of nitrogen via the proxy of proteins** (N-rubisco) using hyperspectral data and in particular SWIR (1300-2500 nm) due to absorption features of proteins located in this spectral domain

- **SWIR is more successful for CNC retrieval than the conventional visible to near infrared (VNIR) region**, together with the development of physically-sound CNC retrieval models for routine and mapping quantifying CNC from space at field scale including inter and within field CNC variability

- **Space-borne imaging spectroscopy sensors (hyperspectral) should be preferred over multispectral sensors**, since they provide the required continuous spectral coverage to capture the subtle spectral signatures related to proteins

- **Current or up-coming science-driven explorative European satellites missions** such as PRISMA, EnMAP, CHIME and FLEX (vegetation fluorescence) will pave the way for improved, robust and not time- or site-specific potato CNS assessment.

Take home message

- **For potato CNS, more generic CNDCs are expected to pave the way for no-cultivar and no-site specific NNI**

- **Transmittance-based handheld-sensors are suitable for local field use providing the use of normalized values are calibrated with NNI values for CNS assessment**

- **Chlorophyll fluorescence- based handheld-sensors refines sensitivity and accuracy for local field use providing normalized values are calibrated with NNI values for CNS assessment**

- **Transmittance based-spaceborne sensors values, together with hyperspectral and combination of modern retrieval methods will pave the way for accurate and generic assessment of vegetation N-based variables leading to CNS assessment (NNI)**

- **CNS status assessment still need to be coupled with decision rules on:**
  - *in-season supplemental N fertilizer rate(s) assessment*
  - *way of supplemental N application (MVZ, VNR) according to maps of within-field variability*

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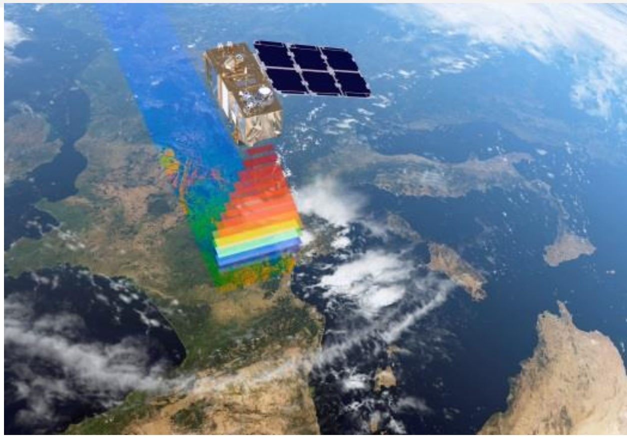
- **CNS status assessment still need to be coupled with decision rules on:**
  - *in-season supplemental N fertilizer rate(s) assessment*
  - *way of supplemental N application (MVZ, VNR) according to maps of within-field variability (soil characteristics + N application maps)*

Thank you for your attention

Belgian inputs from funded projects

Belcam (Belspo)
PotFluo (SPW)

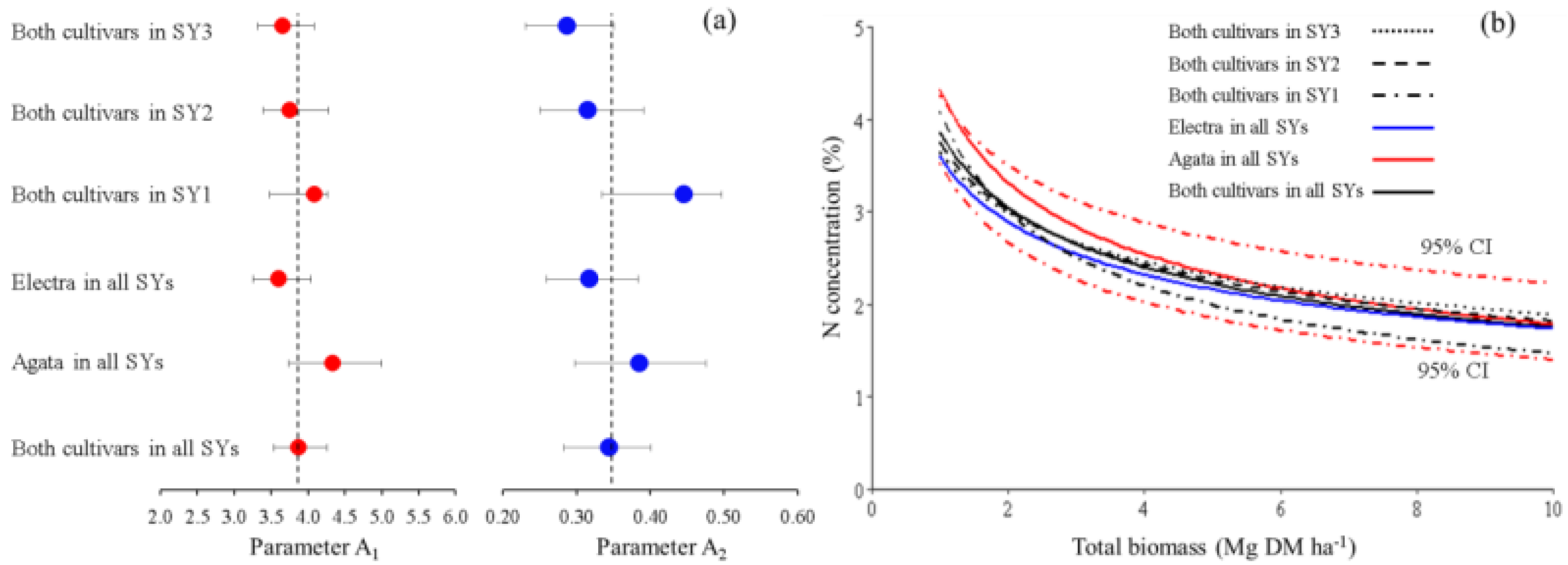
Partners:
CRAW, UCLouvain, VITO, ULiège



CNDCs for potato

Use of a Bayesian statistical approach to analyse uncertainty in different fitted CNDCs

- **Highlights** [from Soratto et al 2022 (Latin America, tropical conditions)]



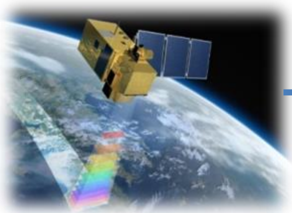
Estimated values (posterior medians) and 95% credibility intervals (CI) of parameters A1 and A2 through the Bayesian approach (a) and corresponding critical N dilution curves (CNDC) for each scenario (b). In (a) the vertical dashed line represents the average of all medians. In (b) the red dotted lines represent the 95% CI for the CNDC fitted to both cultivars in all site-years (SYs) (solid black line).

Reflectance-based sensors and VIs

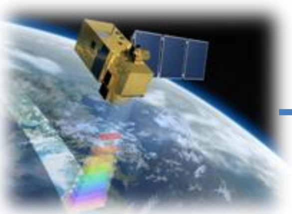
Recent developments for the potato CNS assessment

Satellite S2

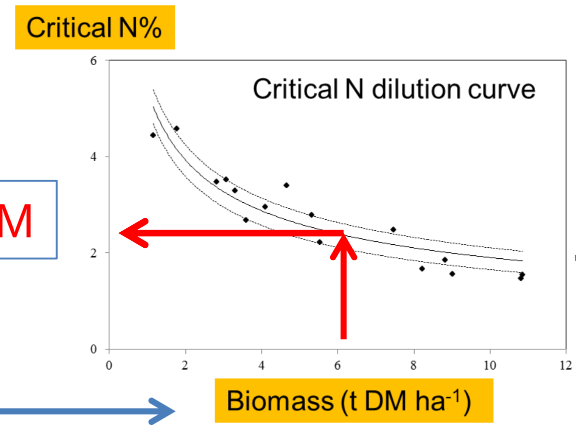
NNI = Current [N] / Critical [N]



LCC or CCC → ? → **Current [N]**



LAI → ? → Biomass DM



Critical [N]

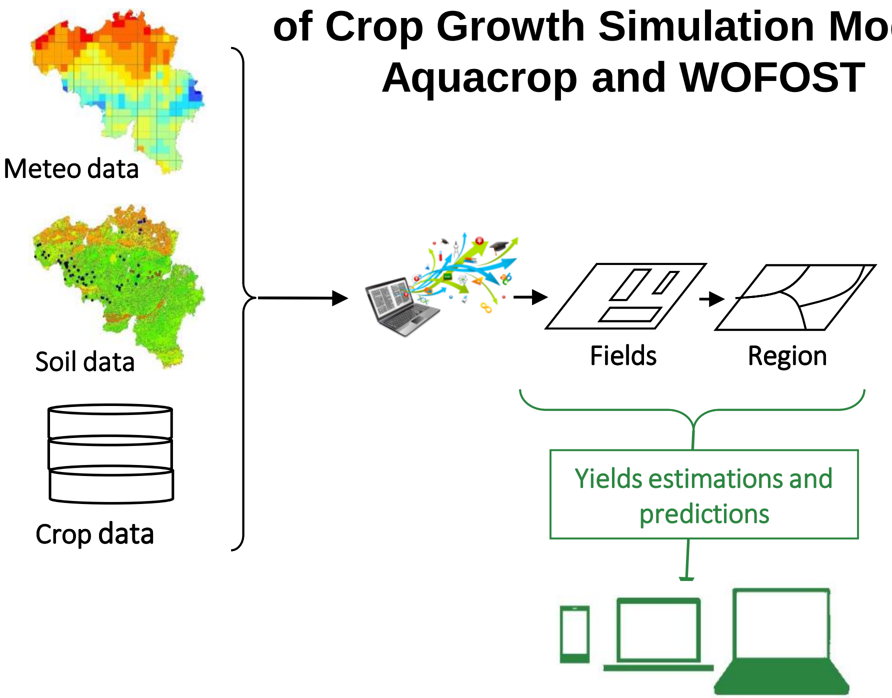
Crop growth simulation model

NNI

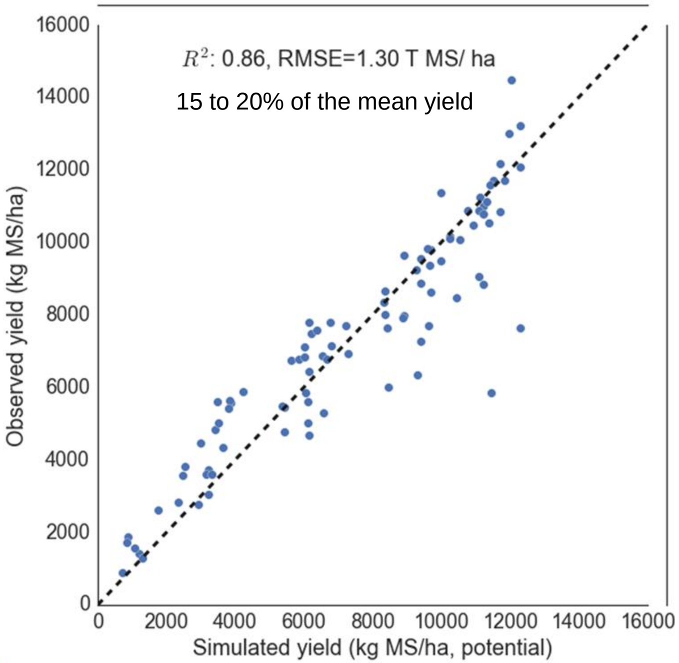
In-season potato CNS monitoring and decision on the rate and way of application on supplemental N fertilizer

- **Decision on the supplemental N rate to apply**

Use of combined of Crop Growth Simulation Models Aquacrop and WOFOST



IPot Project (Belgium, 2014-2018)



Total biomass yield prediction to assess expected final N uptake and to estimate supplemental N rate

In-season potato CNS monitoring and decision on the rate and way of application on supplemental N fertilizer

- **Decision on the way of supplemental N-application according to the degree of within-field variability ?**

Previous characterisation and mapping of within field spatial variability

(based on soil characteristics such as texture, pH, SOC, soil min N…)

+

Maps of CNC from satellite reflectance data