Estimation of crop biophysical and biochemical parameters

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FATIMA

FArming Tools for external nutrient Inputs and water MAnagement

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FATIMA aims at developing innovative agri-environment management that help the intensive farm sector optimize their external input (water, nutrients), with the vision of bridging sustainable crop production and fair economic competitiveness.

WP 2.2 Earth Observation for monitoring plant status and yield

BIOPHYSICAL & BIOCHEMICAL PARAMETERS:

- fAPAR
- Fractional vegetation cover
- Leaf Area Index
- Albedo
- Chlorophyll content (for N- content)

FATIMA looks at improvements of current E.O. methodologies and new developments in relation to new sensors capabilities

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- Testing new algorithms for biophysical-biochemical parameters
- Modeling/benchmarking exercise is being carried out in pilot areas

PARAMETRIC METHODS | NON-PARAMETRIC METHODS

Empirical approaches

BROAD BAND indexes

NARROW band indexes

Artificial Neural Networks

Physically based approach

Radiative Transfer Models (RTM)

$$\rho^{\lambda} = \mathrm{RTM}\left(\rho_{leaf}^{\lambda}\ \tau_{leaf}^{\lambda}\ \rho_{soil}^{\lambda}\ \mathrm{SKYL}\ \ \alpha\ z\ z_{sun}\ \ \mathrm{LAI}\ \ \mathrm{LAD}\right)$$

Optical INPUT | **GEOMETRY** | **CANOPY**

Hybrid methods

Artificial neural networks trained with RTM generated datasets *(Sentinel ToolBox)*

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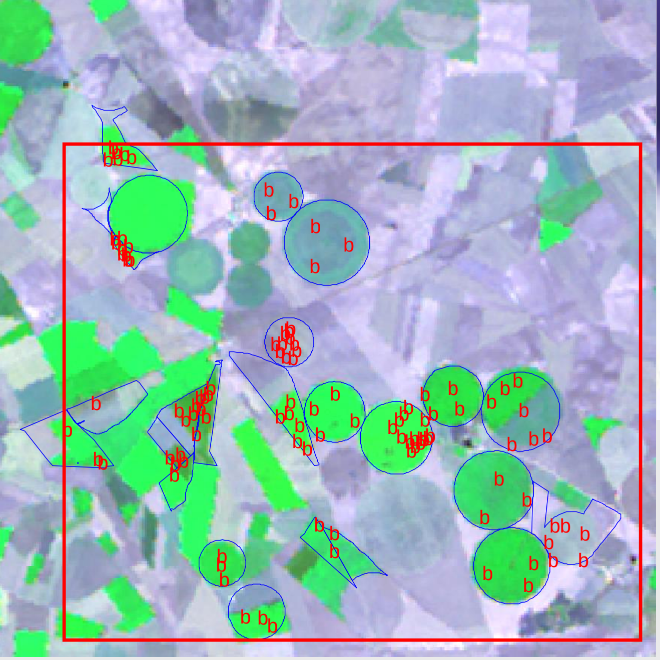
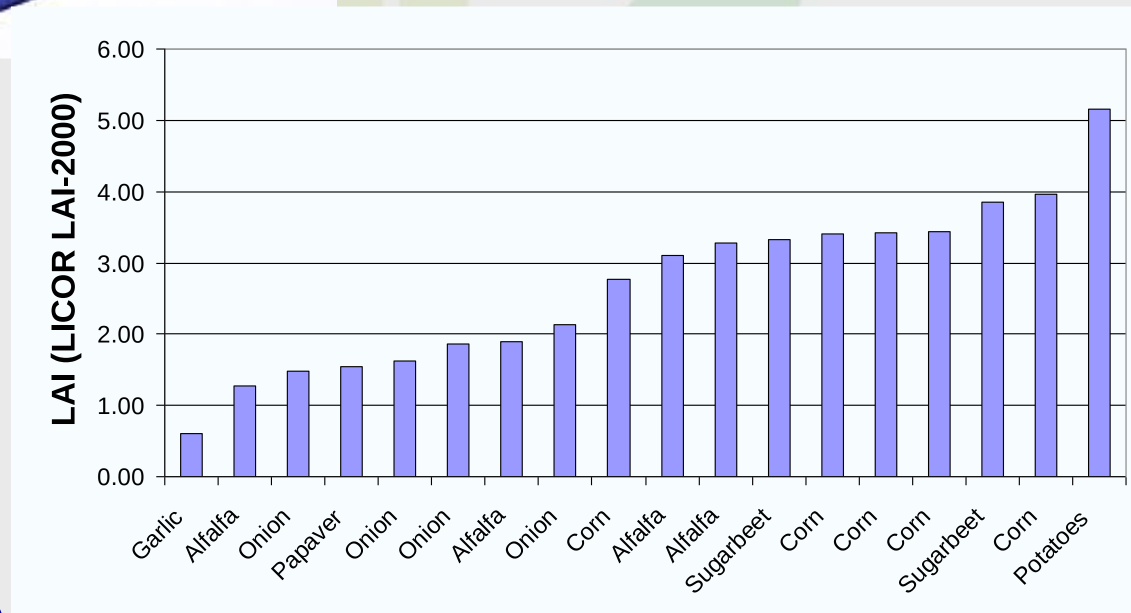


LAI measurements



CLAIR model calibration

$$LAI = -\frac{1}{\alpha}\ln\left(1-\frac{WDVI}{WDVI_{\infty}}\right)$$

The final value of α is taken in correspondence of the minimum error between observed and estimated LAI

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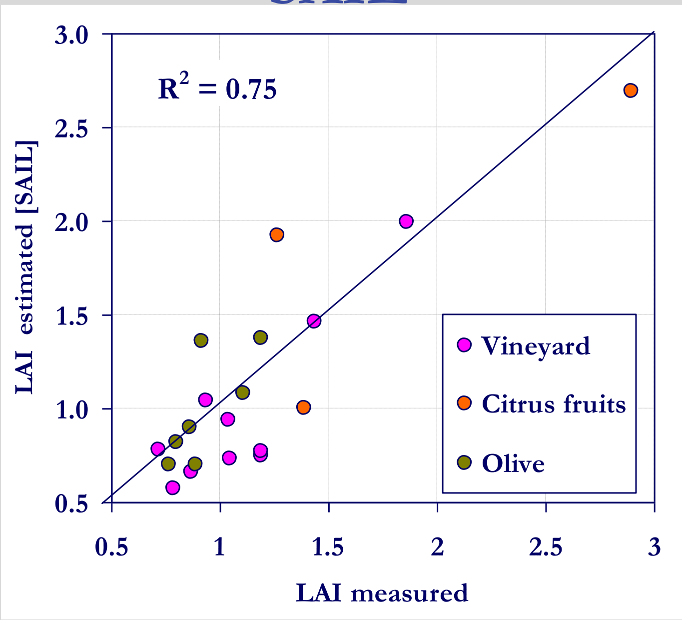
MIVIS (Sicily, 2001-2002): COMPARISON BETWEEN SAIL AND CLAIR MODELS

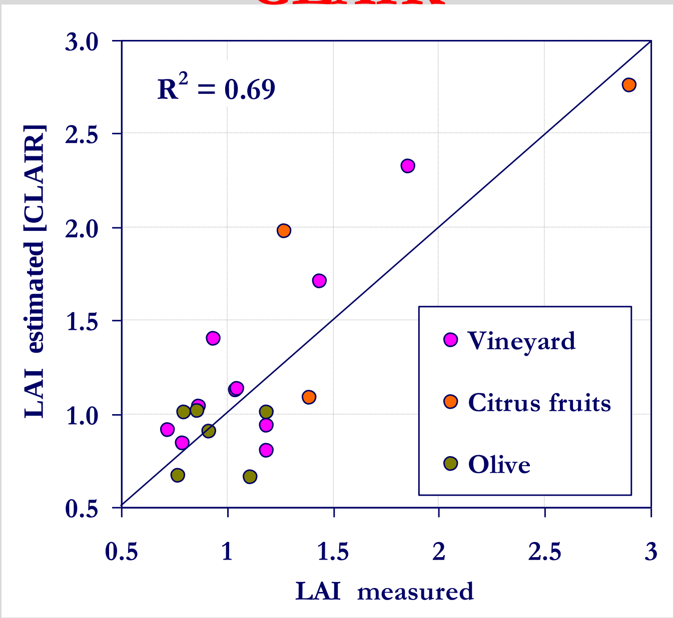
(Minacapilli, D'Urso, Liang)

SAIL



	Citrus Fruits & Olive	Vineyard	ALL
R^2	0.77	0.77	**0.75**
S. E.	0.310	0.220	**0.283**

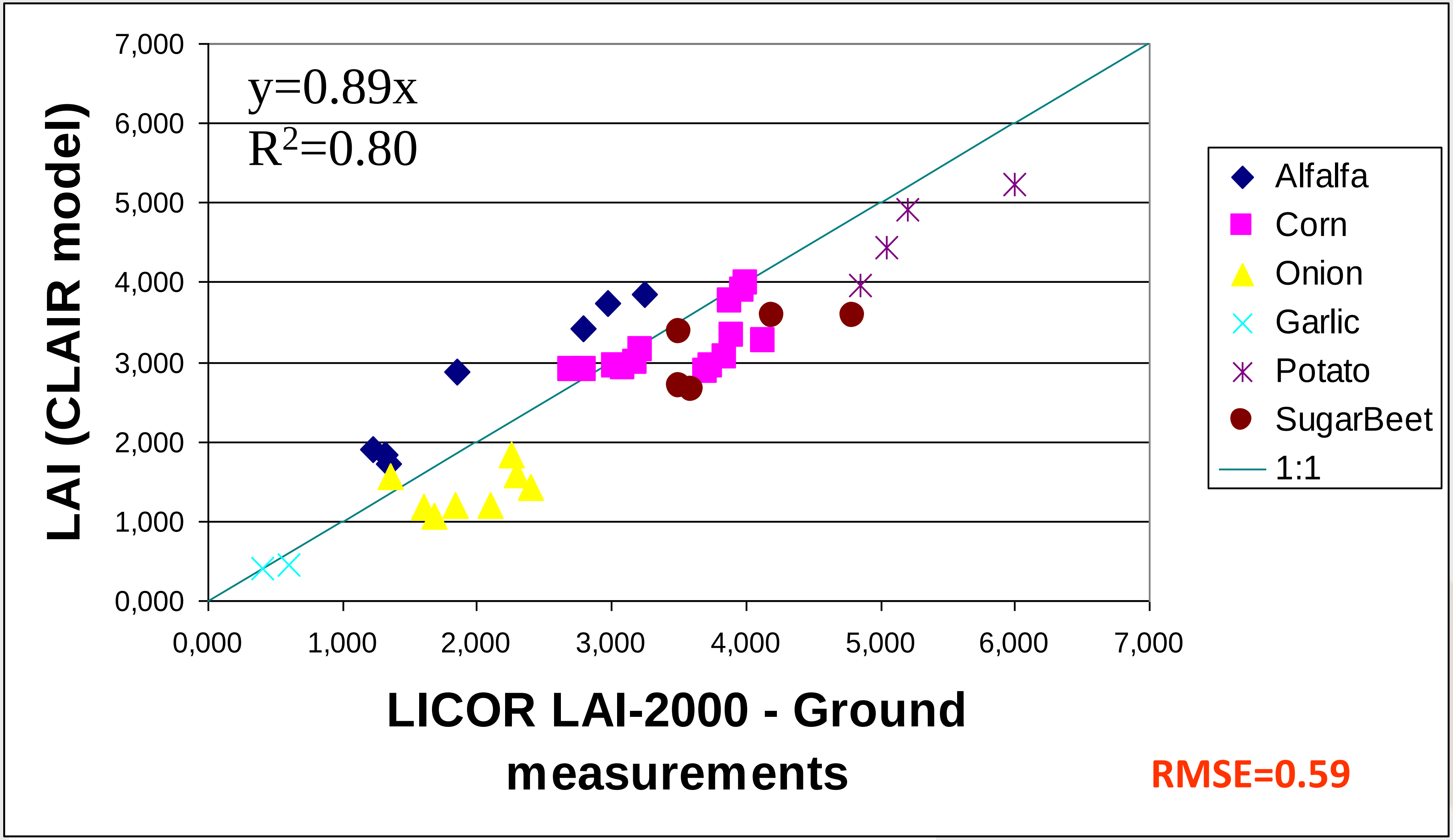
CLAIR



	Citrus Fruits & Olive	Vineyard	ALL
R^2	0.74	0.68	**0.69**
S. E.	0.372	0.285	**0.328**

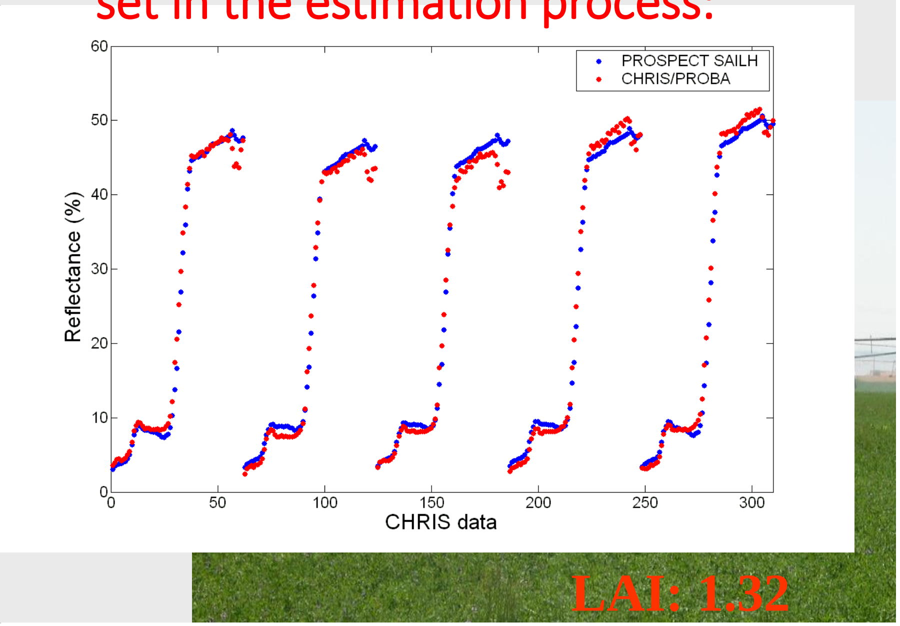
The comparison of the two approaches shows a good correlation between the two sets of LAI estimates, with a better agreement in the SAIL approach respect to the empirical CLAIR.

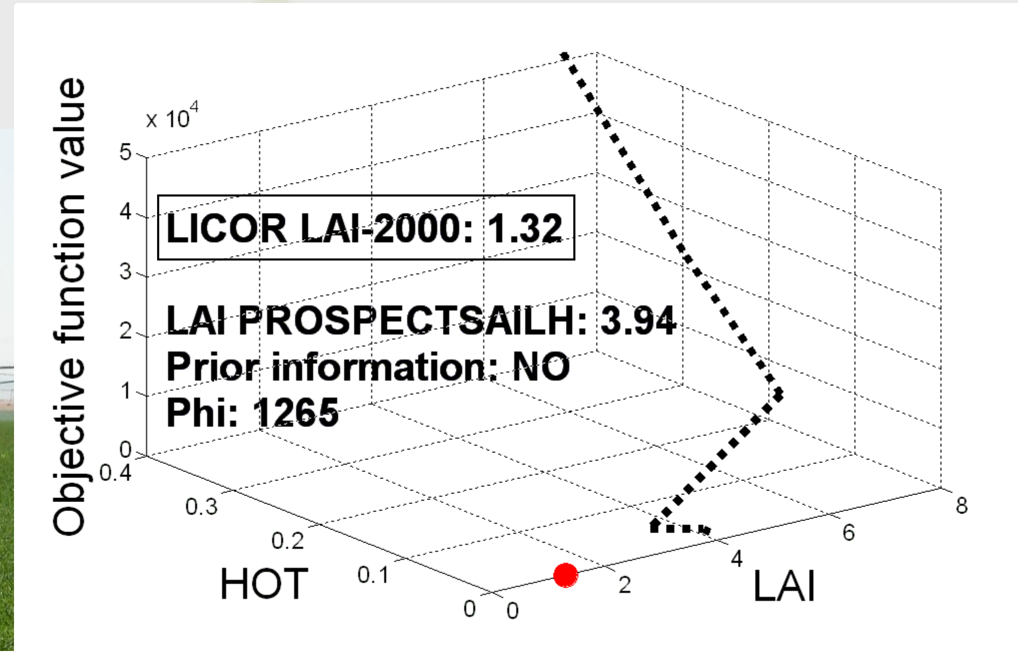
14/07 – Barrax 2003 (Chris Proba)



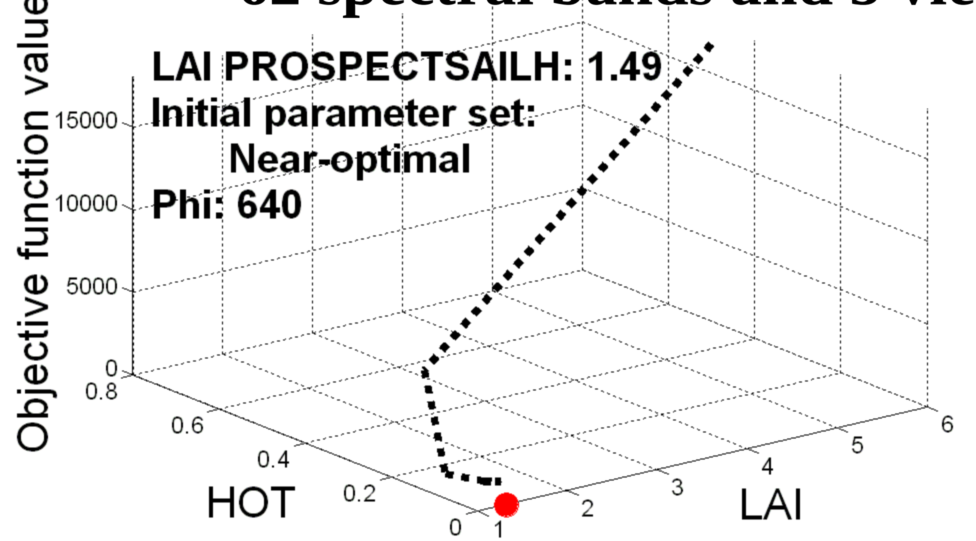
The empirical relationship has been verified by using 40 independent field measurements.

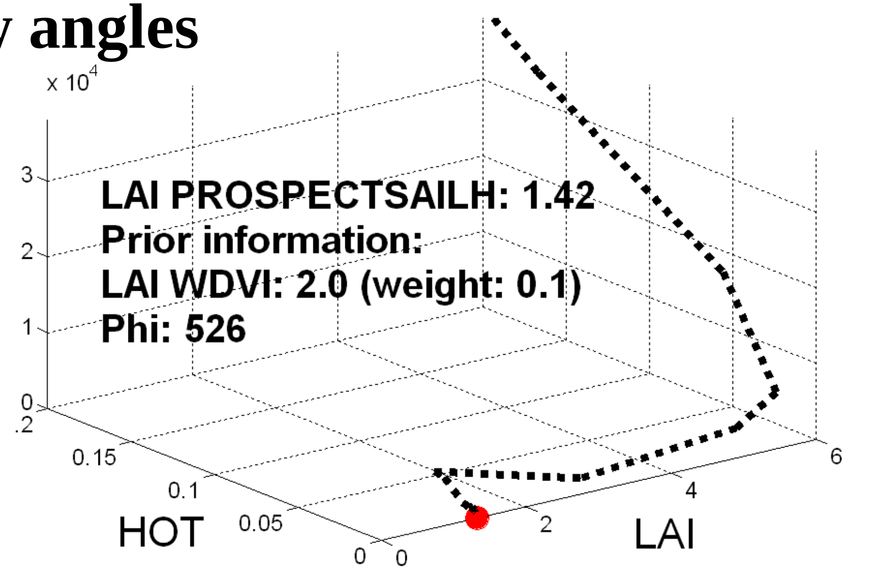
The importance of prior information and the initial parameter set in the estimation process:

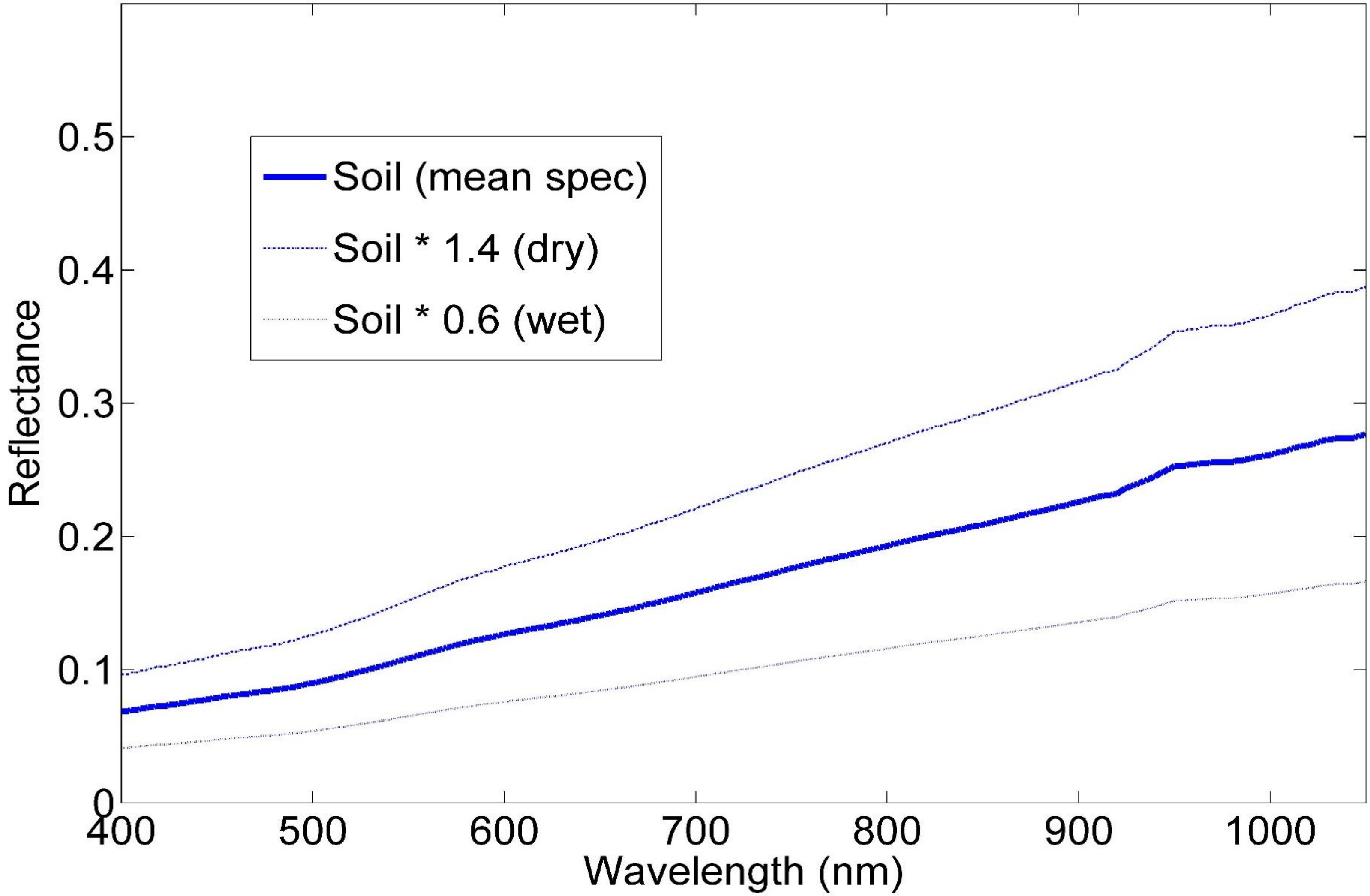




62 spectral bands and 5 view angles



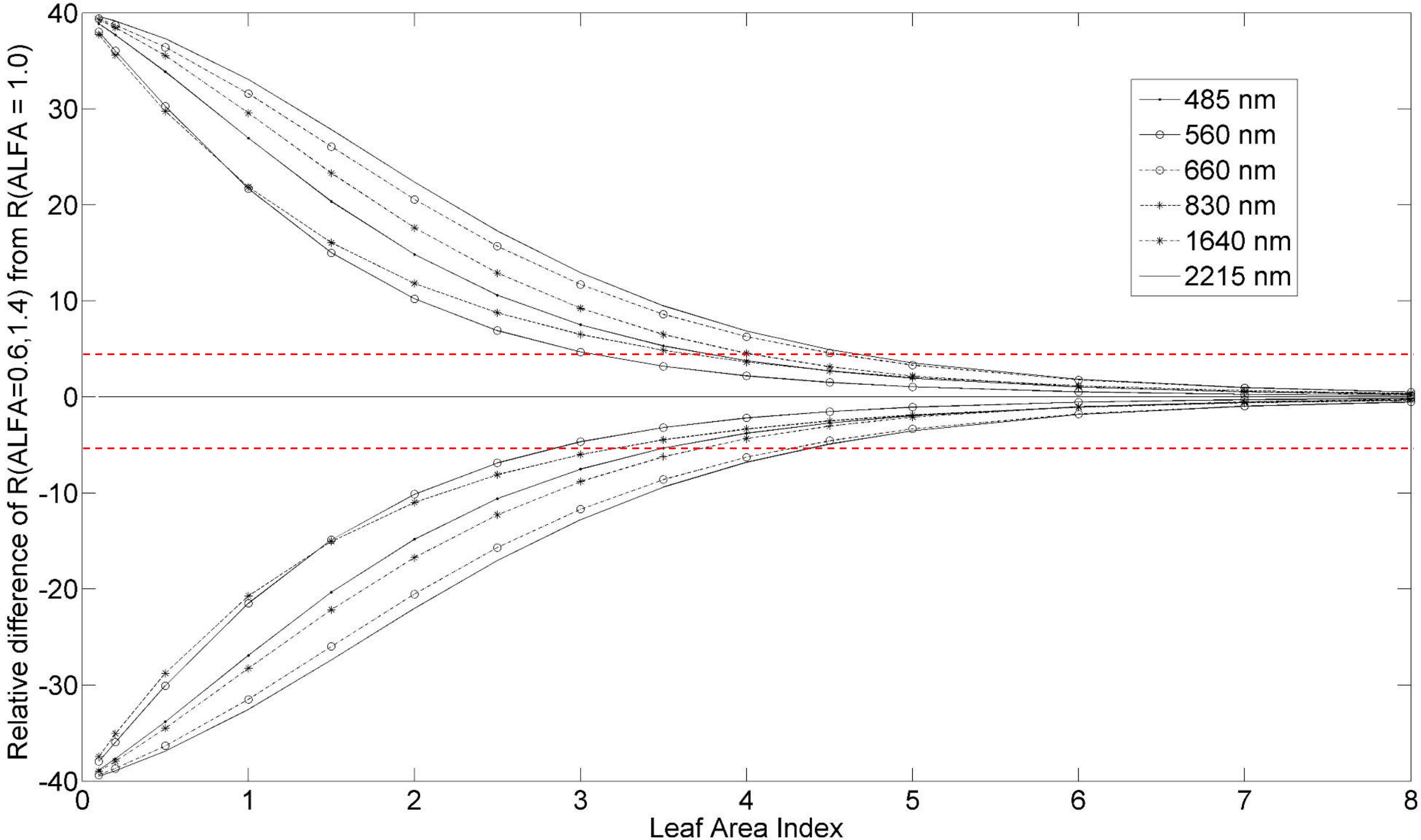




Standard (mean) soil as model input, reflectance variation due to soil moisture:

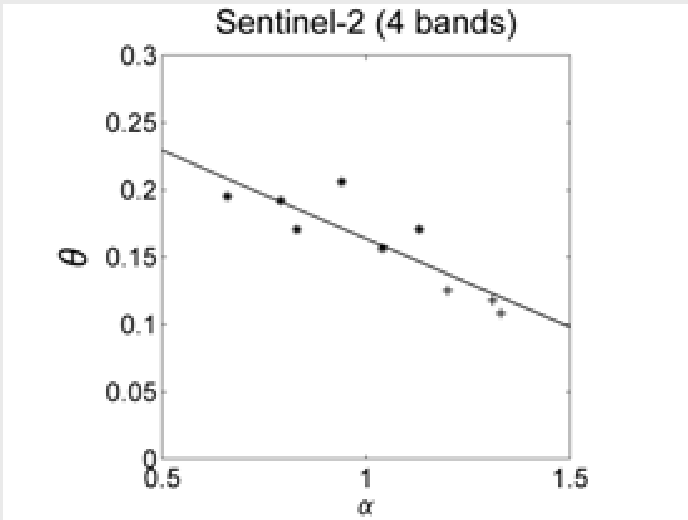
α_{soil} = 0.6 → WET SOIL
α_{soil} = 1.4 → DRY SOIL

Spectral sensitivity to α_{soil} factor



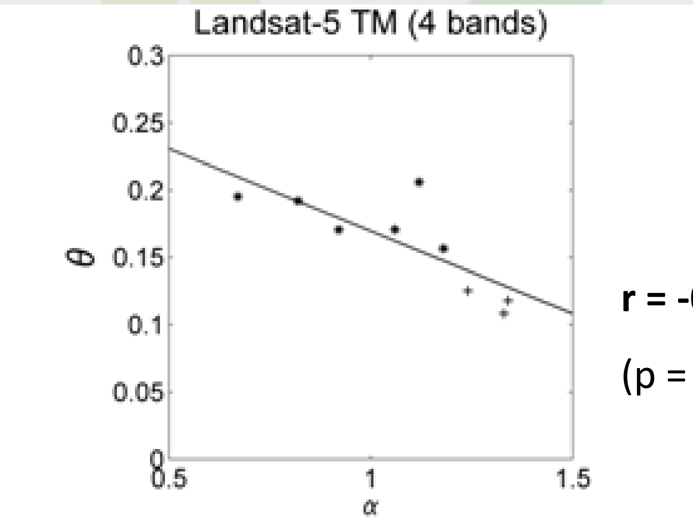
Landsat-7 configuration

Results from PLEIADeS 2007 campaign:
soil moisture and radiometric measurements



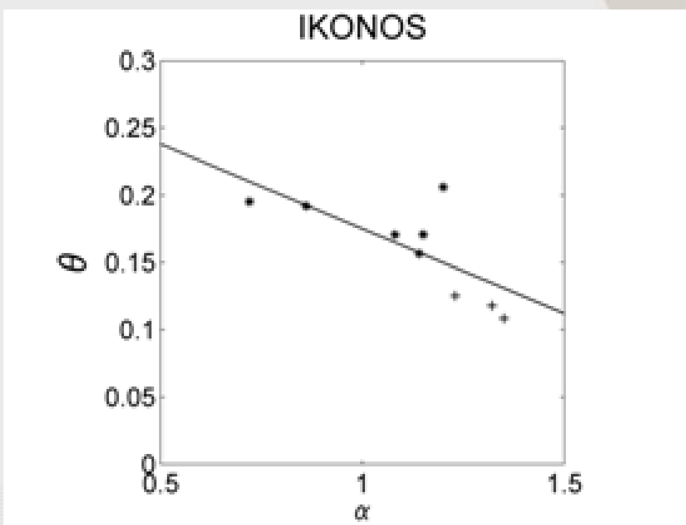
r = -0.87

(p = 0.002)



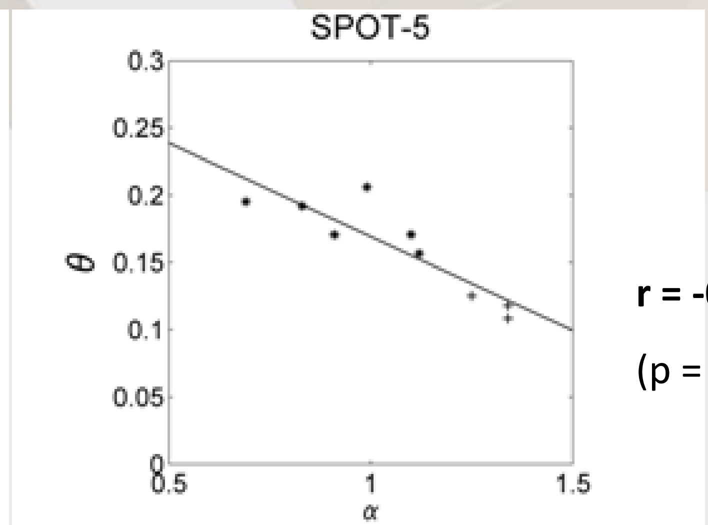
r = -0.79

(p = 0.011)



r = -0.73

(p = 0.027)



r = -0.89

(p = 0.001)

Chlorophyll and Nitrogen estimation

Index	Formulation	Reference
$CI_{red\text{-}edge}$	$\left(\frac{R_{783}}{R_{705}}\right) - 1$	Gitelson et al. (2003, 2006)
CI_{green}	$\left(\frac{R_{783}}{R_{560}}\right) - 1$	Gitelson et al. (2003, 2006)
REP	$705 + 35\frac{(R_{665}+R_{783})/2-R_{705}}{R_{740}-R_{705}}$	Guyot and Baret (1988)
MTCI	$\frac{R_{740}-R_{705}}{R_{705}-R_{665}}$	Dash and Curran (2004)
MCARI/OSAVI[705,750]	$\frac{[(R_{740}-R_{705})-0.2(R_{740}-R_{560})](R_{740}/R_{705})}{(1+0.16)(R_{740}-R_{705})/(R_{740}+R_{705}+0.16)}$	Wu et al. (2008)
TCARI/OSAVI[705,750]	$\frac{3[(R_{740}-R_{705})-0.2(R_{740}-R_{560})(R_{740}/R_{705})]}{(1+0.16)(R_{740}-R_{705})/(R_{740}+R_{705}+0.16)}$	Wu et al. (2008)
NDRE1	$\frac{R_{740}-R_{705}}{R_{740}+R_{705}}$	Gitelson and Merzlyak (1994), Sims and Gamon (2002)
NDRE2	$\frac{R_{783}-R_{705}}{R_{783}+R_{705}}$	Barnes et al. (2000)

Clevers, Gitelson, 2012

http://dx.doi.org/10.1016/j.jag.2012.10.008

The concept of the Nitrogen Nutrition Index NNI

NNI = Na/Nc

ratio between the actual crop N uptake (**Na**)
and the critical N uptake (**Nc**)

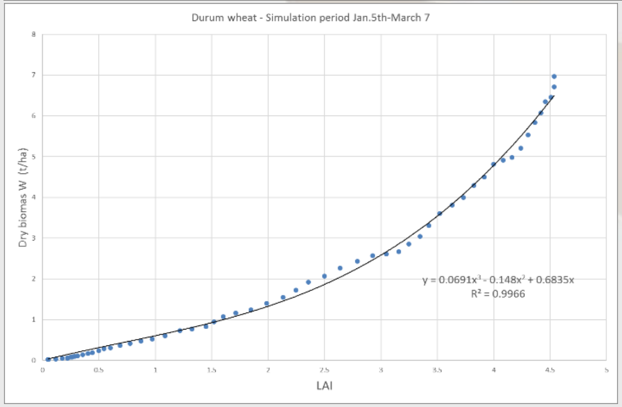
$Nc = a_c W^{-b}$

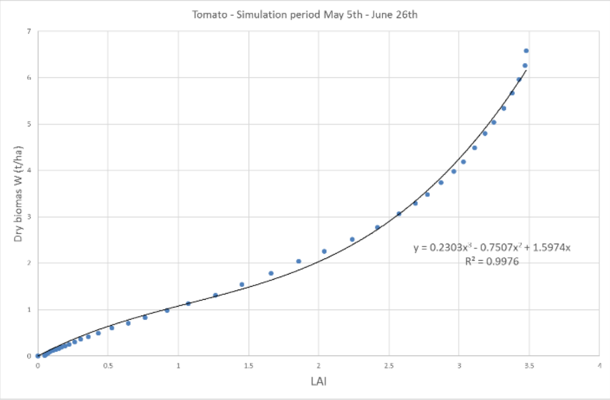
with W being the dry biomass in t/ha. Coefficients a_c and b for different crop species are found in literature (i.e.: Lemaire et al., J. Agronomy 28: 614-624)

Wheat : $a_c = 5.3$; $b = 0.44$
Tomato $a_c = 4.5$; $b = 0.33$

deriving W from LAI

Calibration of W(LAI) relationship based on EPIC and field data – Wheat (left) and Tomato (right)





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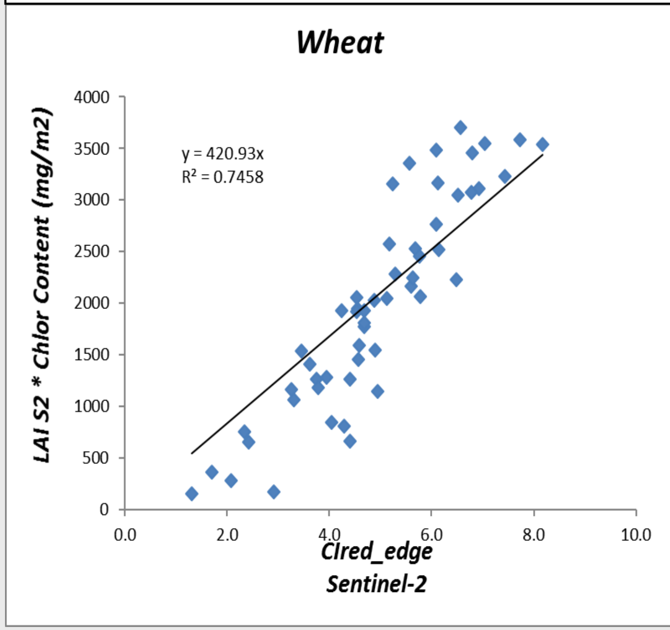
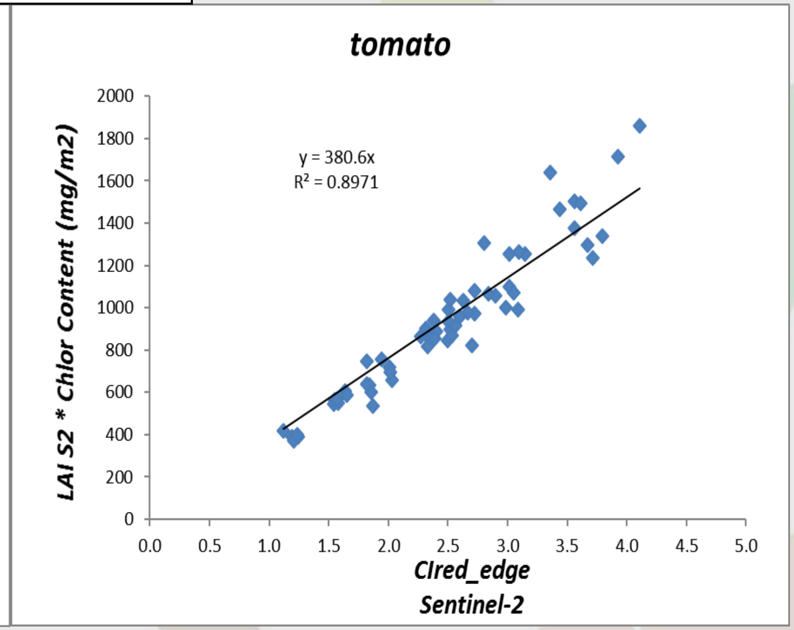
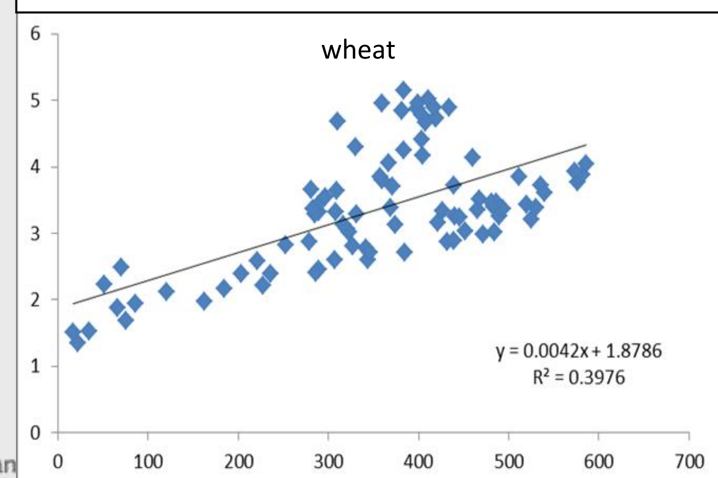
FATIMA test site
Tarquinia, 2016

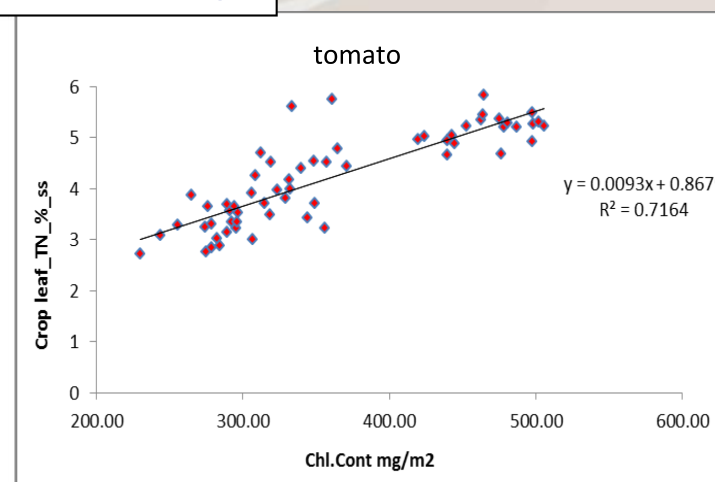
1) Calibration between CI_{red_edge} and canopy Ch cont.





2) Calibration between laboratory N% and MC-100 readings





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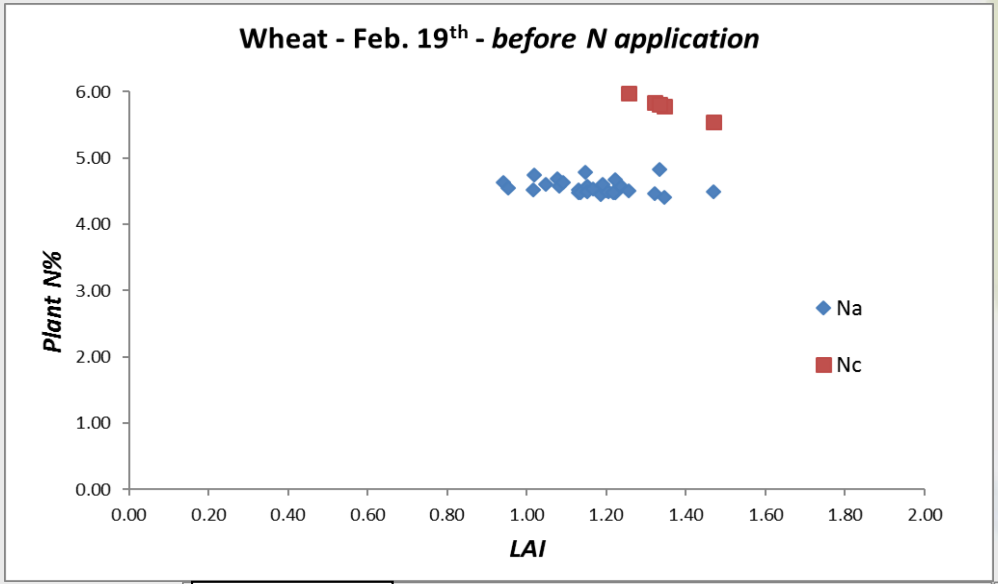
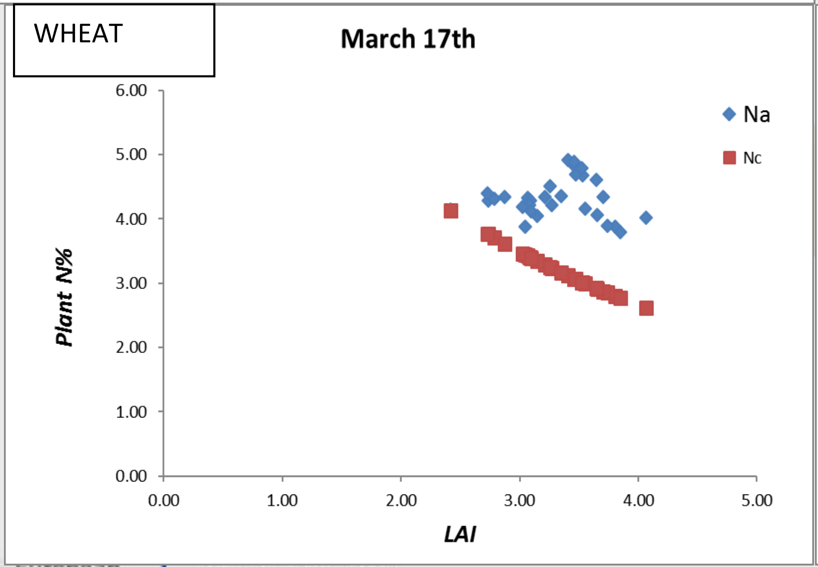
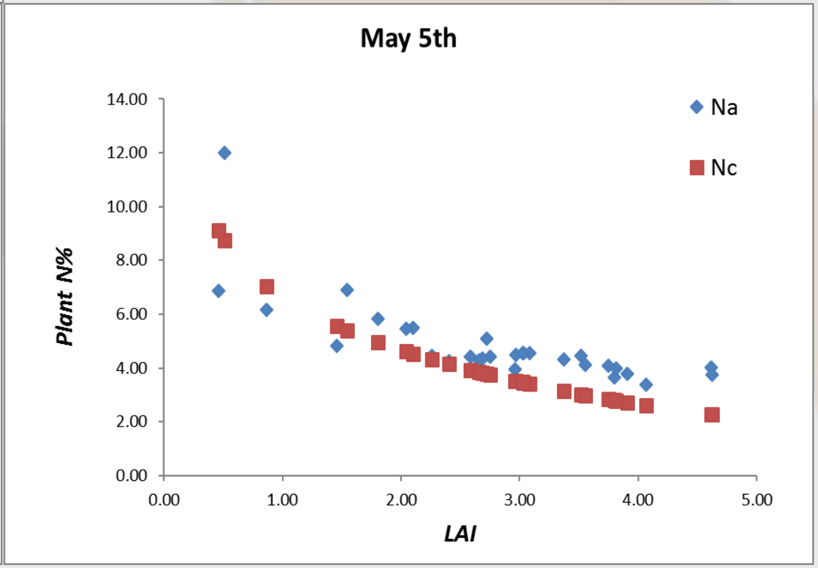
WHEAT: **Na** = 0.0042 * (420.93 *CIred_edge*)/LAI_S2 + 1.8786



FATIMA test site
Tarquinia, 2016





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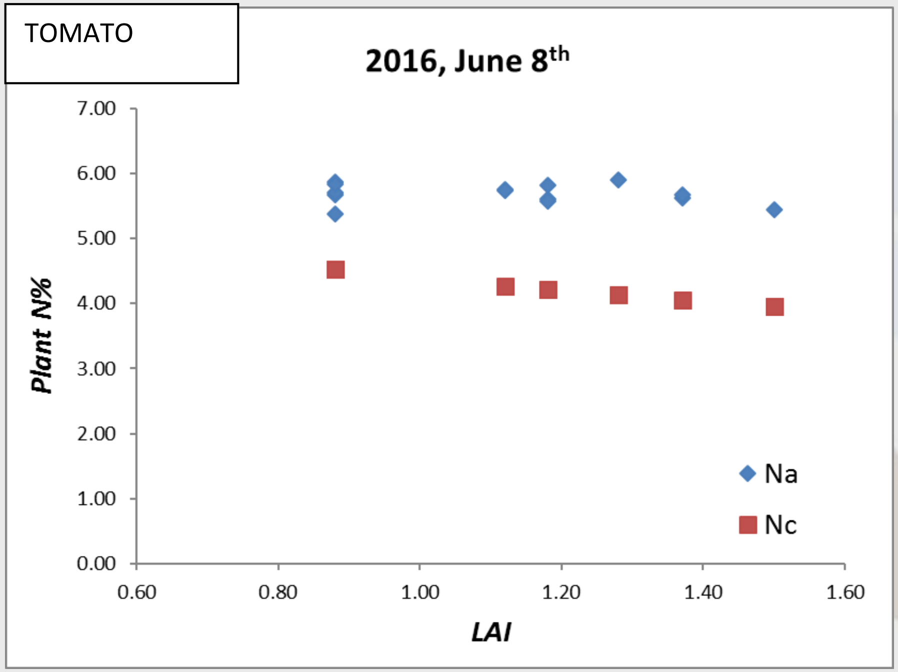
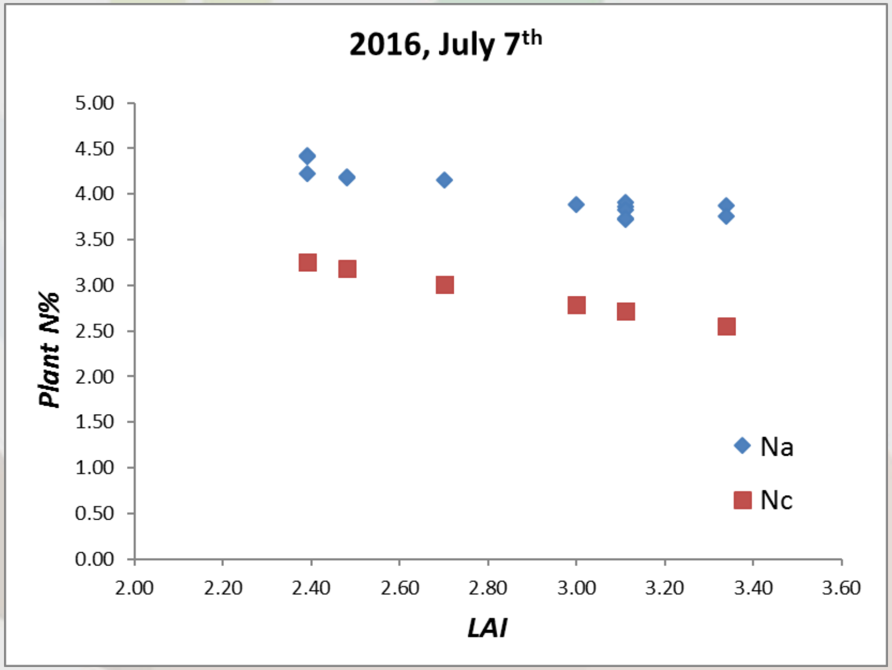
TOMATO: **Na** = 0.0093 * (380.6 *CIred_edge*)/LAI_S2 + 0.8679

TOMATO





FATIMA test site
Tarquinia, 2016

Lessons learnt from past experiences:

Correlations between field measurements of crop biophysical parameters and spectral indexes generally improve when using narrow bands instead of broad bands

Number of bands appears to be the most important advantage of using hyperspectral data over multispectral data to predict LAI in physically based methods

However, work still remains to determine when a predictive model is overfit. Inversion is still computationally heavy and appropriate initialisation is required.

Spectral channels in the red-edge and SWIR regions are generally more important than those in the near-IR for predicting chlorophyll.

Possible advancements :

Hyperspectral data can support the advancement of hybrid methods for estimating crop biophysical and biochemical parameters

Operative applications already available for LAI (e.g. Sentinel toolbox; Cyclopes, MERIS) can be improved by using more efficient methods, such as alternative Machine Learning Regression Algorithms (MLRA) trained with RTM

There is still room for improving the application of hyperspectral vegetation indexes based on the combination of n>2 narrow-bands

Thanks for your attention