Multi crop estimation of LAI from Sentinel-2 VIs with parametric regression approach: comparison of performances and VIs sensitivity

Margherita De Peppo[1], Francesco Nutini[1], Gabriele Candiani[1], Giorgio Ragaglini[2], Andrea Taramelli[3,4], Federico Filipponi[4], Mirco Boschetti[1]

[1] Institute for Electromagnetic Sensing of the Environment, Italian National Research Council, Via Bassini 15, 20133 Milan, Italy; depeppo.m@irea.cnr.it, nutini.f@irea.cnr.it; candiani.g@irea.cnr.it, boschetti.m@irea.cnr.it

[2] Dipartimento di Scienze Agrarie e Ambientali-Produzione, Territorio, Agroenergia, Università degli Studi di Milano, Via Celoria 2, 20133 Milano, Italy; giorgio.ragaglini@unimi.it

[3] Institute for Advanced Study of Pavia (IUSS), Palazzo del Broletto, Piazza della Vittoria 15, 27100 Pavia, Italy; andrea.taramelli@iusspavia.it

[4] Institute for Environmental Protection and Research (ISPRA), via Vitaliano Brancati 48, 00144 Rome, Italy; federico.filipponi@isprambiente.it

Abstract. Leaf Area Index (LAI) is a key variable for spatiotemporal modelling and analysis of several land surface processes. LAI can be successfully estimate by means of Vegetation Indices (VIs), retrieved from multispectral satellite images, however the different VIs show variable estimation uncertainty in relation to vegetation characteristics and soil background condition. In particular, VIs can show saturation behaviour at medium/high vegetation density. Thus, in this study we aimed at implementing parametric approach considering VIs belonging to three different classes computed on visible, red-edge and short-wave infrared spectral band combination provided by MSI sensor onboard Sentinel-2 satellites constellation.

Keywords: Parametric method; Sentinel-2 vegetation Indices, wheat; maize; sensitivity analysis.

1 Introduction

Leaf Area Index (LAI) is a dimensionless variable, defined as the leaf area per unit ground surface area [1,2]. It describes several canopy scale processes related to light interception and crop physiology (e.g. photosynthesis and respiration), as well as soil-plant relationships that affect evapotranspiration and nutrient use efficiency. Therefore, an accurate determination of LAI is a key for spatiotemporal modelling and analysing of several land surface processes related to agroecosystem dynamics [3,4]. Several approaches based on remotely sensed data have been utilized for assessing LAI.

Among the methodologies parametric regression using Vegetation Indices (VIs) is the most widely used. In particular, VIs approach is based on the analysis of the relation between spectral data, combination of spectral bands and biophysical parameters.

However, the use of VIs poses several issues, which currently limit their application to local cases reducing a general exportability in other context differ from the ones where the relation has been generated. The major limitation of using vegetation indices is related to the saturation effect that occurs at certain vegetation densities, which results in a non-linear response of VIs to LAI variation. This effect is particularly evident for the well-known Normalised Different Vegetation Index (NDVI) when [5] computed with broad bands in red and near-infrared (NIR) portion of the electromagnetic spectrum [6]. In order to cope with saturation, many authors had focused on the linearization of VIs response to LAI by the development and the assessment of indices based on spectral bands or calculation procedure more suited to better discriminate the effect of chlorophyll and water content [7–9]. However, assuming a linear relation between VIs and LAI would imply also to assume a non-finite domain of the response variable and that reflectance depend on a oversimplified scheme, made by one or few variables at least. Thus, despite a proliferation of indices, an accurate estimation of LAI from satellite, based on empirical approaches, is still challenging because the analysis and the interpretation of land surface reflectance are influenced by the coexistence of uncertainty sources, varying differently in time and space [10–12]. The difficulty in measuring LAI by remote increases in heterogeneous scenes, such as mosaics of crops at different phenological stages or complex mixtures of woodlands and/or grasslands[13].

Thus, a diversified ground-LAI dataset, including different sources of variability, such as different crop types over different phenology stage (Genetics - G), under different soil and climatic seasons (Environment - E) and farming condition (Management - M) should be used in order to define a generalized regression function for LAI estimation in relation able to deal with G x E x M interaction [4]. With this purpose several authors have already evaluated a number of candidate spectral regions more suited to VIs formulation, considering different crop types and phenology stages [14,15]. In particular, VIs based on visible (VIS) and red-edge (RE) spectral regions were evaluated sensible to green LAI (vegetative stages), while the short-wave infrared (SWIR) region was evaluated suited to senescent stages [16–18]. Past research, based on hyperspectral reflectance data showed that narrow bands VIS-based and RE-based VIs were able to accurately estimate LAI of different crops, maize, soybean, potato, and wheat, using a generalized regression function [12,19]. Moreover, due to the strong absorption by chlorophyll pigments the VIS-based indices are less sensitive at ground-LAI values > 2–3 respect to the RE-based VIs [20], while the RE region due to lower absorption by chlorophyll is more sensitive at moderate-to-high ground-LAI values [21]. Delegido et al [15], using simulated S2 data, demonstrated that RE based VIs were more sensible to a wide range of ground-LAI values of different crop types than VIS-based indices. Xie et al., [13] using real S2 data indicated the RE-based VIs are suitable for LAI estimation of different crop types during the entire period of growth. However, the feasibly of S2-based VIs is still under investigation, and the contribution of different spectral regions should be further assessed in order to improve LAI estimation over a wide range of ground-LAI values, considering different crop types, phenology stages, soil condition and farm management systems [15,22].

All this considered, the objective of this study was to exploit a data set of wide range of ground LAI (monthly measurements for two crops x two seasons x 3 farms) to analyse performances of different Sentinel-2 VIs computed with bands combination in the VIS, RE and SWIR region for the estimation of LAI in mixed-crop scenario.

In order to achieve this, specific objectives were:

1) to evaluate and compare the accuracy of S2-based VIs for LAI estimation by exploiting parametric regression on different crops (winter wheat and maize) under different management conditions;

2) to assess the sensitivity of VIs to ground-LAI variation;

3) to assess influence of different crops on parametric relation.

2 Materials and methods

2.1 Test sites

The study sites were located in Pisa, Tuscany Region, Central Italy, on a flat area over 31,500 hectares, mainly dedicated to the cultivation of arable crops. The climate is Mediterranean with a mean annual precipitation of 907 mm and a mean annual temperature of 15°C (long term average 1986-2016). According to land cover spatial information from the Tuscany regional authorities (http://dati.toscana.it/), in 2018-2019 two prevalent crop types were identified: (i) winter wheat (*Triticum aestivum L.)*, among cold season cereals (ii) maize (*Zea mays L.*) among warm season crops. For the construction of the database three test sites have been identified, characterized by different soil and farm management conditions. Thus, ground-LAI of the two crops, during two fields campaign (2018 and 2019) have been measured in each site according to the following schedule: (i) from March to June for winter wheat, (ii) from July to August for maize.

2.2 round-LAI measurements

Ground-LAI was measured for each crop in each site with a bi-weekly frequency by means of ceptometer SunScan Delta-t Canopy Analysis System (Delta-T Devices, Cambridge, UK). The ground-LAI measurements were collected from March to October in the 2018 and 2019 only on clear-sky days according to Sentinel-2 overpassing (at approximately 11:30 A.M. local time) with a maximum of 5 days' difference. In total 16 sampling date were scheduled for the sampling area. According to the VAlidation of Land European Remote Sensing Instruments (VALERI), the sampling strategy was based on Elementary Sampling Units (ESU) upscaling approach in order to capture the variability across the study area and within the field of each crop [23]. In total 192 samples were collected (4 ESUx 3 fields x 3 Farm x 16 time), 132 during the 2018 and 60 during the 2019 field campaign.

2.3 Sentinel-2 Data

The Copernicus Sentinel-2 (S2) is a satellite mission carrying the Multispectral Instrument (MSI) sensor with a high spatial resolution (10 m, 20 m and 60 m), high revisit capability (5 days with two satellites) and a moderately large band set (13 spectral bands) from the visible to short-wave infrared [24,25]. The S2 Level 2A (L2A) images were downloaded from the Theia Land Data Centre, which provides time series of top canopy surface reflectance orthorectified and atmospherically corrected with MACCS-ATCOR Joint Algorithm (MAJA) [26]. A total of 16 cloud-free images, collected in correspondence of the in-situ monitoring period, were used to analyse the relationship between measured ground-LAI and VIs.

2.4 VIs computation

Spectral reflectance data derived from Sentinel-2 were used to calculate 11 VIs, selected according to previous studies carried out on the two crop types considered in this work [13,17,18,22,27]. (Table 1).

Table 1. Vegetation Indices (VIs) evaluated in the study. The ρ represent reflectance of Sentinel-2.

VIs	Name	Formula	Reference
Visible			
EVI	Enhanced Vegetation Index	2.5*(ρ865-ρ665)/(ρ865+6*ρ665-(7.5*ρ490) +1)	[28]
NDVI	Normalized difference vegetation index	(ρ865-ρ665)/(ρ865+ρ665)	[5]
NIRv	Near-Infrared Reflectance of vegetation	(ρ865-ρ665)/(ρ865+ρ665) *ρ865	[29]
NDVIgr			
WDVI	Weighted Difference Vegetation Index	ρ865-ρ665*(ρ865/ρ665)	[30]
Red-edge			
NDVIre1	NDVIRed-edge 1	(ρ740-ρ705)/(ρ740+ρ705)	
NDVIre2	NDVIRed-edge 2	(ρ783-ρ705)/(ρ783+ρ705)	
SeLI	Simple Sentinel-2 LAI Index	(ρ865-ρ705)/(ρ865+ρ705)	[13]
NDI45	Normalized Difference Index	(ρ705-ρ665)/(ρ705+ρ665)	[15]
SWIR			
NBR	Normalized Burn Ratio	(ρ865-ρ2190)/(ρ865+ρ2190)	[32]
NDII	Normalized Difference Infrared Index	(ρ865-ρ1610)/(ρ865+ρ1610)	[33]

Once the VIs were calculated, the centroid of each ESU was used to extract zonal statistics from raster images for each sampling time of S2 time series in order to couple the ground-LAI value and the VIs value. Only VIs values derived from images acquired within ±5 days from ground data collection were considered. As a result, a complete SQL database, of 192 records, of coupled ground-LAI and VIs values, was obtained for the three crops of each farm in the reference period March 2018 - October 2019.

2.5 Analysis of the ground-LAI to VIs relation

The relationship between ground-LAI and VIs was analysed by using: (i) linear, (ii) logarithmic and (iii) second order polynomial functions. In order to evaluate the performances of the parametric regression approach data were randomly divided in train (75%) and test (25%) dataset and functions performances were evaluated by the coefficient of determination (R^2), the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE). Furthermore, to evaluate the different VIs sensitivity to ground-LAI estimation the noise equivalent (NE) was calculated as:

$$NE\Delta ground - LAI = \frac{RMSE(VIvsgroundLAI)}{d\,(VI)/d\,(groundLAI)}$$

where d(VI)/d(ground-LAI) is the first derivative of the VI with respect to ground-LAI, and RMSE (VI vs. LAI) is the RMSE of the VI vs. ground-LAI relationship. All the statistical analysis was computed in R software. The NEΔground-LAI provides a measure of how well the VI responds to ground-LAI across its entire range of variation [34]. The NEΔground-LAI takes into the sensitivity of the VI to ground-LAI, thus providing a metric accounting for both the scattering of the points from the best-fit function and the slope of the best-fit function. In the end, to test the applicability of the identified regression models to estimate the ground-LAI over different crop type the analysis of covariance (ANCOVA) was performed. ANCOVA allows to identify if crop specific regression is significantly best performing than the mix-crop model hence indicating the capacity of the VI based regression model to be exploited across different cropping systems.

3 Results and discussion

3.1 ground-LAI relation with VIs

For each VIs the best performing function was evaluated according the highest R^2 and the lowest errors (RMSE and MAE). In Table.1 are reported all the analyzed relationship between ground-LAI and VIs over the testing dataset. In general, for all the evaluated VIs, the linear model and the second order polynomial showed the best performances with $R^2 > 0.4$ and RMSE < 0.18. In particular, linear model showed a higher accuracy with EVI, NIRv and NDI45 with R^2 of 0.69, 0.51 and 0.42 and RMSE of 0.13, 0.08 and 0.16 respectively. Similarly, [22] based on 108 ESU of the SPARC 2003 dataset, concluded that the linear model was the most suited regression function for estimating LAI values (R^2=0.82) exploiting a pool of various crops. Conversely for NDVI, WDVI, NDVIgr, SeLI, NDVIre1, NDVIre2, NDII and NBR the second order polynomial function showed the best performances with $R^2 > 0.4$ and RMSE < 0.18. These finding for the VIS and RE VI categories are in agreement with other study results [9]; The authors, using RapidEye sensors, demonstrated that when different crops (winter wheat, barley, alfalfa and maize) and vegetation stages are analysed together, relation between LAI and VIs is non-linear.

In addition, the comparison of the different fitting functions revealed that VIs with saturation behaviour at moderate/high LAI values (i.e. > 3) show polynomial function as best fitting.

Table 2. Best-fit functions for the relationships between ground-LAI and vegetation indices (VIs) obtained over the validation dataset. The reported metrics were: (i) coefficient of determination (R^2) (ii) the Root Mean Square Error (RMSE) and (iii) the Mean Absolute Error (MAE). Model type: lm=linear; poly=second-order polynomial function and log=logarithmic

VIs	model	a	b	c	R^2	MAE	RMSE
EVI	**lm**	**0.095**	**0.289**		**0.69**	**0.11**	**0.13**
EVI	log	0.228	0.355		0.63	0.1	0.12
EVI	poly	-0.031	0.272	0.095	0.66	0.1	0.13
WDVI	lm	0.04	0.23		0.48	0.06	0.07
WDVI	log	0.093	0.26		0.51	0.05	0.07
WDVI	**poly**	**-0.013**	**0.114**	**0.152**	**0.51**	**0.05**	**0.07**
NDVI	lm	0.128	0.359		0.5	0.13	0.16
NDVI	log	0.29	0.466		0.57	0.12	0.15
NDVI	**poly**	**-0.033**	**0.315**	**0.163**	**0.59**	**0.12**	**0.14**
NDVIgr	lm	0.125	-0.121		0.39	0.15	0.19
NDVIgr	log	0.267	-0.004		0.38	0.13	0.18
NDVIgr	**poly**	**-0.01**	**0.18**	**-0.179**	**0.4**	**0.15**	**0.18**
NIRv	**lm**	**0.061**	**0.098**		**0.51**	**0.06**	**0.08**
NIRv	log	0.142	0.147		0.5	0.06	0.08
NIRv	poly	-0.018	0.161	-0.008	0.5	0.06	0.08
SeLI	lm	0.12	0.249		0.38	0.14	0.18
SeLI	log	0.28	0.343		0.46	0.14	0.16
SeLI	**poly**	**-0.032**	**0.3**	**0.056**	**0.48**	**0.14**	**0.16**
NDVIre1	lm	0.132	0.298		0.56	0.12	0.15
NDVIre1	log	0.304	0.404		0.58	0.12	0.15
NDVIre1	**poly**	**-0.034**	**0.324**	**0.092**	**0.61**	**0.11**	**0.14**
NDVIre2	lm	0.123	0.374		0.62	0.14	0.16
NDVIre2	log	0.285	0.468		0.66	0.13	0.15
NDVIre2	**poly**	**-0.032**	**0.305**	**0.173**	**0.69**	**0.12**	**0.14**
NDI45	**lm**	**0.118**	**0.048**		**0.42**	**0.13**	**0.16**
NDI45	log	0.246	0.159		0.36	0.11	0.16
NDI45	poly	-0.009	0.165	-0.001	0.41	0.13	0.16
NBR	lm	0.13	0.202		0.55	0.14	0.16
NBR	log	0.295	0.309		0.67	0.11	0.13
NBR	poly	-0.034	0.322	-0.003	0.7	0.11	0.13
NDII	lm	0.107	-0.007		0.59	0.11	0.13
NDII	log	0.248	0.079		0.63	0.1	0.12
NDII	poly	-0.03	0.275	-0.183	0.68	0.1	0.12

3.2 VIs sensitivity to ground-LAI

Figure.1 shows NE Δ ground-LAI values of the best performing functions (linear and second-order polynomial) for VIS, RE and SWIR group of VIs. Because of first derivative of linear function is constant (slope), the NE values is constant across the range of ground-LAI variation. Therefore, results of linear function showed a shingly variation of NE values among all the VIs with the exception of WDVI that exhibited the highest NE values (the lowest sensitivity to LAI). Conversely, polynomial function showed that for all the VIs the NE values rapidly increase for ground-LAI > 2 m^2/m^2. By means NE analysis, several authors identified VIS and RE most appropriate regions to predict ground LAI below and above 2 respectively, and then suggested the use of composed VIs method for LAI estimation [12,35]. However, in this study NE values, for both linear and polynomial functions, varying according to the different VIs without specific behavior in relation to spectral groups.

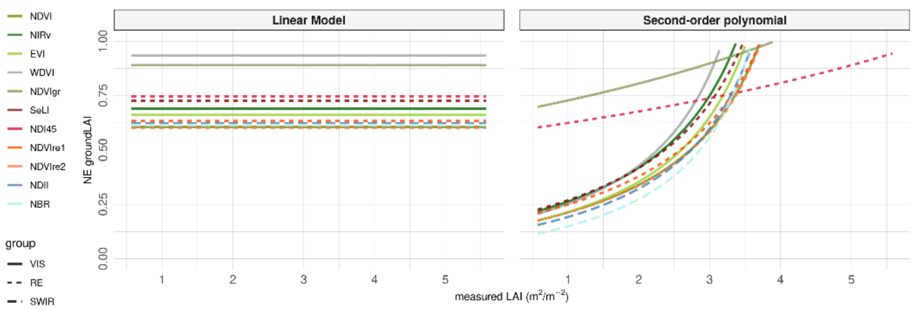

Fig. 1. Noise equivalent (NE) of the ground-LAI and VIs for linear function and second-order polynomial function. Different colours represent the VIs and line type the spectral regions (VIS, RE and SWIR).

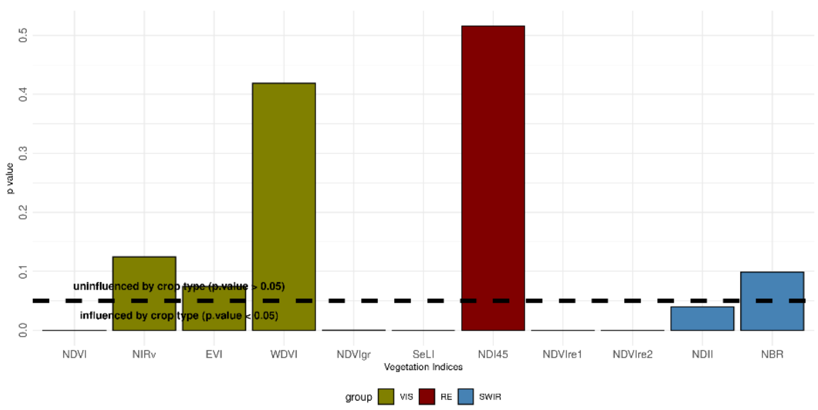

Fig. 2. Graphic representation of ANCOVA test values for the VIs – LAI relation by considering as factor crop types. Colour represents the spectral regions considered in VIs calculation. Dashed line shows the limit (p = 0.05) of statistical significance for evaluate the VIs influenced by crop factor.

The ANCOVA test was performed in order to select the most accurate VIs for LAI prediction of different crop types. Thus, Figure.2 reports the p-values of the ANCOVA test for all the evaluated VIs. Results showed that VIS based indices showed the lowest influence to crop type in the definition of the ground-LAI VIs relation. In particular, relation based on NIRv, EVI and WDVI are not significantly influenced by considered crop as demonstrated by a p-value of 0.12, 0.07 and 0.42 respectively. Conversely for the RE based indices only the NDI45 – LAI relation was uninfluenced by the crop type (p value of 0.52). Moreover, NBR (SWIR based VIs) showed a p value of 0.10 and thus was not influenced by crop type in ground-LAI predictions.

4 Validation and map demonstration

Validation was performed on the best VIs for each category by considering regression performance (R^2 and MAE), sensitivity to LAI variation (NE) and (non)influence of crop typology (ANCOVA test). Results of validation for EVI, NDI45 and NBR are presented in Figure. 3, in general all the considered VIs can provide good LAI estimation with predictive capability ($R^2 > 0.6$ and RMSE < 0.8). The estimated LAI values, using the most suitable VIs and the most accurate function, revealed that linear model with EVI exhibited the highest correlation ($R^2 = 0.72$) and lowest error (RMSE = 0.67). NBR provided lower accuracy with respect to EVI ($R^2 = 0.67$ and RMSE 0.72). According to [13], SWIR band (S2-B12:2190 nm) can improve the LAI estimation when the regression model is calibrated on healthy crops, but it is inadequate when different conditions (phenological or water stress) were considered together. Among the three VIs, the less accurate performances were obtained by using the NDI45 with R^2 of 0.6 and RMSE of 0.78. This results was in contrast with findings of Frampton et al., [18] that identified the NDI45 the best performing VI for ground-LAI estimation over different crop types. An explanation of the different behaviour of NDI45 response according to the crop species could depend on the complex of factors affecting reflectance in relation to the covariation of soil coverage, canopy structure, water and chlorophyll content in the different growth stages [9].

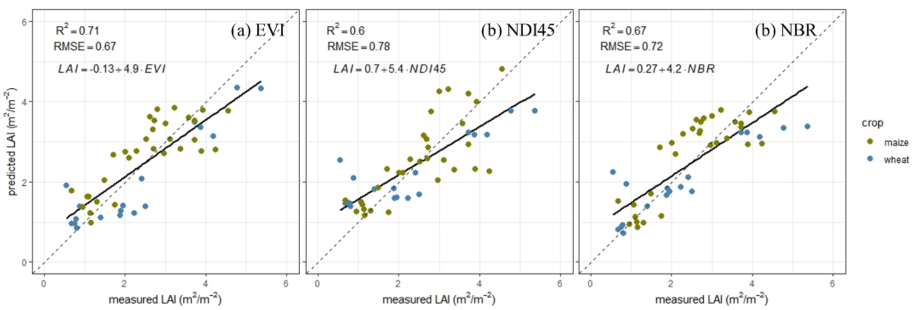

Fig. 3. Validation scatter plot of the best performing VIs colours represents the two crops (maize and winter wheat)

Previous works have pointed out particular emphasis on chlorophyll content, whose level in the canopy significantly affect light absorbance by crop. In particular, Houborg et al., [36], analysing the LAI response to NDVI in relation to the chlorophyll content, evidenced that the decreasing of chlorophyll affects the shape of NDVI-LAI curve, lowering the saturation threshold of the index. Moreover, Xie et al., [9] evidenced that at same LAI values, leaf chlorophyll content may vary significantly among different crops.

Figure 4 provides example of LAI maps obtained with the identified EVI – LAI relation for wheat (panel a, b and c) and maize (panel d, e and f). Values are in the expected range and changes according to crop growth. It is interesting to notice how the maps produced with S2 decametric data can provide useful information to highlight also within field variability, such data are in fact expected input also for precision farming management.

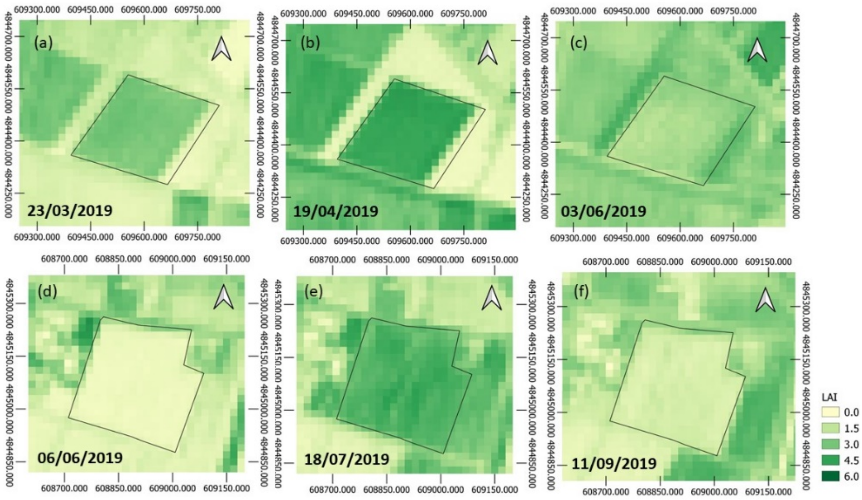

Fig. 4. Maps of estimated LAI with EVI based on linear function. In the figure above are reported the wheat stem elongation (a) booting, (b) maturity stages and in the figure below the (d) emergence, (e) stem elongation and maturity of maize

5 Conclusion

This study investigated performances of different S2 VIs computed with bands combination in the VIS, RE and SWIR region for the estimation of LAI in mixed-crop scenario by exploiting a dataset of wide range LAI values (two crops x two seasons x 3 farms). Results show that all S2-Vis are generally well correlated to ground LAI, among the 11 tested ones EVI, NDI45 and NBR shows best results for the three considered categories. Best parametric model was obtained with linear function, NE is below or comparable to the others one and ANCOVA tested revealed no significant influence of crop type. In fact, the identified VIs were evaluated crop type insensitive, thus may not require re-parameterization under different crop types. From the analyzed experimental data, EVI resulted the best one to be used to generate LAI product for mixed-crop scenario. The identification of VI – LAI relation insensitive to crop type may improve the predictability of LAI from a multi-crop patchiness scene. Moreover, EVI can exploit 10 m S2 bands hence producing products able to highlight within field spatial variability. Nevertheless, further studies are required to test the suitability of these VIs for the remote estimation of ground-LAI not only in wheat and maize but also in other crop type in different environmental conditions.

6 Reference

1. Chen, J.M.; Black, T.A. Measuring leaf area index on plant canopies with brach arquitecture. *Agricultural and Forest Meteorology* **1991**, *57*, 1–12, doi:10.1016/0168-1923(91)90074-Z.
2. Fassnacht, K.S.; Gower, S.T.; Norman, J.M.; McMurtric, R.E. A comparison of optical and direct methods for estimating foliage surface area index in forests. *Agricultural and Forest Meteorology* **1994**, *71*, 183–207, doi:10.1016/0168-1923(94)90107-4.
3. Bréda, N.J.J. Leaf Area Index. In *Encyclopedia of Ecology*; Sven Erik Jørgensen, Brian D. Fath, Eds.; Amsterdam, Netherlands, 2008; pp. 2148–2154 ISBN 9780080454054.
4. Mao, H.; Meng, J.; Ji, F.; Zhang, Q.; Fang, H. Comparison of Machine Learning Regression Algorithms for Cotton Leaf Area Index Retrieval Using Sentinel-2 Spectral Bands. *Applied Sciences* **2019**, *9*, 1459, doi:10.3390/app9071459.
5. Rouse, J.W.; Hass, R.H.; Schell, J.A.; Deering, D.W. Monitoring vegetation systems in the great plains with ERTS. *Third Earth Resources Technology Satellite (ERTS) symposium* **1973**, *1*, 309–317.
6. Mutanga, O.; Skidmore, A.K. Narrow band vegetation indices overcome the saturation problem in biomass estimation. *International Journal of Remote Sensing* **2004**, *25*, 3999–4014, doi:10.1080/01431160310001654923.
7. Pasqualotto, N.; Bolognesi, S.F.; Belfiore, O.; Delegido, J.; D'Urso, G.; Moreno, J. Canopy chlorophyll content and LAI estimation from Sentinel-2: vegetation indices and Sentinel-2 Level-2A automatic products comparison. In Proceedings of the Conference: IEEE International Workshop on Metrology for Agriculture and Forestry At: Portici, Naples; 2019; p. 7.
8. Verrelst, J.; Rivera, J.P.; van der Tol, C.; Magnani, F.; Mohammed, G.; Moreno, J. Global sensitivity analysis of the SCOPE model: What drives simulated canopy-leaving sun-induced fluorescence? *Remote Sensing of Environment* **2015**, *166*, 8–21, doi:10.1016/j.rse.2015.06.002.
9. Xie, Q.; Dash, J.; Huang, W.; Peng, D.; Qin, Q.; Mortimer, H.; Casa, R.; Pignatti, S.; Laneve, G.; Pascucci, S.; et al. Vegetation Indices Combining the Red and Red-Edge Spectral Information for Leaf Area Index Retrieval. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* **2018**, *11*, 1482–1492, doi:10.1109/JSTARS.2018.2813281.
10. Claverie, M.; Vermote, E.F.; Weiss, M.; Baret, F.; Hagolle, O.; Demarez, V. Validation of coarse spatial resolution LAI and FAPAR time series over cropland in southwest France. *Remote Sensing of Environment* **2013**, *139*, 216–230, doi:10.1016/j.rse.2013.07.027.
11. Ding, Y.; Ge, Y.; Hu, M.; Wang, J.; Wang, J.; Zheng, X.; Zhao, K. Comparison of spatial sampling strategies for ground sampling and validation of MODIS LAI products. *International Journal of Remote Sensing* **2014**, *35*, 7230–7244, doi:10.1080/01431161.2014.967889.
12. Viña, A.; Gitelson, A.A.; Nguy-Robertson, A.L.; Peng, Y. Comparison of different vegetation indices for the remote assessment of green leaf area index of crops. *Remote Sensing of Environment*

2011, doi:10.1016/j.rse.2011.08.010.

13. Pasqualotto, N.; D'Urso, G.; Bolognesi, S.F.; Belfiore, O.R.; Van Wittenberghe, S.; Delegido, J.; Pezzola, A.; Winschel, C.; Moreno, J. Retrieval of evapotranspiration from sentinel-2: Comparison of vegetation indices, semi-empirical models and SNAP biophysical processor approach. *Agronomy* **2019**, *9*, doi:10.3390/agronomy9100663.
14. Delegido, J.; Verrelst, J.; Alonso, L.; Moreno, J. Evaluation of sentinel-2 red-edge bands for empirical estimation of green LAI and chlorophyll content. *Sensors* **2011**, *11*, 7063–7081, doi:10.3390/s110707063.
15. Delegido, J.; Verrelst, J.; Meza, C.M.; Rivera, J.P.; Alonso, L.; Moreno, J. A red-edge spectral index for remote sensing estimation of green LAI over agroecosystems. *European Journal of Agronomy* **2013**, *46*, 42–52, doi:10.1016/j.eja.2012.12.001.
16. Amin, E.; Verrelst, J.; Rivera-Caicedo, J.P.; Pipia, L.; Ruiz-Verdú, A.; Moreno, J. Prototyping Sentinel-2 green LAI and brown LAI products for cropland monitoring. *Remote Sensing of Environment* **2021**, *255*, doi:10.1016/j.rse.2020.112168.
17. Delegido, J.; Verrelst, J.; Rivera, J.P.; Ruiz-Verdú, A.; Moreno, J. Brown and green LAI mapping through spectral indices. *International Journal of Applied Earth Observation and Geoinformation* **2015**, *35*, 350–358, doi:10.1016/j.jag.2014.10.001.
18. Frampton, W.J.; Dash, J.; Watmough, G.; Milton, E.J. Evaluating the capabilities of Sentinel-2 for quantitative estimation of biophysical variables in vegetation. *ISPRS Journal of Photogrammetry and Remote Sensing* **2013**, *82*, 83–92, doi:10.1016/j.isprsjprs.2013.04.007.
19. Kira, O.; Nguy-Robertson, A.L.; Arkebauer, T.J.; Linker, R.; Gitelson, A.A. Informative spectral bands for remote green LAI estimation in C3 and C4 crops. *Agricultural and Forest Meteorology* **2016**, *218–219*, 243–249, doi:10.1016/j.agrformet.2015.12.064.
20. Haboudane, D.; Miller, J.R.; Pattey, E.; Zarco-Tejada, P.J.; Strachan, I.B. Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. *Remote Sensing of Environment* **2004**, *90*, 337–352, doi:10.1016/j.rse.2003.12.013.
21. Gitelson, A.A.; Kaufman, Y.J.; Merzlyak, M.N. Use of a green channel in remote sensing of global vegetation from EOS- MODIS. *Remote Sensing of Environment* **1996**, *58*, 289–298, doi:10.1016/S0034-4257(96)00072-7.
22. Verrelst, J.; Rivera, J.P.; Veroustraete, F.; Muñoz-Marí, J.; Clevers, J.G.P.W.; Camps-Valls, G.; Moreno, J. Experimental Sentinel-2 LAI estimation using parametric, non-parametric and physical retrieval methods – A comparison. *ISPRS Journal of Photogrammetry and Remote Sensing* **2015**, *108*, 260–272, doi:10.1016/j.isprsjprs.2015.04.013.
23. Baret, F.; Weiss, M.; Allard, D.; Garrigues, S.; Leroy, M.; Jeanjean, H.; Fernandes, R.; Myneni, R.B.; Privette, J.; Morisette, J.; et al. VALERI : a network of sites and a methodology for the validation of medium spatial resolution land satellite products. *Remote Sensing of Environment* **2005**, *76*, 36–39.
24. Drusch, M.; Del Bello, U.; Carlier, S.; Colin, O.; Fernandez, V.; Gascon, F.; Hoersch, B.; Isola, C.; Laberinti, P.; Martimort, P.; et al. Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services. *Remote Sensing of Environment* **2012**, *120*, 25–36, doi:10.1016/j.rse.2011.11.026.
25. Gascon, F.; Thépaut, O.; Jung, M.; Francesconi, B.; Louis, J.; Lonjou, V.; Lafrance, B.; Massera, S.; Gaudel-Vacaresse, A.; Languille, F.; et al. Copernicus Sentinel-2A Calibration and Products Validation Status. *Remote Sensing* **2017**, *8*, 1–78, doi:10.20944/PREPRINTS201610.0078.V1.

26. Lonjou, V.; Desjardins, C.; Hagolle, O.; Petrucci, B.; Tremas, T.; Dejus, M.; Makarau, A.; Auer, S. MACCS-ATCOR joint algorithm (MAJA). *Remote Sensing of Clouds and the Atmosphere XXI* **2016**, *10001*, 1000107, doi:10.1117/12.2240935.
27. Herrmann, I.; Pimstein, A.; Karnieli, A.; Cohen, Y.; Alchanatis, V.; Bonfil, D.J. LAI assessment of wheat and potato crops by VENμS and Sentinel-2 bands. *Remote Sensing of Environment* **2011**, *115*, 2141–2151, doi:10.1016/j.rse.2011.04.018.
28. Huete, A.R.; Didan, K.; Miura, T.; E.P., R.; Gao, X.; Ferreira, L.G. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment* **2002**, *26*, 195–213, doi:10.1080/0965156x.2013.836857.
29. Badgley, G.; Field, C.B.; Berry, J.A. Supplementary Materials Canopy near-infrared reflectance and terrestrial photosynthesis. *Science Advances* **2017**, *3*, 1602244, doi:10.1126/sciadv.1602244.
30. Clevers, J.G.P.W. Application of a weighted infrared-red vegetation index for estimating leaf Area Index by Correcting for Soil Moisture. *Remote Sensing of Environment* **1989**, *29*, 25–37, doi:10.1016/0034-4257(89)90076-X.
31. Dong, T.; Liu, J.; Qian, B.; He, L.; Liu, J.; Wang, R.; Jing, Q.; Champagne, C.; McNairn, H.; Powers, J.; et al. Estimating crop biomass using leaf area index derived from Landsat 8 and Sentinel-2 data. *ISPRS Journal of Photogrammetry and Remote Sensing* **2020**, *168*, 236–250, doi:10.1016/j.isprsjprs.2020.08.003.
32. Key, C.H.; Benson, N.C. Measuring and remote sensing of burn severity: The CBI and NBR. In Proceedings of the Neuenschwander, L.F.; Ryan, K.C. Proceedings Joint Fire Science Conference and Workshop Vol. II,; University of Idaho and International Association of Wildland Fire, 1999; p. 284.
33. Gonsamo, A. Normalized sensitivity measures for leaf area index estimation using three-band spectral vegetation indices. *International Journal of Remote Sensing* **2011**, *32*, 2069–2080, doi:10.1080/01431161.2010.502153.
34. Gitelson, A.A.; Peng, Y.; Huemmrich, K.F. Relationship between fraction of radiation absorbed by photosynthesizing maize and soybean canopies and NDVI from remotely sensed data taken at close range and from MODIS 250m resolution data. *Remote Sensing of Environment* **2014**, *147*, 108–120, doi:10.1016/j.rse.2014.02.014.
35. Nguy-Robertson, A.; Gitelson, A.A.; Peng, Y.; Viña, A.; Arkebauer, T.; Rundquist, D. Green leaf area index estimation in maize and soybean: Combining vegetation indices to achieve maximal sensitivity. *Agronomy Journal* **2012**, *104*, 1336–1347, doi:10.2134/agronj2012.0065.
36. Houborg, R.; Boegh, E. Mapping leaf chlorophyll and leaf area index using inverse and forward canopy reflectance modeling and SPOT reflectance data. *Remote Sensing of Environment* **2008**, *112*, 186–202, doi:10.1016/j.rse.2007.04.012.