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1. Introduction

The use of satellite sensor data has become more common in precision agriculture technologies (Lee et al. 2010), and various operational services are being developed within the Coperncius initiative (NEREUS 2012). In this context, the data users (i.e., farmers, large and small scale agri-businesses) are mostly interested in monitoring the spatial distribution of some crop characteristics over the growing season and time-series of satellite acquisitions at high spatial resolution are a major source of information.

A key vegetation parameter attracting most interest is the Leaf Area Index (LAI), defined as the total one-sided area of green leaf area per unit ground surface area (Bréda 2003). LAI is used to derive agronomic indicators for various crop management purposes. For instance, LAI maps are used in agro-meteorological models to derive the crop water needs (an example of operative application is given in Irrisat) (D'Urso et al. 2010), to monitor the nitrogen status and to apply fertilizer with variable rates (e.g., FarmSat), as input in crop models to derive agronomic variables (Jégo, Pattey, and Liu 2012; Casa et al. 2012). On a larger scale, LAI and other biophysical variables are used for example for yield predictions at administrative level (Rembold et al. 2012; Doraiswamy et al. 2005; Ma et al. 2013). A general overview of remote sensing contributions to agriculture is given in (Atzberger 2012).

Two groups of techniques have been commonly applied for the estimation of the LAI from optical satellite sensor data using semi-empirical/statistical approaches (i.e., vegetation indices, VI) or physical based approaches of leaf-canopy radiative transfer model (RTM) inversion (Baret and Buis 2008; Dorigo et al. 2007). Most of the empirical or statistical equations, such as regressions between spectral reflectance, vegetation indices (VI) or shape indices (e.g., red edge) and field measurements (Atzberger et al. 2010; Cho, Skidmore, and Atzberger 2008; Darvishzadeh et al. 2009), employ data in two or more wavebands, usually red and near-infrared (Chen et al. 2002; Y. J. Wang et al. 2004). VIs are often the only option for the retrieval of LAI with limited spectral information.

A prerequisite for the quantitative analysis of time-series of satellite sensor data is to perform radiometric and atmospheric corrections (Liu, Pattey, and Jégo 2012), if possible using reliable instantaneous atmospheric measurements (such as aerosol optical thickness, water vapor content) and/or the spectral reflectance of known ground targets either derived from ground measurements (surface and/or atmospheric conditions) or from consolidated library data (Hadjimitsis, Clayton, and Retalis 2009; R. Richter 1998). Several approaches have been proposed for performing atmospheric corrections. An operative procedure is based on the use of look-up-tables (LUT) with pre-calculated atmospheric RTM simulations for different satellite sensor types (R. Richter 1998; Liang, Fang, and Chen 2001). However, model assumptions and simplifications often lead to inaccuracies in the estimated top-of-canopy (TOC) reflectance measurements (Laurent et al. 2011).

For the implementation of this case study, we will use a simple LAI retrieval approach based on a VI using the CLAIR model (Clevers 1989). This approach has been tested using canopy reflectance model data (Clevers 1989), field-based reflectance measurements (Clevers et al. 2000) and satellite data in a number of studies (D'Urso et al. 2010; Vuolo et al., n.d.).

2. Semi-empirical reflectance model for LAI estimation

The CLAIR model is based on an inverse exponential relationship between LAI and the WDVI, which was derived using field spectral radiometer data experimentally (Clevers 1988, 1989). This relationship is built upon a simplified reflectance model of the light extinction through the vegetation canopy. The WDVI is calculated from the reflectance in red (ρ_{red}) and near-infrared (ρ_{nir}) as follows:

$$\textbf{WDVI} = \rho_{nir} - \rho_{red} * \rho_{s\,nir} / \rho_{s\,red} \quad \text{eq. 1}$$

where $\rho_{s\,nir} / \rho_{s\,red}$ represents the 'soil line slope', a linear relationship between red and near-infrared reflectance of bare soils (Baret, Jacquemoud, and Hanocq 1993). The soil line slope parameter accounts for the effects of the soil background on the calculation of the vegetation index and it has to be determined for each test site (Baret and Guyot 1991).

Based on the WDVI, LAI is determined according to the following equation (Clevers 1988):

$$\textbf{LAI} = -1/\alpha * \ln(1 - WDVI/WDVI_{\infty}) \quad \text{eq. 2}$$

where α is a combination of extinction and scattering coefficients and $WDVI_{\infty}$ is the asymptotically limiting value of WDVI for $LAI \rightarrow \infty$.

The α coefficient can be estimated empirically using a set of LAI values from field measurements and contemporaneous reflectance values from satellite sensor data (Clevers 1989).

Generally, $WDVI_{\infty}$ is derived directly from the image data considering the maximum WDVI value for vegetated areas in correspondence of saturation (dense vegetation with an expected LAI value of approximately 6-8 for cropland). Pasqualotto et al (2019) derived this value automatically by considering the mean ($WDVI_{mean}$) and standard deviation ($WDVI_{SD}$) as follows:

$$WDVI_{\infty} = WDVI_{mean} + 6WDVI_{SD} \quad \text{eq. 3}$$

The α coefficient can be calibrated using a regression analysis technique applied to observed and estimated LAI values (D'Urso et al. 2010). This latter parameter describes the canopy architecture and it is dependent on the crop type and the corresponding Leaf Angle Distribution (LAD) value.

Different values of the parameters in Equation (2) can be found in the literature. For instance, Clevers (Clevers et al. 2000) reported an α value ranging between 0.25 and 0.53 and $WDVI_{\infty}$ ranging between 69 and 58 for vegetative and generative growth stages of barley respectively.

3. Case study

For the demonstration of this case study, we prepared a selection of about 60 sample points of bare soils (obtained from visual inspection) and the reflectance of these points will used for calculation of the soil line slope.

The soil line slope will then be used to calculate the WDVI.

The $WDVI_{\infty}$ value can be extracted from the image data using the histogram or the procedure of eq 3.

We will derive the α coefficient using an unconstrained nonlinear optimization method, which minimizes the Root Mean Square Error (RMSE) (our cost function) between measurements and predictions of LAI values. Measurements of LAI will be provided (CSV file). An initial α value of 0.35 will be used as first guess based on previous experimental data.

To quantify the model prediction accuracy, we will use the following statistical measures: RMSE, the coefficient of determination (R^2) between in-situ measured and predicted LAI.

Considering the limited number of the field LAI data that are usually available from in-situ measurements, the validation of the model performance can be achieved by resampling the field dataset using a bootstrapping approaches (Steyerberg et al. 2001) in order to provide an unbiased estimation of the model accuracy (Richter et al. 2012).

This technique will be however not used in this exercise.

Instead, the in-situ LAI dataset will be divided in Training and Testing (50/50 or 80/20) data.

3.1. Description of the case study

The field campaign for the collection of LAI data took place from April to August 2016. Eight different crop types, distributed over 72 parcels, were monitored to represent the prevailing crop types in the study area (Vuolo et al. 2018).

The parcels include 33 ordinary fields and 39 one-hectare experimental plots. In-situ LAI measurements where collected with a Li-Cor LAI-2200 Plant Canopy Analyzer (Li-Cor Inc. 2011).

The LAI-2200's sensor operates a non-destructive method and is sensitive to all light blocking objects in its view. It estimates the LAI from the values of canopy transmittance by identifying the attenuation of the radiation as it passes through the canopy (Li-Cor Inc. 2011). Therefore, measurements were taken above- (A) and below-canopy (B).

LAI estimates represent the effective Plant Area Index (PAIe), because the optical sensor does not distinguish between photosynthetically active leaves and inactive parts of the plants such as senescent leaves or stems. Care was taken to measure LAI only on photosynthetically active vegetation. For example, measurements were interrupted on winter cereals as soon as the first signs of senescence started to appear.

The LAI-2200 was deployed in an elementary sampling units (ESUs) using a radius of 5-10 m of a geo-referenced point (accuracy of ±3-5m). Each unit represented a homogenous area with a single crop type. The ESUs were randomly chosen from the study area, with the only restriction being the fields' accessibility for time restraints. For ordinary fields the centres of the ESUs were placed in a corner of a squared area of 60m by 60m within the field and measured from the field border. It was imperative that the field conditions were relatively homogenous in terms of crop development. The ESUs located in the experimental plots, part of a larger experimental setup, were located in the centre of each one-hectare plot.

Winter cereal, onion, and potato were assessed through three replications of one A and eight B measurements, randomly distributed in the ESU. Row crops like maize, carrot and sugar beet were estimated with four replications of one A and six B measurements, for a total of 24 single measurements to generate a single LAI value per ESU (Wenng 2017).

The final dataset of in-situ collected LAI consists of about 100 measurements and the corresponding L2A reflectance values extracted from the satellite image data. This dataset is made available for the execution of the case study.

3.2. R scripts, data and examples

<u>Materials:</u>

- R Markdown document (LAI_modelling.Rmd) containing the R-based script to be used in the exercise;
- In-Situ LAI measurements (file: LAI_dataset.csv, column: LAI_insitu);
- LAI obtained with an Artificial Neural Network not requiring local calibration (file: LAI_dataset.csv, column: LAI S2 BOKU);
- corresponding Level 2A (atmospherically corrected) reflectance (file: LAI_dataset.csv, column name and spectral region):

1. B02 (490nm)
2. B03(560nm)
3. B04(665nm)
4. B05(705nm)
5. B06(740nm)
6. B07(783nm)
7. B08 (842nm)
8. B08A(865nm)
9. B11(1610nm)
10. B12(2190nm))

4. References

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