RETRIEVAL OF BIOPHYSICAL VEGETATION PRODUCTS FROM RAPIDEYE IMAGERY

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KEYWORDS: Agriculture, Vegetation, Monitoring, Retrieval, Multispectral.

ABSTRACT:

The accurate estimation of canopy biophysical variables at sufficiently high spatial and temporal resolutions is a key requirement for operational applications in the agricultural sector. In this study, recently available multispectral RapidEye sensor data were tested for their operational suitability to estimate canopy biophysical variables in the Italian Campania region. For this purpose, two model inversion methods and two commonly used vegetation indices were applied to estimate leaf area index (LAI), canopy chlorophyll content (CCC) and leaf chlorophyll content (LCC) from a range of crops. The physically based approaches outperformed the empirical methods, with a slightly higher retrieval accuracy of the look-up table (LUT) than of the neural network (NN) approach. However, the NN method performs much faster, rendering it potentially more appropriate for application in large areas. The empirical models showed dependencies of sensor and crops, but still performed reasonable in the estimation of LAI and CCC. Results demonstrated the suitability of RapidEye sensor data to retrieve canopy biophysical variables of agricultural areas.

1. INTRODUCTION

1.1 Crop monitoring

The regular and accurate mapping of crop status is an important requirement for a sustainable agricultural management. It enables, for instance, the early detection of crop water stress or nitrogen deficiencies, thus helping farmers to mitigate potential crop damages while reducing environmental impacts. For this purpose, frequent information of crop status at sufficiently high spatial resolutions is required, being of particular importance for heterogeneous agricultural regions, characteristic for Southern Italy. Remotely sensed data from air- or space-borne platforms offer an interesting alternative to cost and labour intensive ground measurements. Earth observation (EO) data with improved spatial and temporal resolutions, such as those from the RapidEye constellation (http://www.rapideye.de/), offer new opportunities for a sustainable agricultural management.

1.2 Biophysical variables and retrieval techniques

In the present study, three of the key biophysical variables of interest for precision farming applications were examined: leaf area index (LAI) (e.g., Moran et al., 1995), leaf chlorophyll content (LCC) and canopy chlorophyll content (CCC) (e.g., Baret et al., 2007). LAI, a key variable of vegetation, characterizes the leaf surface available for energy and mass exchange between surface and atmosphere (Moran et al., 1995). Different definitions of LAI have been used in the literature depending on vegetation type and measurements (Jonckheere et al., 2004), such as green LAI ('GLAI', e.g. Migdall et al., 2009), effective LAI ('L_e', Chen and Black, 1992) or plant area index ('PAI', Neumann et al., 1989).

Chlorophyll content was found to be directly related to nitrogen (N) availability of the leaves (e.g. Evans, 1989). Therefore, the sensitivity of the solar reflective domain to chlorophyll content is usually used to quantify the plant nitrogen status. Baret et al. (2007) demonstrated that the relationship between canopy chlorophyll content and N is more robust over years and development stages than the correlation at leaf level. Thus, canopy chlorophyll content presents greater potential than leaf chlorophyll content to detect vegetation stress and should be the privileged variable to be retrieved.

A variety of methods have been proposed to estimate these biophysical variables from remotely sensed data (Baret and Buis, 2008). The majority of the studies have used (semi-) empirical relationships between the biophysical variables of interest and a combination of spectral bands, namely vegetation indices (VI). These methods, successfully applied to a number of applications (Glenn et al., 2008), are fast and easily implementable at large data sets and thus suitable for operational purposes. The Weighted Difference Vegetation Index (WDVI) (Clevers, 1989), for instance, is being used for operational retrievals of LAI in the context of Irrigation Advisory Services in Southern Italy (De Michele et al., 2009). Moreover, information on canopy chlorophyll content is being routinely distributed to users through the MERIS Terrestrial Chlorophyll Index (MTCI) (Dash and Curran, 2007). Currently, MTCI is operationally available only at medium spatial resolution, but it will be supplied by future ESA's Sentinel-2 optical system at finer spatial resolution.

Despite the wide use of these approaches, VIs are limited in their global estimation performance since calibration is mostly required to account for changing conditions. This includes for instance differences in sensor types and crop canopy architecture, changing illumination and viewing geometries or

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varying soil backgrounds (Colombo et al., 2003). With the advancement in developing radiative transfer models (RTM), these aspects can be considered by means of physical principles. Therefore, new perspectives have opened up for reliable and accurate estimations of biophysical products in the context of operational applications (Bacour et al., 2006).
However, these models have also limitations, such as the need for parameterization and high computational demand. Furthermore, the ill-posed inverse problem must be considered: different parameter combinations may produce almost identical spectra, resulting in significant uncertainties in the estimation of biophysical vegetation variables (Atzberger, 2004). Even though this problem affects as well empirical approaches, it is often only discussed in the context of RTM model inversion.

The objective of this study is to evaluate the performance of RapidEye sensor data to estimate LAI, leaf chlorophyll content and canopy chlorophyll content. Two model inversion techniques, i.e. look-up tables (LUT) and neural networks (NN), are applied for this purpose. In order to evaluate the performance of current operational VIs, the analysis is extended to the estimations of LAI and canopy chlorophyll content by using pre-calibrated equations based on WDVI and MTCI. The suitability of the data and the retrieval techniques are discussed.

2. MATERIAL AND METHODS

2.1 Field Campaign

The data used in this study are based on satellite acquisitions and a ground measurement campaign at the "Piana del Sele" study site (Lat. 40.52 N, Long. 15.00 E), which is one of the largest agricultural areas of the Italian Campania region, Southern Italy. The area is characterized by irrigated agriculture (mainly forages and fruit trees) with an average field size of about 2 hectares (De Michele et al., 2009).
A total number of 36 LAI and leaf chlorophyll measurements were acquired simultaneously at different sites and for a range of crops, including fruit trees (such as peach and apricot), maize, cereals and different vegetables. LAI measurements were carried out by means of the Plant Canopy Analyzer LAI-2000 instrument (LICOR Inc., Lincoln, NE, USA). Due to its measurement principle, the sensor does not distinguish photosynthetically active leaf tissue from other plant elements, such as stems, flowers or senescent leaves. Moreover, the clumping effect, i.e. non-random positioning of canopy elements, is neglected. Thus, the here used term 'LAI' stands for effective PAI ('PAI_e') (Darvishzadeh et al., 2008).
Measurements were performed in order to cover an Elementary Surface Unit (ESU) of approximately 400 m^2 geolocated by means of a GPS device (accuracy 3-5 m). The average value of LAI, resulting from a set of 20 above and below canopy readings, was considered to be representative for the respective ESU. The standard deviations of the measurements were kept as a measure of uncertainty.
Leaf chlorophyll content was measured by using a SPAD-502 Leaf Chlorophyll Meter (MINOLTA, Inc.). At each ESU, 30 measurements of leaves in different layers were randomly performed and averaged to a final representative value. Crop specific calibration functions (peach tree: Marchi et al., 2005; maize: Haboudane et al., 2001; other crops: SPARC, 2004) were applied to convert the SPAD values into leaf chlorophyll content [$\mu m\ cm^{-2}$]. The total canopy chlorophyll content [$g\ m^{-2}$] was finally obtained by multiplying leaf chlorophyll content with the corresponding LAI of each ESU.

2.2 Remote Sensing data

Multispectral remote sensing data from RapidEye sensor were acquired on 17th August 2009 (at 10:35 UTC). This recently launched constellation (August 2008) of five identical EO satellites records radiance in five broad bands corresponding to blue, green, red, red-edge and near-infrared (NIR) part of the electromagnetic spectrum. The sensors provide a spatial resolution of 5 m and are therefore potentially very suitable for agricultural applications.
Four images, acquired within a few seconds, with a maximum across-track incident angle of 5° were adequate to cover the study site (about 560 km^2). Radiometrically calibrated Level 3A data were provided with a geometric accuracy of 13.95 m (root mean square error, RMSE = 6.50 m). Further geometric correction was performed using Ground Control Points (GCPs), resulting in a final geolocation accuracy of about 3 m.
The first image tile was atmospherically corrected by using ATCOR-2/3 (Richter, 1998). The spectral reflectance of known reference targets (i.e., asphalt, sea water, concrete and sand) was used for the retrieval of atmospheric properties. Subsequently, an empirical line method was applied to correct the other three images. For this purpose, uniform areas in the overlapping regions between adjacent images were considered: twenty zones of about 200 m^2 representing dark and bright surfaces were selected for each image and correction functions were derived for each spectral band.
To account for the accuracy of geometric correction and ground biophysical variable measurements, the final mosaicked image was resampled to a spatial resolution of 15 m.

2.3 Radiative Transfer Modelling

The well-known and widely used coupled PROSPECT+SAILH model ('PROSAIL', Jacquemoud et al., 2009) was chosen for the study. PROSAIL is a combination of the leaf model PROSPECT–4 (Feret et al., 2008) and the canopy model SAILH (Verhoef 1984, 1985; Kuusk 1991). It calculates the bi-directional reflectance of homogeneous canopies as a function of several structural and biophysical variables (see Table 1), soil reflectance, illumination and viewing geometry.

2.3.1 Model inversion with look-up tables (LUT)

Even though it is a relatively simple method, the look-up table (LUT) approach is one of the most robust and accurate model inversion strategies. It has been applied in combination with the PROSAIL model by a number of studies (e.g. Darvishzadeh et al., 2008; Richter et al., 2009; Weiss et al., 2000), successfully retrieving biophysical variables of different crop types and at different sites.
To set up the inversion, a synthetic data base was established with the PROSAIL model simulating RapidEye spectral band configuration using the specific band sensitivity functions. A LUT size of 100000 different combinations of variables was chosen according to Weiss et al. (2000). The variables and model parameters were randomly sampled using uniform distribution laws and according to typical ranges found in the literature for agricultural land use (Table 1). Model inversion was performed using a simple cost function calculating the RMSE between measured and simulated spectra. The solution was regarded as the average of the variable combinations found within less than 20 % of the lowest RMSE value (e.g. Richter et al., 2009).

2.3.2. Model inversion with neural networks (NN)

Neural networks were included in this study as an alternative mean to (rapidly) invert RTM over large areas. The synthetic data base generated for the LUT approach was used to train the network. Training permits a net to learn the intrinsic relation between some input variables (here the canopy reflectance spectra) and one or more output variables (here the sought biophysical variables). Setting up the network structure and network training may be a time consuming process. However, once trained, the sought biophysical variables can be retrieved immediately.
To prevent overfitting and overspecialisation several measures were taken. First, the network was kept compact using a single hidden layer with only five neurons. Second, three variables were modelled at the same time to avoid over-specialisation: LAI, leaf chlorophyll content and soil reflectance scaling factor (α_{soil}). Finally, the early stopping technique was applied to further improve network generalization. For this purpose, the patterns generated with PROSAIL were divided into two subsets. The first subset (75 % of the pattern) was used for updating the weights and biases of the network (training dataset). The error on the test dataset (the remaining 25 %) was monitored during the training process. The training was stopped automatically when the error in the test dataset started to rise as this indicates network overfitting.

Model Variables		Units	Range
PROSPECT			
N	Leaf structure index	unitless	1.3-2.0
C_{ab}	Leaf chlorophyll content	[µg cm^{-2}]	10-70
C_m	Leaf dry matter content	[g cm^{-2}]	0.004-0.007
SAILH:			
LAI	Leaf area index	[m^2 m^{-2}]	0-6
ALA	Average leaf angle	[degree]	35-70
HotS	Hot spot parameter	[m m^{-1}]	0.01-1
α_{soil}	Soil reflectance scaling factor	unitless	0.6-1.4
θ_s	Sun zenith angle	[degree]	28
θ_v	View zenith angle	[degree]	5
ϕ	Sun – sensor azimuth angle	[degree]	71

Table 1. Range of model input variables used to establish the synthetic canopy reflectance data base for NN and LUT based model inversions.

2.3.3. Empirical model: vegetation indices (VI)

The WDVI is based on the reflectance in the NIR and red wavelength ranges. Calculation of WDVI requires information of the soil line slope, which can be directly derived from the imagery. A logarithmic relationship was used to estimate LAI from WDVI, which was calibrated during several field campaigns in the study site in the last years (R^2=0.64) (D'Urso and Belmonte, 2006).
The MTCI (Dash and Curran, 2007) was calculated from NIR, red edge and red spectral bands. A linear equation calibrated using ground data (R^2=0.80) (Dash at al., 2010) was adopted in this study to estimate the canopy chlorophyll content. Detailed description of the indices can be found in D'Urso and Belmonte (2006) and Dash and Curran (2007), respectively.

3. RESULTS AND DISCUSSION

3.1 Retrieval of leaf and canopy variables

Estimations of LAI using the two inversion methods performed well with a slightly higher accuracy from the LUT (RMSE=0.64; R^2=0.76) than from the NN method (RMSE=0.72; R^2=0.71). With the WDVI, a lower estimation accuracy was achieved (RMSE=1.14; R^2=0.57). Measured against simulated LAI values are presented in Fig.1a-c.
For canopy chlorophyll content, a high retrieval accuracy was obtained from the LUT (RMSE=0.39 g m^{-2} and R^2= 0.78) and a slightly lower from the NN (RMSE=0.43 g m^{-2} and R^2=0.74). Application of the MTCI achieved a lower accuracy than the physically based approaches (RMSE=0.86 g m^{-2} and R^2=0.73). Correlations between estimated and measured canopy chlorophyll content values are shown in Fig.1d-f.
In case of leaf chlorophyll content, all approaches failed to give reliable estimates: by the LUT a RMSE of 15.1 µg cm^{-2} and by the NN a RMSE of 11.3 µg cm^{-2} was achieved (not shown).
Regarding crop specific differences in retrieval accuracy (Table 3), LAI values were generally estimated best for fruit trees. Estimation uncertainties may be explained by the non-linear relationship between reflectance and LAI, leading to saturation at higher LAI values, as visible in Fig. 1 for all approaches. Moreover, a possible presence of clumped leaves may strengthen the underestimation of higher LAI values (i.e., LAI > 3), especially in case of maize.
Canopy chlorophyll content was obtained with a reasonable accuracy for maize and partly fruit trees using the model inversion techniques.
The overall poor retrieval accuracy of leaf chlorophyll content is also reflected in the crop specific RMSE. Only for maize, the LUT achieved reasonable results with RMSE of 5.9 µg m^{-2}.
The retrieval accuracy of leaf characteristics from canopy spectra depends on the strength of the signal transmitted from leaf to canopy level, which is mainly controlled by structural variables such as LAI or leaf angle (Asner, 1998). Thus, compensations between LAI and leaf chlorophyll content may occur, leading to the well-known ill-posed inverse problem (Combal et al., 2002). Strong improvements in the estimation accuracy were also observed in other studies when using the product between these two variables (Baret et al., 2007).
A further explanation for the poor estimation of leaf chlorophyll content may be the presence of heterogeneous canopies (such as fruit trees and maize), not corresponding to the turbid medium assumption of the used model. The application of more complex models, such as GeoSAIL proposed by Huemmrich (2001), might improve the retrieval performance (Richter et al., 2009). A further improvement may result from object-based inversion strategies (Atzberger, 2004).
The lower retrieval accuracy of the VI confirms the need of sensor-specific calibration, in particular for the MTCI, which was specifically designed for narrow visible/NIR wavebands. The red edge band originally used to calculate the MTCI is based on MERIS spectral band characteristics with a spectral bandwidth of about 10 nm (703.75 - 713.75 nm). RapidEye red edge band is instead sampled in a spectral bandwidth of 40 nm (690 - 730 nm). Therefore, adaptation of the equation to broad band spectral characteristics, as for RapidEye sensors, might be required. Further investigation is needed for this issue.
Results obtained with WDVI confirm that a sensor and crop specific calibration is required.

A map of spatially distributed canopy chlorophyll content (using the NN) is depicted in Fig. 4, representing the area of "Piana del Sele" in the Italian Campania region. Such maps are possible inputs in the context of precision farming applications.

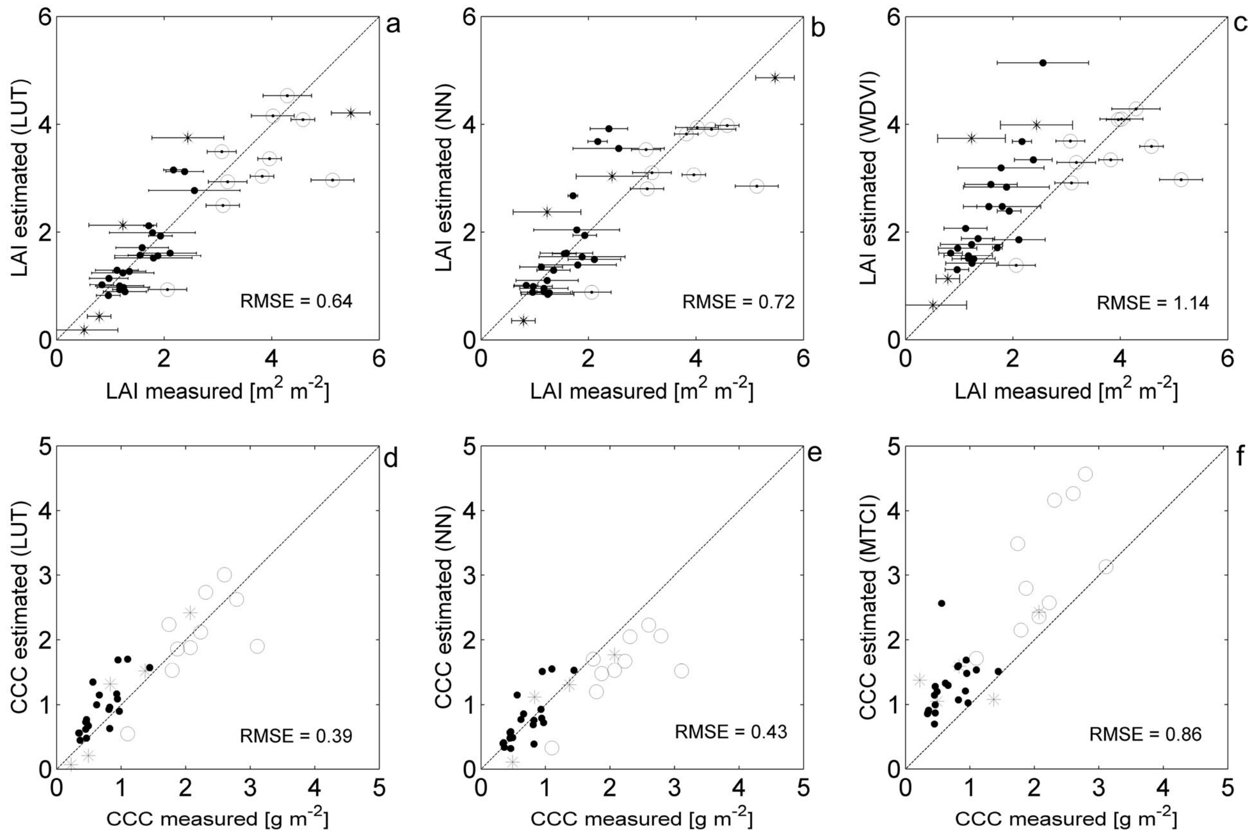

Figure 2. Estimated versus measured biophysical variables of different crops (Piana del Sele, Italian Campania region). 1a: LAI with LUT approach, 1b: LAI with NN approach, 1c: LAI from WDVI, 1d: canopy chlorophyll content (CCC) from LUT, 1e: CCC estimated with NN, 1f: CCC from MTCI. Symbols correspond to: '·' fruit trees, 'o' maize and '*' other crops. Error bars in 1a-c indicate standard deviations of the LAI measurement.

Crop type	LAI [m^2 m^{-2}]			CCC [g m^{-2}]			LCC [µg m^{-2}]	
	LUT	NN	VI	LUT	NN	VI	LUT	NN
Fruit trees[(1)]	0.35	0.61	0.95	0.34	0.25	0.7	18.3	8.7
Maize	0.89	0.91	0.82	0.50	0.70	1.18	5.9	10.4
Others [(2)]	0.93	0.72	2.03	0.31	0.28	0.7	13.1	19.4
Combined	0.64	0.72	1.14	0.39	0.43	0.86	15.1	11.3

[(1)] includes peach, apricot, kiwi and plum trees
[(2)] includes aubergines, alfalfa, pepper, artichokes and cereal

Table 3. Crop specific (and combined) RMSE between measured and estimated biophysical variables using LUT, NN and the two VI approaches (MTCI for CCC and WDVI for LAI estimation).

3.2 Operational suitability

An important issue for the use of physically based retrieval techniques in the context of operational applications is the time required for inverting RTM over large areas. Both inversion methods perform rather fast in comparison to traditional approaches, such as iterative optimisation techniques. However, the NN method outperforms clearly the LUT in this regard.

In pixel-based inversions, redundant LUT searches are being performed since many signatures are similar. Therefore, in order to render the LUT inversion procedure more effective and faster, an unsupervised classification was applied to the imagery before further processing, grouping the reflectance spectra into a certain number of classes. This number depends on the heterogeneity of the region and sensitivity analyses must be carried out to obtain the optimal number of classes, reducing redundancy without losing important spectral information. For the study area, 2000 classes were chosen, reducing the computational load almost 850 times (original number of pixel 1.7 mil.). The ISODATA clustering method of the Erdas Imagine software, which uses minimum spectral distance formula, was applied. Maximum number of iterations was set to '6' and the convergence threshold to '0.95'.

Each of the 2000 input spectra was calculated as the average of all spectra contained in one class. Processing of the LUT inversion was then performed as described in sect. 2.3.1.

In this way, the speed of the LUT based inversion was comparable with the NN based approach. However, the resulting estimation accuracy decreased significantly (LAI:

RMSE=0.8, LCC: RMSE=17.4 μg cm^{-2} and CCC: RMSE=0.46 g m^{-2}) despite this high number of classes. This lower estimation accuracy in comparison to the pixel based approach may be due to the loss of spectral information, especially affecting high values of LAI. Enhancing the number of classes may increase the accuracy, but also the computation time.
Although the neural nets may be more suitable for such fast operations, a drawback relates to their reduced availability. For the current work, the networking was performed under the Matlab processing environment (The Mathworks, 2007). Unfortunately, standard image processing software does not yet include this mapping technique. To foster the use of physically based approaches, providers of image processing software should add modules for direct and inverse modelling.

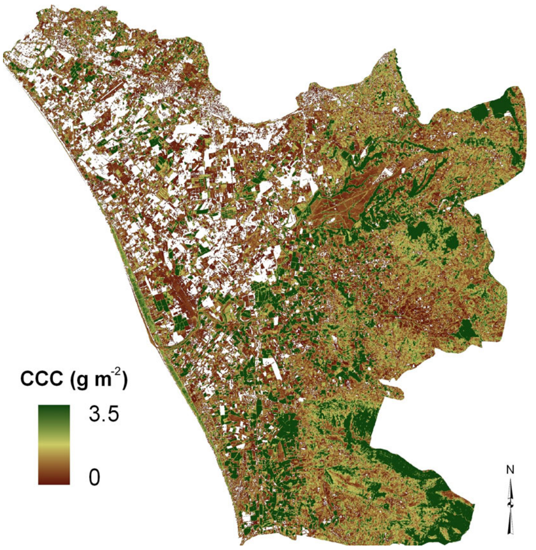

Figure 4. Spatial distribution of canopy chlorophyll content in the “Piana del Sele”, Italian Campania region, derived from the neural network (white zones correspond to urban areas or greenhouses).

4. CONCLUSIONS

Recently available multispectral RapidEye data were tested for their operational suitability to estimate canopy biophysical variables in an agricultural area of Southern Italy. The physically based retrieval approaches outperformed the empirical methods, whereas the retrieval accuracy of the LUT was slightly better than the neural networks approach. However, the latter, already used in operational applications for coarse resolution data (Bacour et al., 2006), is much faster rendering it more suitable in this context. An unsupervised classification of the imagery prior to the RTM inversion was applied to reduce calculation time, as proposed by Baret and Buis (2008), but results were less accurate than pixel based procedures.
Generally, the canopy based variables (LAI and canopy chlorophyll content) could be estimated with much higher accuracy than variables on leaf level (leaf chlorophyll content), confirming previous findings of the literature (Baret et al., 2007). This might be a drawback for certain applications, where properties of the leaves are required. For general precision farming applications, however, information at the canopy level can be sufficient or even of advantage over the leaf level (Baret et al., 2007).
Conclusively, RapidEye sensor provides useful data to derive biophysical variables for operational applications in the agricultural sector. Such applications may include, for instance, the modelling of crop water requirements, needing LAI as input, or the assessment of plant nitrogen status, requiring the information of canopy chlorophyll content. The use of physically based approaches to estimate these variables is suggested. Further validation work is required to test the applicability of these techniques for different areas and crops.

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ACKNOWLEDGEMENTS

Funding for this research was provided by ESA under the MTCI-EVAL project, additional information available at: http://www.sen2chl.co.uk. Logistical support from Ariespace srl spin-off company (http://www.ariespace.com) was crucial in the success of the field campaign. Satellite data were funded by the University of Naples "*Federico II*" and acquired in the context of Irrigation Advisory Services of Campania Region (http://www.consulenzairrigua.com).