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Retrieval of canopy water content of different crop types with two new hyperspectral indices: Water Absorption Area Index and Depth Water Index

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ABSTRACT

Crop canopy water content (CWC) is an essential indicator of the crop's physiological state. While a diverse range of vegetation indices have earlier been developed for the remote estimation of CWC, most of them are defined for specific crop types and areas, making them less universally applicable. We propose two new water content indices applicable to a wide variety of crop types, allowing to derive CWC maps at a large spatial scale. These indices were developed based on PROSAIL simulations and then optimized with an experimental dataset (SPARC03; Barrax, Spain). This dataset consists of water content and other biophysical variables for five common crop types (lucerne, corn, potato, sugar beet and onion) and corresponding top-of-canopy (TOC) reflectance spectra acquired by the hyperspectral HyMap airborne sensor. First, commonly used water content index formulations were analysed and validated for the variety of crops, overall resulting in a R^2 lower than 0.6. In an attempt to move towards more generically applicable indices, the two new CWC indices exploit the principal water absorption features in the near-infrared by using multiple bands sensitive to water content. We propose the Water Absorption Area Index (WAAI) as the difference between the area under the null water content of TOC reflectance (reference line) simulated with PROSAIL and the area under measured TOC reflectance between 911 and 1271 nm. We also propose the Depth Water Index (DWI), a simplified four-band index based on the spectral depths produced by the water absorption at 970 and 1200 nm and two reference bands. Both the WAAI and DWI outperform established indices in predicting CWC when applied to heterogeneous croplands, with a R^2 of 0.8 and 0.7, respectively, using an exponential fit. However, these indices did not perform well for species with a low fractional vegetation cover (< 30%). HyMap CWC maps calculated with both indices are shown for the Barrax region. The results confirmed the potential of using generically applicable indices for calculating CWC over a great variety of crops.

1. Introduction

Water is the most abundant molecule in leaves and its availability in leaf tissues is essential for cell enlargement, and, hence, plant growth. The knowledge of leaf water content (LWC) is important for assessing the physiological state, especially for detecting drought stress of the plant. Shortage in water content can produce not only environmental impacts such as an increase in fire risk, but moreover social and economic negative effects caused by food production decrease (Carlson and Burgan, 2003; Chuvieco et al., 2004; Riaño et al., 2005; Stimson et al., 2005). In agriculture fields, crop water content provides vital information for making correct decisions regarding irrigation planning (Jackson et al., 2004) and is used for productivity estimation (Peñuelas et al., 1993; Zhang et al., 2010). What is more, the success of sustainable agriculture, mainly in arid and semi-arid regions of the world, depends entirely on water availability (Alderfasi and Nielsen, 2001). Because the quantity of water in leaf tissues is a critical factor in plant survival (Kumar, 2007), assessing water stress symptoms accurately using spectral reflectance measurements has been an important goal for remote sensing research during the past decades. Remote sensing can play a unique and essential role because of its ability to acquire synoptic information at different time and space scales (Jackson, 1986; Oppelt and Mauser, 2004; Peñuelas et al., 1993).

Vegetation biophysical variables, such as chlorophyll (Chl), leaf area index (LAI) and water content, are considered to be the most important indicators of vegetation health, growth and productivity

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(Gitelson et al., 2003). At leaf level, LWC is usually calculated by the weight difference of freshly harvested leaves and their weight after a drying process, i.e. a time-consuming procedure, especially for large-scale study areas. At this large spatial scale, canopy water content (CWC), defined as the amount of water in the vegetation per surface unit (g/m^2 ground surface), is a physiological variable of high interest which can be estimated multiplying the leaf water content (LWC, g/cm^2 of leaf) with the LAI (m^2 leaf per m^2 surface or dimensionless) to obtain CWC. Therefore, alternative non-destructive methods have been developed by means of linking water content with optical remote sensing data (Pu et al., 2003). The rationale for doing so is as follows. Water absorbs light energy along the entire spectrum, but in the near-infrared (NIR, 750–1300 nm), and short-wave infrared (SWIR, 1300–2500 nm) regions, water produces maximum absorptions features concretely at 970, 1200, 1450, 1940 and 2500 nm (Carter, 1991; Knipling, 1970; Tucker, 1980). Thus, with the understanding of the water absorption spectra, spectroradiometers provide the opportunity to quantify CWC through non-destructive methods (Inoue et al., 1993).

At the same time, an important process to consider in the study of CWC is the atmospheric correction because atmospheric water vapour (WV) absorption effects in the air column affect the reflected radiance in the 900–1000 nm region measured at the remote sensor, at the aircraft or satellite platform (Datt, 1999; Gao and Goetz, 1990; Goetz and Boardman, 1995). The atmospheric correction process aims to retrieve top-of-canopy (TOC) reflectance by removing the atmospheric effects. This correction is one of the critical steps to obtain good information related to the surface properties. Thus, the overall accuracy of CWC retrieval will strongly depend on the accuracy achieved by the atmospheric correction process (Sabater et al., 2014; Vicent et al., 2015, 2017).

Statistical methods are most widely used to identify sensitive wavelength bands from atmospherically corrected TOC reflectance data for the development of simple vegetation indices (VIs), which relate the biophysical variable of interest to an arithmetic formulation of bands (Verrelst et al., 2015a). These indices are defined in a way that enhance the spectral characteristics associated with a given vegetation property (Glenn et al., 2008). The potential of VIs for the biophysical variables determination has been widely demonstrated in numerous studies: they are intuitive, simple and fast (Broge and Leblanc, 2000; Colombo et al., 2003; Gitelson et al., 2005). Over the last several decades, some authors have proposed indices for LWC or CWC estimation, generally used for monitoring different aspects of vegetation health, such as fire risk assessment (Peñuelas et al., 1997) or disease monitoring (Pu et al., 2003). These indices typically use an insensitive band to water absorption (e.g., 820 and 900 nm) and a sensitive band to change in this variable (e.g., 970 and 1600 nm). Some of them have been defined in order to provide LWC (e.g., Datt, 1999; Hunt et al., 1987; Peñuelas et al., 1993; Pu et al., 2003). These authors have proposed LWC indices for the study of a specific plant species. For example, Datt (1999) proposed two normalized indices to determinate water content of various species of Eucalyptus, and Pu et al. (2003) established two ratio indices in order to calculate LWC of oak leaves. On the other hand, several authors established indices to calculate CWC (e.g., Hardisky et al., 1983; Hunt and Rock, 1989; Rollin and Milton, 1998; Wang and Qu, 2007). Some of these CWC indices are derived from indices developed at the leaf scale, such as the Water Index proposed by Peñuelas et al. (1997) being a modification of the Water Band Index (Peñuelas et al., 1993) used for calculating LWC.

Despite the positive aspects of VIs, their major weakness is the lack of a generally applicable index for multiple vegetation types. A universal relationship between a biophysical variable and a spectral signature cannot be expected since the reflected signal depends on complex interrelationships between internal and external physical factors, which can involve significant variation in time, space, and between one type of crop and another (Colombo et al., 2003). The best way to find efficient and robust indices is to use large and diverse field datasets, with a large variety in canopy structures (Glenn et al., 2008; le Maire et al., 2008). This applies as well for different crop development stages, representing instraspecies variability in canopy structure and biophysical variables. Moreover, VIs have been traditionally developed for sensors configured with only a few spectral bands. Several studies have confirmed that applying indices composed of a few bands to hyperspectral data is suboptimal and not recommended (Kira et al., 2016; Verrelst et al., 2015b). It is more optimal to use a larger number of bands, thereby always taking into account multiple sensitive bands along the spectral range (Verrelst et al., 2016). Accordingly, several authors have shown that exploiting a contiguous reflectance curve instead of using a few single bands sensitive to biophysical variables tend to be more promising to obtain good parameter retrieval results (Delegido et al., 2010; Malenovský et al., 2006; Mutanga et al., 2005; Oppelt and Mauser, 2004). This thus suggests that there is a need for the development of VIs not just based on a few bands as is commonly done, but rather based on multiple bands along the spectral range.

When aiming to develop generically applicable CWC indices, an ideal tool for studying general relationships between biophysical variables and VIs are Radiative Transfer Models (RTMs). RTMs are physically-based models that describe the absorption and scattering of light throughout the leaf, canopy and atmosphere. In several studies, RTMs have been used to develop optimized indices sensitive to water content at leaf and canopy scales (Clevers et al., 2010; Haboudane et al., 2002; Malenovský et al., 2006). One of the most popular leaf RTMs is PROSPECT (Jacquemoud et al., 1996; Jacquemoud and Baret, 1990), which considers the leaf as a succession of absorption layers. And one of the most popular canopy RTMs is SAIL (Verhoef, 1984), which describes the canopy as a homogenous and horizontal turbid-medium. The coupling of PROSPECT and SAIL, also known as PROSAIL (Jacquemoud et al., 2009), has been widely used to study canopy directional reflectance and their relationships with biophysical variables, including CWC (Clevers et al., 2010).

The main goal of this study is to develop generically applicable CWC indices, which are capable of providing CWC in heterogeneous crop types areas, based on remote sensing measurements of the leaf spectral behaviour when varying water content. For this purpose, PROSAIL simulations and a large field dataset are used to tackle the following two objectives. The first objective is to identify the spectral bands that present the highest correlation (R^2) for the estimation of CWC, tested with commonly used VIs by the scientific community. Based on this analysis and on a subsequent spectral sensitivity study of the multiple crop types in response to changes in CWC, a second objective is to develop and validate two new CWC indices, i.e. respectively applicable to data with high and low spectral resolution. The performances of the newly developed indices and established VIs sensitive to CWC are evaluated and CWC maps are generated.

2. Materials and methods

2.1. SPARC03 experimental dataset

The used dataset is based on the Spectra Barrax Campaign (SPARC03) (Delegido et al., 2013). This campaign took place between 12th and 14th of July (2003) in Barrax, La Mancha, Spain (coordinates 39°3′ N, 2°6′ W, 700 m a.s.l., *Datum* ETRS89). The SPARC03 dataset has been earlier used in various studies because it covers multiple crop types, growth phases, canopy geometries and soil conditions. Specifically, field data of lucerne (*Medicago sativa*), corn (*Zea mays*), potato (*Solanum tuberosum*), sugar beet (*Beta vulgaris*), garlic (*Allium sativum*) and onion (*Allium cepa*) were collected. Table 1 describes the biophysical and structural variables for each crop, indicating low structural and biophysical differences between the different elementary samplings units (ESUs) for each crop. The considered crops were in different development stage at the moment of flight overpass. Lucerne was in the pre-bloom phase, bud stage, in addition to being sparse with ray grass.

Table 1
Mean values and standard deviation of the obtained variables for each crop species used in the SPARC03 campaign.

Crop species	N° of ESUs	Growth phase	Chl (μg/cm²)	FVC (%)	LAI (m²/m²)	LWC (g/m² leaf)	CWC (g/m² surface)
Lucerne	18	Bud stage	48.51 ± 0.98	60 ± 17	2.71 ± 0.75	137 ± 8	368 ± 102
Corn	14	Swelling ear	51.02 ± 0.74	65 ± 6	3.4 ± 0.42	180 ± 10	612 ± 75
Potato	12	Tuber bulking	35.51 ± 0.59	96 ± 1	5.29 ± 0.37	223 ± 15	1165 ± 90
Sugar beet	22	Maturity	44.09 ± 1.72	94 ± 1	4.05 ± 0.51	448 ± 11	1805 ± 225
Garlic	14	Maturity	14.51 ± 1.94	12 ± 3	0.58 ± 0.11	595 ± 15	344 ± 60
Onion	10	Maturity	20.38 ± 1.47	64 ± 1	1.96 ± 0.46	681 ± 14	1334 ± 316

During the campaign (12th–14th of July), airborne hyperspectral HyMap flight-lines were.

Corn crop was beginning to produce ears. Potato and sugar beet were dense and well developed, ready to be harvested. Garlic crop was in a maturity stage, but this crop type was in poor state and very sparse. And, finally, onion was in a maturity stage, with mature bulbs.

Regarding the variables used, chlorophyll content (Chl), fraction of green vegetation cover (FVC), effective LAI (green LAI) and leaf water content (LWC) were measured for a total of 100 ESUs of 20 × 20 m. Each ESU was assigned a Chl value, measured using a CCM-200 Chlorophyll Content Meter and calibrated through laboratory analysis of specific samples (Gandia et al., 2004); a FVC value, which was estimated through hemispherical photographs; a LAI value with LicorLAI-2000 digital analyser (Welles and Norman, 1991), which uses a fish-eye lens with an hemispheric field view (± 148°) to calculate the interception of blue light (320–490 nm); and a LWC value, obtained through a drying and weighing method, collecting three leaves at the top level, due to this is the part of the plant observed by the sensor. For CWC estimation, leaf area was obtained by digital photographs of each leaf over squared grid paper. From the two masses and the known sampled area, LWC was calculated. LWC multiplied with LAI values (m^2 leaf/m^2 surface) provided CWC in g/m^2 of ground surface.

During the campaign (12th–14th of July), airborne hyperspectral HyMap flight-lines were acquired for the study site, obtaining the TOC reflectance value for each of the ESUs. HyMap is a hyperspectral sensor that spans the 430–2490 nm wavelength range with 125 usable bands. Spectral bandwidth varied between 11 and 21 nm and the pixel size at overpass was 5 m. The ESU TOC reflectance was computed as the mean value of the central pixel and all adjacent pixels. The images obtained were geometrically corrected (Alonso and Moreno, 2005) and then atmospherically corrected by the ATCOR4-r (Atmospheric and Topographic Correction – rugged terrain) method at the German Aerospace Center (DLR), according to Guanter et al. (2005).

The total field and airborne dataset consisted of 100 CWC values and their corresponding radiometric hyperspectral information, covering multiple crop types, i.e., 18 lucernes, 14 corns, 12 potatoes, 22 sugar beets, 14 garlics, 10 onions and 10 bare soils, in which LAI and CWC values were zero.

2.2. Analysis of generic vegetation indices

The systematic analysis of the predicted power of VIs was mainly conducted by using the Automated Radiative Transfer Models Operator (ARTMO) scientific software package (Verrelst et al., 2012). ARTMO consists of RTMs (e.g., PROSAIL) and several retrieval toolboxes that enable the development and optimization of retrieval algorithms to convert optical images into maps of vegetation properties. The spectral indices assessment toolbox (Rivera et al., 2014) was used to calibrate and validate established and generic indices by providing all the possible band combinations in the NIR region (750–1300 nm).

Based on established CWC indices in the literature, a series of VIs was introduced into the toolbox together with the multi-crop TOC reflectance data. The indices introduced in ARTMO were a series of generic indices, i.e. formulas in which the specific bands to be used are not defined, whose formulation was based on commonly used CWC indices (Table 2, in shading), among other VIs typically used to estimate various biophysical variables (mainly Chl).

The first analysis was to test with different types of fitting functions (linear, exponential and polynomial) the performance of commonly used CWC indices, with their specific bands as defined by the original authors, given the SPARC03 field TOC reflectance dataset acquired over a variety of crops.

Secondly, for each generic CWC index introduced (Table 2), all band combinations were analysed, resulting in a best performing combination of bands. Only the NIR region was evaluated because of its high sensitivity to mainly liquid water, whereas the signal from the SWIR region is additionally heavily influenced by cellulose (Delegido et al., 2015). A cross-validation method was used to ensure more robust results. To cross-validate each index with the SPARC03 dataset, the *k*-fold method was used (Snee, 1977; Yang and Huang, 2014). This method divides the available data into *k* subsets. From these *k* sub-datasets, *k*-1 sub-datasets are selected as a calibration dataset and a single *k* sub-dataset is used for model validation. The cross-validation process is then repeated *k* times, with each of the *k* sub-datasets used as a validation dataset. Thus, all data are used for both calibration and validation. Here, we used a 10-fold ($k = 10$) cross-validation procedure (Pérez-Planells et al., 2015; Verrelst et al., 2015b).

2.3. CWC spectral sensitivity analysis for real and simulated data

As mentioned above, water produces maximum absorptions features mainly at 970, 1200, 1450, 1940 and 2500 nm (Carter, 1991; Knipling, 1970; Tucker, 1980). These maximum absorptions can be observed for several crop types of the SPARC03 campaign with contrasting CWC (Fig. 1).

In Fig. 1 the maximum CWC-related absorptions in the NIR region, i.e. around 970 and 1200 nm, can be inspected. In these points, the depth of the spectrum (difference between the absorption minimums, 850 nm and 1080 nm, and the NIR shoulder) is maximized as the CWC increases. For this reason, the sugar beet spectrum (CWC = 2200 g/m^2) has the largest depth while the lucerne spectrum (CWC = 359 g/m^2) the smallest.

These water absorption maxima can also be observed when simulating vegetation reflectance with PROSAIL. In Fig. 2, two PROSAIL simulations are plotted where CWC is expressed as the water sheet thickness of the leaf (Cw, in cm). One spectrum (solid line) corresponds with a high CWC (Cw = 0.05 cm) and the other (dashed line) with a low CWC (Cw = 0.025 cm), both with LAI = 3. In addition, the atmospheric WV transmittance simulated with the atmospheric RTM MODTRAN (Berk et al., 2006) is shown (blue lines in Fig. 2).

Next, a spectral sensitivity analysis for varying CWC was conducted to inspect the spectral behaviour when water content is approaching zero, while varying LAI. In Fig. 3, TOC reflectance spectra were modelled for multiple LAI values ranging between 0.5 and 6 (in m^2 leaf/m^2 surface or without units) and three representative values of Cw: the minimum (0 cm), intermediate (0.025 cm) and maximum (0.05 cm) of the variable setting. The other model variables, maintained default values (Chl = 30 μg/cm^2; Dry matter = 0.012 g/cm^2).

Fig. 3 shows that for the simulations when Cw is zero, the TOC reflectance is characterized by a straight line without absorptions

Table 2
Generic vegetation indices introduced in ARTMO, where indices based on commonly CWC indices are shown shaded. Rλ represents reflectance at the wavelength λ (nm). The generic name of each index has been established in this study. Dash and Curran (2004), Gao (1996), Gitelson et al. (2002), Gower (1980), Hunt et al. (2013), Vincini et al. (2008), Zarco-Tejada and Ustin (2001).

Based reference	Formula	Generic name	Abbreviation	Generic formula
Hunt & Rock, 1989	$\frac{R_{1600}}{R_{820}}$	Ratio Generic Index	RGI	$\frac{R_1}{R_2}$
Peñuelas et al., 1997	$\frac{R_{900}}{R_{970}}$			
Zarco-Tejada & Ustin, 2001	$\frac{R_{860}}{R_{1240}}$			
Hardisky et al., 1983	$\frac{R_{820} - R_{1650}}{R_{820} + R_{1650}}$	Normalized Difference Water Generic Index	NDWGI	$\frac{R_1 - R_2}{R_1 + R_2}$
Gao, 1996	$\frac{R_{860} - R_{1240}}{R_{860} + R_{1240}}$			
Rollin & Milton, 1998	$\frac{R_{1116} - min(R_{1120}, R_{1150})}{R_{1116}}$ x 100	Relative Depth Generic Index	RDGI	$\frac{R_1 - R_2}{R_1}$ x 100
Wang & Qu, 2007	$\frac{R_{860} - (R_{1640} - R_{2130})}{R_{860} + (R_{1640} - R_{2130})}$	Normalized Multi-band Drought Generic Index	NMDGI	$\frac{R_1 - (R_2 - R_3)}{R_1 + (R_2 - R_3)}$
Vincini et al., 2008	$\frac{R_{500-590} + R_{610-680}}{R_{780-890}}$	Three Ratio Band Generic Index	TRBGI	$\frac{R_1 + R_2}{R_3}$
Dash and Curran, 2004	$\frac{R_{753} - R_{708}}{R_{708} - R_{681}}$	Multi-band Simple Generic Ratio	MSGR	$\frac{R_1 - R_3}{R_2 - R_3}$
Gitelson et al., 2002 - le Maire et al., 2008	$\frac{R_{520-600} - R_{630-690}}{R_{520-600} + R_{630-690} - 2R_{450-520}}$	Multi-band Normalized Generic Index	MNGI	$\frac{R_1 - R_2}{R_1 + R_2 - 2R_3}$
Hunt et al., 2013	$0.02(R_{670} - R_{550}) + 0.01(R_{670} - R_{480})$	Triangular Difference Generic Index	TDGI	$0.02(R_1 - R_2) + 0.01(R_2 - R_3)$
Gower, 1980	$R_{676} - 0.5(R_{746} + R_{665})$	Water Line Height Generic Index	WLHGI	$R_1 - 0.5(R_2 + R_3)$

features between 800 nm and 1200 nm approximately. The slope and the magnitude of this reflectance line varies only as a function of LAI. This water absorption-free reference line between 800 and 1200 nm was subsequently used as a starting point to define a new index.

2.4. Development of the Water Absorption Area Index

Here, the so-called Water Absorption Area Index (WAAI), is proposed with the purpose of being generally applicable to a diversity of

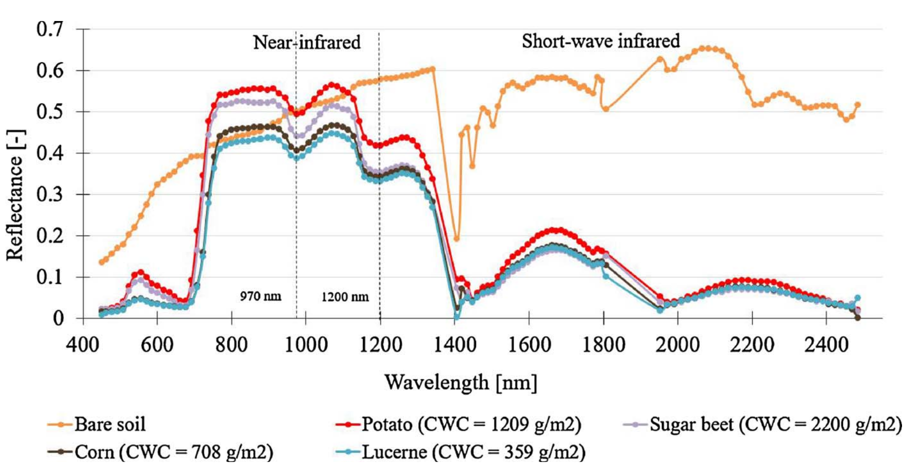

Fig. 1. Lucerne, corn, sugar beet and potato TOC spectra, with a bare soil spectrum of the field campaign SPARC03. CWC is expressed in g water/m^2 surface.

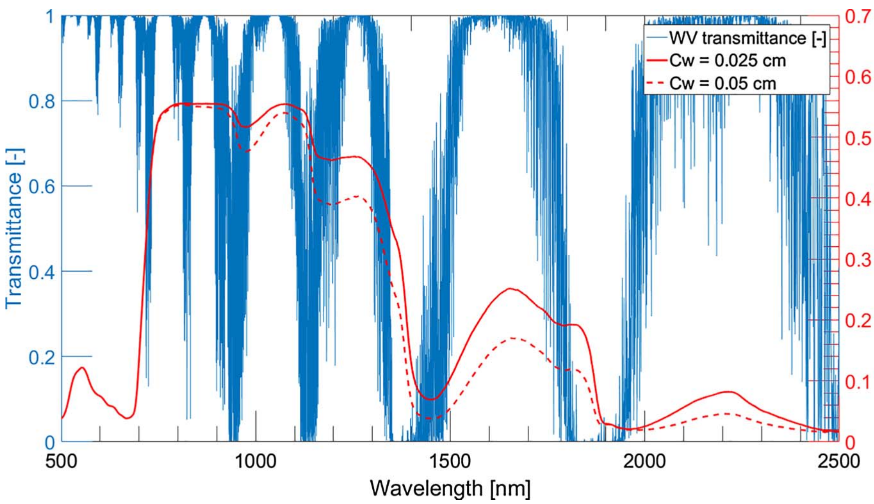

Fig. 2. Vegetation reflectance spectrum with more (solid line) and less (dashed line) CWC expressed as leaf water sheet thickness (Cw), LAI = 3, simulated with PROSAIL, together with atmospheric water vapour transmittance, simulated with MODTRAN (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

crop types. WAAI is based not only on the reflectance of a few bands, but instead on a wide spectral range with the purpose of minimizing estimation errors. The WAAI is defined as the difference between the area under the reference line (Cw = 0 cm) and the area under the curve, between the integration limits 800 nm and 1200 nm. The specific area covered by this index is shown in Fig. 4, with Cw the leaf water thickness in cm.

The first step to calculate WAAI, therefore, was to obtain the reference line. Fig. 5 shows R_{1200} as a function of R_{800} with Cw = 0 cm of PROSAIL simulations of varying LAI, in which a clearly linear relation ($R^2 = 1$) is observed.

The linear relationship contained in Fig. 5 together with the area under the line formed between 800 nm and 1200 nm (Eq. (1)) and the integral between these same limits (Eq. (2)) were required for defining the area index:

$$\text{Area under the reference line (Trapezium area)} = \frac{R_{800} + R_{1200}}{2}(1200 - 800) \tag{1}$$

$$\text{Area under curve} = \int_{800}^{1200} R(\lambda)d\lambda \tag{2}$$

where R_λ represents reflectance at the wavelength λ.

Thus, substituting the linear relationship ($R_{1200} = 0.857{*}\underline{R}_{800} + 0.097$) into Eq. (1) and subtracting (2) from Eq. (1), the Water Absorption Area Index is defined as:

$$WAAI = 200(1.857R_{800} + 0.097) - \int_{800}^{1200} R(\lambda)d\lambda \tag{3}$$

After the WAAI calculation, the optimal integration limits were determined. To do so, multiple spectral analyses were conducted on the SPARC03 dataset, i.e. by varying both integration limits within the NIR region (750–1300 nm) to observe the index response and to determine the spectral range that leads to the best correlation for estimating water content.

2.5. Development of the Depth Water Index

The WAAI is an area index essentially developed for high spectral resolution data, i.e. coming from hyperspectral imaging spectrometers. However, since hardly any of the currently operational satellite sensors are equipped with such a high spectral resolution the so-called Depth Water Index (DWI) is proposed as a possible guide for the configuration of future optical superspectral sensors. The DWI makes use of only four specific bands, providing the sum of the depth at 970 nm (d_1) and at 1200 nm (d_2), i.e., the difference between the corresponding reflectance at the baseline (y_i) and the TOC reflectance at 970 nm for d_1 and 1200 nm for d_2 (Fig. 6). The baseline y_i is formed from the TOC reflectance points at 850 nm and 1080 nm.

Therefore, the Depth Water Index presents the following general form:

$$DWI = (y_1 - R_{970}) + (y_2 - R_{1200}) \tag{4}$$

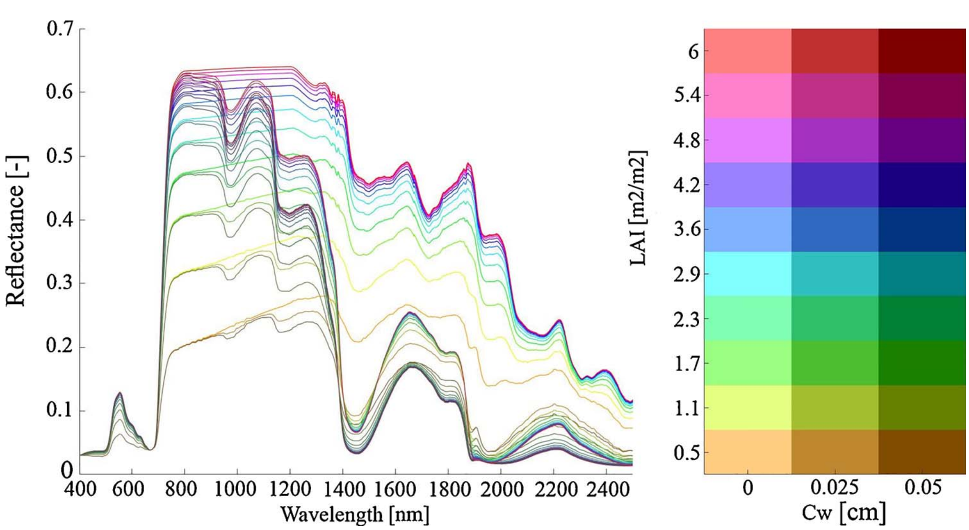

Fig. 3. TOC reflectance modelled by PROSAIL varying LAI and water content (Cw) variables.

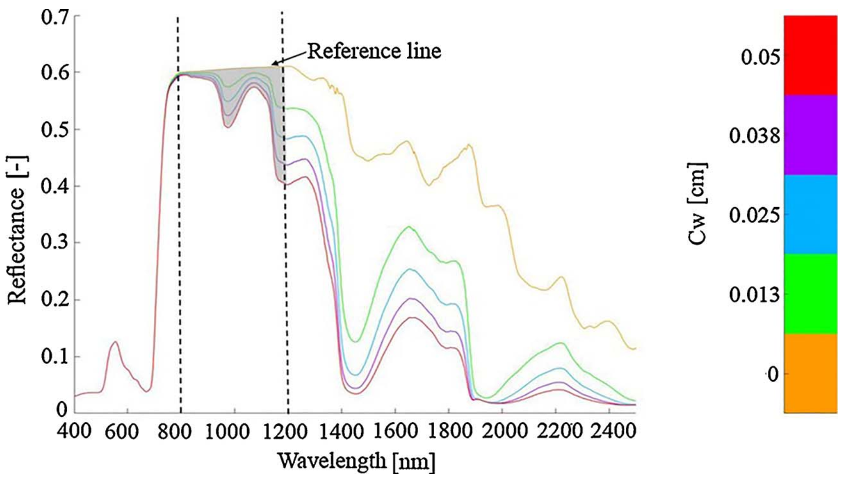

Fig. 4. TOC reflectance obtained with PROSAIL with different water content (Cw: leaf water thickness in cm), at a fixed LAI = 4.5, the shaded area corresponds with the area calculated by the WAAI.

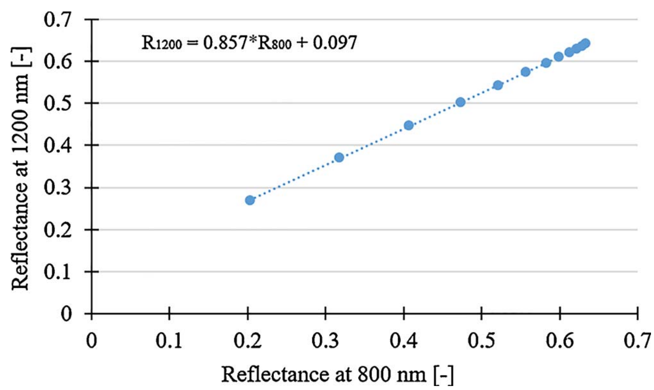

Fig. 5. Relationship between R_{800} and R_{1200} in vegetation spectra modelled, with Cw = 0 cm for LAI ranging from 0 to 6.

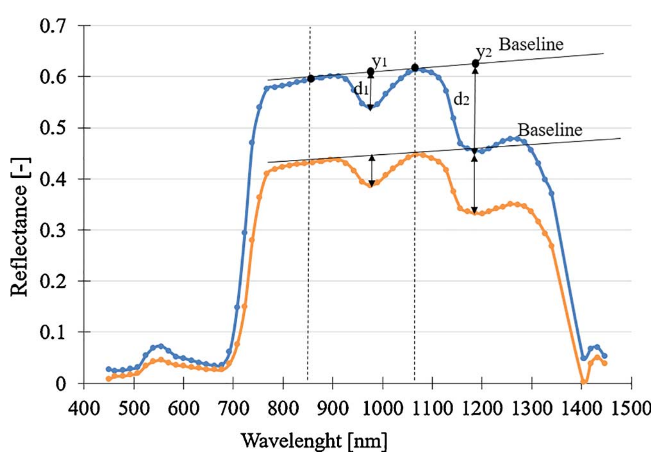

Fig. 6. Graphic representation of the DWI, which is the sum of the depths at 970 and at 1200 nm of the TOC reflectance, with respect to the baseline formed between the peaks at 850 and 1080 nm. The two spectra correspond to different CWC value (blue spectrum 459 g/m^2, orange spectrum 359 g/m^2). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Specifically, the baseline has the following form, from which y_i can be calculated for x_i = 970 and 1200 nm:

$$y_i = \frac{R_{1080} - R_{850}}{230} x_i + \frac{R_{1080}{*}850 - R_{850}{*}1080}{-230} \quad (5)$$

Consequently, substituting Eq. (5) into (4), the Depth Water Index equation is obtained:

$$DWI = 2.044R_{1080} - 0.044R_{850} - R_{970} - R_{1200} \quad (6)$$

Lastly, to analyse the statistical response of the WAAI and DWI, the coefficient of determination, R^2 (ranging from 0 to 1), is used.

3. Results

3.1. Performance of established CWC indices for a multi-crop dataset

The above-described established indices as given in Table 2 were evaluated with the multi-crop SPARC03 dataset. To start with, the established CWC indices have been tested with their default bands. The R^2 obtained with different types of fitting functions ranged between 0.114–0.598 when applying the respective indices on the multi-crop dataset (Table 3). Hence, the accuracies of each index obtained with linear, exponential and polynomial fitting were rather low. All three fitting functions performed similar, with the linear fitting performing slightly better than the exponential and polynomial fitting. Therefore, only linear fitting is used in further analysis.

In order to be more generic, the following step involved systematically calculating all bands combinations. Table 4 lists the best statistical results obtained for each of the generic indices and the corresponding bands with a linear fit.

Comparing to the afore-tested established indices, these results already show a more promising correlation with a R^2 ranging between 0.811 and 0.908. However, questions arose when evaluating the obtained wavelengths of the resulting best-performing bands from a physical point of view. In most cases, the selected bands were physically not only influenced by CWC, but also by other leaf constituents such as Chl pigments (e.g., 738 nm, 753 nm, etc.), while other bands were located in the NIR (e.g., 1272 nm, 927 nm, 943 nm) but not closely

Table 3
R^2 obtained with a linear, exponential and polynomial fitting for each index with their default bands.

Index	Formula	R^2 (linear fitting)	R^2 (exponential fitting)	R^2 (polynomial fitting)
RGI	$\frac{R_{1600}}{R_{820}}$	0.485	0.478	0.473
	$\frac{R_{900}}{R_{970}}$	0.576	0.565	0.542
	$\frac{R_{860}}{R_{1240}}$	0.598	0.592	0.584
NDWGI	$\frac{R_{820} - R_{1650}}{R_{820} + R_{1650}}$	0.556	0.551	0.564
	$\frac{R_{860} - R_{1240}}{R_{860} + R_{1240}}$	0.597	0.585	0.579
RDGI	$\frac{R_{1116} - min(R_{1120}, R_{1150})}{R_{1116}} \times 100$	0.525	0.521	0.491
NMDGI	$\frac{R_{860} - (R_{1640} - R_{2130})}{R_{860} + (R_{1640} - R_{2130})}$	0.124	0.119	0.114

Table 4
Best combination of bands for each generic vegetation indices introduced in ARTMO, ordered from highest to lowest R^2, with a linear fitting.

Index	Bands	RMSE (g/m^2)	NRMSE (%)	R^2
MNGI	1006;753;1113	210	10	0.908
TDGI	1022;829;738	220	11	0.895
WLHGI	1022;829;738	220	11	0.895
MSGR	1022;927;753	240	12	0.876
TRBGI	943;539;1272	230	11	0.876
NMDGI	1157;1006;753	250	12	0.867
RDGI	1272;738	270	13	0.825
RGI	738;1272	270	13	0.825
NDWGI	1006;943	290	14	0.811

located at the depth features 970 and 1200 nm. Consequently, the development of alternative multi-band indices with a stronger physically meaningful basis is needed.

3.2. Fitting and validation of the Water Absorption Area Index

As outlined in Eq. (3), the WAAI was defined as an integration index between the limits of 800 and 1200 nm. After multiple spectral analyses, the best regression result was achieved with the integration limits set at 911 nm and 1271 nm (R^2 of 0.808, RMSE = 290 g/m^2), using Eq. (7), with an exponential fitting (Eq. (8)). This may be due to the fact that at 911 nm the first absorption peak begins and at 1271 nm the water content maximum influence ends. Fig. 7 shows the area index response between these values.

$$WAAI_{optimized} = 180(1.812R_{911} + 0.271) - \int_{911}^{1271} R(\lambda)d\lambda \tag{7}$$

$$CWC\,(g/m^2) = 42.98exp^{0.061WAAI_{optimized}} \tag{8}$$

This optimized WAAI led to a good correlation and at the same time is physically sound since the crop types with low CWC (garlic and lucerne) have minimum index values, and crop types with high CWC (sugar beet and potato) show maximum WAAI values. It should be mentioned that garlic usually has a high LWC, but because it also has low LAI (lower than 1), the derived CWC is consequently also low. Moreover, garlic has a scarce and dispersed coverage which translates into a low FVC. In the case of corn, the crop was planted late on the season and the plants were not fully grown at the time of measurements, it was in the swelling ear stage. Also, lucerne has a low CWC because it was in a bud stage and sparse with ray grass. On the other hand, potato and sugar beet crops typically have high CWC because these plants are usually leafy.

3.3. Fitting and validation of the Depth Water Index

The DWI, a four-bands index (Eq. (6)), was defined based on the hyperspectral WAAI with the purpose of being applicable to lower spectral resolution sensors. After fitting the DWI with the SPARC03 dataset, a good statistical behaviour, (R^2 = 0.719, RMSE = 400 g/m^2) with an exponential fit was obtained:

$$CWC\,(g/m^2) = 113.9exp^{10.72\mathrm{DWI}} \tag{9}$$

The DWI varies from −0.01, corresponding to bare soils, to a maximum of 0.26, in the case of sugar beet, in which CWC is high, around 2000 g/m^2 (Fig. 8). This index functions in a similar way than the WAAI, with sugar beet showing highest CWC values and, therefore, likewise expressing DWI values. By contrast, garlic leads to lowest CWC (344 g/m^2) estimations given by its low FVC (12%) and low LAI (0.58 m^2 leaf/m^2 surface), despite having a high LWC (595 g/m^2).

In order to demonstrate the validity of the four-bands DWI index for CWC estimation, DWI-estimated CWC values were plotted against the WAAI-estimated CWC values (Fig. 9). When comparing both CWC estimations, a R^2 of 0.85 is obtained. Although the WAAI index presents more accurate results because it uses information from a greater number of bands influenced by CWC, this result suggests that the four-bands DWI index closely approaches the original WAAI integration index, despite some over- and under-estimations.

Finally, we applied both indices to the 14th of July HyMap flight line as acquired over the Barrax region. The resulting maps are shown in Fig. 10. A visual inspection reveals that both indices estimate the CWC consistently with higher CWC values in the irrigated circular parcels. When observing the maps with more detail, the WAAI estimates CWC sometimes higher and sometimes lower than the DWI, depending on the crop type. Given that DWI is a simplification of WAAI and somewhat poorer validated, it can be reasonably assumed that the WAAI map displays CWC with a better accuracy.

4. Discussion

Established vegetation indices commonly used for CWC estimation are usually simple arithmetic formulations based on two spectral bands, i.e. a water content sensitive band and another control band that is not influenced by any variable. At the same time, these indices have been typically developed for a specific plant species. The challenge arose when we tried using these established indices in a general way for a multi-crop dataset, i.e. the SPARC03 dataset, because very low correlations (R^2 between 0.114 and 0.598) were obtained. In an attempt to improve estimations over this multi-crop dataset, all band combinations were systematically calculated for each index in order to achieve the highest possible correlation for the estimation of CWC. For the simple ratio index, the best combination of bands (R^2 = 0.825) was achieved with R_{738}/R_{1272}, and for the normalized index was $(R_{1006} - R_{943})/$

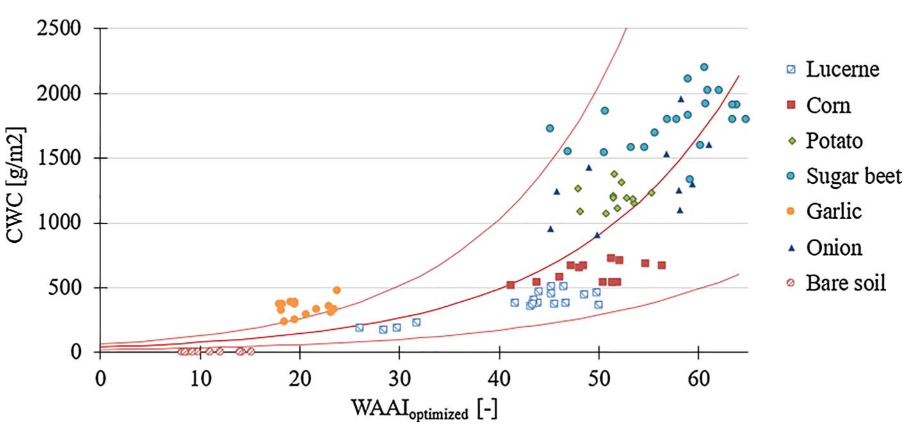

Fig. 7. CWC as a function of WAAI between the limits 911 and 1271 nm, with exponential fit and 95% of confidence interval.

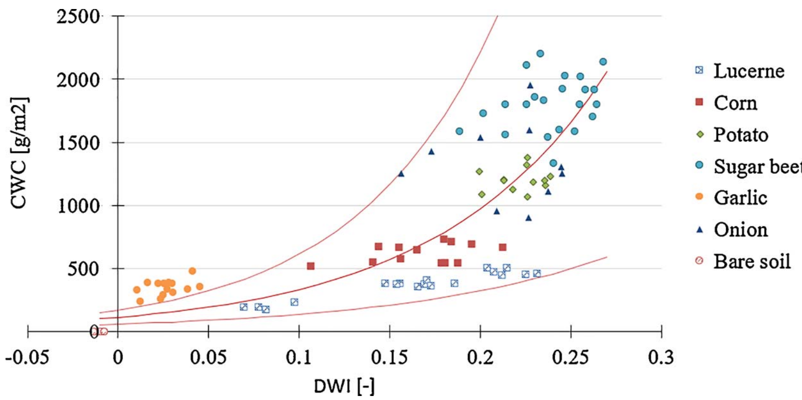

Fig. 8. CWC as a function of DWI, with exponential fit and 95% of confidence interval.

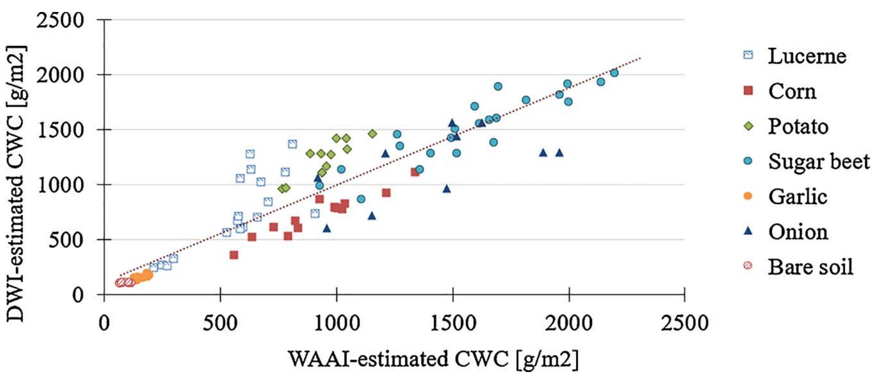

Fig. 9. CWC estimations, calculated with DWI and WAAI.

$(R_{1006} + R_{943})$ with $R^2 = 0.811$. However, when inspecting these sensitive bands whether they are physically meaningful, i.e. if the selected bands are actually influenced only or mostly by water absorption features, then these indices turned out to be questionable. For instance, the band at 738 nm in the ratio index is mainly influenced by Chl content (Peng et al., 2017; Zarco-Tejada et al., 2004) and, thus, it cannot be used as a reference band. Also in the case of the normalized index, both bands (1006 nm and 943 nm) are influenced by water content, which potentially increases the level of error because there is no reference band to compare with.

At the field or landscape scale, canopy reflectance patterns represent the integrated effects of all biophysical parameters. Because at this scale most aircraft and satellite remote sensing instrument observations are made, interpreting the data can be challenging. Co-variation mechanisms of leaf constituents is typically causing the selection of bands related to other covarying biochemicals such as pigments, starch or lignin due to their high effect on spectral variability (Ollinger, 2011). Similarly, it was earlier observed that due to the covariation between water content and Chl content, typically bands in the Chl absorption region are selected as most sensitive (Van Wittenberghe et al., 2014).

It was shown that given a dataset of five common crop types (lucerne, corn, potato, sugar beet and onion) the two newly proposed indices, i.e. WAAI and DWI, estimate CWC with R^2 of 0.8 and 0.7, respectively, outperforming established indices in predicting CWC (Table 3) and being applicable to zones with different crop types (Fig. 10). When inspecting these indices more closely, there are some aspects that indicated that WAAI and DWI may be promising indices for CWC estimation. One aspect is that both have been designed in such a way that they are applicable to hyperspectral (WAAI) and multispectral

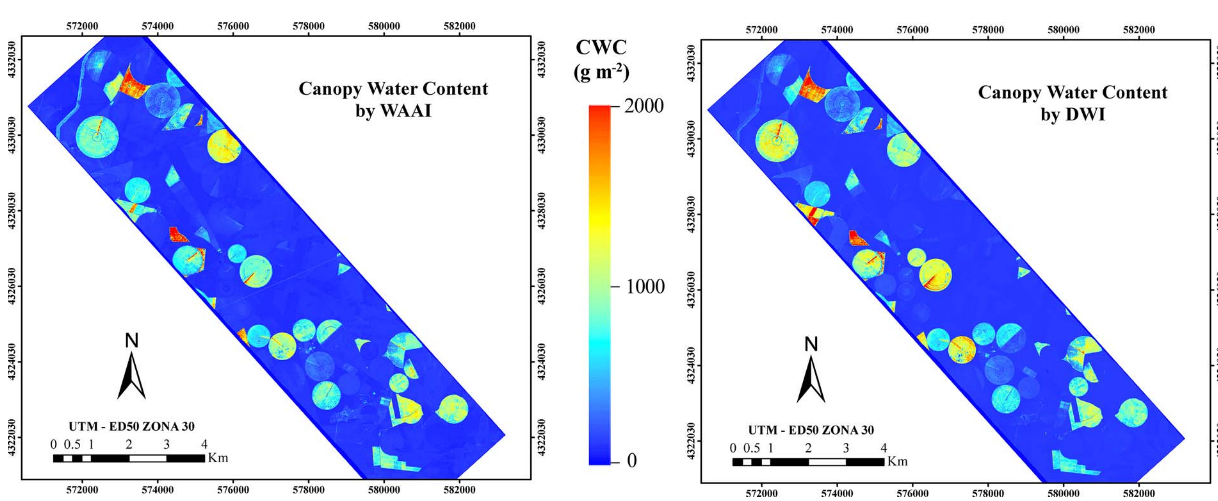

Fig. 10. CWC maps estimated with WAAI (left) and DWI (right) for the Barrax crop fields, using the 14th of July atmospherically corrected HyMap data.

(DWI) sensors. They are able to generate estimations closer to reality than established two-bands indices due to the greater number of bands located in the water absorption spectral regions. Results also suggested that the more bands influenced by CWC are used, the better correlation is obtained; the WAAI, an integration index that uses spectral information contained from 911 nm to 1271 nm, led to better results (R^2 of 0.808) than the four-bands DWI ($R^2 = 0.719$). However, another aspect to be remarked is that the performances of both WAAI and DWI are only optimal when there is presence of a minimal FVC; in our experience, typically higher than 30%. The role of bare soil is a common problem for the majority of VIs and is mostly apparent over the garlic fields, for which both indices do not provide adequate values. Garlic fields are characterized by an extremely low FVC, about 12% (Table 1). Earlier CWC studies already noted poor estimations for crop types where FVC values were very low due to the predominant role of soil reflectance (Zarco-Tejada et al., 2003). It is therefore not recommended to apply these indices for crop types with low FVC values, e.g. below 30%. Another limitation is that the CWC data is based on the LAI variable, which is actually an effective LAI with accumulation of errors, i.e. mainly the internal error of the LiCor LAI-2000 digital analyser and the human error in taking the measures. It is important to realize this when extrapolating these results to CWC estimation obtained with direct and destructive measures. Moreover, atmospheric correction is essential in VIs studies and especially for water indices because the observed TOC reflectance will be strongly influenced by atmospheric WV in the water absorbing regions (Goetz and Boardman, 1995). A precise removal of atmospheric effects to obtain good physical parameter retrievals by vegetation indices is therefore critical. Also, a widely applicable CWC index should not only work for multiple species with various structures and FVC, but also for temporal intra-species variability due to changing crop development stages. Since different crop development stages of multiple species were represented in the dataset, we have good assumptions that intra-species structural variability (and resulting biophysical changes) will also be better dealt by WAAI/DWI as opposed to simple VIs.

Finally, in order to avoid underestimating CWC in crops with scarce coverage, further work should focus on introducing a FVC-based adjustment in the newly proposed indices, as well to include data from other crop types in the analysis to confirm their generic validity. In addition, given that the DWI already leads to satisfactory estimations, when moving towards delivering CWC maps in a more operational framework, it would be interesting to configure operational optical superspectral sensors with the specific bands used in DWI. For instance, both indices can be applied to data of forthcoming imaging spectroscopy missions such as the German EnMAP–Environmental Mapping and Analysis Program (Guanter et al., 2015) and the Italian PRISMA–PRecursore IperSpettrale della Missione Applicativa (Candela et al., 2016).

5. Conclusions

Although numerous VIs have been proposed for the estimation of water content over various crop types, the problem found with these indices is that they show low estimation accuracies when applied to heterogeneous crop zones. Also, when systematically deducing the VIs best band combinations, the optimal bands produced a good correlation (R^2) but lacked physical meaning with water absorption. Hence, new indices are required that not only lead to accurate estimations but also are physically sound, and thus applicable to a great variety of crop types. Two new spectral indices were formulated capable of estimating canopy water content (CWC) over common crop types and therefore applicable to large spatial scales. The validity of these indices was based on a large multi-crop dataset (SPARC03), composed of field CWC and LAI values, as well as their corresponding hyperspectral TOC reflectance coming from a HyMap image. On the one hand, the WAAI was defined as the area between the line formed when the CWC is zero and the spectrum between the limits 911 and 1271 nm. On the other hand, DWI was formulated as a simpler and thus more applicable index to conventional sensors, which is based on the estimation of the spectral depths produced by the absorption of water at 970 and 1200 nm. Both WAAI and DWI improved the CWC estimations ($R^2 = 0.8$ and 0.7, respectively) compared to established indices, and are applicable to heterogeneous agricultural areas, given crop areas with sufficiently high FVC (> 30%). The validation of both indices proved good, with a RMSE of 290 and 400 g/m^2 for WAAI and DWI respectively, resulting in HyMap-generated maps over the Barrax agricultural area.

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