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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.