Chapter 22
Beyond NDVI: Extraction of Biophysical Variables From Remote Sensing Imagery

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22.1 Introduction

By sight humans can use visible differences in the reflection of the sunlight to recognize vegetation colour. Part of the reflected radiation observed with remote sensing (RS) techniques coincides with the part visible to the human eye. When looking at the electromagnetic (EM) spectrum used for optical RS, visible light (VIS) constitutes the first range of wavelengths. In the VIS, ranging from 0.4 to 0.7 μm, various pigments, such as chlorophyll (green), xanthophyll (yellow), and carotene (orange), influence the reflection. This reflectance is a characteristic of an object and it is often plotted against wavelength. It is called the spectral signature. In most plant species two types of chlorophyll (*a* and *b*) determine the reflection, mainly by absorption of blue and red light and to a lesser degree of green light (cf. Fig. 22.1). The energy in these spectral bands is used for the displacement of electrons and initiates the synthesis of carbohydrates from atmospheric CO_2 and absorbed groundwater. Green-yellow chlorophyll *a* is present in all photosynthesizing plants. Higher plants and green algae contain blue-green chlorophyll *b*, although in small quantities. Both chlorophylls absorb the visible light to a large extent, and have two absorption peaks: one in the blue (approx. 0.45 μm) and one in the red (approx. 0.65 μm) region of the EM spectrum. As a result of this and also of the hypersensitivity of the eye to green, vegetation reveals itself to the eye in various shades of green. Subsequently, the peak of the reflectance in the VIS occurs at approx. 0.54 μm. Spectral measurements in the VIS thus may provide information on pigment concentrations of vegetation, although the signal coming from vegetation is relatively low due to the large absorption. This strong absorption also causes that in the VIS the reflectance of only the top canopy layer determines the total reflectance of a vegetation canopy. Soils do not show this strong absorption

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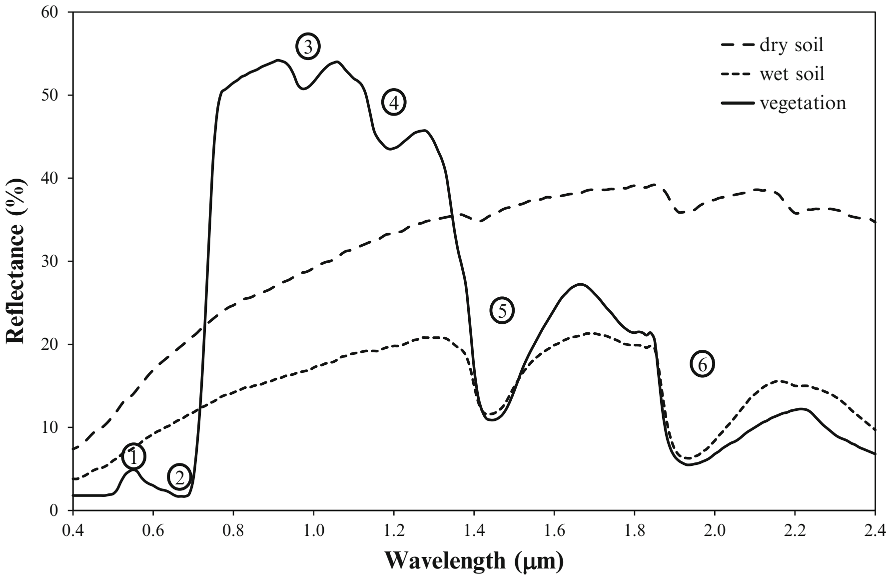

Fig. 22.1 Typical spectral reflectance curves for dry soil, wet soil and vegetation. *1*: 0.54 µm; *2*: 0.65 µm; *3*: 0.97 µm; *4*: 1.20 µm; *5*: 1.40 µm; *6*: 1.90 µm

due to pigments and therefore they mostly show a strong contrast with green vegetation in the VIS. As a result, spectral measurements in the VIS not only provide information on pigments, but also on the percentage of soil covered by vegetation (fCover) and properties related to this quantity, such as the fraction of absorbed photosynthetically active radiation (fAPAR).

The second range of wavelengths from 0.7 to 1.3 µm (near-infrared radiation, NIR) is mainly determined by the absence of absorption by pigments (see Fig. 22.1). This means that the radiation passes through the leaf (the leaf is transparent) or that it is reflected. Approximately 50 % of the NIR radiation is reflected by the leaf. However, this percentage varies widely for different plant species. It has been established for this range of wavelengths that a leaf becomes very transparent if the air channels between the cells of the leaf are filled with fluid. This gave reason to a theory that reflection takes place in the leaf at the transition of air and cell walls (Knipling 1970). Since a green leaf hardly absorbs any NIR radiation, leaves or canopy layers under the top layer contribute significantly to the total measured reflectance. This multiple reflectance denotes the NIR reflectance to be particularly suitable for estimating the so-called leaf area index (LAI) ("counting the number of leaf-layers").

In the third region of wavelengths ranging from 1.3 to 2.5 µm (called middle-infrared (MIR) or shortwave infrared (SWIR)), a great deal of radiation is absorbed by water in the cells (see Fig. 22.1). The figure shows that the major absorption peaks fall at 1.90 and 1.40 µm. It should be pointed out that weak absorption bands of water also occur at 1.20 and 0.97 µm.

Clevers (1999) has shown that the VIS can be considered as one region providing information for estimating plant properties. Since spectral bands (either narrow-band or broad-band) mutually are highly correlated, there is little added value to be expected by combining spectral bands in indices based on just the VIS. The NIR is another principal region for estimating vegetation properties. Again, spectral bands in the NIR are highly correlated and little added value is to be expected by combining spectral bands in just the NIR. A third region is the SWIR, which mainly provides information on water content in vegetation studies, and the same conclusion can be drawn as for the VIS and NIR. Clevers (1999) showed that there is a fourth region that may provide significant information on vegetation properties, in addition to the mentioned three regions. This is the so-called red-edge region exhibiting a steep rise in plant reflectance between 0.67 and 0.78 μm.

In addition to the above-mentioned main spectral regions for deriving vegetation properties, some specific regions related to specific absorption features may be of interest. This is, e.g., used by applying spectroscopy in soil mineralogy. In dry vegetation samples information on nitrogen can be obtained in the SWIR region. E.g., at 1.51 μm an absorption feature occurs due to the first overtone of the N-H band vibration and at 2.18 μm an absorption feature occurs due to the second overtone (Curran 1989). In living plant material these features are obscured by the absorption effects of water. Only the minor water absorption features at 0.97 and 1.20 μm are features that provide specific information on vegetation that is detectable from a remote sensing point of view (see Sect. 22.4.4).

To describe the relationship between spectral measurements and biophysical and chemical variables of vegetation both statistical and physical approaches have been used. As an example of statistical methods, numerous indices have been developed for estimating leaf and canopy properties (Myneni et al. 1995a). Radiative transfer (RT) models are highly suitable for studying the relationship between biophysical variables and reflectance or vegetation indices (VIs) and to study the effect of sources of variability (Combal et al. 2003). Subsequently, RT models may be used to determine 'universal' VIs that are site and species independent by calibrating VIs on large simulated datasets. A good index would be an index only sensitive to the variable of interest and not to other variables (cf. Verrelst et al. 2008). Section 22.2 provides some remarks on using radiative transfer models, whereas Sect. 22.3 gives an overview of the field of vegetation index development.

22.2 Radiative Transfer Models

A number of physically-based models, which account for the interactions of incident radiation with vegetation canopies, have been developed. Radiative transfer (RT) models have been used both in forward and inverse mode. In forward mode, RT model simulation allows validation and intercomparison of different RT model implementations (Myneni et al. 1995b) and sensitivity studies of canopy variables relative to diverse observation specifications, for an improved understanding of the RS signals and an optimized instrument design for future Earth observation systems (Bacour et al. 2002). For the retrieval of vegetation properties, RT models need to be inverted with RS data as input. For a successful inversion, one has to choose an appropriate and well-validated RT model that matches the spatial scale and correctly represents the RT of the observed target (Pinty and Verstraete 1992).

Models are traditionally being developed at the leaf and at the canopy level. Leaf RT models physically simulate reflectance and transmittance of plant leaves, which can be used by canopy level RT models to compute phase functions for multiple scattering. Canopy RT models can be classified either based on their dimensionality or based on the RT solution. In terms of dimensionality, there are two types of models: (i) one-dimensional (1D) models that require homogeneity in the horizontal dimension, such as turbid medium models, and (ii) three-dimensional (3D) models that handle heterogeneity and discontinuity in both horizontal and vertical dimensions (like needed for modeling forests), such as geometric-optical or hybrid models. The latter combine features from turbid medium and geometric models.

The combined PROSPECT leaf optical properties model and SAIL canopy bidirectional reflectance model, also referred to as PROSAIL, is the most popular RT model to study plant canopy spectral and directional reflectance in the solar domain (Jacquemoud et al. 2009). The PROSPECT model is a radiative transfer model for individual leaves. It simulates leaf spectral reflectance and leaf spectral transmittance as a function of leaf chlorophyll content (C_{ab}), leaf water content (C_w) and a leaf structure parameter (N). PROSPECT is also including leaf dry matter (C_{dm}) as a simplification for the leaf biochemistry (protein, cellulose, lignin). The one-layer SAIL radiative transfer model simulates canopy reflectance as a function of canopy parameters (leaf reflectance and transmittance, LAI and leaf inclination angle distribution), soil reflectance, ratio of diffuse/direct irradiation and solar/view geometry (solar zenith angle, zenith view angle and sun-view azimuth angle). It also takes the hot spot effect into account by considering the relative leaf size. This hot spot is a peak in the directional reflectance commonly observed in vegetation canopies when the sun and observer are at the same position, meaning that no shadows are observed. The output of the PROSPECT model can be used directly as input into the SAIL model. As a result, these models can be used as a combined PROSPECT-SAIL model.

Deriving biophysical properties from PROSAIL is feasible due to the relatively small number of input variables required for PROSAIL (Jacquemoud et al. 2000). In principle, inversion is performed by minimizing the difference between simulated and measured reflectance based on some sort of cost function and possible constraints for the model input variables (either set to an a priori value or allowed to vary within a plausible range). For the inversion process, a wide range of minimization techniques have been used: classical iterative optimization, simulated annealing, genetic algorithms, look-up tables, Monte-Carlo Markov chains and generalized likelihood uncertainty estimation. However, classical iterative optimization techniques, look-up tables and neural networks have been the most widely used (Liang 2004). Although the number of input variables is limited, we mostly still are dealing with an underdetermined problem since the number of unknowns to be estimated is larger than the number of independent spectral observations (even in case of hyperspectral sensors). Use of constraints then becomes necessary. Another problem is the ill-posedness of the inversion, meaning that different combinations of input variables yield the same spectral model output. Regularization techniques are then required for obtaining stable solutions. An overview of the state-of-the art is provided by Baret and Buis (2008). For deriving biophysical variables first the top-of-canopy (TOC) is ascertained. Inversion of TOC observations has proven to be successful in the last decades, enabling the production of high level data products (Garrigues et al. 2008). Recently, Laurent et al. (2011) demonstrated the direct use of measured top-of atmosphere (TOA) radiance data to estimate forest biophysical and biochemical variables, by using a coupled canopy–atmosphere radiative transfer model. Advantages of this approach are that no atmospheric correction is needed and that atmospheric, adjacency, topography, and surface directional effects can be directly and more accurately included in the forward modelling.

22.3 Vegetation Indices

Many investigations have been conducted to assess vegetation characteristics, such as biomass and LAI, by means of combinations of reflectances in various spectral bands. Such a combination of reflectance values, the vegetation index (VI), also serves to correct for undesirable influences of varying soil reflectance or atmospheric conditions on the results. These kinds of disturbances are particularly undesirable in spatial and multitemporal analyses. Most commonly used VIs are based on red and NIR spectral bands, because the large difference between red and NIR reflectance of dense green vegetation is a unique feature. Generally, indices are divided into ratio and orthogonal indices. Whereas ratio-based indices are calculated independently of soil reflectance properties, orthogonal indices refer to a base line specific for the soil background. More recently, indices have emerged that can be considered hybrid versions of the classic ratio and orthogonal indices.

The first investigations into vegetation indices concerned the NIR/red ratio by Rouse et al. (1974, 1973). Rouse and his colleagues found this ratio to be suitable – when applied to satellite data – for the estimation of crop characteristics owing to a partial correction for the solar position and atmospheric influence. They also used the normalized vegetation index for the same purpose. Often, this type of vegetation index is called the normalized difference vegetation index (NDVI):

$$NDVI = \frac{(NIR - red)}{(NIR + red)} \tag{22.1}$$

In order to find an index independent of the influence of the soil, Richardson and Wiegand (1977) introduced the so-called perpendicular vegetation index (PVI):

$$PVI = \sqrt{(red_v - red_s)^2 + (NIR_v - NIR_s)^2} \tag{22.2}$$

where subscripts v and s refer to the vegetation and the underlying bare soil, respectively. The increase in the amount of vegetation agreed with the offset of the reflectances perpendicular (orthogonal) to a so-called soil line in a NIR-red feature space plot.

A similar approach for suppressing variations of the soil influence has been developed by Kauth and Thomas (1976). They applied a linear transformation to the four-dimensional data space of Landsat MSS measurements of agricultural regions with various soil types, called the tasselled cap transformation. This transformation of the four Landsat-1 MSS bands resulted in a so-called brightness index dominated by soil differences and a so-called greenness index dominated by green vegetation:

$$\text{Soil brightness} = 0.43 \times \text{MSS4} + 0.63 \times \text{MSS5} + 0.59 \times \text{MSS6} + 0.26 \times \text{MSS7} \tag{22.3}$$

$$\text{Greenness} = -0.29 \times \text{MSS4} - 0.56 \times \text{MSS5} + 0.60 \times \text{MSS6} + 0.49 \times \text{MSS7} \tag{22.4}$$

MSS4: 0.5–0.6 μm, MSS5: 0.6–0.7 μm, MSS6: 0.7–0.8 μm, MSS7: 0.8–1.1 μm.

Later the tasselled cap transformation was also applied to the spectral bands of the Landsat Thematic Mapper (Crist and Cicone 1984). The soil brightness can be considered as a multidimensional soil line and the greenness is orthogonal to this soil line, in essence similar to the PVI concept.

In order to obtain a more precise correction for soil background, Huete (1988) developed the soil adjusted vegetation index (SAVI). This index was further improved by Baret et al. (1989) yielding the transformed soil adjusted vegetation index (TSAVI). Different researchers made further versions of the SAVI, resulting e.g. in an adjusted TSAVI (ATSAVI), second version of SAVI (SAVI2) and a second modified SAVI (MSAVI2) (Broge and Leblanc 2000).

A semi-empirical approach for estimating LAI of a green canopy, introduced by Clevers (1988, 1989), resulted in the so-called weighted difference vegetation index (WDVI). In this model it is assumed that in the multitemporal analysis the soil type is given and the soil moisture content is the only varying property of the soil. For estimating LAI a weighted difference between the measured NIR and red reflectances was ascertained, assuming that the ratio of NIR and red reflectances of bare soil is constant, independent of soil moisture content (which assumption is valid for many soil types). Subsequently, this WDVI was used for estimating LAI according to the inverse of an exponential function. Basically, the WDVI is a 2-dimensional greenness index, and as such also strongly related to the PVI. WDVI is calculated as:

$$WDVI = NIR - C \times red \tag{22.5}$$

$$C = NIR_s / red_s \tag{22.6}$$

where subscript s again refers to soil reflectances.

Up till now, a large set of vegetation indices have been developed, mainly for estimating vegetation cover, LAI, biomass, pigment content, water content and related (indirect) quantities. Various studies have compared many different indices for estimating one of these vegetation variables (Broge and Mortensen 2002; Gong et al. 2003; Haboudane et al. 2004; Schlerf et al. 2005; Thenkabail et al. 2002; Zarco-Tejada et al. 2005). The performance of the various indices always is different, depending on the specific data sets used for the study, resulting each time in different indices as being the best one. This makes it difficult to compare the various studies. One should always consider the theoretical background of an index, its validity range and its purpose, and then use one index as much as possible rendering results that are mutually comparable spatially and temporally. In the next section focus will be on the main biophysical variables that can be estimated with RS techniques.

22.4 Biophysical Variables

22.4.1 Chlorophyll and Nitrogen

In vegetation studies nitrogen and chlorophyll have always played an important role. A sufficient supply of nitrogen is crucial for the biochemistry of plants since nitrogen is an important component in proteins, nucleic acids (e.g., DNA, RNA) and chlorophyll (*a* and *b*). Photosynthesis is the source of energy and of carbon in all organic compounds in plants. This photosynthesis takes place in reaction centers that contain chlorophylls. Plants having a shortage of nitrogen will have a lower chlorophyll concentration resulting into a non-optimal photosynthesis. This results into not only a reduced plant growth but also a reduced carbon fixation. We see that nitrogen and chlorophyll concentrations often are highly correlated in plants (Jongschaap and Booij 2004; Yoder and Pettigrew-Crosby 1995). Actual estimates are relevant for many application fields ranging from local scale such as precision farming up to global scales dealing with the global carbon cycle.

Since the VIS should be considered as one band of information, few vegetation indices have been developed based on bands in the VIS solely. For estimating chlorophyll content actually the main one is the photochemical reflectance index (PRI) as developed by Gamon et al. (1990). The PRI is presented as an index for estimating the green shift, centered near 531 nm, caused by reflectance changes associated with the de-epoxidation of violaxanthin to zeaxanthin. As such this provides information on canopy photosynthesis, in particular the light use efficiency (Gamon et al. 1997). Recently, Garbulsky et al. (2011) provided a review of the scientific literature on the relationship between PRI and photosynthetic efficiency or related variables across a range of plant functional types and ecosystems. However, experiences with the PRI are varying.

Haboudane et al. (2002) gave a typical example how radiative transfer (RT) models can be used for development of an index for estimating the chlorophyll content from hyperspectral data. They established and tested the ratio of two optical indices, namely the transformed chlorophyll absorption in reflectance index, TCARI (Daughtry et al. 2000), and the optimized soil-adjusted vegetation index, OSAVI (Rondeaux et al. 1996). This resulted into the TCARI/OSAVI ratio. Similarly, the ratio of the modified chlorophyll absorption in reflectance index, MCARI, and the OSAVI was tested, MCARI/OSAVI (Daughtry et al. 2000).

The red-edge region as mentioned before is a special region that has often been used for estimating chlorophyll and nitrogen content at both leaf and canopy level. Physically it is the content at canopy level that we expect to estimate with RS. Collins (1978) and Horler et al. (1983) were among the first researchers to point out the importance of the red-NIR wavelength transition for vegetation studies. Both the position and the slope of this red-edge change under stress conditions, resulting in a shift of the slope towards shorter wavelengths (Horler et al. 1983). As an index mostly the position of the inflexion point on the red-NIR slope is used. This is called the red-edge position (REP), and it will be influenced by both the LAI and the chlorophyll concentration (Clevers et al. 2001). It was shown before to be a good estimate for chlorophyll content, but being less sensitive at higher contents. This saturation effect is still a problem. There are various ways to calculate this REP (Clevers et al. 2004). Guyot and Baret (1988) applied a simple linear model to the red-infrared slope. This approach is feasible for satellite data like obtained with the Medium Resolution Imaging Spectrometer, MERIS (Clevers et al. 2002).

Another type of index based on the red-edge slope has been developed specifically with the advent of MERIS: the MERIS terrestrial chlorophyll index, MTCI (Dash and Curran 2004). It is proposed as a better index than the REP.

Wu et al. (2008) suggested to replace the traditional red and NIR spectral bands in indices like MCARI, TCARI and OSAVI by spectral bands in the red-edge region, particularly a band at 705 nm instead of the traditional red band at 670 nm, and a band at 750 nm instead of the band at 800 nm in the traditional MCARI and TCARI. They found that this resulted into indices that have better linearity with chlorophyll content and are thus more suitable. This band replacement is also consistent with the results of the sensitivity analysis by Gitelson and Merzlyak (1996).

Gitelson et al. (2003, 2006a, b) presented a simple index based on a NIR band and a red-edge band (e.g., at 710 nm) to estimate chlorophyll concentration: the so-called chlorophyll index ($CI_{red\text{-}edge} = R_{780}/R_{710}-1$). He also presented a variant using a green band instead of the red-edge band (CI_{green}). Major advantage of these latter two indices would be their linear relationship with chlorophyll and the absence of the saturation effect as obtained with the REP indices.

Clevers and Kooistra (2012) tested the potential of the above-mentioned VIs for retrieving canopy chlorophyll and nitrogen content. The formulae of the indices are given in Table 22.1. Main results are summarized in Table 22.2. They showed through PROSAIL model simulations that out of the above-mentioned VIs the $CI_{red\text{-}edge}$ performed best in estimating canopy chlorophyll content showing a linear

Table 22.1 Vegetation indices evaluated in the study of Clevers and Kooistra (2012)

Index	Formulation
REP	$700 + 40\frac{(R_{670}+R_{780})/2-R_{700}}{R_{740}-R_{700}}$
MTCI	$(R_{754} - R_{709})/(R_{709} - R_{681})$
MCARI/OSAVI	$\frac{[(R_{700}-R_{670})-0.2(R_{700}-R_{550})](R_{700}/R_{670})}{(1+0.16)(R_{800}-R_{670})/(R_{800}+R_{670}+0.16)}$
TCARI/OSAVI	$\frac{3[(R_{700}-R_{670})-0.2(R_{700}-R_{550})(R_{700}/R_{670})]}{(1+0.16)(R_{800}-R_{670})/(R_{800}+R_{670}+0.16)}$
MCARI/OSAVI[705,750]	$\frac{[(R_{750}-R_{705})-0.2(R_{750}-R_{550})](R_{750}/R_{705})}{(1+0.16)(R_{750}-R_{705})/(R_{750}+R_{705}+0.16)}$
TCARI/OSAVI[705,750]	$\frac{3[(R_{750}-R_{705})-0.2(R_{750}-R_{550})(R_{750}/R_{705})]}{(1+0.16)(R_{750}-R_{705})/(R_{750}+R_{705}+0.16)}$
$CI_{red\text{-}edge}$	$(R_{780}/R_{710}) - 1$
CI_{green}	$(R_{780}/R_{550}) - 1$

R_λ refers to the reflectance factor at wavelength λnm

Table 22.2 Overview of R^2 values of the linear relationships between indices and chlorophyll (PROSAIL) and nitrogen (grass and potato) content (Clevers and Kooistra 2012)

Index	PROSAIL	Grass	Potato
REP	0.49	0.79	0.84
MTCI	0.83	0.80	0.89
MCARI/OSAVI	0.25	0.06	0.09
TCARI/OSAVI	0.39	0.58	0.19
MCARI/OSAVI[705,750]	0.93	0.57	0.87
TCARI/OSAVI[705,750]	0.91	0.75	0.71
CI_{green}	0.94	0.77	0.88
$CI_{red\text{-}edge}$	0.94	0.77	0.88

relationship over the full range of potential values. In contrast, highly non-linear relationships of chlorophyll content with most traditional red-edge indices were found. Subsequently, they performed tests with field data for sampling locations within an extensively grazed fen meadow using ASD FieldSpec measurements and within a potato field with a Cropscan radiometer for estimating canopy nitrogen content. Also at these study sites the $CI_{red\text{-}edge}$ was found to be a good and linear estimator of canopy nitrogen content (no chlorophyll was measured) for both the grassland site and the potato field (Clevers and Kooistra 2012). Currently, this approach can, e.g., be applied with MERIS, Hyperion and RapidEye data and with the upcoming Sentinel-2 and -3 systems. An example of the relationship between $CI_{red\text{-}edge}$ and nitrogen content of potatoes is shown in Fig. 22.2. For a more detailed analysis of the data and description of results the reader is referred to Clevers and Kooistra (2012).

22.4.2 Vegetation Cover Fraction (fCover) and fAPAR

As stated in the introduction, radiation in the VIS can be used by plants for photosynthesis. Therefore, this is called photosynthetically active radiation (PAR). The rate of photosynthesis can be calculated from the amount of absorbed PAR (the APAR) and the photosynthesis-light response of individual leaves.

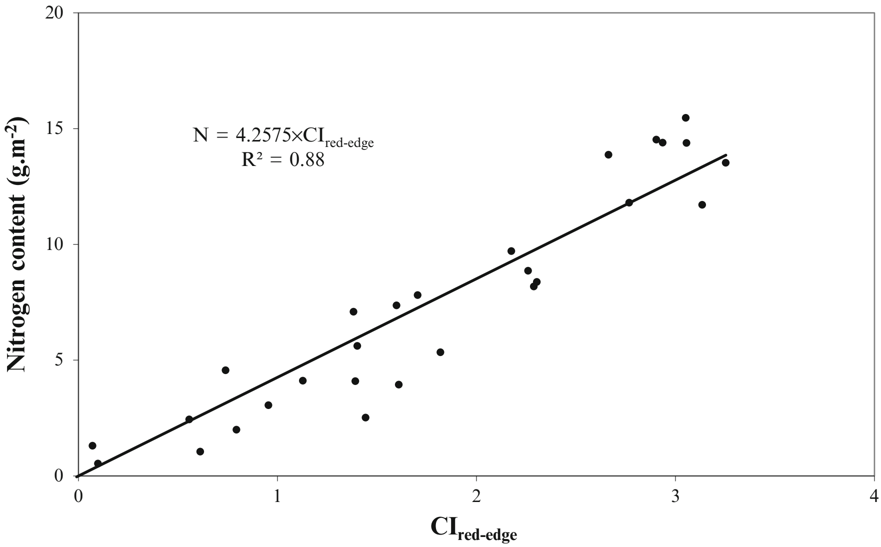

Fig. 22.2 Relationship between $CI_{red\text{-}edge}$ and canopy nitrogen content for a potato study site in The Netherlands (Clevers and Kooistra 2012)

Estimating APAR over some time interval (e.g., daily APAR) requires both incident PAR and the (average) fraction of APAR by vegetation, which is called fAPAR. Daughtry et al. (1992) showed that daily APAR may be reliably computed from measurements of the fAPAR near solar noon and daily incident PAR. The fAPAR is considered one of the main essential climate variables related to the terrestrial ecosystem (WMO/IOC 2010). It is strongly correlated to the vegetation cover fraction (fCover) (Bacour et al. 2006). fCover corresponds to the gap fraction of vegetation either measured from above or from below in the nadir viewing direction. fAPAR, conversely to fCover, depends on the illumination conditions.

The large contrast in reflectance between bare soil and vegetation in the VIS will be most suitable for estimating fCover and fAPAR. Since this contrast not only depends on the amount of vegetation but also on the moisture content of the soil, a single band is not suitable and a vegetation index should be used. Again, due to the strong mutual correlation of bands in the VIS, mostly a combination of VIS and NIR bands is used. Clevers et al. (1994) showed that a linear relationship may be assumed between WDVI or NDVI and fAPAR. External factors such as soil brightness, diffuse/direct irradiation ratio and solar zenith angle only have a minor influence on such a relationship between WDVI and fAPAR. Moreover, leaf parameters such as chlorophyll content, mesophyll structure and hot spot parameter (see Sect. 22.2) also have quite a small influence for green leaves. The leaf angle distribution (LAD) is the main parameter influencing the relationship between WDVI and fAPAR. So, for different LADs different regression functions should be used. Although the relationship between NDVI and fAPAR is slightly less influenced by LAD and solar zenith angle, important disturbing factors are the soil brightness and leaf chlorophyll content. Similar results have been found in other studies (Asrar et al. 1992; Goward and Huemmrich 1992). So, the WDVI is to be preferred over the NDVI.

22.4.3 Leaf Area Index

Leaf area index (LAI) is defined as the total one-sided green leaf area per unit ground area and it is regarded a very important canopy characteristic because photosynthesis takes place in the green plant organs. Moreover, it is also considered an essential climate variable (WMO/IOC 2010). Most of the vegetation indices mentioned in Sect. 22.2 have been used for estimating LAI. Clevers and Verhoef (1993) have performed an extensive sensitivity analysis using a combination of the PROSPECT leaf reflectance model and the SAIL canopy reflectance model towards the relationship between WDVI and LAI. As expected according to the Lambert-Beer law for light extension in a canopy, this is an exponential relationship. The influence of external factors such as soil brightness, diffuse/direct irradiation ratio and solar-view geometry hardly have an effect on the relationship between WDVI and LAI. Moreover, leaf parameters such as chlorophyll content, mesophyll structure and hot spot parameter also have only a small influence for green leaves at near nadir observation (like is the case for many satellite observations). The main variable influencing the relationship between WDVI and LAI is the leaf angle distribution (LAD). So, for different LADs different regression functions should be used. An example of calibration lines for estimating LAI using the WDVI for a range of agricultural crops in the Netherlands is provided by Bouman et al. (1992). Figure 22.3 shows an example of the WDVI – LAI relationship for barley from the original WDVI paper of Clevers (1989). He applied the inverse of a special case of the Mitscherlich function (Mitscherlich 1920) for estimating LAI:

$$LAI = -1/ \propto \times Ln(1 - WDVI/WDVI_{\infty}) \tag{22.7}$$

22.4.4 Canopy Water

Currently, one of the main scientific issues in studying global climate change is to understand the role of terrestrial ecosystems and the changes they may undergo. The water cycle is one of their most important characteristics (ESA 2006). In this respect, the canopy water content (CWC) is of interest, also in view of the water use efficiency of plants. As stated in Sect. 22.1, the SWIR region of the EM spectrum mainly is sensitive for canopy water. Water absorption features as a result of absorption by O-H bonds in liquid canopy water can be found at approximately 0.97, 1.20, 1.45 and 1.95 μm (Curran 1989). The features at 1.45 and 1.95 μm are

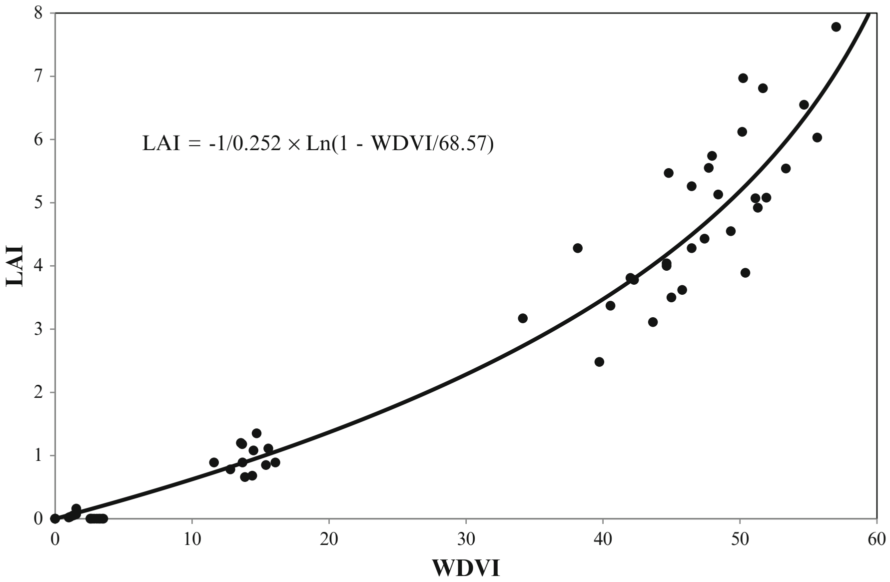

Fig. 22.3 Regression of LAI on WDVI for a field trial with a barley crop at the vegetative stage (Clevers 1989)

most pronounced. However, when using remotely sensed observations, one should also consider water vapour in the atmosphere, which also results in several absorption bands in the infrared part of the spectrum. Main atmospheric absorption features occur around 1.40 and 1.90 μm. As a result, those bands will result in very noisy measurements and should not be used for remote sensing. Spectral bands outside these main features in the shortwave infrared (SWIR) region are suited for the remote sensing of canopy water content (Tucker 1980). Landsat Thematic Mapper band 5 (1.55–1.75 μm) was designed because of this sensitivity to canopy water content. Also Thematic Mapper band 7 (2.08–2.35 μm) is sensitive to canopy water content. Various broad-band vegetation indices are based on these wavelength regions. One of the first ones is the infrared index (II) as defined by Hardisky et al. (1983).

The canopy water absorption features at 0.97 and 1.20 μm are not that pronounced, but still clearly observable (Danson et al. 1992; Sims and Gamon 2003). Therefore, these offer interesting possibilities for deriving information on canopy water content. In these regions one should consider the water vapour band absorptions at 0.94 and 1.14 μm when observing through the atmosphere (Gao and Goetz 1990; Iqbal 1983). One can notice that the centers of the liquid water bands (in the canopy) are shifted to longer wavelengths as compared to the corresponding water vapour band centers. Due to the development of imaging spectrometers, accurate measurements on these minor absorption features in the near-infrared (NIR) have become feasible.

Various spectral techniques, based on the water absorption features at 0.97 and 1.20 μm, have been proposed to estimate CWC. Often these techniques are equivalent to those applied to the chlorophyll absorption feature in the red part of the electromagnetic spectrum. Thus far, approaches based on spectral indices, continuum removal and derivative spectra have been studied in literature. Concerning spectral indices, Peñuelas et al. (1993, 1996) focused on the 0.95–0.97 μm slope and defined the so-called water band index (WI) as the ratio between the reflectance at 0.97 μm and the one at 0.90 μm (as a reference wavelength). Gao (1996) defined the normalized difference water index (NDWI), analogously to the well-known normalized difference vegetation index (NDVI), by using the 1.20 μm feature and 0.86 μm as a reference wavelength. In addition, a continuum removal approach can be applied to the two absorption features at about 0.97 and 1.20 μm. This is a way of normalizing the reflectance spectra (Kokaly and Clark 1999). The maximum band depth, the area under the continuum, and the band depth normalized to the area (Curran et al. 2001) have been used thus far for estimating foliar biochemicals like chlorophyll. Few studies have applied this to the water absorption features at 0.97 and 1.20 μm (Kokaly et al. 2003; Stimson et al. 2005).

Danson et al. (1992) showed that the first derivative of the reflectance spectrum corresponding to the slopes of the absorption features provides better correlations with leaf water content than those obtained from the direct correlation with reflectance. Rollin and Milton (1998) found moderate correlations between the first derivative at the left slope of both absorption features and CWC for a grassland site in the UK. Clevers et al. (2008) applied derivatives in a preliminary study at the field and airborne level. These studies showed that spectral derivatives at the slopes of the 0.97 μm and (to a lesser extent) 1.20 μm absorption feature have good potential as predictors of CWC. Recently, Clevers et al. (2010) showed that the first derivative of the reflectance spectrum at wavelengths corresponding to the left slope of the minor water absorption band at 0.97 μm was highly correlated with CWC. PROSAIL model simulations showed that it was insensitive to differences in leaf and canopy structure, soil background and illumination and observation geometry. However, these wavelengths are located close to a water vapour absorption band at about 0.94 μm (Gao and Goetz 1990). In order to avoid interference with absorption by atmospheric water vapour, the potential of estimating CWC using the first derivative at the right slope of the 0.97 μm absorption feature were studied by Clevers et al. (2010). Their results of PROSAIL simulations showed a linear relationship between the first derivative over the 1015–1050 nm interval and CWC. This result was confirmed, e.g., using an ASD FieldSpec spectroradiometer for a range of grassland plots at a fen meadow. Consistency between simulation results and actual field data confirmed the potential of using simulation results for calibrating the relationship between the first derivative and CWC. An example of this is provided in Fig. 22.4.

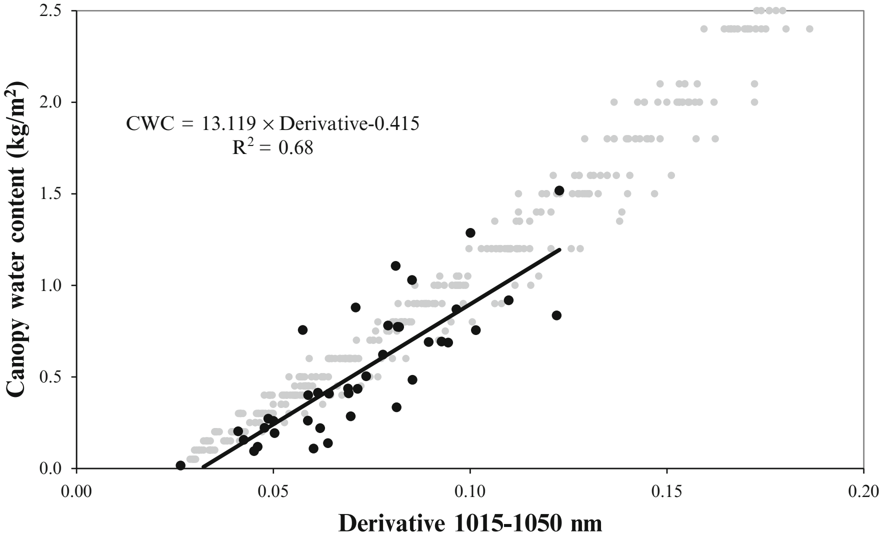

Fig. 22.4 Relationship between first derivative of canopy reflectance over the interval 1015–1050 nm and canopy water content for a fen meadow study site in The Netherlands (Clevers et al. 2010). At the background the simulated relationship for PROSAIL with varying input parameters is shown

22.5 Outlook

Within Europe the application of Earth observation data, particularly as acquired in the reflective solar domain, is reaching a state of maturity. Especially the availability of data will boost applications. For successful applications the user requirements in terms of spatio-temporal continuity, consistency and quality of products have to be fulfilled. Users require univocal numbers. Currently a multitude of satellite data is available already, and this availability will increase enormously in the near future. ESA has for long focused on research instruments, but is now developing five new missions called Sentinels specifically for the operational needs of the Copernicus programme (previously known as GMES). For land applications using the solar reflective domain, in particular two systems are relevant. Sentinel-2 (equipped with the Multi Spectral Instrument MSI) will provide images with high spatial, spectral and temporal resolution and it aims at ensuring continuity of Landsat and SPOT (Système pour l'Observation de la Terre) observations. In addition, it incorporates three new spectral bands in the red-edge region, which are very important for retrieval of chlorophyll (Delegido et al. 2011). It has a swath width of 290 km by applying a total field-of-view (FOV) of about 20°. Sentinel-3 is a medium resolution land and ocean mission, to be seen as a continuation of the Envisat mission. The Ocean and Land Color Instrument (OLCI) has a swath width of 1,270 km (FOV of about 68°, but slightly tilted) and a spatial resolution of 300 m. It will provide data continuity of MERIS on Envisat. Both Sentinel-2 and Sentinel-3 missions are based on a constellation of two satellites each in order to fulfill revisit and coverage requirements, providing robust datasets for Copernicus services.

As discussed in this chapter, RS can provide a number of key biophysical and biochemical products of vegetation, such as the fraction of absorbed photosynthetically active radiation (fAPAR), leaf area index (LAI), chlorophyll content and water content. The first two have been identified as essential climate variables (ECVs) by the UNFCCC and are key variables that are both used in surface process models and retrieved from remote sensing observations in the reflective solar domain. Various algorithms are used to derive these products, but they mostly relate to nadir or directionally normalized observations (Baret et al. 2007). For operational RS applications multisensor data usage will be required to increase the number of observations within a given time period, particularly relevant in regions with frequent cloud cover (Verger et al. 2011). This will result in an increase of high-quality data in time-series for monitoring activities. However, instability of retrieval algorithms to directional effects will degrade the accuracy of derived products.

A major research item for the coming years is assessing the anisotropic reflectance behavior of vegetation and soils, as described by the bidirectional reflectance distribution function (BRDF). With the advent of remote sensing systems with off-nadir viewing capabilities like SPOT and commercial high-spatial resolution systems (like IKONOS, QuickBird, GeoEye and WorldView), and sensors with wide FOV (like the OLCI on Sentinel-3) information on the BRDF characteristics of surface features is becoming very important for the retrieval of surface parameters. Moreover, directional information may also be significant for sensors with a limited FOV (like the MSI on Sentinel-2) for accurate retrieval of surface parameters. As a result, information on the BRDF of targets is relevant for normalizing images taken under different illumination and/or viewing conditions (Baret et al. 2007), but on the other hand it has been shown that multi-angular observations provide additional information that can be used to improve the accuracy of retrieved products (Coburn et al. 2010; Laurent et al. 2011; Verger et al. 2011). The BRDF of surface targets contains information on structure and composition that cannot be inferred from spectral properties alone (Barnsley et al. 1994). As such, it provides an additional dimension to remote sensing observations.

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