



Spaceborne Imaging Spectroscopy for Sustainable Agriculture: Contributions and Challenges

Tobias B. Hank¹  · Katja Berger¹ · Heike Bach² · Jan G. P. W. Clevers³ · Anatoly Gitelson⁴ · Pablo Zarco-Tejada⁵ · Wolfram Mauser¹

Received: 16 February 2018 / Accepted: 14 July 2018 / Published online: 26 July 2018
© The Author(s) 2018

Abstract

Agriculture faces the challenge of providing food, fibre and energy from limited land resources to satisfy the changing needs of a growing world population. Global megatrends, e.g., climate change, influence environmental production factors; production and consumption thus must be continuously adjusted to maintain the producer–consumer–equilibrium in the global food system. While, in some parts of the world, smallholder farming still is the dominant form of agricultural production, the use of digital information for the highly efficient cultivation of large areas has become part of agricultural practice in developed countries. Thereby, the use of satellite data to support site-specific management is a major trend. Although the most prominent use of satellite technology in farming still is navigation, Earth Observation is increasingly applied. Some operational services have been established, which provide farmers with decision-supporting spatial information. These services have mostly been boosted by the increased availability of multispectral imagery from NASA and ESA, such as the Landsat or Copernicus programs, respectively. Using multispectral data has arrived in the agricultural commodity chain. Compared to multispectral data, spectrally continuous narrow-band sampling, often referred to as hyperspectral sensing, can potentially provide additional information and/or increased sampling accuracy. However, due to the lack of hyperspectral satellite systems with high spatial resolution, these advantages mostly are not yet used in practical farming. This paper summarizes where hyperspectral data provide additional value and information in an agricultural context. It lists the variables of interest and highlights the contribution of hyperspectral sensing for information-driven agriculture, preparing the application of future operational spaceborne hyperspectral missions.

Keywords Agriculture · Hyperspectral · Spaceborne imaging spectroscopy · Food security · Biophysical and biochemical variables

✉ Tobias B. Hank
tobias.hank@lmu.de

Extended author information available on the last page of the article

1 Current Challenges of the Global Food System

In pre-industrial times, producers and consumers in the food system were identical. Before the late eighteenth and middle of the nineteenth century, the majority of the European country’s population settled in rural areas and was occupied with agricultural activities (Goodwin et al. 2008). Consumption and production of food happened parallel to each other. Nowadays, global large-scale processes like urbanization, which has exponentially increased in the last three decades (Chen et al. 2014), have led to a more complex and spatially divided manifestation of the commodity flows. The global food system, whose most prominent flows are sketched in generalized form in Fig. 1, is supposed to be in a more or less balanced state between the demand by consumers, who increasingly live in cities, and the supply by the producers, who farm the land in a predominantly rural environment. Sites of food production and consumption have become spatially dislocated (Gunasekera and Finnigan 2010) and are now connected via a globally operating food industry, which works within food security frameworks that have been established by regional governance systems (Danbom 1995). The food industry on one side processes agricultural goods and provides food according to the consumer’s needs, values and preferences, while it steers the flow of money back to the farmers on the other hand, thus maintaining farm economy.

Profitability is the key of global food production, driving technological and infrastructural investments. In economic terms, agricultural land use, intensification and land expansion take place, under given regulations, where it is profitable to do so (Byerlee et al. 2014). Market forces increase with the number of farmers connected to the global agricultural markets. Thus, economic and regulatory factors, paired with the underlying continued processes of globalization and global environmental change, determine how much food will be produced. Farmers work the land and produce agricultural products with the use of capital, water, energy and technology. The environment, characterized by soil

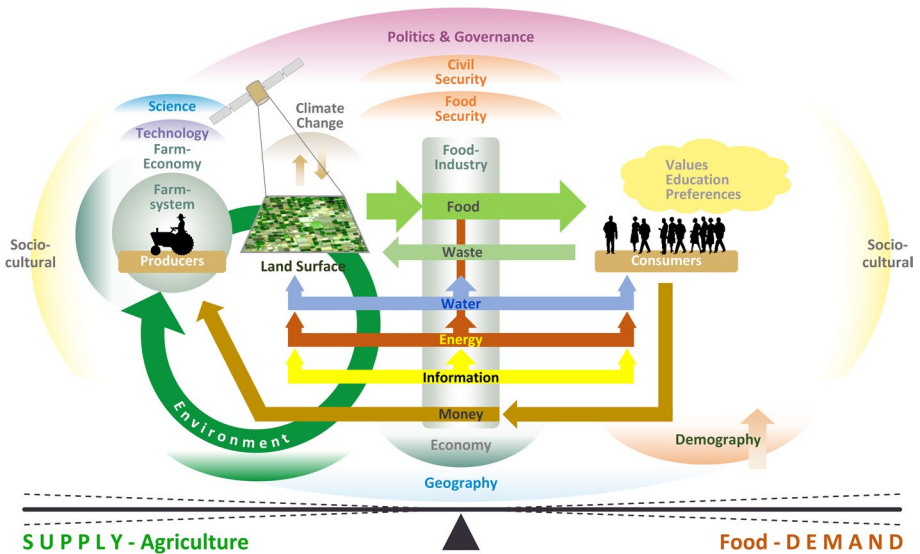


Fig. 1 Generalization of the most important flows in the Global Food System [modified after www.shift.n.com; figure originally developed for the UK Government Office for Science (GOS 2011)]. It can be observed that one of the important flows is information, which is partly derived from satellite observations

fertility, temperature conditions and available water resources, is their main production factor. Farmers thereby increasingly use science and technology (machinery, fertilizers and plant protection agents, seeds and information, e.g., from remote sensing) to optimize the use of the naturally available production factors and to improve economic benefit (Walter et al. 2017). Environmental production factors, on the other hand, are subject to climate change and environmental degradation within unsustainable farming systems (FAO 2016). At the same time, a growing and increasingly wealthy global population relies on the global food system to satisfy daily food, fibre and energy demands. The global meg-trends (climate change, population change, technological change, etc.) gradually cause the supply–demand–balance to shift. The suppliers, i.e. the farmers, are continuously striving to reinstall the equilibrium by adapting and optimizing agricultural production methods. Given the current demographic development, farmers are forced to increase the yields achieved by cultivating a certain acreage of bioproductive land surface, while at the same time protecting their most important production factor, i.e. the environment, from degradation and from emissions (FAO 2016). The threat emanating from emissions thereby is based on two different pathways. The leaching of NO_3 , which has not been taken up by the crop during growth, pollutes groundwater and thus has a direct effect on human health (Ritter et al. 2002). At the same time, gaseous emissions of NO_x enter the atmosphere and lead to the formation of tropospheric ozone, a greenhouse gas pushing climate change, but also potentially harming crops directly (Robertson et al. 2013). In addition, emissions from excessive use of plant protection agents contribute to environmental pollution (Ritter et al. 2002). One recent trend to mitigate these problems in agricultural production is the application of organic farming methods, which do not rely on the application of mineral fertilizers and plant protection agents (Shams et al. 2017). However, organic farming still is a trade-off between increased environmental protection and reduced overall yields and yield security. Besides organic production, site-specific precision farming is another farming perspective (Blackmore 1994). Thereby, all means of production are spatially optimized to prevent unnecessary expenses and unwanted emission at the same time. Precision farming is an important component of smart farming, which aims at an information-driven optimization of all aspects of a farming system (Bach et al. 2016). Some of the most important applications of smart farming are:

- Using computer-aided information technology, such as Farm Management Information Systems (FMIS), for administration and documentation of work helps the farmer to keep track of expenses on and revenues from individual fields (Zhang et al. 2002).
- Using satellite-guided precision navigation prevents overlap between driving lanes and helps optimizing the distribution of different machines on the farm thus saving fuel and person-hours (Zhang et al. 2002).
- Using long-term Earth Observation helps to identify different soil qualities on a farm and thus helps to optimize soil sampling (Plant et al. 2000).
- Using long-term Earth Observation also helps to identify persistent growth patterns, which indicate the variability of different growth conditions on a farm (e.g., www.talkingfields.de/en/base-map/). This information can be used for the planning of long-term soil enrichment measures, such as increasing soil organic matter content through ploughing green manure. It also can be applied for site-specific planning of seeding density.
- Using real-time Earth Observation, either from satellites, planes, drones or vehicles, can contribute to site-specific planning of four very important management measures (Mulla 2013), as there are (1) fertilization (e.g., Ciudad et al. 2001), (2) plant protection

(e.g., Herwitz et al. 2004), (3) irrigation (e.g., Calera et al. 2017), and (4) harvesting (e.g., Yang et al. 2013). Thereby, so-called map-overlay approaches combining different data sources, e.g., satellite sensors and ground-based sensors, seem to represent the most promising method (Auernhammer et al. 1999).

Precision farming thus holds potential for increasing yields on limited land while at the same time saving resources and preventing environmental pollution (Plant et al. 2000). Current studies show that increased yield levels not necessarily need to be connected to environmental degradation (see review Balafoutis et al. 2017). The so-called green water productivity (kg grain produced per kg water used) has been observed for wheat, rice and maize crops to more or less linearly increase with rising yield levels until an average yield level of 8 tons per hectare is reached (Rockström et al. 2007). Above this point, no further increase in the green water productivity can be observed. Sustainability thus becomes a matter of balancing yield levels in a dimension around this average, because obviously low yield levels, which do not make efficient use of the environmental production factors, are just as unsustainable as too high yields, which drain the natural resources and lead to degradation.

One very important aspect of precision farming is that the method not only is associated with ecologic advantages but also economic profitability can be increased through site-specific farming (Balafoutis et al. 2017), which makes an actual large-scale implementation of precision farming likely. However, the most efficient use of the land surface and thus the most economic and ecologic profit, can only be achieved by farmers who have access to all information concerning the individual needs of their worked land. While in some parts of the world smallholder farming is still the dominant form of agricultural production (Lowder et al. 2016), in developed countries the use of digital information for the highly efficient cultivation of large areas has become part of agricultural practice in recent years (Walter et al. 2017). Thereby, the use of satellite data to support site-specific management is a major trend at least in some developed countries. For instance, in the USA, the market area share of satellite data has tripled during the last 10 years, as can be observed in Fig. 2.

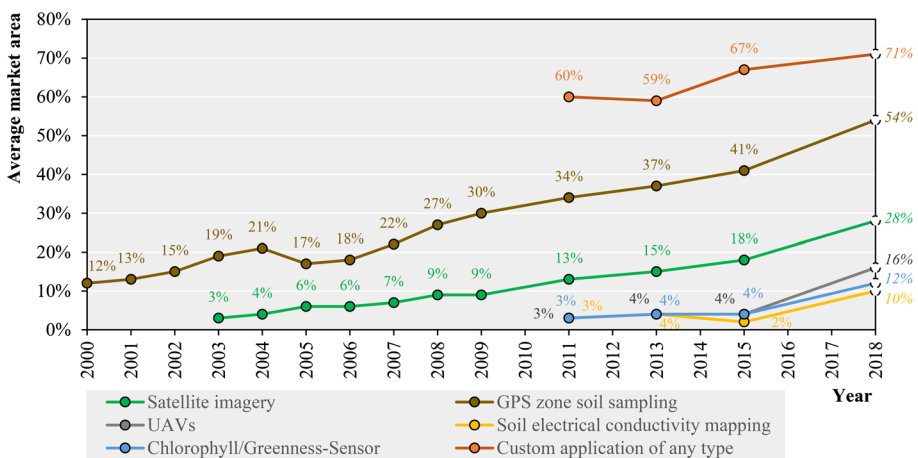


Fig. 2 Development of market area using precision services over time as estimated by dealers of farm equipment in the USA (2018 predicted), showing the strong increase in use of satellite-based information technology in agricultural practice; based on data by Erickson and Widmar (2015)

Although the most prominent use of satellite technology in farming still is navigation via GNSS (Global Navigation Satellite Systems, e.g., for GPS-based soil sampling, see Fig. 2), also Earth Observation (EO) has been increasingly applied (Satellite imagery, Fig. 2). The highest share, however, is allotted to custom applications, which are individually tailored to the information needs of the farmer and which, according to Erickson and Widmar (2015), in many cases also are based on satellite-derived data (e.g., field mapping with GPS) but also on statistical data (e.g., yield monitor analysis). Some operational services have been recently established, which provide farmers with decision-supporting spatial information, e.g., talkingfields (VISTA, Germany; Bach and Angermair 2017; Bach and Mauser 2018) or Irrisat (Ariespace, Italy; Ariespace 2017) etc. The development of these services has mostly been boosted by the increased availability of (cost-free) multispectral imagery from NASA and ESA, such as the Landsat or Copernicus programs, respectively. Using multispectral data has arrived in the agricultural commodity chain. This development comes along with new challenges such as handling big data. Currently, the large amount of data is mostly due to high revisit rates at reasonably high spatial resolution (e.g., Sentinel-2). The big data load so far is not so much due to a detailed spectral sampling of the Earth's surface, although spectrally continuous narrow-band sampling, often referred to as hyperspectral remote sensing (HRS) or imaging spectroscopy (IS; Goetz et al. 1985), can potentially provide additional information and/or increased sampling accuracy compared to multispectral data. Since a few years, HRS-IS technologies have been well accepted by the remote sensing community as an innovative tool for various research applications, not only in agriculture but also in atmospheric sciences, geology, ecology, soil science, limnology, pedology and other areas. However, due to the lack of large-scale hyperspectral EO systems, these advantages mostly are not yet used in practical farming. With some new spaceborne hyperspectral missions being currently developed, e.g., the Italian PRISMA (Labate et al. 2009), US HypSIRI (Roberts et al. 2012), or the German EnMAP (Guanter et al. 2015), the availability of hyperspectral data and its use and application in practical farming will soon be demonstrated and scientifically justified with on-farm research.

This paper summarizes where hyperspectral data can provide additional value and information in an agricultural context. It lists the variables of interest, reviews the retrieval methods and highlights the additional value of hyperspectral sensing for agricultural applications, thus preparing the application of operational spaceborne hyperspectral missions in modern agriculture.

2 Earth Observation Opportunities to Support Food Production Efficiency

“Remote sensing data can greatly contribute to the monitoring task by providing timely, synoptic, cost-efficient and repetitive information about the status of the Earth's surface” [Justice et al. (2002) in Atzberger (2013)]. The basis for retrieving information in a spatial way from multispectral data is the assumption of a relation between structural and biochemical traits that describe the state of the canopy and the spectral reflectance that results from the specific variable composition (Mauser et al. 2012). From an agricultural point of view, soil and vegetation properties are of special interest. Observing soils with hyperspectral observation systems for instance allows retrieving information on soil organic carbon and soil iron-oxide content (Stevens et al. 2010), which both can be important indicators for soil fertility. However, the impact of soil analysis through remote sensing for agricultural

practice is strongly limited due to three reasons: (1) Retrieval of soil organic carbon content is highly influenced by the current moisture state of the soil, because different moisture states strongly influence soil brightness. Soil moisture, however, is very variable in space and time so that difficulties arise when acquisitions should be compared to in situ measurements (Stevens et al. 2010). (2) Optical sensors operating in the visible (VIS), near-infrared (NIR) and shortwave-infrared (SWIR) are not capable of penetrating the canopy, so soil observations are only feasible for surfaces with very low vegetation coverage (Haubrock et al. 2008). This excludes analysing permanent crops and strongly limits continuous soil monitoring during the growth cycle. (3) Sensors in the VIS, NIR and SWIR domain also are not capable of penetrating the soil surface. The information that might be extracted from optical remote measurements of the soil is restricted to the uppermost soil surface (Haubrock et al. 2008). The true production potential of soils nonetheless lies in the deeper soil horizons that are accessed by the roots of the canopy and which provide water and nutrients to the crop. However, this hidden information on soil column properties becomes secondarily accessible when the plant itself is used as sensor, because the vigour of plants sensitively reacts to soil-related environmental conditions, e.g., to drought and nutrient stress (Basu et al. 2016). In order to make use of the plant response, the relation between crop biochemical and structural traits and the reflectance must precisely be known. It is a commonly promoted limitation of vegetation remote sensing that the spectral signal of actively growing vegetation looks pretty similar across a wide range of different plant types and cultivars (e.g., Nidamanuri and Zbell 2011; Wilson et al. 2014; Zomer et al. 2009). This similarity in the opinion of the authors should not be perceived as drawback, but should rather be interpreted as proof that the underlying physical and chemical processes that contribute to vegetation growth on the Earth's surface (light collection, gas exchange, phenological cycles, carbon assimilation and allocation) more or less apply uniformly for all vegetation types. Due to these uniformly and globally applicable mechanisms, the states of those vegetation variables that leave traces in the spectral reflectance of the canopy can potentially be observed by remote sensing and, consequently, can be analysed through non-crop-specific approaches. Figure 3 gives an overview of spectral domains, which respond to changes in specific vegetation variables, regardless of vegetation type and cultivar.

Figure 3 supports two important findings: (1) Information contained in a vegetation spectrum is rich and diverse. It reaches from biochemical information (pigments and water content) over process information (light use efficiency, LUE) to structural information (leaf area index, LAI, leaf inclination, etc.). (2) The partial disagreement between the hyperspectral and the multispectral reflectance spectrum indicates the limited information content of multispectral sensors for diverse vegetation properties and processes. Very advanced multispectral EO systems, such as ESA's Sentinel-2, already allow deriving valuable information of vegetation properties, e.g., shown by Clevers et al. (2017), Frampton et al. (2013), Herrmann et al. (2011), Vuolo et al. (2016). Nevertheless, hyperspectral sensors, dealing with narrow spectral bands over a continuous spectral range, will be able to detect properties more accurately, especially in the VIS and SWIR domain. Characteristic shapes of individual absorption features caused by diverse biochemical or biophysical plant components may be located spectrally very close to each other. In contrast to hyperspectral data, broadband scanners are not able to resolve the specific wavelength position of these features, which relate for instance to several pigments (anthocyanins, carotenoids) or proteins [see studies from Kokaly et al. (2007), Kokaly and Skidmore (2015), Sahoo et al. (2015), Thenkabail et al. (2000)].

Potentially, all information contained in the spectrum is of interest to farmers. The value of specific variables, i.e. biophysical or biochemical products, for practical precision

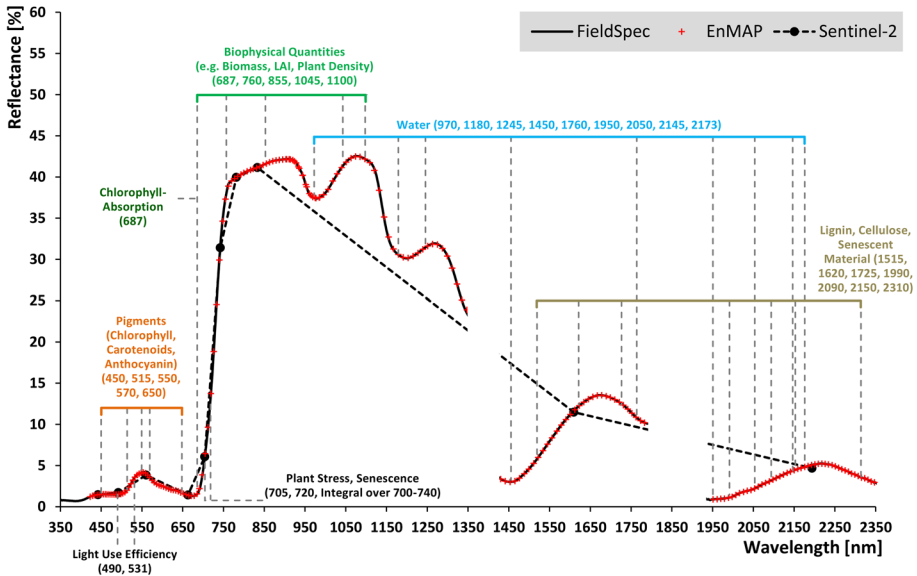


Fig. 3 Spectral domains that respond to changes of specific variables in vegetation [absorption lines modified after Thenkabail et al. (2013)]. The vital vegetation (*Triticum aestivum*) spectra in the background are displayed for a quasi-continuous spectral resolution of an ASD FieldSpec4 Standard (black solid line), for a multispectral configuration corresponding to the spectral bands of ESA Sentinel-2 (black dashed line) and for the narrow-band configuration of the future EnMAP Hyperspectral Imager (red crosses). In the case of vital vegetation, specific absorptions of, e.g., cellulose and lignin are obscured by water absorptions in the SWIR and only can be detected when the crop is senescing (see Fig. 4)

farming depends on the scientist’s capabilities of retrieving a variable with adequate precision. In order to unlock the information contained in the hyperspectral readings as biophysical and biochemical products for precision farming purposes, several steps are required. This includes the choice of a suitable and capable retrieval method that also accounts for measurement errors of the radiometric data (sensor noise) and field validation data (sampling errors, natural heterogeneity; Baret and Buis 2008). The retrieval process further deals with complex reflectance anisotropies (Walthall 1997), discriminates the signal of overlapping absorption features and finally yet importantly follows the direct relation between cause and effect. For this purpose, physical laws were established inferring biophysical and biochemical variables based on specific knowledge, typically obtained with radiative transfer functions (Verrelst et al. 2015).

The abundance of information that can potentially be derived from vegetation spectra has to be carefully selected for applications in agricultural practice. In short, remotely measured information that is of direct relevance for practical farming should meet four criteria:

1. The derived information must be biophysical/biochemical in the sense that it can be described in physical units: “In particular, the broader availability of air- and space-borne directional imaging spectrometer data supports the estimation of biophysical and biochemical variables with unprecedented accuracy and in calibrated physical units...” (Schaeppman et al. 2005). Relative measures, as they are, e.g., derived via vegetation

- indices, are of marginal help in agricultural practice, because comparability and transferability are limited (Baret and Buis 2008).
2. The derived information must be directly observable in the spectrum. This means that a direct relation between state variable and the reflectance in a specific spectral domain exists, which can be analysed using different retrieval methods (for a review, see Verrelst et al. 2015).
 3. The derived information must be retrievable at a generalized level independent from specific cultivars, because cultivars in most cases are not known to the analysers and thus cannot be taken into account during the retrieval. Generalization capabilities of inversion/retrieval methods are discussed by Durbha et al. (2007) and Kimes et al. (2000).
 4. The derived information must be of importance for practical farming (Moran et al. 1997).

The following section aims to identify the biophysical and biochemical variables that are relevant for practical farming according to the criteria mentioned above. The variables are described and their importance for practical precision farming is elaborated. Section 3.1 describes the biochemical leaf (canopy) variables, Sect. 3.2 the canopy biophysical variables and Sect. 3.3 is dedicated to the two variables soil and land use.

3 Overview of Biophysical and Biochemical Variables with Direct Relevance for Practical Farming

Providing an overview of the diversity of agriculturally relevant information addressed in the context of this review paper, Table 1 lists the different variables together with their most commonly used physical units, highlights the variable's respective use in practical farming and compares field and remote sampling techniques with special emphasis on the benefits expected from imaging spectroscopy. Note that the variables and retrieval techniques listed in Table 1 primarily apply to homogeneous crop farming. With this, we refer to uniformly cultivated fields at least in the size of several pixels captured by imaging spectrometers. For smallholder farming and geometrically complex crops, other scanning techniques, such as unmanned aerial vehicles (UAV) or low-altitude manned aircrafts, are more appropriate and different types of variables can be derived from such high spatial resolution imagery.

3.1 Leaf and Canopy Biochemical Variables

3.1.1 Leaf/Canopy Chlorophyll Content

Leaf chlorophyll content (LCC) usually is measured in units of μg chlorophyll per cm^2 leaf area, whereas canopy chlorophyll content (CCC) is measured in g chlorophyll per m^2 ground area. Both variables indicate the presence of chlorophyll pigments in vegetation. Since chlorophyll is the pigment responsible for the absorption of energy, the abundance of chlorophyll indicates the potential of a plant cell to provide energy for photosynthetic processes and thus forms the basis for vegetation growth on the Earth's surface (Peng et al. 2017). Leaf chlorophyll content and canopy chlorophyll content are one of the most important variables for farming. Because chlorophyll molecules are constructed with the help of four nitrogen atoms in the chlorine-magnesium ligand, a direct relation between the nitrogen supply and the accumulation of chlorophyll exists. CCC was therefore recognized as a

Table 1 Biochemical and biophysical variables with relevance for agricultural management, which are measured by optical Earth Observation, including their most commonly used physical units, their use in practical farming, common field sampling techniques and the potential of hyperspectral measurements for their retrieval

Variable	Definition	Physical unit	Use in farming	Field sampling technique	Potential of hyperspectral sensing
<i>Canopy/leaf biochemical variables</i>					
LCC/CCC	Leaf/Canopy Chlorophyll Content	[$\mu\text{g cm}^{-2}$ leaf surface] [g m^{-2} canopy surface]	Nutrient monitoring	Destructive: extraction via organic solvents Non-destructive: SPAD ¹ CCC: LCC multiplied with leaf area index (LAI), measured with LI-COR ²	Continuous sampling of VIS and red edge leads to better discrimination of different pigments
C _{ex}	Leaf carotenoid content	[$\mu\text{g cm}^{-2}$ leaf surface]	Nutrient monitoring	Destructive: extraction via organic solvents	Continuous sampling of blue and red edge spectral domains leads to better discrimination of different pigments
C _{ANTH}	Leaf anthocyanin content	[$\mu\text{g cm}^{-2}$ leaf surface]	Disease monitoring, air pollution	Liquid chromatography in the laboratory	Pigment content can only be measured by sensors with high spectral resolution in the VIS
Cp/N	Leaf protein content/nitrogen content	[$\mu\text{g cm}^{-2}$ leaf surface]/%	Fertilization planning, growth regulation	Dumas combustion/Kjeldahl digestion method (nitrogen)	Canopy chlorophyll content is a proxy of canopy N during vegetative phase. Exploitation of protein absorption features in the SWIR still not fully explored
LMA	Leaf Mass Area	[kg m^{-2} leaf surface]	Growth modelling, phenological monitoring	Cutting and drying until constant weight, Planimetry	Can only be assessed via spectral models, which per se are of a hyperspectral nature
EWT/CWC	Equivalent Water Thickness, Canopy water content	[mm]	Maturation monitoring, Irrigation monitoring in humid environments	Cutting and drying until constant weight	Hyperspectral observations of the different water absorption features allow discriminating the three phases of water: gas, liquid, ice

Table 1 (continued)

Variable	Definition	Physical unit	Use in farming	Field sampling technique	Potential of hyperspectral sensing
NPV	Non-photosynthetically active vegetation (lignin + cellulose)	Relative change	Crop residue assessment (Carbon/Nitrogen storage), crop response to seasonal and long-term drought	Cutting, drying and weighing	Spectral resolution ≤ 15 nm in the SWIR required to resolve cellulose and lignin absorption features
<i>Canopy biophysical variables</i>					
LAI	Leaf Area Index	[m ² leaf surface m ⁻² ground surface]	Biomass monitoring	Destructive: Leaf traps, leaf scanning Non-destructive: Li-Cor	Continuous sampling in red edge and NIR regions provides required retrieval accuracy: Discrimination of structural and chemical variables is improved Discrimination of angular effects is improved Hyperspectral approaches reduce ambiguity in retrieval
ALA	Average Leaf inclination Angle	[°]	Phenological monitoring/drought monitoring	Inclinometer, high-resolution horizontal photograph interpretation	Hyperspectral approaches reduce ambiguity in retrieval
Albedo	Average surface reflectivity	[%]	Energy balance modelling	Double pyranometer	Continuous spectrum can be integrated
fCOVER	Fractional Cover	[%]	Erosion monitoring	Vertical photographs, planimetry	Hyperspectral approaches reduce ambiguity in spectral unmixing
fAPAR	Fraction of absorbed photosynthetically active radiation	[%]	Growth modelling, nutrient monitoring, Phenological monitoring	Line quantum sensors	Hyperspectral observations allow for integrating over the photosynthetically active spectral range.
SIF	Sun induced chlorophyll fluorescence	[mW m ⁻² sr ⁻¹ nm ⁻¹]	Multiple stress monitoring	Field spectroscopy	Impossible with multispectral sensors. Hyperspectral observation systems with < 3 nm spectral resolution required

Table 1 (continued)

Variable	Definition	Physical unit	Use in farming	Field sampling technique	Potential of hyperspectral sensing
<i>Soil and land cover variables</i>					
LULC	Land use/land cover	[class]	Documentation	Field mapping, statistics	Better discrimination of cultivars through precise spectral measurements
SOC	Soil organic carbon content	[%]	Nutrient modelling	Destructive laboratory analysis	Water absorptions must be resolved to discriminate between soil moisture and soil organic carbon content

¹SPAD-502Plus handheld non-destructive Chlorophyll-Meter by Konica Minolta Business Solutions Inc.

²LAI-2200C handheld non-destructive Plant Canopy Analyzer by LICOR Biosciences Inc.

valid proxy for canopy nitrogen content (Baret et al. 2007; Clevers and Gitelson 2013) and crop primary production (e.g., Gitelson et al. 2006; Peng et al. 2011). Increasing levels of chlorophyll in the crop indicate the amount of nitrogen that has successfully entered the canopy and thus has contributed to the construction of proteins and light-harvesting pigments. This balance is summarized under the term nitrogen use efficiency (NUE). Rapidly generating high levels of chlorophyll content thus has ecological and economic advantages. On the other hand, over-fertilization can result in unhealthy accumulation of chlorophyll in the leaves, i.e. necrosis, or in weakened structural stability, i.e. lodging, which again inhibits growth. Hyperspectral sensors, due to their continuous sampling of the VIS and red edge spectral domain, are ideally suited to measure leaf chlorophyll content (Gitelson et al. 2003), which is the reason why spectrometers are the tool predominantly used for chlorophyll measurements in laboratory analysis, where the easily soluble chlorophyll can be extracted from the plant tissue using organic solvents (Parry et al. 2014). Satellites, however, observe the canopy as a whole from above. This synoptic view of the canopy is accompanied by ambiguity problems, since for specific spectral domains interaction effects among multiple vegetation traits on measured reflectance exist (Combal et al. 2003). From a practical farming point of view, the leaf chlorophyll content is the most important information for planning fertilization measures during the vegetative phase (Arregui et al. 2006). The challenge remains to discern between structural and chemical traits of the canopy (e.g., Daughtry et al. 2000; Haboudane et al. 2002). This can only be achieved through hierarchical retrieval methods, which take the continuous spectrum into account and where structural canopy properties are determined first and chemical properties are delineated through secondary retrieval iterations, (e.g., Danner et al. 2017).

3.1.2 Total Leaf Carotenoid Content

The total carotenoid content of leaves (Car) is mainly composed of the xanthophyll cycle pigments and carotenes. They play an important role in photoprotection, accessory light harvesting and energy transfer (Gitelson et al. 2002; Kong et al. 2017). Carotenoids are present in variable proportions during the differentiation and ageing of leaves, but abiotic stress can inhibit carotenoid production. This includes, for instance, ozone or sulphur dioxide air pollution (Agrawal et al. 1982), heavy metals (Panda et al. 2003), viral attacks (Ibdah et al. 2014) or water deficiency (Mibei et al. 2017). Therefore, carotenoids may serve as indicators for down-regulation of photosynthesis due to environmental stressors.

A review study by Blackburn (2007) confirmed the growing value of hyperspectral remote sensing for plant pigment estimations in ecophysiology, environmental, agricultural and forestry sciences. Extraction of biochemical properties has been accomplished from hyperspectral data using various methods. Thereby the presence of carotenoids is commonly expressed in different units, e.g., as mass per unit surface area (g m^{-2}), as mass per unit leaf area (g cm^{-2}), or as mass per unit fresh leaf weight (mg g^{-1}) e.g., by Yi et al. (2014).

Compared to leaf chlorophyll, there are much fewer studies estimating leaf carotenoid content (Yi et al. 2014) and even less dealing with agricultural crops. Generally, the benefit of hyperspectral data for separating the subtle signals of the different pigments was recognized by several studies (Blackburn 1998; Chappelle et al. 1992; Feret et al. 2008).

3.1.3 Total Leaf Anthocyanin Content

Anthocyanins are the most common class of flavonoids. They are responsible for the orange to red, or purple to blue coloration in the tissue depending on the molecule, temperature and pH value, as it can be found, for instance, in blueberry, raspberry, black rice or black soybean (Tanaka et al. 2008). From all the red pigments, including carotenoids and betalains, anthocyanins are the most widespread. Though the full role of anthocyanins still is not completely understood, some essential functions of these pigments have been identified, such as protection against photoinhibition from intense light and mitigation of environmental stresses such as freezing or air pollution. In crops, anthocyanins typically are present when the plants are suffering from drought, freezing or nutrient deficiency (Lee and Gould 2002; Springob et al. 2003).

Leaf anthocyanin content was introduced in the latest version of the leaf optical properties model PROSPECT-D (Féret et al. 2017). The model simulates directional–hemispherical reflectance and transmittance for the spectral range from 400 to 2500 nm and, besides the anthocyanin content, requires leaf chlorophyll content, a leaf structure parameter, carotenoid content, brown pigments, equivalent water thickness and leaf mass per unit area as inputs. Variables can be retrieved from measured leaf spectra by model inversion or from canopy spectra by coupling PROSPECT-D with a radiative transfer model, such as 4SAIL (Jacquemoud et al. 2009; Verhoef and Bach 2003). The use of the model for anthocyanin retrieval is limited to hyperspectral data with high spectral resolution in the VIS spectral domain. The use of narrow-band vegetation indices allows quite accurate retrieval of anthocyanin content against the background of very variable chlorophyll content (Gitelson and Solovchenko 2017; Gitelson et al. 2001, 2009).

3.1.4 Leaf Protein Content/Nitrogen Content

With rubisco accounting for 30–50% of nitrogen (N) in green leaves, proteins are the principal N-containing biochemical constituent of plants (Kokaly et al. 2009). Nitrogen, on the other hand, is probably the most important nutrient that plants acquire from the soil. A proper management of nitrogen is a prerequisite for sustainable fertilization in modern agriculture: optimal crop yield from, e.g., high-quality grains, can only be obtained with high uptakes of N (Barraclough et al. 2010). Nitrogen deficiency leads to decreased photosynthetic assimilation and to reduced crop yield in terms of quantity and quality (Jay et al. 2017). Hyperspectral data have been recognized as a promising tool for the non-destructive detection of crop nitrogen for several reasons: the wavelengths important for nitrogen estimation have been found over the whole spectrum due to correlation between nitrogen and other variables (Curran 1989; Homolová et al. 2013). The absorption features of nitrogen-containing biochemical leaf components, such as LCC (6.5% by weight) and proteins may serve as proxies for crop N. The chlorophyll absorption features in the VIS and red edge can be used for nitrogen estimation due to a close relationship of LCC to N during early growth stages (le Maire et al. 2008). During senescence, however, the decomposition of light-harvesting pigments and the translocation of N from leaves, stems and roots lead to gradual changes in the spectral signal of VIS and NIR without being connected to significant changes of total N in the plant. Moving away from the leaf level perspective towards the integration of the full canopy within a specified surface, area acted as a normalization factor, improving the N versus Chl relationship. A very strong linear relationship was established across growing seasons between maize N and Chl contents at the canopy level

(Schlemmer et al. 2013). While monitoring crop nitrogen uptake during the early vegetative growth phases is of major importance for the planning of fertilization measures, nitrogen monitoring during senescent growth stages provides valuable information on yield quality. Continuous information of crop nitrogen during the different growth stages would consequently be of high economic impact. Absorption features of proteins can be found in the SWIR. Recently, protein absorption coefficients also have been integrated into leaf reflectance models and first applications for woody and herbaceous species have been explored (Wang et al. 2015). However, protein absorptions are very shallow and are largely obscured by water absorption features, so that measuring protein content from crop canopies with spectroscopy remains a challenge.

3.1.5 Leaf Mass Area

Leaf Mass Area (LMA) denotes the relation of leaf mass to leaf area in a unit of kg dry matter per m² leaf area. In some publications also its reverse is used, i.e. specific leaf area (SLA, leaf area per unit dry mass; e.g., Ali et al. 2017). This fundamental leaf functional trait plays a key role in ecosystem modelling (Ali et al. 2017; Asner et al. 2011). LMA is a measure of the leaf composition: the first leaves developed by a plant at the beginning of its individual growth cycle usually are rather lightweight, so that the area available for the interception of solar radiation expands rapidly during early growth phases. During later development stages, plants tend to invest more biomass into the structural stability of the leaves, causing the LMA to increase over the course of a growing period and, depending on the crop type, also with increasing LAI of the canopy. However, this process is highly crop-specific and can only be observed through labour-intensive destructive measurements, so that only few data on this variable exist.

LMA is an essential indicator of plant functioning, including photosynthetic and respiratory rates, chemical composition or resistance to herbivory (de la Riva et al. 2016). The importance of LMA for farming compared to the other variables is therefore rather indirect but nonetheless important, in particular regarding the relationship of LMA to photosynthesis–nitrogen relationships (Poorter and Evans 1998).

The spectral recognition of LMA is difficult, because the effect caused by increasing LMA in the leaf reflectance spectrum results in a gradual decrease in reflectance in the NIR shoulder region. A similar effect is achieved by the variations of other structural canopy variables, such as LAI and ALA, and is influenced by illumination/viewing angles. Consequently, a study by Asner et al. (2011) demonstrated that the best-suited wavelengths for accurate LMA determination are found in sections of the spectrum, where the overlap effects with other variables are less pronounced, i.e. in the shortwave-infrared (SWIR) between 1900 and 2500 nm and from 1300 to 1700 nm, as well as in the visible region from 400 to 800 nm. A derivation of LMA from spectral measurements thus is only possible if (1) the full spectrum is taken into account, and (2) all potentially confounding variables are retrieved simultaneously. This can best be achieved through inversion of canopy reflectance models exploiting the full spectral data cube, such as PROSAIL (Jacquemoud et al. 2009) or SLC (Migdall et al. 2009; Verhoef and Bach 2007).

3.1.6 Equivalent Water Thickness/Canopy Water Content

The variable Equivalent Water Thickness (EWT) or leaf water content describes the thickness of a theoretical layer of water (in cm), which absorbs radiation according to

the Lambert–Beer law (Nobel 2009). Thus, EWT corresponds to the volume of water that is stored within the cells of living vegetation.

A well-known problem is the decoupling of the spectral signal of the three different aggregate states of water, which is necessary for a correct retrieval of EWT. A study showed that the use of hyperspectral data can strongly support the simultaneous estimation of the abundance of gaseous, liquid and frozen water for a defined environment (Green et al. 2006). The authors obtained uncertainties $< 1.5\%$ for all three phases, but there were still problems in retrieving the liquid water in vegetation, making more research in this domain necessary.

For a remote sensor with a defined field of view, it is difficult to decouple the contributions of leaf water content and LAI. Thus, the total canopy water content per unit ground area (CWC, g m^{-2}), rather than leaf EWT is usually “observed” or retrieved (Clevers et al. 2010). CWC is a measure for the moisture state of a canopy, which is of interest for practical farming in two aspects:

First, CWC is a variable that describes the maturity state of a crop. Depending on the crop type, crops are harvested at specific thresholds of residual moisture (e.g., Peters 2012). This guarantees optimal storage stability and documents the yield quality in the sense of the true net weight of the harvest. Assessing the residual moisture in a spatially explicit way through remote sensing enables farmers to develop harvesting strategies, e.g., which field or which part of a field to harvest first, and to document the quality of the harvest. Actually, modern harvesting systems already are measuring residual moisture during the harvesting process with infrared sensors installed in combine harvesters (Peters 2012). However, the proximity of the measurement leads to failures, such as clogging of the grain elevators, and the sampling occurs more or less at random and not in a spatially comprehensive way, so that these measurements still are of limited use. Deriving spatial maps, which describe the temporal dynamics of residual moisture based on satellite data, thus would be of high interest for practical farming.

Secondly, CWC can be used to monitor irrigation, which causes significant environmental changes in many parts of the world. Precise information on the extent of irrigation measures is fundamental for global change research, where, e.g., water exchange between the land surface and the atmosphere is explicitly modelled to assess impacts on global food security (Ozdogan et al. 2010). In arid environments, irrigation can be easily detected, because vegetation only prevails in irrigated areas. In humid environments, such as the temperate zone or even within the boundaries of irrigated fields, however, detecting irrigation becomes more difficult (Ozdogan et al. 2010). Only few studies have approached the problem of irrigated area mapping in humid areas (e.g., Thenkabail et al. 2005). Although CWC and EWT are directly connected to the water supply state of crops and the use of CWC or EWT to monitor drought seems rational, the variable may not be directly suited as early drought indicator. This is due to the fact that one of the earliest reactions of plants to water deficit is the maintenance of EWT through stomatal control (Yang and Ling 2004). A decline in EWT, as it can be detected with hyperspectral sensors, thus can be used to document the dehydration of the tissue, but the signal would be detected at a too late point in time to initiate counter management measures. Thermal imaging systems are far better suited to indicate early signs of drought based on the leaf energy balance (Prashar and Jones 2016). For instance, the crop water stress index (CWSI) proved to detect drought stress earlier than EWT estimates (Yang and Ling 2004).

3.1.7 Non-photosynthetically Active Vegetation (Lignin + Cellulose)

Non-photosynthetically active vegetation (NPV) elements refer to vegetation compounds that cannot perform photosynthesis, such as plant litter, crop residues, senescing foliage, branches and stems (Zhaoqin and Xulin 2015). NPV is mainly composed of lignin, cellulose and starch, being the most abundant molecules produced by terrestrial photosynthesis. Therefore, the importance of estimating NPV, or vegetation brownness, for understanding terrestrial ecosystem dynamics and changes is evident (Dennison et al. 2016; Okin 2010). For agricultural applications, NPV is particularly interesting in three aspects: (1) Variations in NPV—or the ratio of vital to senescent foliage—can indicate (seasonal) drought events. (2) Non-photosynthetic crop residues on the soil surface significantly reduce soil erosion and enhance soil organic C through improvement of the soil structure. (3) Non-photosynthetic crop residues may contain significant amounts of nitrogen, which enter the soil through ploughing and which must be taken into account when balancing the nitrogen inputs during the following season.

Effective crop residue management systems therefore require rapid site-specific quantification of crop residues over large areas, which can only be obtained with the help of remote sensing technologies (Daughtry et al. 2005). Several studies developed hyperspectral indices for NPV estimation, which are based on the absorption features of cellulose and lignin in the SWIR. For a review of the topic, e.g., see Zhaoqin and Xulin (2015). Comparable to the nitrogen absorption features, the cellulose and lignin absorptions overlap with other variables, e.g., with atmospheric water vapour, and thus must be analysed with high spectral resolution in the SWIR. Figure 4 shows that spectral signatures of soil and NPV, depending on the soil brightness, may appear very similar in VIS and NIR (Fig. 4a, c) or in the SWIR (Fig. 4b, c), respectively. The narrow cellulose absorptions in the SWIR, which cannot be discriminated by broadband sensors (dots in Fig. 4), must be resolved to discriminate between soil and crop residues.

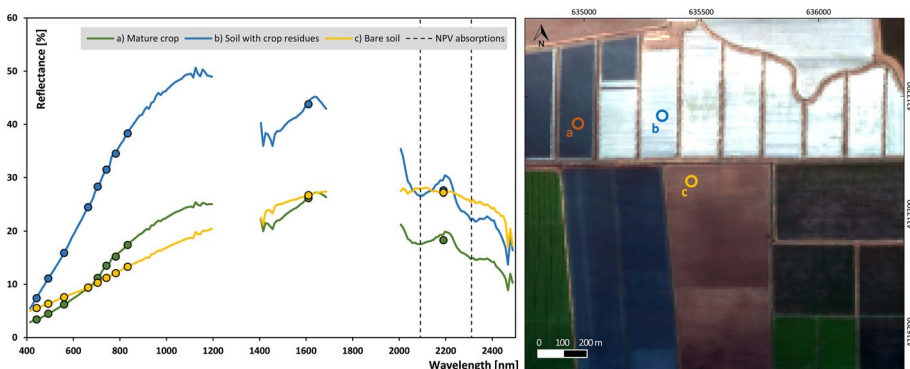


Fig. 4 Comparison of spectral signatures of senescent cereals (a), crop residues (b) and bare soil (c). The spectra were recorded by the airborne spectrometer AVIRIS (AVIRIS-NG acquisition from 09 October 2016, displayed in true colour, https://avirisng.jpl.nasa.gov/alt_locator/, downloaded 14 February 2018). The dots indicate the reflectance signal, if the AVIRIS spectrum is degraded according to the spectral response function of the Sentinel-2 MSI. It can be observed that high spectral resolution in the SWIR is required to discriminate between non-photosynthetic biomass and soil via the lignin and cellulose absorptions at 2090 and 2310 nm

3.2 Canopy Biophysical Variables

3.2.1 Leaf Area Index

Leaf Area Index (LAI) denotes the one-sided leaf surface area per square metre ground area, as firstly defined by Watson (1947). LAI has a physical unit of m^2 leaf surface per m^2 ground surface and therefore is a dimensionless quantity. This variable is of specific importance for practical farming, since LAI defines the leaf surface that is available for exchange processes between the leaf mesophyll and the atmosphere. The entire flux of CO_2 and O_2 as well as the absorption and emission of radiative energy are scaled via the LAI (Breda 2003). LAI therefore is an important input variable for carbon assimilation models and it helps identifying phenological progress (e.g., Savoy and Mackay 2015), and the accumulation of biomass (e.g., Hank et al. 2015; Vaesen et al. 2001).

For definition, the variable LAI considers the entire leaf surface regardless of the leaf state. LAI therefore must be distinguished from green LAI, which only takes the photosynthetically active leaf surface (i.e. the parts of the canopy that are characterized by the presence of chlorophyll) into account (Haboudane et al. 2004). Additional confusion may arise from using Plant Area Index (PAI; Jonckheere et al. 2004). While the LAI by definition is limited to the leaf fraction of canopies, the PAI takes into account that also stems and fruits contribute to the canopy surface and, at least during some phenological phases, also bear chlorophyll and stomata. Remote sensors, observing the canopy from a large distance, receive mixed signals from all components of the canopy. Moreover, the possible non-random position of all canopy elements, called “clumping effect”, influences the spectral signal. Without correcting for clumping, the green LAI or PAI should be considered as effective LAI (or PAI; Chen and Black 1992; Richter et al. 2009). Nevertheless, the leaf surface normally is the most prominently visible physiological element and hence optical sensors are well suited to measure LAI (Jonckheere et al. 2004; Zheng and Moskal 2009). Variations in LAI cause variations in reflectance in visible, red edge and the NIR spectral domains (Berger et al. 2018; Richter et al. 2012; Viña et al. 2011). The more leaf layers are stacked on top of each other, the higher the reflectance in the NIR will become until saturation occurs (Neuwirthová et al. 2017). LAI retrieval methods consequently are based on quantifying the height of the NIR shoulder. Empirical relations between Normalized Difference Vegetation Index (NDVI; Rouse et al. 1973) or similar indices and LAI have been established in the past, which may seem valid for early vegetative growth stages, where LAI and chlorophyll content develop simultaneously. However, a better and more direct estimation of LAI is possible when red edge and NIR (Kira et al. 2016, 2017; Richter et al. 2012; Viña et al. 2011) and the SWIR domain, which provides information on cellulose accumulation (Jacquemoud et al. 1996), are analysed simultaneously.

Hyperspectral systems, together with physically based or hybrid retrieval methods, can help to improve the estimation accuracy of LAI by providing simultaneous sampling of the chlorophyll absorption, the red edge, the NIR shoulder and the SWIR (Lee et al. 2004; Liu et al. 2016). This allows assessing the variable LAI directly and discriminating the structural variable LAI from the biochemical variable leaf chlorophyll content (LCC). It has to be noted that rather precise LAI mapping is also possible with advanced multispectral observation systems, such as ESA’s Sentinel-2 Multispectral Imager (MSI), which also covers the spectral domain that is important for measuring LAI. For precise LAI mapping it nonetheless is important that the observation and illumination geometry is well known, because the spectral signals of LAI and observation angle overlap strongly in the NIR

shoulder region. Consequently, only retrieval methods that are capable of considering non-linear angular effects are suited for LAI retrieval, such as the inversion of canopy reflectance models. These models, among them the PROSAIL model being the most prominently applied model in the last years for (agricultural) vegetation studies (Berger et al. 2018; Jacquemoud et al. 2009), originally are of a hyperspectral nature, because they have been developed based on laboratory spectroscopy. Using hyperspectral observation systems in combination with hyperspectral canopy reflectance models thus is expected to improve the stability of LAI mapping from time-series observations, which usually are composed of images with different observation and illumination angles.

3.2.2 Average Leaf Inclination Angle

The flux of solar radiation per unit leaf area is directly determined by the angle of a leaf's surface to the horizontal, i.e. the leaf angle. Whereas steeper leaf angles enhance the light capture during low solar zenith angles (early morning/late afternoon and winter), they decrease the light absorption during higher solar zenith angles (midday and summer; Falster and Westoby 2003). Therefore, the leaf angle is one of the essential factors for plant thermoregulation, avoiding overheating during midday/summer, while at the same time increasing water use efficiency (King 1997).

The leaf inclination angle distribution (LAD) is commonly categorized into six typical types: spherical, planophile, erectophile, uniform, extremophile or plagiophile (Liang 2003). Several mathematical functions, i.e. leaf inclination distribution functions (LIDF), have been proposed to describe LAD, such as polynomial, ellipsoidal or elliptic distribution, which in turn can be characterized by the average leaf inclination angle (ALA; Jacquemoud et al. 2000). In particular, the ellipsoidal function has been successfully implemented for the SAIL model (Jacquemoud et al. 2000). ALA and LAD also show dynamic behaviour both in diurnal and seasonal cycles, while they may also vary in different canopy layers. In the early morning hours, leaves tend to be more horizontally inclined. Under the influence of sunlight, the transpiration stream in the xylem is activated and the leaves assume a more erect position due to increased cell turgor. Seasonally, growing plants initially penetrate the Earth's surface with vertically inclined leaves. The leaf angle then gradually declines with progressing phenology until the leaves eventually go limp, either temporarily in phases of drought, or finally when the plant matures.

ALA is of prominent interest for farming because measuring leaf angles helps keeping track of the phenological development and potentially allows detecting drought situations (Zhou et al. 2017). Due to its impact on radiative transfer, it also is a very important input parameter for surface energy balance modelling, which is a prerequisite for growth modelling.

Increasing leaf angles lead to reduced reflectance in the NIR shoulder region. This spectral effect is similar to that of decreasing LAI, so that the discrimination of ALA and LAI induced effects on canopy reflectance is difficult (Atzberger 2004). Both structural variables are the dominant drivers of canopy reflectance with the exception of soil reflectance in sparse canopies. However, hyperspectral sensors that equally resolve the NIR shoulder and the far SWIR potentially can help to discriminate these two vegetation traits.

3.2.3 Albedo

The albedo of (vegetated) land surfaces is a non-dimensional ratio of the radiation flux reflected from a surface unit into the whole hemisphere and the incoming irradiance from the upper hemisphere (CEOS 2017). Technically, albedo is known as the bi-hemispherical reflectance factor (BHR; Schaepman-Strub et al. 2006), with a value range from 0 to 1. Albedo belongs to the group of Essential Climate Variables (ECV) as defined by the Global Climate Observing System (GCOS) and requires measurement uncertainty of maximal 5% (0.0025) for climate change monitoring purposes.

Moreover, albedo is an essential input parameter for the calculation of evapotranspiration (ET; Su 2002). ET, combining evaporation and transpiration fluxes from the vegetated surface to the atmosphere, plays a key role in the water and energy balance on the Earth's surface and thus is of particular interest for agriculture regarding irrigation management (D'Urso et al. 2010). The advantage of hyperspectral satellite data in estimating surface broadband albedo can be found in the continuous sampling of the electromagnetic spectrum.

3.2.4 Fractional Vegetation Cover

The fractional vegetation cover (fCover) corresponds to the complement of the gap fraction in nadir direction (Weiss et al. 2000). FCover is intrinsic to the vegetation canopy implying that it does not depend on illumination geometry. Since fCover belongs to the group of the main biophysical variables and is involved in agriculturally relevant surface processes such as erosion or interception of precipitation, it sometimes can be considered as an indicator of land degradation and thus is important for regional and global climate (change) modeling, and global change monitoring (Jiménez-Muñoz et al. 2009). Fractional cover is a variable that normally becomes visible at scales below the geometric resolution of optical sensors (e.g., Gitelson 2013). Delineation of fractional cover therefore is a prominent example for spectral unmixing techniques, where hyperspectral data provide improved unambiguity compared to multispectral data, as has been demonstrated for example by Asner and Heidebrecht (2002).

3.2.5 Fraction of Absorbed Photosynthetically Active Radiation

The fraction of absorbed photosynthetically active radiation (fAPAR) constitutes a key variable for the energy and carbon balance of ecosystems for various temporal and spatial scales (Gobron and Verstraete 2009). fAPAR depends on canopy structure, optical properties of plant components and on illumination conditions and is very useful as input to a number of primary production models and thus to agricultural information systems.

Today, several operational coarse resolution fAPAR products are available, approximating the daily-integrated value (e.g., the 10:30 solar time instantaneous black-sky fAPAR at time of sensor overpass). NASA, for instance, provides MODIS/TERRA fAPAR Collection 5 products (MOD15A2) continuously since 2000 through the U.S. Geological Survey portal (Martínez et al. 2013).

The use of hyperspectral data for fAPAR delineation seems logical, because only continuous spectral sampling over the VIS spectral domain can measure the amount of radiation that is absorbed by the leaf. Since fAPAR and fCover are secondary variables, which

are calculated from primary state variables such as LAI and LCC describing structure and optical properties of leaves and canopy (Weiss et al. 2000), highly accurate estimations of primary state variables from hyperspectral data also contribute to improved information on secondary variables.

3.2.6 Solar-Induced Fluorescence

Solar radiative energy absorbed by chlorophyll molecules in leaves will exit the leaf again via three main de-excitation mechanisms: (1) driving photosynthesis, (2) excess energy dissipation as heat or (3) re-emission in the form of chlorophyll fluorescence (ChlF; Maxwell and Johnson 2000). Since these three mechanisms are coupled, ChlF emitted by vegetation can be seen as indicator of the instantaneous plant photosynthetic functioning (e.g., carbon fixation). ChlF carries information on LUE and therefore captures the dynamic behaviour of photosynthesis, or gross primary productivity (GPP), at the relevant scale (Porcar-Castell et al. 2014; Zarco-Tejada et al. 2013a, 2016). Indirectly, ChlF can be used to detect stress in the actual functional status of vegetation before a response in LCC or LAI becomes visible (Meroni et al. 2009). Remote sensing techniques offer the unique ability to assess photosynthesis continuously over large areas by quantifying solar-induced chlorophyll fluorescence (SIF) from satellite or airborne platforms. Unfortunately, the signal is very small compared to land surface reflectance, so that the radiometric sensitivity of the sensors in most cases limits the geometric resolution of SIF that can be achieved. Due to that, the use of unmanned aerial vehicles (UAV) for near-range SIF sensing is promising for some agricultural applications: e.g., key drought-related variables could be obtained via ChlF signals using a micro-hyperspectral imager on board a UAV (Murchie and Lawson 2013; Zarco-Tejada et al. 2012). Moreover, ChlF imaging is recognized as a well-established effective tool for the assessment of bacterial, fungal and viral infections on crop leaves (Bauriegel et al. 2011). For a comprehensive review of the topic see Meroni et al. (2009). Multispectral systems are not able to provide appropriate SIF signals for land surface applications, because the SIF signal is obscured by the bright reflectance of the land surface in the far red. To discriminate the SIF signal, very high spectral resolution is required to measure the fluorescence spectrum within the two oxygen absorption bands (O_2A and O_2B), where interference with land surface reflectance is avoided. Data of this kind will for instance be provided by the FLEX (Fluorescence Explorer) mission. The FLORIS (Fluorescence Imaging Spectrometer) instrument on FLEX will provide very high spectral resolution data with 0.3 nm in the spectral domain of the oxygen absorption bands (Coppo et al. 2017). To discriminate the different energy pathways in the leaf, also leaf temperature and the amount of absorbed photosynthetically active radiation (APAR) must be measured. While the temperature measurements can be provided by thermal imagers, e.g., in the case of FLEX this is achieved through a tandem orbit with Sentinel-3, APAR can be measured via spectroscopy. Remote measurements of photosynthetic activity via SIF therefore combine high spectral resolution and spectrally continuous sampling and thus are a true and exclusive hyperspectral application.

Currently, the limited spatial resolution of spaceborne SIF instruments—the future FLEX mission, for instance, will provide 300 m geometric resolution—does not allow small-scale precision farming applications of SIF products. Newest findings, however, reveal that SIF can potentially be used to discriminate between different sources of crop stress, e.g., water-, temperature-, nitrogen-stress (Ač et al. 2015), making SIF measurements one of the most promising future applications in precision farming. To optimally

exploit SIF signals from large areas for practical farming, future hyperspectral satellite sensors should aim to simultaneously provide adequate high spectral (~ 0.3 nm) and high spatial resolution (~ 20 m).

3.3 Soil and Land Cover Variables

3.3.1 Soil Organic Carbon Content

Soil organic carbon (SOC) content is a key soil property. Hyperspectral remote sensing of SOC effectively supports the identification of several environmental concerns, such as soil erosion (e.g., caused by tillage), salinity or soil contamination (Vaudour et al. 2016). Numerous studies have demonstrated the usefulness of imaging spectroscopy to predict SOC compared to time-consuming field-based methods (Castaldi et al. 2018; Forkuor et al. 2017). A good overview of the use of airborne hyperspectral imagery for the monitoring of SOC contents at within-field scale is given by Vaudour et al. (2016).

3.3.2 Land Use/Land Cover

The ability of hyperspectral sensors to differentiate terrestrial features by unique spectral signatures is very valuable for classifying distinct land use/cover features, in particular of the vegetative (cropped) surface. Accurate and detailed land use and land cover monitoring is a prerequisite for documenting farming activities such as crop rotation, or intertillage in particular for large agricultural areas. Several studies exploited hyperspectral data capabilities for agricultural land cover classifications and found improvements over multispectral data (Thenkabail et al. 2004). From a practical farming point of view, increased information depth of land cover maps is of particular interest. Hyperspectral sensors providing detailed spectral analysis of pigment composition can be a key for species and/or weed discrimination (Sykas et al. 2013).

4 Advantages of Hyperspectral Versus Multispectral Sensing in an Agricultural Context

The rare availability of spaceborne hyperspectral sensors has led to an exchange of arguments between promoters of multispectral and hyperspectral data. Since the construction of hyperspectral sensors compared to multispectral instruments is complicated as well as expensive, users of hyperspectral sensing are encouraged to carefully justify the requirement for high spectral resolution as well as for full spectral coverage for their specific application. While the positive aspects of high spectral resolution can easily be demonstrated for specific applications (e.g., high spectral resolution is needed to discern narrow absorptions of different pigments for vegetation studies, see Sect. 3), the benefits generated from spectrally continuous sampling cannot be explained in such a straightforward way. In some cases, the detection problems in the case of vegetation can indeed be solved by adding one or two very specific bands, while still maintaining a multispectral setup. For instance, the ESA Sentinel-2 MSI was equipped with two extra bands that now can be used to characterize the shape of the chlorophyll absorption. For vegetation science in an agricultural context, the benefits from continuous spectral sampling rather can be found in the fact that the spectral response of different biophysical/

biochemical traits are interacting with each other across different parts of the electromagnetic spectrum. Changes in canopy structure, which can be observed in the NIR/SWIR, will influence the way in which variations in plant chemistry can be observed in the VIS. Constructing observation systems that are capable of tracking only selected parts of the spectrum thus limits the quality of the analysis.

The exhaustive description of variables with relevance for practical farming in Sect. 3 has shown that the number of different traits targeted with remote sensing largely exceeds the number of spectral bands of conventional multispectral sensors. To avoid underdetermined problems, additional spectral measurements are inevitable. Consequently, hyperspectral approaches already have contributed largely to a more effective and more detailed use and exploitation of remotely sensed data in precision agriculture (Nellis et al. 2009). Several studies exploited hyperspectral data capabilities for agricultural land cover classifications. For agricultural crop species discrimination, Thenkabail et al. (2004) found an increase in classification accuracy of up to 43% when using hyperspectral bands compared to broadband Landsat (ETM+). Although there are many examples for improved retrieval accuracy, in some cases hyperspectral data may not provide significant improvement for variable retrieval (Broge and Leblanc 2001; Spanner et al. 1994). Even then, hyperspectral data have large potential to reduce retrieval uncertainties and thus enhance accuracy and stability of the biophysical and biochemical products indirectly. Although some studies confirm this, e.g., Liu et al. (2016), Richter et al. (2012), Verrelst et al. (2016), still more research is needed to properly quantify the gain of hyperspectral measurements compared to multispectral data for specific applications. Generally, advantages of imaging spectroscopy for agriculture can be summarized as follows:

- Higher accuracy of variable retrieval (Lee et al. 2004; Liu et al. 2016);
- Reduced uncertainties in space and time (Ustin et al. 2001);
- Improved automatic interpretation of EO signals by spectrally separating atmosphere, soil, leaves and canopy effects, since ambiguities are reduced;
- Higher accuracy of crop species discrimination (Thenkabail et al. 2004).
- Novel approaches that provide access to variables hidden for multispectral sensors, e.g., SIF.

To make these potentials of hyperspectral data accessible for agricultural management, pre-processing is required to address the problems associated with the high spectral dimensionality provided by hyperspectral sensors: long processing times and the “curse of dimensionality” or Hughes phenomenon. Several approaches exist to solve these issues and to concurrently optimize the retrieval of the variables of interest. In the spectral domain, for instance, feature (band) selection, feature extraction or dimensionality reduction (DR) techniques can be applied (Rivera-Caicedo et al. 2017; van der Maaten et al. 2009). This may include band selection procedures for individual variable retrievals, as for instance performed by Verrelst et al. (2016), who, using two airborne hyperspectral datasets, identified the most sensitive spectral bands for LCC, LAI and CWC measurements. Another example for successful band selection was provided by Thenkabail et al. (2004), who identified a hyperspectral set of optimal bands that best characterize agricultural crop types. The benefits of hyperspectral sensing for crop discrimination can be traced to the fact that different cultivars may show subtle differences in colour (the green colour of the leaves either shifting towards the blue or towards yellowish tones), which cannot be resolved by multispectral sensors. This positive aspect of hyperspectral sensing so far has not been adequately

studied and provides a promising opportunity for more research, once hyperspectral sensing from space becomes operational.

Apart from the discipline-specific advantages listed above, bringing hyperspectral observation systems into orbit also enables the use of one sensor for a wide range of different applications. While high spectral resolution may be required for water analysis above all in the VIS, geological applications will require the same spectral resolution in the SWIR. Vegetation studies again, be it for agricultural applications, for natural ecosystems research, or for combined studies investigating the neighbouring effects of managed and natural vegetation, will require the full range of the spectrum. Instead of constructing a number of different multispectral satellites tuned to either application, a hyperspectral sensor can easily serve different applications and the data may be shared across disciplines following the “one key fits all” principle.

Almost no experience so far exists with the use of spaceborne hyperspectral EO, simply because no operational high-quality system has successfully been installed yet. The new kind of data expected from future hyperspectral spaceborne EO missions may enable the development of innovative analysis methods and applications. Hyperspectral algorithm development for vegetation studies so far has been mostly limited to airborne data, which is very heterogeneous in quality, temporal availability and spatial coverage. Hyperspectral algorithms thus are limited in terms of transferability across sensors and space and cannot make full use of the temporal signal, which is of predominant importance for vegetation studies. The temporal characteristics of vegetation development will perfectly be incorporated in hyperspectral time-series, because spaceborne hyperspectral systems will enable repeated measurements of the reflectance of the Earth’s surface with homogeneous quality and characteristics all around the globe by applying the same instrument at every location (Houborg et al. 2017).

The installation of hyperspectral sensors thereby will not make the construction of multispectral systems obsolete, but rather will trigger new developments also in the multispectral domain. For instance, the adding of specific spectral bands to multispectral observation systems to assist detecting specific phenomena, such as red edge, can be traced back to hyperspectral studies, which have been used to define the position of these bands (Clevers et al. 2001).

Due to the contradicting effects of increased information content, which comes along with increased noise, the margins of increased accuracy may only be small for some variables. However, most of the variables retrieved from remote sensing are not used directly, but rather are assimilated into complex decision support information systems (e.g., Hank et al. 2015). According to the laws of error propagation, even small margins of increased accuracy may reduce uncertainties in a processing chain significantly. Besides that, some variables can only be uniquely addressed with hyperspectral sensors, because narrow-band high-resolution data are required with the ability to discriminate components that may be grouped by multispectral bands (Adão et al. 2017):

- Hyperspectral data offer the possibility to retrieve biochemicals via specific pigments such as chlorophyll, anthocyanins or carotenoids, and thus give farmers access to primary production, pest and disease monitoring.
- Hyperspectral data allow discriminating the absorptions of atmospheric water vapour from those of cellulose and lignin to quantify non-photosynthetic vegetation and thus give farmers access to improved crop residue management.
- Hyperspectral data support the discrimination of the three phases of water (ice, liquid, gas; Green et al. 2006) and thus give farmers access to plant water status monitoring.

- Hyperspectral data can help to discriminate protein absorptions from the overlaying cellulose, lignin and water absorptions and thus give farmers access to improved fertilization efficiency monitoring.
- Hyperspectral sensing, by combining the strengths of high resolution and wide range continuous spectral sampling, is the only technique that allows tracing the pathways of energy transformation in the leaves of living vegetation via solar-induced fluorescence and thus gives farmers access to investigating impacts of different stress sources (temperature, nitrogen, water).

5 Mission Requirements

This paper reviewed the potentials of spaceborne spectroscopy missions for agriculture. It largely discussed aspects of EO, which have not been sufficiently addressed with currently available EO systems. The elements described in this study rather draw a picture of possible improvements and new possibilities using future operational imaging spectroscopy space missions. The following collection of requirements, where no claim is made of completeness, is meant to shape this vision with special emphasis on the challenges, which are encountered when applying hyperspectral data in the context of practical agriculture.

5.1 User Requirements for Satellite-Based Technologies

Providing large amounts of satellite data will not per se contribute to the implementation of more efficient farming strategies. Users of satellite-based information in practical agriculture rather require elaborated information products, which must be tailored to the specific needs of farm management. The continuous stream of data, which is generated by EO missions, must be transferred into information products, which assist farmers with decisions on management actions such as irrigation, fertilization or plant protection. A selection of biophysical and biochemical variables, also defined as Level 2B/3 products including fAPAR, LAI, fCover or LCC, is usually generated by special service providers such as the Sentinel toolboxes (Weiss and Baret 2016). To integrate the satellite-based measurements into farming practice, these variables identified as agriculturally relevant in Sect. 3 (Table 1) need to be further refined to directly address the requirements of individual farmers for specific farming decisions. For instance, for fertilization planning, the absolute amount of nitrogen (N) actually stored in the leaves and especially in the grains as well as the remaining N storage in the soil is needed (in kg N ha^{-1}). For plant protection and yield management, spatial maps of dry biomass in leaves, stems and grains, provided in units of $\text{g dry matter m}^{-2}$ ground surface, are important. The biophysical and biochemical agriculturally relevant variables, which are directly derived from remote sensing, therefore must be processed to higher-level information products, e.g., by assimilating them into models of agricultural production and by embedding them into integrated information systems, which then provide decision-supporting guidance to farmers. To render these EO products valuable for precision agriculture and to increase their acceptance in practical farming, according to the experience of the authors, the following user requirements apply:

- *Data Accuracy* Accuracies must be optimized and remaining uncertainties must be clearly defined. According to the laws of error propagation, even small margins of increased accuracy at the beginning of a processing chain can have large impact on the

accuracy of the final result. This applies especially for the variables retrieved from EO, which are used as spatial input parameters for models of agricultural production. As has been elaborated in Sects. 3 and 4, hyperspectral data can help minimizing uncertainties by providing measurements of very specific variables and by contributing to more accurate and stable retrievals. Accuracies with respect to information content must exceed the expert's present capabilities of estimating a variable's value. Uncertainties of satellite-based products normally are defined through comparison with in situ measurements. These measurements again are subject to errors depending on the variable measured and the sampling method applied. The error of the in situ measurement thus defines the maximum detectable accuracy of a satellite measurement. In order to base the decision-making of farmers on remotely sensed products, the retrieval uncertainties therefore should not exceed the uncertainties of in situ measurements. However, one has to realize that in situ measurements mostly are point measurements, whereas farmers need so-called task maps, indicating zones in a field that should be treated as a separate unit with respect to irrigation, fertilization or plant protection. A big advantage of satellite data is the provision of spatial data or maps.

- *Spatial Accuracy* Most information in the context of precision farming refers to spatial datasets, which provide decision-supporting guidance to farmers by being used as map-overlay for the spatial execution of actual management measures. Since spatial applications in practical farming are frequently based on very high precision navigation, such as real-time-kinematic (RTK) in combination with auto-steering, geometric accuracy must be high, i.e. in the metre domain.
- *Time Constraints* Growing crops is a temporally highly dynamic process, which requires different management decisions throughout a growing cycle. For all decisions, up-to-date spatial information on crop and/or soil status is required. Three important time-related aspects must be considered: sensor repetition rate, time for data-processing and transfer of the products to the users. Since farm management measures usually are planned in accordance with the short-term weather forecast, the actual design of the measures occurs on very short notice, i.e. one or two days in advance. Near real-time transfer of the EO-based information products to the users thus is fundamental. Since the satellite data must be processed and ingested into the final information products, the transfer time of the actual satellite data to the value-adding agents must be kept as short as possible (< 3 h).
- *Cost Efficiency* Apart from ecological motivation, profit is the major driver in agricultural innovation. The amount of money a farm is going to invest in optimized production depends on the revenue, which is expected from the measure. For site-specific measures, the potential savings in terms of labour, fuel, machinery hours, fertilizers, plant protection agents, water, etc. and the potential increase in revenues in terms of higher yield levels and higher yield quality largely depend on the spatial heterogeneity of the managed sites. The willingness to invest in spatial information therefore depends on the cost efficiency of the solution.

5.2 Observational Requirements for Satellite-Based Technologies

As has been described in Sect. 4, hyperspectral satellite missions can potentially be applied to a wide range of different scientific and practical questions. The technical requirements for an imaging spectroscopy mission should not be exclusively driven by a

single application. Nonetheless, from the user requirements for agricultural applications listed in Sect. 5.1, some requirements for the design of satellite missions can be derived:

- *Spatial Resolution* The central application of satellite data in agriculture is improved spatial parameterization of models, which are used as decision support systems for site-specific management measures. The requirements for spatial resolution thus are determined by the spatial detail with which farmers are capable of applying measures on their fields. This level of spatial detail currently is limited by the size and type of the available agricultural machinery (fertilizer spreaders, irrigation systems, etc.). Fertilizer spreaders, as they are nowadays applied, usually have working widths of 40 m. A ground sampling distance (GSD) of 20 m thus would optimally resolve ground heterogeneities for the use with these machines, while a GSD of 30 m can be considered to represent the upper limit. However, technology is constantly evolving towards finer resolution. For instance, newest spreader and irrigation systems allow for an independent adjustment of individual sprayer nozzles along the boom. A GSD of 10 metres consequently should be targeted for future missions.
- *Spectral Resolution* Biophysical/biochemical information exhibits various absorption types. For proteins, lignin and cellulose, exhibiting rather shallow but broad absorption features, moderate spectral resolution of about 10 nm in the SWIR seems to be adequate. Other variables instead, such as anthocyanin and carotene, show more narrow absorptions in the VIS and therefore should be addressed at higher spectral resolutions of approx. 6 nm. This level of spectral resolution seems reasonable for spaceborne missions from a technical point of view. However, for the exploitation of SIF signals on the land surface very high spectral resolution < 3 nm would be required. The provision of such high spectral resolutions conflicts with the requirements for spatial resolution described above.
- *Spectral Coverage* According to Fig. 3, the spectral features which give access to biophysical/biochemical properties are distributed over a spectral range between 400 and 2500 nm. While some variables can be targeted through specific narrow absorptions, others require analysing contiguous bands. The so-called full range spectral coverage thus should be aimed for.
- *Radiometric Quality* Especially for hyperspectral systems, where the limited amount of available reflected energy is divided into small portions of the electromagnetic spectrum, radiometric quality is of utmost importance for the success of a satellite mission. Since the analysis of vegetation biophysical/biochemical properties is based on different parts of the spectrum, the considered absorptions can either be narrow or shallow or both. Accurate variable retrieval requires both, high signal-to-noise ratio (SNR) as well as high radiometric resolution. Since SNR is highly determined through the characteristics of the detector, it usually decreases with increasing wavelength. For the agriculturally relevant variables addressed by this study, a minimum SNR of approx. 500 in the VNIR and not lower than 150 in the SWIR should be targeted.
- *Radiometric Resolution* Imaging spectroscopy is characterized by high amounts of data. To ensure the success of spaceborne missions, it would be reasonable to keep data rates as low as possible. However, to adequately resolve also subtle differences in reflectance as caused by shallow absorptions, at least 14-bit quantification should be aimed at.
- *Repeat Cycle* The data from an operational mission can be used in nearly all stages of the crop cycle. The phenological development of crops occurs in time-steps of weeks

rather than months. Taking the problems of cloud cover for an optical mission into account, a revisit time of 5 days would be optimal.

- *Platform Agility* Atmospheric correction is a very important but also critical task for the proper use of hyperspectral imagery. Hyperspectral atmospheric retrieval algorithms, being developed based on airborne measurements, are able to deal with reflectance anisotropies. Thus, repeated data takes for the compilation of time-series do not necessarily need to be conducted at nadir but could also be achieved through across-track pointing. Vegetation canopies show strong anisotropy effects through various geometric complexities. Therefore, pointing capabilities of future satellite sensors, both across and along track, could help to improve variable retrieval and thus could trigger the development of new or more sophisticated multiangular retrieval techniques.
- *Spatial Coverage* Since agriculture happens globally and ensuring food security is a global challenge, the data should at least cover the global croplands between 49°S and 66°N, amounting to 1.873 billion hectares of land surface (Thenkabail 2017).
- *Data Policy* The successful transfer of environmental information into practical agriculture largely depends on the acceptance of the guiding information by farmers. Acceptance is generated from high quality and reasonable pricing of the data products. Taking into account that the actual value for practical farming cannot be found in the data itself, but rather enters the product by processing and value adding, data costs should be kept as low as possible. Apart from commercial applications, continuous high-quality data from a hyperspectral mission would also be important for science and education. Following the example of large operational missions such as Landsat or Copernicus, also the data from future hyperspectral missions should be open, free and easily accessible.

The technical requirements summarized in this section were compiled from a scientific point of view, mostly neglecting technical and financial difficulties. Although we took care not to reach too far from technical feasibility, we are aware that not all of the listed requirements will be feasible in the short term and not by one sensor only. Possible trade-offs between the different requirements therefore must be taken into account, which may be judged very differently depending on the application. We believe that some of the valuable work currently done in the context of preparing spectroscopy missions worldwide should be directed to define priorities for technical requirements in a quantitative way.

6 Challenges and Future Directions

Currently observed large-scale global developments, such as climate, population and land use changes, challenge the suppliers of food, fibre and energy to a most efficient use of the bioproductive land surface. This paper aimed at summarizing the potential contributions of spaceborne imaging spectroscopy to increased efficiency in practical farming and derived some user and mission requirements from the state of the art as it has been documented in the literature. Although scientific techniques, such as multi-sensor data fusion and 3D modelling, potentially allow for using spaceborne data also for very small-scale applications, we think that the main use of future spaceborne imaging spectroscopy data in operational precision farming will take place on the spatial scale of the satellite data. Accordingly, the findings with respect to the variables and retrieval techniques described here mainly apply to homogeneous crop farming, i.e. to crops that form geometrically homogeneous

stands compared to the observation scale of spaceborne sensors and which are cultivated in areas with individual field sizes in the order of 1 hectare and above. Special cultures like vineyards, orchards, plantations may have different requirements, mostly with respect to spatial resolution (e.g., Zarco-Tejada et al. 2013b), which were not reflected in the mission requirements summarized in Sect. 5. Also, smallholder farming, which still is practiced on about 12% of global farmland (Lowder et al. 2016), probably will most likely not be able to adapt the new technologies in near future. Efficiency in agriculture is not limited to crop farming; a large part of farming is concerned with livestock husbandry. This implies for instance the monitoring of different grassland biophysical or biochemical variables for the derivation of management characteristics such as degradation or grazing intensity. In summary, for the case of homogeneous crop farming, several variables have been identified and described, which can be measured by hyperspectral sensors and which provide crucial information for decision support tools in the context of farm management. The door for those tools, to enter into practical farming, already is wide open because of several reasons:

- Service providers exist and are growing, who offer EO-based information in an integrative way, so that farmers do not need to specialize in Earth Observation or Geographical Information Systems themselves.
- Most of the farming equipment installed today is capable of performing at least simple variable rate applications, e.g., through variable forward motion speed, which can be used for site-specific management measures. Meanwhile, technology is rapidly evolving, continuously introducing new site-specific management options. The concept of fertigation, where fertilization and irrigation management are coupled through a single spreader system, is one example.
- Finally yet importantly, farmers already are used to trust spectroscopy measurements, because near-infrared spectroscopy (NIRS) is a standard tool in animal feed analysis (e.g., for measuring residual moisture, crude protein, crude oils and fats, starch, sugar, acid/neutral detergent fibre). However, spectroscopy in agricultural practice so far mainly is limited to laboratory spectroscopy and/or near-range measurements, e.g., inside harvesters.

To introduce information derived from spaceborne spectroscopy into agricultural management practice, farmers need to be convinced. They will base their decisions on satellite spectroscopy, if high quality and high stability of the spatial measurements can be demonstrated and confirmed. This can only be achieved through global satellite missions, which are operated based on a dedicated acquisition plan. If high-quality datasets can be compiled on a regular basis, this would allow for a frequent collection of in situ data through dedicated field campaigns and long-term instrumented outdoor research sites. The high spatial and temporal coverage as well as the fact that the same instruments are globally applied through a satellite mission will allow for testing the transferability of all retrieval approaches that have been developed so far using ground-based or airborne data. Moreover, future hyperspectral spaceborne data sets will trigger the development of new and so far unknown applications. The sensor requirements for measuring relevant agricultural variables are very diverse. An imaging spectrometer designed according to the requirements summarized in this document surely is the key to answering some of the questions. Nevertheless, some applications will require different specifications that cannot be achieved with a single instrument. For example, the exploitation of SIF for agricultural purposes will not only need a high-resolution full-range spectrometer, but will additionally require ultra-high spectral resolution in selected parts of the electromagnetic spectrum and surface

temperature measurements at the same time. Installing different instruments along one orbit to follow each other in a so-called train constellation would be a sensible strategy, allowing the integration of new technologies into the chain as they become available. Also, vegetation is a dynamic surface, which shows strong diurnal and seasonal variations. To exploit the full potential of multiangular observations, a tandem concept of two identical instruments in parallel flight could be envisioned. Current ambitious satellite programs, such as the ESA Copernicus program, already have proven that Earth Observation activities with data rates in the domain of 10 Petabyte per year are technically feasible. The even increased data rates expected with high-resolution spectroscopy missions will pose new challenges for efficient data downlinking, data storage and data distribution. Advanced on-board processing strategies should be developed to mitigate the data rate problems.

Although information derived from spaceborne imaging spectroscopy can be applied to increase efficiency in agricultural production, one question cannot yet conclusively be answered: Will increased efficiency in agricultural production also result in sustainability, and if so, to what degree? This issue will have to be investigated by future long-term studies.

Acknowledgements The paper arises from the Workshop on “Exploring the Earth’s Ecosystems on a Global Scale: Requirements, Capabilities and Directions in Spaceborne Imaging Spectroscopy”, held at the International Space Science Institute (ISSI), Bern—Switzerland, on 21–25 November 2016. AVIRIS data are copyright 2016 California Institute of Technology and provided by Jet Propulsion Laboratory, California Institute of Technology, under contract with the National Aeronautics and Space Administration (NASA). Thanks to Martin Danner for the simulation of Sentinel-2 like reflectance from field spectrometer and AVIRIS data and to Lukas Graf for the analyses of AVIRIS data. The help of the reviewers and editors is gratefully acknowledged.

Open Access This article is distributed under the terms of the Creative Commons Attribution 4.0 International License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made.

References

- Ač A, Malenovský Z, Olejníčková J, Gallé A, Rascher U, Mohammed G (2015) Meta-analysis assessing potential of steady-state chlorophyll fluorescence for remote sensing detection of plant water, temperature and nitrogen stress. *Remote Sens Environ* 168:420–436. <https://doi.org/10.1016/j.rse.2015.07.022>
- Adão T, Hruška J, Pádua L, Bessa J, Peres E, Morais R, Sousa J (2017) Hyperspectral imaging: a review on UAV-based sensors. *Data Process Appl Agric For Remote Sens* 9:1110
- Agrawal M, Nandi PK, Rao DN (1982) Effect of ozone and sulphur dioxide pollutants separately and in mixture on chlorophyll and carotenoid pigments of *Oryza sativa* Water. *Air Soil Pollut* 18:449–454. <https://doi.org/10.1007/bf02426052>
- Ali AM, Darvishzadeh R, Skidmore AK, van Duren I (2017) Specific leaf area estimation from leaf and canopy reflectance through optimization and validation of vegetation indices. *Agric For Meteorol* 236:162–174. <https://doi.org/10.1016/j.agrformet.2017.01.015>
- Ariospace (2017) Irrisat. <https://www.irrisat.com/en/>. Accessed 9/11/2017 2017
- Arregui LM, Lasa B, Lafarga A, Irañeta I, Baroja E, Quemada M (2006) Evaluation of chlorophyll meters as tools for N fertilization in winter wheat under humid Mediterranean conditions. *Eur J Agron* 24:140–148. <https://doi.org/10.1016/j.eja.2005.05.005>
- Asner GP, Heidebrecht KB (2002) Spectral unmixing of vegetation, soil and dry carbon cover in arid regions: comparing multispectral and hyperspectral observations. *Int J Remote Sens* 23:3939–3958. <https://doi.org/10.1080/01431160110115960>

- Asner GP et al (2011) Taxonomy and remote sensing of leaf mass per area (LMA) in humid tropical forests. *Ecol Appl* 21:85–98
- Atzberger C (2004) Object-based retrieval of biophysical canopy variables using artificial neural nets and radiative transfer models. *Remote Sens Environ* 93:53–67. <https://doi.org/10.1016/j.rse.2004.06.016>
- Atzberger C (2013) Advances in remote sensing of agriculture: context description, existing operational monitoring systems and major information needs. *Remote Sens* 5:949
- Auernhammer H, Demmel M, Maidl FX, Schmidhalter U, Schneider T, Wagner P (1999) An on-farm communication system for precision farming with nitrogen real-time application. Paper presented at the 1999 ASAE/CSAE-SCGR annual international meeting, Toronto, 18–21 July 1999
- Bach H, Angermair W (2017) TalkingFields. <http://www.talkingfields.de/>. Accessed 9.11.2017 2017
- Bach H, Mauser W (2018) Sustainable agriculture and smart farming. In: Mathieu P-P, Aubrecht C (eds) *Earth observation open science and innovation*. Springer, Cham, pp 261–269. https://doi.org/10.1007/978-3-319-65633-5_12
- Bach H, Mauser W, Klepper G (2016) Earth observation for food security and sustainable agriculture. In: *ESA special publication SP-740 ESA living planet symposium 2016*, Prague
- Balafoutis A et al (2017) Precision agriculture technologies positively contributing to GHG emissions mitigation. *Farm Prod Econ Sustain* 9:1339
- Baret F, Buis S (2008) Estimating canopy characteristics from remote sensing observations: review of methods and associated problems. *Advances in land remote Sensing*. Springer, Dordrecht, pp 173–201
- Baret F, Houles V, Guerif M (2007) Quantification of plant stress using remote sensing observations and crop models: the case of nitrogen management. *J Exp Bot* 58:869–880. <https://doi.org/10.1093/jxb/erl231>
- Barraclough PB, Howarth JR, Jones J, Lopez-Bellido R, Parmar S, Shepherd CE, Hawkesford MJ (2010) Nitrogen efficiency of wheat: genotypic and environmental variation and prospects for improvement. *Eur J Agron* 33:1–11. <https://doi.org/10.1016/j.eja.2010.01.005>
- Basu S, Ramegowda V, Kumar A, Pereira A (2016) Plant adaptation to drought stress. *F1000Research* 5:F1000, Faculty Rev 1554. <https://doi.org/10.12688/f1000research.7678.1>
- Bauriegel E, Giebel A, Herppich WB (2011) Hyperspectral and chlorophyll fluorescence imaging to analyse the impact of *Fusarium culmorum* on the photosynthetic integrity of infected wheat ears. *Sensors (Basel, Switzerland)* 11:3765–3779. <https://doi.org/10.3390/s110403765>
- Berger K, Atzberger C, Danner M, D'Urso G, Mauser W, Vuolo F, Hank T (2018) Evaluation of the PRO-SAIL model capabilities for future hyperspectral model environments: a review study. *Remote Sens* 10:85
- Blackburn GA (1998) Quantifying chlorophylls and carotenoids at leaf and canopy scales: an evaluation of some hyperspectral approaches. *Remote Sens Environ* 66:273–285. [https://doi.org/10.1016/S0034-4257\(98\)00059-5](https://doi.org/10.1016/S0034-4257(98)00059-5)
- Blackburn GA (2007) Hyperspectral remote sensing of plant pigments. *J Exp Bot* 58:855–867. <https://doi.org/10.1093/jxb/erl123>
- Blackmore S (1994) Precision farming: an introduction. *Outlook Agric* 23:275–280. <https://doi.org/10.1177/003072709402300407>
- Breda NJ (2003) Ground-based measurements of leaf area index: a review of methods, instruments and current controversies. *J Exp Bot* 54:2403–2417. <https://doi.org/10.1093/jxb/erg263>
- Broge NH, Leblanc E (2001) Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density. *Remote Sens Environ* 76:156–172. [https://doi.org/10.1016/S0034-4257\(00\)00197-8](https://doi.org/10.1016/S0034-4257(00)00197-8)
- Byerlee D, Stevenson J, Villoria N (2014) Does intensification slow crop land expansion or encourage deforestation? *Glob Food Secur* 3:92–98. <https://doi.org/10.1016/j.gfs.2014.04.001>
- Calera A, Campos I, Osann A, D'Urso G, Menenti M (2017) Remote sensing for crop water management: from ET modelling to services for the end users. *Sensors (Basel)*. <https://doi.org/10.3390/s17051104>
- Castaldi F, Chabrilat S, Jones A, Vreys K, Bomans B, van Wesemael B (2018) Soil organic carbon estimation in croplands by hyperspectral remote APEX data using the LUCAS topsoil database. *Remote Sens* 10:153
- CEOS E (2018) <http://database.eohandbook.com/climate/gcosecv.aspx?gcospid=22>. Accessed 18 July 2018
- Chappelle EW, Kim MS, McMurtrey JE (1992) Ratio analysis of reflectance spectra (RARS): an algorithm for the remote estimation of the concentrations of chlorophyll A, chlorophyll B, and carotenoids in soybean leaves. *Remote Sens Environ* 39:239–247. [https://doi.org/10.1016/0034-4257\(92\)90089-3](https://doi.org/10.1016/0034-4257(92)90089-3)
- Chen JM, Black TA (1992) Defining leaf area index for non-flat leaves *Plant. Cell Environ* 15:421–429. <https://doi.org/10.1111/j.1365-3040.1992.tb00992.x>

- Chen M, Zhang H, Liu W, Zhang W (2014) The global pattern of urbanization and economic growth: evidence from the last three decades. *PLoS ONE* 9:e103799. <https://doi.org/10.1371/journal.pone.0103799>
- Cidad VG, Vrindts E, Baerdemaeker JD Use of very high resolution satellite images for precision farming: recommendations on nitrogen fertilization. In: Europto remote sensing, 2001. SPIE, p 10
- Clevers JGPW, Gitelson AA (2013) Remote estimation of crop and grass chlorophyll and nitrogen content using red-edge bands on sentinel-2 and-3. *Int J Appl Earth Obs Geoinf* 23:344–351. <https://doi.org/10.1016/j.jag.2012.10.008>
- Clevers JGPW, de Jong SM, Epema GF, van der Meer F, Bakker WH, Skidmore AK, Addink EA (2001) MERIS and the red-edge position. *Int J Appl Earth Obs Geoinf* 3:313–320. [https://doi.org/10.1016/S0303-2434\(01\)85038-8](https://doi.org/10.1016/S0303-2434(01)85038-8)
- Clevers JGPW, Kooistra L, Schaepman ME (2010) Estimating canopy water content using hyperspectral remote sensing data. *Int J Appl Earth Obs Geoinf* 12:119–125. <https://doi.org/10.1016/j.jag.2010.01.007>
- Clevers JGPW, Kooistra L, Van den Brande MM (2017) Using Sentinel-2 data for retrieving LAI and leaf and canopy chlorophyll content of a potato crop. *Remote Sens* 9:405. <https://doi.org/10.3390/rs9050405>
- Combal B et al (2003) Retrieval of canopy biophysical variables from bidirectional reflectance: using prior information to solve the ill-posed inverse problem. *Remote Sens Environ* 84:1–15. [https://doi.org/10.1016/S0034-4257\(02\)00035-4](https://doi.org/10.1016/S0034-4257(02)00035-4)
- Coppo P, Taiti A, Pettinato L, Francois M, Taccola M, Drusch M (2017) Fluorescence imaging spectrometer (FLORIS) for ESA FLEX mission. *Remote Sens* 9:649
- Curran PJ (1989) Remote sensing of foliar chemistry. *Remote Sens Environ* 30:271–278. [https://doi.org/10.1016/0034-4257\(89\)90069-2](https://doi.org/10.1016/0034-4257(89)90069-2)
- Danbom DB (1995) From Columbus to ConAgra: the globalization of agriculture and food. In: Bonanno A, Busch L, Friedland WH, Gouveia L, Mingione E (eds) (Lawrence: University Press of Kansas, 1994. viii, 294 pp. Cloth, \$40.00, ISBN 0-70060660-2. Paper, \$17.95, ISBN 0-7006-0661-0.) *J Am Hist* 82:676–677. <https://doi.org/10.2307/2082206>
- Danner M, Berger K, Woche M, Mauser W, Hank T (2017) Retrieval of biophysical crop variables from multi-angular canopy spectroscopy. *Remote Sens* 9:726. <https://doi.org/10.3390/rs9070726>
- Daughtry CST, Walthall CL, Kim MS, de Colstoun EB, McMurtrey JE (2000) Estimating Corn leaf chlorophyll concentration from leaf and canopy reflectance. *Remote Sens Environ* 74:229–239. [https://doi.org/10.1016/S0034-4257\(00\)00113-9](https://doi.org/10.1016/S0034-4257(00)00113-9)
- Daughtry CST, Hunt ER, Doraiswamy PC, McMurtrey JE (2005) Remote sensing the spatial distribution of crop residues. *Agron J* 97:864–871. <https://doi.org/10.2134/agronj2003.0291>
- de la Riva EG, Olmo M, Poorter H, Ubersa JL, Villar R (2016) Leaf mass per area (LMA) and its relationship with leaf structure and anatomy in 34 mediterranean woody species along a water availability gradient. *PLoS ONE* 11:e0148788. <https://doi.org/10.1371/journal.pone.0148788>
- Dennison P et al (2016) Global measurement of non-photosynthetic vegetation. NASA, Washington
- Durbha SS, King RL, Younan NH (2007) Support vector machines regression for retrieval of leaf area index from multiangle imaging spectroradiometer. *Remote Sens Environ* 107:348–361. <https://doi.org/10.1016/j.rse.2006.09.031>
- D’Urso G et al (2010) Earth observation products for operational irrigation management in the context of the PLEIADeS project. *Agric Water Manag* 98:271–282. <https://doi.org/10.1016/j.agwat.2010.08.020>
- Erickson B, Widmar DA (2015) Precision agricultural services dealership survey results. Purdue University Indiana, West Lafayette
- Falster DS, Westoby M (2003) Leaf size and angle vary widely across species: what consequences for light interception? *New Phytol* 158:509–525. <https://doi.org/10.1046/j.1469-8137.2003.00765.x>
- FAO (2016) The state of food and agriculture 2016. Climate change, agriculture and food security. Food and Agriculture Organization of the United Nations, FAO, Rome
- Feret J-B et al (2008) PROSPECT-4 and 5: advances in the leaf optical properties model separating photosynthetic pigments. *Remote Sens Environ* 112:3030–3043. <https://doi.org/10.1016/j.rse.2008.02.012>
- Féret JB, Gitelson AA, Noble SD, Jacquemoud S (2017) PROSPECT-D: towards modeling leaf optical properties through a complete lifecycle. *Remote Sens Environ* 193:204–215. <https://doi.org/10.1016/j.rse.2017.03.004>
- Forkuor G, Hounkpatin OKL, Welp G, Thiel M (2017) High resolution mapping of soil properties using remote sensing variables in south-western burkina faso: a comparison of machine learning and multiple linear regression models. *PLoS ONE* 12:e0170478. <https://doi.org/10.1371/journal.pone.0170478>

- Frampton WJ, Dash J, Watmough G, Milton EJ (2013) Evaluating the capabilities of Sentinel-2 for quantitative estimation of biophysical variables in vegetation. *ISPRS J Photogramm Remote Sens* 82:83–92. <https://doi.org/10.1016/j.isprsjprs.2013.04.007>
- Gitelson AA (2013) Remote estimation of crop fractional vegetation cover: the use of noise equivalent as an indicator of performance of vegetation indices. *Int J Remote Sens* 34:6054–6066. <https://doi.org/10.1080/01431161.2013.793868>
- Gitelson A, Solovchenko A (2017) Generic algorithms for estimating foliar pigment content. *Geophys Res Lett* 44:9293–9298. <https://doi.org/10.1002/2017GL074799>
- Gitelson AA, Merzlyak MN, Chivkunova OB (2001) Optical properties and nondestructive estimation of anthocyanin content in plant leaves. *Photochem Photobiol* 74:38–45
- Gitelson AA, Zur Y, Chivkunova OB, Merzlyak MN (2002) Assessing carotenoid content in plant leaves with reflectance spectroscopy. *Photochem Photobiol* 75:272–281
- Gitelson AA, Gritz Y, Merzlyak MN (2003) Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. *J Plant Physiol* 160:271–282. <https://doi.org/10.1078/0176-1617-00887>
- Gitelson AA et al (2006) Relationship between gross primary production and chlorophyll content in crops: Implications for the synoptic monitoring of vegetation productivity. *J Geophys Res Atmos* 111:n/a–n/a. <https://doi.org/10.1029/2005jd006017>
- Gitelson AA, Chivkunova OB, Merzlyak MN (2009) Nondestructive estimation of anthocyanins and chlorophylls in anthocyanic leaves. *Am J Bot* 96:1861–1868. <https://doi.org/10.3732/ajb.0800395>
- Gobron N, Verstraete MM (2009) ECV T10: fraction of absorbed photosynthetically active radiation (FAPAR) essential climate variables. Global Terrestrial Observing System, Rome
- Goetz AF, Vane G, Solomon JE, Rock BN (1985) Imaging spectrometry for Earth remote sensing. *Science* 228:1147–1153. <https://doi.org/10.1126/science.228.4704.1147>
- Goodwin N, Nelson JA, Ackermann F, Weisskopf T (2008) Consumption and the consumer society. Global Development And Environment Institute, Tufts University, Medford
- GOS (2011) Foresight. The future of food and farming—challenges and choices for global sustainability. The Government Office for Science, London
- Green RO, Painter TH, Roberts DA, Dozier J (2006) Measuring the expressed abundance of the three phases of water with an imaging spectrometer over melting snow. *Water Resour Res*. <https://doi.org/10.1029/2005WR004509>
- Guanter L et al (2015) The EnMAP spaceborne imaging spectroscopy mission for earth observation. *Remote Sens* 7:8830
- Gunasekera D, Finnigan J (2010) Track social and economic impacts of food production. *Nature* 466:920. <https://doi.org/10.1038/466920e>
- Haboudane D, Miller JR, Tremblay N, Zarco-Tejada PJ, Dextraze L (2002) Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. *Remote Sens Environ* 81:416–426. [https://doi.org/10.1016/S0034-4257\(02\)00018-4](https://doi.org/10.1016/S0034-4257(02)00018-4)
- Haboudane D, Miller JR, Pattey E, Zarco-Tejada PJ, Strachan IB (2004) Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: modeling and validation in the context of precision agriculture. *Remote Sens Environ* 90:337–352. <https://doi.org/10.1016/j.rse.2003.12.013>
- Hank T, Bach H, Mauser W (2015) Using a remote sensing-supported hydro-agroecological model for field-scale simulation of heterogeneous crop growth and yield: application for wheat in Central Europe. *Remote Sens* 7:3934
- Haubrock S, Chabrillat S, Kuhnert M, Hostert P, Kaufmann HJ (2008) Surface soil moisture quantification and validation based on hyperspectral data and field measurements. *J Appl Remote Sens* 2:26
- Herrmann I, Pimstein A, Karnieli A, Cohen Y, Alchanatis V, Bonfil DJ (2011) LAI assessment of wheat and potato crops by VEN μ S and Sentinel-2 bands. *Remote Sens Environ* 115:2141–2151. <https://doi.org/10.1016/j.rse.2011.04.018>
- Herwitz SR et al (2004) Imaging from an unmanned aerial vehicle: agricultural surveillance and decision support. *Comput Electron Agric* 44:49–61. <https://doi.org/10.1016/j.compag.2004.02.006>
- Homolová L, Malenovský Z, Clevers JGPW, García-Santos G, Schaepman ME (2013) Review of optical-based remote sensing for plant trait mapping. *Ecol Complex* 15:1–16. <https://doi.org/10.1016/j.ecocom.2013.06.003>
- Houborg R, McCabe MF, Angel Y, Middleton EM (2017) Time series from hyperion to track productivity in pivot agriculture in saudi arabia. In: 2017 IEEE international geoscience and remote sensing symposium (IGARSS), 23–28 July 2017. pp 3047–3050. <https://doi.org/10.1109/igarss.2017.8127641>

- Ibdah M, Dubey NK, Eizenberg H, Dabour Z, Abu-Nassar J, Gal-On A, Aly R (2014) Cucumber Mosaic Virus as a carotenoid inhibitor reducing *Phelipanche aegyptiaca* infection in tobacco plants. *Plant Signal Behav* 9:e972146. <https://doi.org/10.4161/psb.32096>
- Jacquemoud S, Ustin SL, Verdebout J, Schmuck G, Andreoli G, Hosgood B (1996) Estimating leaf biochemistry using the PROSPECT leaf optical properties model. *Remote Sens Environ* 56:194–202. [https://doi.org/10.1016/0034-4257\(95\)00238-3](https://doi.org/10.1016/0034-4257(95)00238-3)
- Jacquemoud S, Bacour C, Poilvé H, Frangi JP (2000) Comparison of four radiative transfer models to simulate plant canopies reflectance: direct and inverse mode. *Remote Sens Environ* 74:471–481. [https://doi.org/10.1016/S0034-4257\(00\)00139-5](https://doi.org/10.1016/S0034-4257(00)00139-5)
- Jacquemoud S et al (2009) PROSPECT + SAIL models: a review of use for vegetation characterization. *Remote Sens Environ* 113(Supplement 1):S56–S66. <https://doi.org/10.1016/j.rse.2008.01.026>
- Jay S, Maupas F, Bendoula R, Gorretta N (2017) Retrieving LAI, chlorophyll and nitrogen contents in sugar beet crops from multi-angular optical remote sensing: comparison of vegetation indices and PROSAIL inversion for field phenotyping. *Field Crops Res* 210:33–46. <https://doi.org/10.1016/j.fcr.2017.05.005>
- Jiménez-Muñoz J, Sobrino J, Plaza A, Guanter L, Moreno J, Martínez P (2009) Comparison between fractional vegetation cover retrievals from vegetation indices and spectral mixture analysis: case study of PROBA/CHRIS data over an agricultural area. *Sensors* 9:768
- Jonckheere I, Fleck S, Nackaerts K, Muys B, Coppin P, Weiss M, Baret F (2004) Review of methods for in situ leaf area index determination: part I. Theories, sensors and hemispherical photography. *Agric For Meteorol* 121:19–35. <https://doi.org/10.1016/j.agrformet.2003.08.027>
- Justice CO et al (2002) An overview of MODIS Land data processing and product status. *Remote Sens Environ* 83:3–15. [https://doi.org/10.1016/S0034-4257\(02\)00084-6](https://doi.org/10.1016/S0034-4257(02)00084-6)
- Kimes DS, Knyazikhin Y, Privette JL, Abuelgasim AA, Gao F (2000) Inversion methods for physically-based models. *Remote Sens Rev* 18:381–439. <https://doi.org/10.1080/02757250009532396>
- King DA (1997) The functional significance of leaf angle in eucalyptus. *Aust J Bot* 45:619–639. <https://doi.org/10.1071/BT96063>
- Kira O, Nguy-Robertson AL, Arkebauer TJ, Linker R, Gitelson AA (2016) Informative spectral bands for remote green LAI estimation in C3 and C4 crops. *Agric For Meteorol* 218–219:243–249. <https://doi.org/10.1016/j.agrformet.2015.12.064>
- Kira O, Nguy-Robertson AL, Arkebauer TJ, Linker R, Gitelson AA (2017) Toward generic models for green LAI estimation in maize and soybean: satellite observations. *Remote Sens* 9:318
- Kokaly RF, Skidmore AK (2015) Plant phenolics and absorption features in vegetation reflectance spectra near 1.66µm. *Int J Appl Earth Obs Geoinf* 43:55–83. <https://doi.org/10.1016/j.jag.2015.01.010>
- Kokaly RF, Despain DG, Clark RN, Livo KE (2007) Spectral analysis of absorption features N for mapping vegetation cover and microbial communities in yellowstone national park using AVIRIS data. In: Morgan LA (ed) *Integrated geoscience studies in the greater yellowstone area—volcanic, tectonic, and hydrothermal processes in the yellowstone geoecosystem*. U.S. Geological Survey Professional Paper 1717, 532 p., vol Paper 1717. p 532
- Kokaly RF, Asner GP, Ollinger SV, Martin ME, Wessman CA (2009) Characterizing canopy biochemistry from imaging spectroscopy and its application to ecosystem studies. *Remote Sens Environ* 113:S78–S91. <https://doi.org/10.1016/j.rse.2008.10.018>
- Kong W et al (2017) Estimation of canopy carotenoid content of winter wheat using multi-angle hyperspectral data. *Adv Space Res* 60:1988–2000. <https://doi.org/10.1016/j.asr.2017.07.015>
- Labate D et al (2009) The PRISMA payload optomechanical design, a high performance instrument for a new hyperspectral mission. *Acta Astronaut* 65:1429–1436. <https://doi.org/10.1016/j.actastro.2009.03.077>
- le Maire G et al (2008) Calibration and validation of hyperspectral indices for the estimation of broad-leaved forest leaf chlorophyll content, leaf mass per area, leaf area index and leaf canopy biomass. *Remote Sens Environ* 112:3846–3864. <https://doi.org/10.1016/j.rse.2008.06.005>
- Lee D, Gould K (2002) Why leaves turn red: pigments called anthocyanins probably protect leaves from light damage by direct shielding and by scavenging free radicals. *Am Sci* 90(6):524–531
- Lee K-S, Cohen WB, Kennedy RE, Maier-sperger TK, Gower ST (2004) Hyperspectral versus multispectral data for estimating leaf area index in four different biomes. *Remote Sens Environ* 91:508–520. <https://doi.org/10.1016/j.rse.2004.04.010>
- Liang S (2003) *Quantitative remote sensing of land surfaces*. Wiley, Hoboken
- Liu K, Zhou Q-B, Wu W-B, Xia T, Tang H-J (2016) Estimating the crop leaf area index using hyperspectral remote sensing. *J Integr Agric* 15:475–491. [https://doi.org/10.1016/S2095-3119\(15\)61073-5](https://doi.org/10.1016/S2095-3119(15)61073-5)
- Lowder SK, Skoet J, Raney T (2016) The number, size, and distribution of farms, smallholder farms, and family farms worldwide. *World Dev* 87:16–29. <https://doi.org/10.1016/j.worlddev.2015.10.041>

- Martínez B, Camacho F, Verger A, García-Haro FJ, Gilabert MA (2013) Intercomparison and quality assessment of MERIS, MODIS and SEVIRI FAPAR products over the Iberian Peninsula. *Int J Appl Earth Obs Geoinf* 21:463–476. <https://doi.org/10.1016/j.jag.2012.06.010>
- Mausser W, Bach H, Hank T, Zabel F, Putzenlechner B How spectroscopy from space will support world agriculture. In: 2012 IEEE international geoscience and remote sensing symposium, 22–27 July 2012. pp 7321–7324. <https://doi.org/10.1109/igarss.2012.6351970>
- Maxwell K, Johnson GN (2000) Chlorophyll fluorescence—a practical guide. *J Exp Bot* 51:659–668. <https://doi.org/10.1093/jxbot/51.345.659>
- Meroni M, Rossini M, Guanter L, Alonso L, Rascher U, Colombo R, Moreno J (2009) Remote sensing of solar-induced chlorophyll fluorescence: review of methods and applications. *Remote Sens Environ* 113:2037–2051. <https://doi.org/10.1016/j.rse.2009.05.003>
- Mibei EK, Ambuko J, Giovannoni JJ, Onyango AN, Owino WO (2017) Carotenoid profiling of the leaves of selected African eggplant accessions subjected to drought stress. *Food Sci Nutr* 5:113–122. <https://doi.org/10.1002/fsn3.370>
- Migdall S, Bach H, Bobert J, Wehrhan M, Mausser W (2009) Inversion of a canopy reflectance model using hyperspectral imagery for monitoring wheat growth and estimating yield. *Precis Agric* 10:508–524
- Moran MS, Inoue Y, Barnes EM (1997) Opportunities and limitations for image-based remote sensing in precision crop management. *Remote Sens Environ* 61:319–346. [https://doi.org/10.1016/S0034-4257\(97\)00045-X](https://doi.org/10.1016/S0034-4257(97)00045-X)
- Mulla DJ (2013) Twenty five years of remote sensing in precision agriculture: key advances and remaining knowledge gaps. *Biosyst Eng* 114:358–371. <https://doi.org/10.1016/j.biosystemseng.2012.08.009>
- Murchie EH, Lawson T (2013) Chlorophyll fluorescence analysis: a guide to good practice and understanding some new applications. *J Exp Bot* 64:3983–3998. <https://doi.org/10.1093/jxb/ert208>
- Nellis DM, Price KP, Rundquist D (2009) Remote sensing of cropland agriculture. In: Warner TA, Nellis DM, Foody GM (eds) *The SAGE handbook of remote sensing*. SAGE Publications. <https://doi.org/10.4135/978-1-8570-2105-9.n26>
- Neuwirthová E, Lhotáková Z, Albrechtová J (2017) The effect of leaf stacking on leaf reflectance and vegetation indices measured by contact probe during the season. *Sensors (Basel, Switzerland)* 17:1202. <https://doi.org/10.3390/s17061202>
- Nidamanuri RR, Zbell B (2011) Use of field reflectance data for crop mapping using airborne hyperspectral image. *ISPRS J Photogramm Remote Sens* 66:683–691. <https://doi.org/10.1016/j.isprsjprs.2011.05.001>
- Nobel PS (2009) *Physicochemical and environmental plant physiology*, 4th edn. Academic Press, San Diego. <https://doi.org/10.1016/B978-0-12-374143-1.00001-6>
- Okin GS (2010) The contribution of brown vegetation to vegetation dynamics. *Ecology* 91:743–755
- Ozdogan M, Yang Y, Allez G, Cervantes C (2010) Remote sensing of irrigated agriculture: opportunities and challenges. *Remote Sens* 2:2274
- Panda SK, Chaudhury I, Khan MH (2003) Heavy metals induce lipid peroxidation and affect antioxidants in wheat leaves. *Biol Plant* 46:289–294. <https://doi.org/10.1023/a:1022871131698>
- Parry C, Blonquist JM, Bugbee B (2014) In situ measurement of leaf chlorophyll concentration: analysis of the optical/absolute relationship *Plant. Cell Environ* 37:2508–2520. <https://doi.org/10.1111/pce.12324>
- Peng Y, Gitelson AA, Keydan G, Rundquist DC, Moses W (2011) Remote estimation of gross primary production in maize and support for a new paradigm based on total crop chlorophyll content. *Remote Sens Environ* 115:978–989. <https://doi.org/10.1016/j.rse.2010.12.001>
- Peng Y, Nguy-Robertson A, Arkebauer T, Gitelson A (2017) Assessment of canopy chlorophyll content retrieval in maize and soybean: implications of hysteresis on the development of generic algorithms. *Remote Sens* 9:226
- Peters J (2012) On-farm moisture testing of corn silage. *Focus Forage* 2(6):1–3
- Plant RE, Pettygrove GS, Reinert WR (2000) Precision agriculture can increase profits and limit environmental impacts. *Calif Agric* 54:66–71. <https://doi.org/10.3733/ca.v054n04p66>
- Poorter H, Evans JR (1998) Photosynthetic nitrogen-use efficiency of species that differ inherently in specific leaf area. *Oecologia* 116:26–37. <https://doi.org/10.1007/s004420050560>
- Porcar-Castell A et al (2014) Linking chlorophyll a fluorescence to photosynthesis for remote sensing applications: mechanisms and challenges. *J Exp Bot* 65:4065–4095. <https://doi.org/10.1093/jxb/eru191>
- Prashar A, Jones HG (2016) Assessing drought responses using thermal infrared imaging. *Methods Mol Biol* 1398:209–219. https://doi.org/10.1007/978-1-4939-3356-3_17
- Richter K, Atzberger C, Vuolo F, Weihs P, D’Urso G (2009) Experimental assessment of the Sentinel-2 band setting for RTM-based LAI retrieval of sugar beet and maize. *Can J Remote Sens* 35:230–247
- Richter K, Hank TB, Vuolo F, Mausser W, D’Urso G (2012) Optimal exploitation of the sentinel-2 spectral capabilities for crop leaf area index mapping. *Remote Sens* 4:561

- Ritter L, Solomon K, Sibley P, Hall K, Keen P, Mattu G, Linton B (2002) Sources, pathways, and relative risks of contaminants in surface water and groundwater: a perspective prepared for the Walkerton inquiry. *J Toxicol Environ Health A* 65:1–142
- Rivera-Caicedo JP, Verrelst J, Muñoz-Marí J, Camps-Valls G, Moreno J (2017) Hyperspectral dimensionality reduction for biophysical variable statistical retrieval. *ISPRS J Photogramm Remote Sens* 132:88–101. <https://doi.org/10.1016/j.isprsjprs.2017.08.012>
- Roberts DA, Quattrochi DA, Hulley GC, Hook SJ, Green RO (2012) Synergies between VSWIR and TIR data for the urban environment: an evaluation of the potential for the Hyperspectral Infrared Imager (HyspIRI) Decadal Survey mission. *Remote Sens Environ* 117:83–101. <https://doi.org/10.1016/j.rse.2011.07.021>
- Robertson GP, Bruulsema TW, Gehl RJ, Kanter D, Mauzerall DL, Rotz CA, Williams CO (2013) Nitrogen–climate interactions in US agriculture. *Biogeochemistry* 114:41–70. <https://doi.org/10.1007/s10533-012-9802-4>
- Rockström J, Lannerstad M, Falkenmark M (2007) Assessing the water challenge of a new green revolution in developing countries. *Proc Natl Acad Sci USA* 104:6253–6260. <https://doi.org/10.1073/pnas.0605739104>
- Rouse JW, Haas RH, Schell JA, Deering DW (1973) Monitoring vegetation systems in the Great Plains with ERTS. Paper presented at the Third ERTS Symposium
- Sahoo RN, Ray SS, Manjunath KR (2015) Hyperspectral remote sensing of agriculture. *Curr Sci* 108(5):848–859
- Savoy P, Mackay DS (2015) Modeling the seasonal dynamics of leaf area index based on environmental constraints to canopy development. *Agric For Meteorol* 200:46–56. <https://doi.org/10.1016/j.agrfor.2014.09.019>
- Schaepman ME, Koetz B, Schaepman-Strub G, Itten KI (2005) Spectrodirectional remote sensing for the improved estimation of biophysical and-chemical variables: two case studies. *Int J Appl Earth Obs Geoinf* 6:271–282. <https://doi.org/10.1016/j.jag.2004.10.012>
- Schaepman-Strub G, Schaepman ME, Painter TH, Dangel S, Martonchik JV (2006) Reflectance quantities in optical remote sensing—definitions and case studies. *Remote Sens Environ* 103(1):27–42. <https://doi.org/10.1016/j.rse.2006.03.002>
- Schlemmer M, Gitelson A, Schepers J, Ferguson R, Peng Y, Shanahan J, Rundquist D (2013) Remote estimation of nitrogen and chlorophyll contents in maize at leaf and canopy levels. *Int J Appl Earth Obs Geoinf* 25:47–54. <https://doi.org/10.1016/j.jag.2013.04.003>
- Shams A, Hooshmandan Z, Fard M (2017) Factors affecting wheat farmers’ attitudes toward organic farming. *Pol J Environ Stud* 26:2207–2214. <https://doi.org/10.15244/pjoes/69435>
- Spanner M, Johnson L, Miller J, McCreight R, Freemantle J, Runyon J, Gong P (1994) Remote sensing of seasonal leaf area index across the oregon transect. *Ecol Appl* 4:258–271. <https://doi.org/10.2307/1941932>
- Springob K, Nakajima J, Yamazaki M, Saito K (2003) Recent advances in the biosynthesis and accumulation of anthocyanins. *Nat Prod Rep* 20:288–303
- Stevens A, Udelhoven T, Denis A, Tychon B, Liroy R, Hoffmann L, van Wesemael B (2010) Measuring soil organic carbon in croplands at regional scale using airborne imaging spectroscopy. *Geoderma* 158:32–45. <https://doi.org/10.1016/j.geoderma.2009.11.032>
- Su Z (2002) The surface energy balance system (SEBS) for estimation of turbulent heat fluxes. *Hydrol Earth Syst Sci* 6:85–100. <https://doi.org/10.5194/hess-6-85-2002>
- Sykas D, Karathanassi V, Fountas S A new methodology for the discrimination of plant species and their varieties using hyperspectral data: application on vetch and lentil. In: First international conference on remote sensing and geoinformation of environment, 2013. SPIE, p 8
- Tanaka Y, Sasaki N, Ohmiya A (2008) Biosynthesis of plant pigments: anthocyanins, betalains and carotenoids. *Plant J* 54:733–749. <https://doi.org/10.1111/j.1365-313X.2008.03447.x>
- Thenkabail PS (2017) <https://www.usgs.gov/news/new-map-worldwide-croplands-supports-food-and-water-security>. Accessed 18 July 2018
- Thenkabail PS, Smith RB, De Pauw E (2000) Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. *Remote Sens Environ* 71:158–182. [https://doi.org/10.1016/S0034-4257\(99\)00067-X](https://doi.org/10.1016/S0034-4257(99)00067-X)
- Thenkabail PS, Enclona EA, Ashton MS, Van Der Meer B (2004) Accuracy assessments of hyperspectral waveband performance for vegetation analysis applications. *Remote Sens Environ* 91:354–376. <https://doi.org/10.1016/j.rse.2004.03.013>
- Thenkabail PS, Schull M, Turrall H (2005) Ganges and Indus river basin land use/land cover (LULC) and irrigated area mapping using continuous streams of MODIS data. *Remote Sens Environ* 95:317–341. <https://doi.org/10.1016/j.rse.2004.12.018>

- Thenkabail PS, Mariotto I, Gumma MK, Middleton EM, Landis DR, Huemmrich KF (2013) Selection of hyperspectral narrowbands (HNBS) and composition of hyperspectral twoband vegetation indices (HVIs) for biophysical characterization and discrimination of crop types using field reflectance and hyperion/EO-1 data. *IEEE J Selc Top Appl Earth Obs Remote Sens* 6:427–439. <https://doi.org/10.1109/JSTARS.2013.2252601>
- Ustin S, Zarco-Tejada PJ, Asner GP (2001) The role of hyperspectral data in understanding the global carbon cycle. In: *Avisir Workshop, Pasadena, California, 27/02–02/03 2001*. NASA/JPL
- Vaesens K, Gilliams S, Nackaerts K, Coppin P (2001) Ground-measured spectral signatures as indicators of ground cover and leaf area index: the case of paddy rice. *Field Crops Res* 69:13–25. [https://doi.org/10.1016/S0378-4290\(00\)00129-5](https://doi.org/10.1016/S0378-4290(00)00129-5)
- van der Maaten LJP, Postma EO, van den Herik HJ (2009) Dimensionality reduction: a comparative review. Technical Report TiCC TR 2009-005, Maastricht University
- Vaudour E, Gilliot JM, Bel L, Lefevre J, Chehdi K (2016) Regional prediction of soil organic carbon content over temperate croplands using visible near-infrared airborne hyperspectral imagery and synchronous field spectra. *Int J Appl Earth Obs Geoinf* 49:24–38. <https://doi.org/10.1016/j.jag.2016.01.005>
- Verhoef W, Bach H (2003) Simulation of hyperspectral and directional radiance images using coupled biophysical and atmospheric radiative transfer models. *Remote Sens Environ* 87:23–41
- Verhoef W, Bach H (2007) Coupled soil-leaf-canopy and atmosphere radiative transfer modeling to simulate hyperspectral multi-angular surface reflectance and TOA radiance data. *Remote Sens Environ* 109:166–182
- Verrelst J, Camps-Valls G, Muñoz-Marí J, Rivera JP, Veroustraete F, Clevers JGPW, Moreno J (2015) Optical remote sensing and the retrieval of terrestrial vegetation bio-geophysical properties—a review. *ISPRS J Photogramm Remote Sens* 108:273–290. <https://doi.org/10.1016/j.isprsjprs.2015.05.005>
- Verrelst J, Rivera JP, Gitelson A, Delegido J, Moreno J, Camps-Valls G (2016) Spectral band selection for vegetation properties retrieval using Gaussian processes regression. *Int J Appl Earth Obs Geoinf* 52:554–567. <https://doi.org/10.1016/j.jag.2016.07.016>
- Viña A, Gitelson AA, Nguy-Robertson AL, Peng Y (2011) Comparison of different vegetation indices for the remote assessment of green leaf area index of crops. *Remote Sens Environ* 115:3468–3478. <https://doi.org/10.1016/j.rse.2011.08.010>
- Vuolo F et al (2016) Data service platform for sentinel-2 Surface reflectance and value-added products: system use and examples. *Remote Sens* 8:938
- Walter A, Finger R, Huber R, Buchmann N (2017) Opinion: smart farming is key to developing sustainable agriculture. *Proc Natl Acad Sci U S A* 114:6148–6150. <https://doi.org/10.1073/pnas.1707462114>
- Walthall CL (1997) A study of reflectance anisotropy and canopy structure using a simple empirical model. *Remote Sens Environ* 61:118–128. [https://doi.org/10.1016/S0034-4257\(96\)00245-3](https://doi.org/10.1016/S0034-4257(96)00245-3)
- Wang Z, Skidmore AK, Wang T, Darvishzadeh R, Hearne J (2015) Applicability of the PROSPECT model for estimating protein and cellulose+lignin in fresh leaves. *Remote Sens Environ* 168:205–218. <https://doi.org/10.1016/j.rse.2015.07.007>
- Watson DJ (1947) Comparative physiological studies in the growth of field crops. I. Variation in net assimilation rate and leaf area between species and varieties, and within and between years. *Ann Bot* 11:41–76
- Weiss M, Baret F (2016) S2ToolBox level 2 products: LAI, FAPAR, FCOVER. Institut National de la Recherche Agronomique (INRA), Avignon
- Weiss M, Baret F, Myneni RB, Pragnere A, Knyazikhin Y (2000) Investigation of a model inversion technique to estimate canopy biophysical variables from spectral and directional reflectance data. *Agronomie* 20:3–22
- Wilson J, Zhang C, Kovacs J (2014) Separating crop species in northeastern ontario using hyperspectral data. *Remote Sens* 6:925
- Yang Y, Ling PP (2004) Non-contacting techniques for plant drought stress detection. *Am Soc Agric Biol Eng*. <https://doi.org/10.13031/2013.16168>
- Yang C, Everitt JH, Du Q, Luo B, Chaussoot J (2013) Using high-resolution airborne and satellite imagery to assess crop growth and yield variability for precision agriculture. *Proc IEEE* 101:582–592. <https://doi.org/10.1109/JPROC.2012.2196249>
- Yi Q, Jiapaer G, Chen J, Bao A, Wang F (2014) Different units of measurement of carotenoids estimation in cotton using hyperspectral indices and partial least square regression. *ISPRS J Photogramm Remote Sens* 91:72–84. <https://doi.org/10.1016/j.isprsjprs.2014.01.004>
- Zarco-Tejada PJ, González-Dugo V, Berni JAJ (2012) Fluorescence, temperature and narrow-band indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera. *Remote Sens Environ* 117:322–337. <https://doi.org/10.1016/j.rse.2011.10.007>

- Zarco-Tejada PJ, Catalina A, González MR, Martín P (2013a) Relationships between net photosynthesis and steady-state chlorophyll fluorescence retrieved from airborne hyperspectral imagery. *Remote Sens Environ* 136:247–258. <https://doi.org/10.1016/j.rse.2013.05.011>
- Zarco-Tejada PJ, Guillén-Climent ML, Hernández-Clemente R, Catalina A, González MR, Martín P (2013b) Estimating leaf carotenoid content in vineyards using high resolution hyperspectral imagery acquired from an unmanned aerial vehicle (UAV). *Agric For Meteorol* 171–172:281–294. <https://doi.org/10.1016/j.agrformet.2012.12.013>
- Zarco-Tejada PJ, González-Dugo MV, Fereres E (2016) Seasonal stability of chlorophyll fluorescence quantified from airborne hyperspectral imagery as an indicator of net photosynthesis in the context of precision agriculture. *Remote Sens Environ* 179:89–103. <https://doi.org/10.1016/j.rse.2016.03.024>
- Zhang N, Wang M, Wang N (2002) Precision agriculture—a worldwide overview. *Comput Electron Agric* 36:113–132. [https://doi.org/10.1016/S0168-1699\(02\)00096-0](https://doi.org/10.1016/S0168-1699(02)00096-0)
- Zhaoqin L, Xulin G (2015) Remote sensing of terrestrial non-photosynthetic vegetation using hyperspectral, multispectral, SAR, and LiDAR data. *Prog Phys Geogr* 40:276–304. <https://doi.org/10.1177/0309133315582005>
- Zheng G, Moskal LM (2009) Retrieving leaf area index (LAI) using remote sensing: theories, methods and sensors. *Sensors* 9:2719
- Zhou R et al (2017) Drought stress had a predominant effect over heat stress on three tomato cultivars subjected to combined stress. *BMC Plant Biol* 17:24. <https://doi.org/10.1186/s12870-017-0974-x>
- Zomer RJ, Trabucco A, Ustin SL (2009) Building spectral libraries for wetlands land cover classification and hyperspectral remote sensing. *J Environ Manag* 90:2170–2177. <https://doi.org/10.1016/j.jenvm.2007.06.028>

Affiliations

Tobias B. Hank¹  · Katja Berger¹ · Heike Bach² · Jan G. P. W. Clevers³ · Anatoly Gitelson⁴ · Pablo Zarco-Tejada⁵ · Wolfram Mauser¹

¹ Department of Geography, Faculty of Geosciences, Ludwig-Maximilians-Universität München (LMU), Luisenstrasse 37, 80333 Munich, Germany

² VISTA – Remote Sensing in Geosciences GmbH, Gabelsbergerstrasse 51, 80333 Munich, Germany

³ Laboratory of Geo-Information Science and Remote Sensing, Wageningen University and Research, Droevendaalsesteeg 3, 6708 PB Wageningen, The Netherlands

⁴ Mapping and Geoinformation Engineering, Faculty of Civil and Environmental Engineering, Israel Institute of Technology (TECHNION), Haifa, Israel

⁵ Instituto de Agricultura Sostenible (IAS), Consejo Superior de Investigaciones Científicas (CSIC), Alameda del Obispo S/n, 14004 Córdoba, Spain