Turkish Journal of Agriculture and Forestry

http://journals.tubitak.gov.tr/agriculture/

Review Article

Turk J Agric For
(2021) 45: 730-742
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doi:10.3906/tar-2012-79

Analysis of designs used in monitoring crop growth based on remote sensing methods

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Received: 22.12.2020 • **Accepted/Published Online:** 11.04.2021 • **Final Version:** 16.12.2021

Abstract: Choosing appropriate designs and methods for monitoring crop growth is a challenging process of major importance. Remote sensing from space and manned or unmanned airborne operations are used to measure crop reflectance and a wide variety of other agricultural parameters. While some experiments use only a few, specific methods and designs and organize the results in lists of evidence, other experiments use a wider range of techniques to create a more credible and comprehensive assessment of crop yield. Particular situations related to the available resources in terms of data collection and expertise in addition to the intended use of the results may require specific designs or a combination of methods and design. This review intended to explore the challenges and document a range of possible approaches for remote evaluation of crop growth. The scope of the analysis was designed to provide information on methods that work under different circumstances and why and how effective a particular method is an approach to monitoring crop growth. Considering the agricultural ecosystems as complex systems and the working methodology as having a high degree of complexity, we propose an approach suitable for complex systems. New sets of models and methods need to be developed for approaching complex systems, which are characterized by self-organization, nonlinearity, ongoing adaptation, and networking.

Key words: Chlorophyll, crop growth, precision agriculture, remote sensing, yield prediction

1. Introduction

Earth observation with remote sensing (RS) techniques has major practical significance in establishing the interaction between terrestrial ecosystems and global environmental change.

Recent climate change has had a significant impact on both ecosystem structure and distribution of plant species (Dobrota et al., 2020). At this moment, 12% of the global land area is used for cultivation of agricultural crops, 28% is considered forestland, and 35% comprises grasslands and woodland ecosystems. Low and erratic precipitation and global warming often make soil inadequate for cultivation. Current trends and simulated models indicate that a 70% increase in global demand of agricultural production is expected by 2050. Meanwhile, many challenges concerning the exploitation of land and water resources have been identified. In the last 30 years, a decline has been recorded of about 3.3% in forested areas, suggesting that the expansion in the cultivated area could have been partly achieved through the conversion of previously forested areas (FAO, 2011). Rainfed agriculture as well as irrigated farming systems are performing well below their potential. A 'yield gap' affecting many zones of the globe was calculated by FAO by comparing current productivity with potentially achievable productivity. In this context, a global need to obtain stable and reliable supplies of food by improving land and water productivity has been identified.

Vegetation, which is the major target of earth observation with RS techniques, is an essential indicator of the change of the land ecological environment. Advances in remote sensing technology link leaf and canopy biochemical characteristics to remote sensing measurements in reliable and operational ways (Yu et al., 2014). In precision agriculture, the assessment and monitoring of plant parameters are made for addressing crucial issues, such as crop growth, vegetation stress, forecasting, and management practices (Haboudane et al., 2002). Several remote sensing (RS) approaches are available to quantify plant physiological variables. Photosynthesis, transpiration, and growth have indirect measurable biophysical and biochemical parameters that can be remotely recorded and estimated (Zhou et al., 2020). Chlorophyll is used as an important index of crop growth conditions (Haboudane et al., 2002), stress detection, nutritional state diagnosis, yield prediction (Yu

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et al., 2014), and for assisting field precision fertilization and pesticide application (Cao et al., 2020).

In this review, we propose an approach suitable for complex systems, which accounts for the complexity of both agricultural ecosystems (Khumairoh et al., 2012) and the current working methodology. RS approaches must be able to address a complex array of variables. Research in the field of RS is thus characterized by a high diversity of methodological frameworks, measuring approaches, instrumentation, and experimental setups. Even if lab measurements can be reduced to simple systems in which environmental factors are strictly controlled, any RS approach must be applicable to complex systems. Each individual plant interacts through allelopathic signals with other plants as well as with microorganisms from the rhizosphere or leaves and is, thus, subjected to uncontrolled environmental factors that can influence the radiance or reflectance emitted by the plant's leaves. Ground validation methods through lab measurements, in which plants are extracted from their natural environment, are the initial sources of error in RS research. Modifications to the core methods that address key ecosystem attributes, including soil and site stability, watershed function, and biotic integrity, limit the ability of researchers to combine and compare datasets and to properly describe ecosystem attributes on varying scales (Herrick et. al., 2017). A scientific gap exists due to the fragmentary knowledge of crops in agricultural conditions (Lew et al., 2020). The existing standard methods require improvements to adapt to real-world complexity and to enhance measurement accuracy (Lang, 2008).

No matter how complex a system is, the research process follows a general sequence of steps which consist of establishing goals, identifying problems, identifying and refining objectives, designing research, collecting, analyzing, and interpreting data, and setting further prospects. When designing a monitoring plan, several specific steps should be considered, including establishing management objectives and selecting additional ecosystem indicators to monitor, setting the study area, establishing sample size and frequency, collecting and evaluating data, selecting and applying appropriate statistical methodology, and creating a management plan (Herrick et. al., 2017). Collected data are calibrated to provide evidence that is consistent and trustworthy. The integrity of the collected data is ensured through quality assurance and control methods to minimize errors. There are diverse methods for calibration, such as line-point intercept, canopy gap intercept, vegetation height, species inventory, and soil texture. After calibration, the data can be organized and analyzed prior to initiating a robust data management plan (Herrick et al., 2017). Observations of the system can lead to new theories and hypotheses (Montgomery, 2017), but adequate validation processes are ultimately needed to assess whether these theories are correct.

This review identifies and discusses factors, which need to be addressed in order to improve RS research on growth monitoring of crops. It identifies theoretical assumptions, research gaps in working methodology, advantages and drawbacks of certain methods, and perspectives for future research. The effective use of well-designed research benefits not only researchers in the field of crop science, but also the farmers who gain reliable information for use in their daily activities.

2. Goals in remote sensing research

Research designs, which properly incorporate key technologies, can lead to both breakthrough and incremental innovations. In monitoring studies, a design is selected according to the aims of the research. Trend monitoring design identifies large-scale changes and uses descriptive, correlative, and causal comparative research. Effect-oriented monitoring design identifies changes in plants in response to certain environmental conditions or after a specific treatment at levels ranging from individual plants to whole communities. Predictive-oriented monitoring design is used in conditions in which the cause-effect relationship is known to ascertain an effect at an early stage when a given cause is detected.

Considering the goals of the research, one may have exploratory research in which researchers are establishing what method to use in collecting data and which is the best approach to be deployed. RS exploratory investigations are used to establish priorities among several alternatives or to improve the working methodology. In descriptive research, a particular phenomenon or pattern is defined and described. Descriptive studies in the remote sensing field are focused on the collection of data, establishing correlation between variables, and categorizing the data. In explanatory studies, the researcher is trying to identify the causes and effects (Blackstone, 2020) and in predictive research, future events are anticipated. RS explanatory studies attempt to elucidate causitive relationships between variables, while predictive research seeks to provide predictive theories for specific events or situations based on existing and similar situations.

Regarding the depth of a research project, idiographic research describes a phenomenon exhaustively, while nomothetic research provides a more general explanation or description of a topic (Blackstone, 2020). Regardless of research type, good research design begins by defining a set of goals. High-quality research has its purposes clearly defined and unambiguously formulated, providing a focus for the study. After defining the research goals, the specific problems and an appropriate study design should be identified.

In RS crop growth investigations, research objectives involve scientific, technical, methodological, economic, and practical concerns. Objectives of RS research can therefore be very diverse and may consist of the followings: developing spectral indices (Yu et al., 2014), detecting and characterizing specific features of plants, such as spatial heterogeneity of pigment and chlorophyll concentration in canopies (Haboudane et al., 2008) and screening the adaxial and abaxial reflectance of leaf surfaces (Lu et al., 2015). Another class of objectives focuses on establishing causal relationships between plants and stress factors or environmental conditions such as agricultural drought (Zhang et.al., 2020; Sun et al., 2015; Maes and Steppe, 2018), water stress (Gerhards et al., 2018), heat stress (Song et al., 2018), infectious disease (Calderón et al., 2013), sunlight conditions (He et al., 2017), surface temperatures, and meteorological recordings (Dabrowska-Zielinska et al., 2020). Causal relationships are not only limited to simple plant-environment interactions but also involve relationships among leaf, canopy, and soil parameters (Yue et al., 2020) or between vegetation indices and grain yield (Shafian et al., 2018). Finally, objectives in the field of RS can also focus on assessing signal quality, evaluating, for instance, the variability of remote sensing signals related to plant communities (Bandopadhyay et al., 2019), seasons (Zarco-Tejada et al., 2016), or vegetation type (Rascher et al., 2015).

Various approaches have been proposed to address the systematic differences in RS research design with regards to methods, systems, approaches, and models (Ludbroock, 1997). Differences exist concerning issues such as data acquisition, spatial resolution, retrieval precision, accuracy, performance, and cost. Several recent studies have sought to compare and evaluate RS-related questions, including the utility of two optical imaging approaches, namely, LiDAR and surface motion photogrammetry (Sofonia et al., 2019); the performance of these two systems (Maimaitijiang et al., 2020); the potential of GOME-2 SIF data to estimate gross primary productivity (GPP) with other model-derived outcomes such as the light use efficiency (LUE)-based vegetation photosynthesis model (VPM) and the process-based SCOPE model (Wagle et al., 2016); solar-induced chlorophyll fluorescence (SIF) detectable satellite products, such as the GOSAT, the GOME-2, and the newer OCO-2 SIF products (Sun et al., 2017), partial least squares regression (PLSR) methods with stepwise regression (SWR) (Tao et al., 2020), and the differences between OCO-2 and GOME-2 SIF products and how these impact GPP model optimization (Bacour et al., 2019).

Studies on technical issues in RS have focused on objectives that include providing a basis for technique development (Haboudane et al., 2008; Urschel and Pocock, 2018), implementing instruments for monitoring plant growth (Cogliati et al., 2015; Pacheco-Labrador et al., 2019), using the hyperspectral Unmanned Aircraft System (HyUAS) for measuring visible and near-infrared (VNIR) spectral reflectance and SIF signals (Garzonio et al., 2017), investigating the potential of Remotely Piloted Aircraft Systems (RPAS) to facilitate rapid and flexible chlorophyll monitoring (Vanbrabant et al., 2019), reporting instrumental descriptions, calibration procedures, and uncertainties related to the application of the PICCOLO-DOPPIO system for SIF measurements (Mac Arthur et al., 2014), investigating laser-induced fluorescence (LIF) technology applied to monitor vegetation growth status (Yang et al., 2019), documenting details of system components, instrument installation and calibration, data collection and processing using the SIFSpec system (Du et al., 2019), and estimating the chlorophyll content from 3D images using a photogrammetric approach called "structure from motion" (Itakura et al., 2019).

Another group of objectives involves seeking to improve estimation and retrieval methods and to develop predictive models. Studies related to these objectives have focused on, in part, the followings: increasing estimation accuracy through modified vegetation indices (VIs), such as the modified triangular VI (MTVI2) for leaf chlorophyll content (LCC) retrieval (Zhou et al., 2020), establishing accurate predictive models through model simulations and ground-measured data (Haboudane et al., 2008), establishing the advantages of using correlative relationships to assess plant growth stage (Miao et al., 2009), assessing the impact of spectral resolution and signal-to-noise ratio (SNR) when used to retrieve signals from spaceborne sensors (Liu et al., 2015), and reviewing the OCO-2 SIF product, retrieval process, cross-mission comparison, and GPP estimation potential (Sun et al., 2017). Other general objectives involve identifying potential problems and suggesting practical solutions (Haboudane et al., 2008), obtaining economic advantages using remotely measured proxies for plant growth without computationally expensive data processing (Urschel and Pocock, 2018), and converting multispectral imagery into maps of plants (Shafian et al., 2018; Tao et al., 2020).

3. Independent and dependent variables

Independent variables are the presumed cause of an experiment, systematically manipulated by an investigator. In RS research, there are only few examples in which the entire protocol is designed as an experiment. Most studies are comprised of several stages with differing research designs. Independent variables in RS studies are usually related to varying levels of spatial scales (e.g., leaf-canopy, ground, airborne, or spaceborne). For example, one study assessed flying altitude at various levels from 300 to 3000 m as an independent variable (Moya et al., 2006). In other studies, independent variables included factors on temporal scales, such as plant growth stage, time of day, season, and treatment dosage for fertilizer, herbicides or water.

A dependent variable is the outcome of what is measured in an experiment or evaluated in a mathematical equation. Measurements of dependent variables can be made on different time scales, that is, on a continuous time scale, a growth cycle stage scale, a seasonal scale, or a scale related to time-of-day. Measurements can also occur on various horizontal spatial scales, including local, regional, global, and on vertical scales as well as at the ground, airborne, or spaceborne level. In designed experiments in which dependent variables have a nonconstant variance, transformation of the variables to stabilize the variance of the response should be considered (Montgomery, 2017).

Traditional optical RS-based vegetation monitoring approaches consist of measuring radiance, reflectance, or apparent reflectance of vegetation with different spectrometers at varying wavelengths. These three parameters can be used interchangeably, but because reflectance is a property of the vegetation itself, the most reliable vegetation index (VI) values can be obtained using reflectance (Terill, 1994). VIs are derived from ground and airborne-based spectrometer measurements and are designed to provide information about the quality of photosynthetic pigments in vegetation (Dobrota et al., 2015), chlorophyll content (Baret et al., 2002), water content (Penuelas et al., 1993), plant biomass (Huete et al., 2002), and many other variables. Several of these indices are susceptible to error and uncertainty due to variable atmospheric, canopy, and soil background conditions (Liu and Huete, 1995). Further, calculation errors can result from indices involving mathematical operations. Thus, attempts to develop new indices seek to improve or combine existing VIs in order to increase estimation and predictive accuracy. For example, Lu et al. (2015) introduced a modified Datt index to improve assessments of LCC regardless of phenotypic differences in leaves when the reflectance comes from both adaxial and abaxial surfaces. Yu et al. (2014) proposed the ratio of reflectance difference index (RRDI), which significantly improves the estimation of chlorophyll content by reducing noise from soil background, canopy structure, and multiple scattering. Additionally, a visible and near-infrared (NIR) angle index (VNAI) was proposed as a method for the multi-stage estimation of chlorophyll content of soybean canopy by Yue et al. (2020). Finally, Piegari et al. (2020) studied the performance of several VIs using simulated and modelled reflectance values, such as the MERIS terrestrial chlorophyll index (MTCI), the Macc index, and the modified chlorophyll absorption reflectance index/optimized soil-adjusted index (MCARI/OSAVI).

Combinations of VIs are frequently used to provide better crop yield estimates. For example, Tao et al. (2020) used a combination of vegetation indices and red-edge parameters to estimate and map the distributions of above-ground biomass (AGB) and leaf area index (LAI) values for various growth stages of winter wheat. Further, Fu et al. (2020) reported that a VI obtained from combining the red edge band and near-infrared band from unmanned aerial vehical (UAV) data was significantly correlated with LAI and leaf dry matter index values in wheat.

An alternative to VIs is solar-induced chlorophyll fluorescence (SIF), which is a relatively novel remote sensing parameter that is used to estimate actual photosynthetic rate (Schikling et al., 2016). SIF represents a small fraction of the solar radiance reflected by plants and measured through high-resolution spectrometers (Cendrero-Mateo et al., 2019). Many studies have attempted to underline the advantages of using SIF instead of VIs, arguing that SIF reflects more physiological information than various VIs (Yang et al., 2015) and is more sensitive to environmental factors. Because SIF signal is much weaker than reflected solar radiation, the use of spaceborne sensors and SIF signal quantification require significant improvements (Frankernberg et al., 2013).

A trend in developing new indices is to consider specific features of plants and/or environmental conditions. Starting with a study by Guanter et al. (2007) that reported the first space-based SIF observations on board the ENVIronmental SATellite (ENVISAT) and continuing with SIF measurements acquired by the Japanese GOSAT mission launched in 2009 (Frankenberg et al., 2018), indices related to SIF have been evolved and refined in order to better manage environmental factors, such as soil moisture. For instance, SIF has been reported to show a significant reduction under serious drought (Liu et al., 2018), and the resulting downscaled SIF value combined with land surface temperature (LST) data was used to develop the temperature fluorescence dryness index (TFDI), which is able to show enhanced spatial details and is suitable to be used in agricultural drought condition studies (Zhang et al., 2020).

Assessing a given VI can be performed continuously using signals received from the canopy level and spanning from seeding to maturity (Daumard et al., 2012). Assessments can also be made based on the monitoring of certain growing season stages or environmental conditions. The Normalized Difference Vegetation Index (NDVI), which is one of the most widely used VIs to predict LAI, fractional vegetation cover (fc), and grain yield, is suitable for use from early- to mid-growing season (Shafian et al., 2018). Several other measurements are related to specific times of the day. For example, thermal infrared (TIR)-based indices proposed by Gerhards et al. (2018) show significant sensitivity when using data collected during early morning and noontime. Using GOME-2 data, Joiner et al. (2013) proposed a simplified radiative transfer model based on fluorescence retrieval techniques, providing global coverage for SIF estimation during short days. In subsequent works, the same group tracked the seasonal cycle of photosynthesis (Joiner et al., 2014) and mapped the reliable values of global monthly SIF anomalies (Joiner et al., 2016). Diurnal and seasonal variations in canopy SIF and its yield (SIFyield) have also been analyzed to show that growth stage can influence the SIF-GPP relationship (Li et al., 2020).

Other measurements are conditioned by environmental factors. For example, one study tracked the canopy photosynthesis process in a stable atmospheric condition only (Zarco-Tejada et al., 2013). Another study that explored the differences between SIF and NDVI values in response to drought reported that average SIF values were significantly reduced under relatively serious drought, while NDVI values were affected only by extreme drought (Liu et al., 2018).

3.1 Ground measurements

The functional activity of plants and stress level changes induced by environmental factors can be detected through radiance signals emitted by the leaves using ground-based instruments. Several spectrometers and sensors of varying resolutions have been developed to measure fluorescence signals from the leaf to the canopy level. The complexity and performance of these ground instruments vary from lab-developed prototypes and commercial products to standardized platforms for automated measurement of canopies. Some examples of this equipment being used in recent literature include the followings: a passive multiparameter sensor that was employed to assess the yield of maize plants in water stress conditions (Evain et al., 2002), a TriFLEX passive fluorosensor that was able to calculate the SIF emission of a crop field during the growing period (Daumard et al., 2012), a field spectrometer (HR4000) with SPECFull and SPECFluo modules that was employed for collecting continuous and long-term SIF measurements (Cogliati et al., 2015), an automated system that was used for collecting irradiance and canopy radiance (FluoSpec2) and for measuring diurnal and seasonal SIF variations from various ecosystems (Yang et al., 2015), a QE Pro spectrometer component of the FloX box that provided continuous SIF observation (Magney et.al, 2017), and, lastly, a dual-field-of-view spectrometer system, PICCOLO-DOPPIO, that was used to measure fluorescence under natural light conditions (Mac Arthur et al., 2014). One important advantage of using ground-based instruments is that the spectra are not influenced by atmospheric disturbances such as water vapor, dust particles, or aerosols (Meroni et al., 2009).

Importantly, fluorescence ground measurements can be scaled up from the leaf to the canopy level (Moya et al., 2004), and the resulting measurements can be used to obtain chlorophyll fluorescence values and to correlate these with environmental conditions (for example, photosynthetic active radiation, or gas exchange) (Moya et al., 2006) as well as to detect plant stress. Several studies have established the existence of a significant relationship between SIF and various environmental stressors, including plant water stress (Evain et al., 2002), extreme temperature (Ac et al., 2015), nitrogen (N) and phosphorous (P) treatments (Kebanian et al., 1999; Martini et al., 2019; Migliavaca et al., 2017), ozone stress (Meroni et al., 2008), and stress induced by herbicide treatment (Van Rensen, 1989). Ground measurements are also able to estimate GPP (Yang et al., 2015; Wolfhart et al., 2018).

Ground data are necessary for performing retrieval method estimations and for the calibration and validation of airborne, unmanned aerial vehicle (UAV), and spaceborne fluorescence signals. For instance, SIF datasets collected during the ongoing FLuorescence EXplorer (FLEX) Earth Explorer 8 Mission of ESA have used ground measurements for calibration and validation (Bandopadhyay et al., 2020).

3.2 Airborne measurements

Research studies at both the local and regional scale have sought to deploy airborne platforms that can capture surface-reflected radiance and to assess the validity of data obtained from various spectrometers. Fluorescence signals reflected by vegetation are captured by airborne sensors, which may or may not be coupled to imaging spectrometers. Nonimaging data are mostly reliant on the spectral properties of the sensor. The florescence of the vegetation captured in images offers information related to the characteristics of a given ecosystem. In both data types, data validation using ground measurements is required before further processing can be performed.

UAVs are also widely employed at both the local and regional scale. These vehicles fly slowly at low altitudes and, thus, can obtain images with high spatial resolution and long integration times (Mohammed et al., 2019). UAV-based SIF measurements offer a compromise between temporally continuous ground measurements and spatially coarse satellite retrievals (Atherton et al., 2018).

One disadvantage of airborne data collection is the uncertainty induced by atmospheric noise. Several atmospheric correction models are required to eliminate noise. Other disadvantages of airborne observation include the limited geometric accuracy of the obtained images, which frequently require correction and the need for proper instrument calibration (Meroni et al., 2009).

In a series of recent studies, Zarco-Tejada et al. used a variety of retrieval methods and fluorescence indices to track the canopy photosynthesis process (Zarco-Tejada et al., 2016), detect water stress (Zarco-Tejada et al., 2013), and investigate seasonal stomatal conductance (Zarco-Tejeda et al., 2003). Additionally, Rossini et al. (2015) used thermal and optical airborne data to discriminate between irrigated and rainfed maize plants, and Gerhards et al. (2018) analyzed water stress symptoms using high-resolution airborne thermal infrared (TIR) images in combination with sun-induced fluorescence (SIF) images.

3.3 Spaceborne measurements

On a global scale, researchers have been deploying satellites operated by space agencies and designed for dedicated missions. The FLORIS satellite under the ESA FLEX mission was explicitly designed to monitor and to assess the photosynthetic activity of terrestrial vegetation using SIF signals (Drusch et al., 2017). As fluorescence signals cannot be measured independently from vegetation, they must be retrieved thorough specific methods and require validation (Zhou et al., 2020). Accurate validation is made by using ground measurements and involves sensor and instrument calibration, troubleshooting of any uncertainties, and correct interpretation of reflectance values (Meroni et al., 2009).

Among SIF retrieval methods, several multispectral, hyperspectral, radiance- and reflectance-based methods have been documented, establishing the reflectance ratio, the derivative index, and the infilling index (Meroni et al., 2009). Along with retrieval algorithms, numerous models have been developed to overcome technical limitations and increase estimation accuracy, including radiative transfer models (RTMs), the SCOPE model, and the fluorescence–reflectance–transmittance (FRT) model (Mohammed et al., 2019). Hybrid regression methods using active learning techniques together with Gaussian process regression for LCC modeling have also been applied (Zhou et al., 2020). Further, radiometric and biological data have been used to set up an inversion procedure based on the radiative transfer model PROSAIL followed by theoretical canopy reflectance data set modeling (Piegari et al., 2020). Sonobe et al. (2021) applied preprocessing techniques used in conjunction with machine learning algorithms to estimate chlorophyll content and reported that the kernel-based extreme learning machine (KELM) and Cubist algorithms were the best performers. Finally, Li et al. (2018) constructed an estimation model based on remote sensing imaging using the back-propagation neural network (BPNN) and support vector machine regression (SVMR).

When comparing spaceborne values recorded by satellites with ground-based fluorescence values, errors between 5 and 35% have been reported (Liu et al., 2015). However, previous studies have indicated that spaceborne SIF signals along with calibration validation through airborne and ground systems are adequate estimators of crop photosynthetic capacity (Zhang et al., 2014).

4. Errors and limitations

Many types of errors have been identified in RS research. These errors are usually related to the methods used to obtain measurements, variability induced by environmental factors, vegetation characteristics, or shortcomings of the applied mathematical operations. RS measurement errors often occur due to environmental factors such as changes in solar zenith angle, subpixel contamination of clouds, and variation in local topography (Chen, 1996). Some VIs are susceptible to errors and uncertainty over variable atmospheric and canopy background conditions (Liu et Huete, 1995). Another source of error is related to mathematical operations other than ratio calculation, which can retain and even amplify these errors (Chen, 1996). All error sources should be carefully considered and minimized to reduce these limitations and improve the feasibility of RS studies.

The limitations of a study are usually, but not always, characteristics of the study design or methodology. When analyzing the limitations of a study, problem identification should be restricted to the objectives proposed at the beginning of the research project. Each limitation should be explained in detail followed by a description of how the limitation impacts the results. Normal methodological limitations consist of factors related to small sample size, lack of reliable data, lack of prior research on a given topic, and measurement reliability (Brutus et al., 2013).

In RS research in particular, many common limitations occur because of the dynamic nature of the results and the rapid development of technology, leading to multiple issues or events being simultaneously investigated. Due to limited access and expertise of cutting-edge technology, the reproducibility of RS investigations is low. Usually, each new study introduces a different system and new variables to expand on the findings of a previous work.

Within the category of limitations related to research design, different studies have reported the following problems: a limited availability of plant biophysical data during the growth season (Molijn et al., 2018), a low number of variables included in the modeling of plant growth (Sofonia et al., 2019), a lack of specificity for detection methods that rely on phenotypic changes following decreases in chlorophyll concentrations and plant water potential, which can be caused by manifold stress types (Mahlein, 2016), uncertainties and error propagation associated with data processing due to a general lack of systematic analysis and calibration (Bandopadhyay et al., 2019), a lack of atmospheric data corrections, particularly for aerosol optical thickness and terrain altitude corrections (Davidson et al., 2006), the use of chemical and chlorophyll meter methods, which do not provide real-time measurements on a regional or global scale (Yu et al., 2014), the limited specificity of wavelengths related to crop/species that have been optimized for RRDIs, which cannot be extrapolated to other crops under different conditions (Yu et al., 2014), and the practice of attributing large changes in spectral shape to a given variable when data acquisition is temporally sparse (Magney et al., 2017).

Another group of limitations are related to the reductionist approach that is used to simplify models. These limitations can include the following: simplification and idealization of processes during radiative transfer modeling, which may introduce inaccuracies regarding canopy reflectance (Dorigo et al., 2012; Damm et al., 2010), failure to consider N fertilization in conjunction with other nutrients (especially K) to obtain an accurate assessment of crop yield (Ingram and Hilton, 1986), the need for a comprehensive simulation comprising a broader crop-soil management system for assessing production systems (Keating et al., 1999), the fact that results obtained at smaller scales cannot be easily applied to larger scales (Yu et al., 2014), the need to incorporate leaf parameters such as stomatal conductance as references for comparison with soil moisture, leaf water content, and SIF (Liu et al., 2018), the fact that the use of certain spectral indices to calibrate general purpose models for the entire growing season can neglect to account for chlorophyll variation during individual critical stages (Yu et al., 2014), and, lastly, a lack of consideration for the effects of soil background (Yue et al., 2020).

The next group of limitations is related to technical shortcomings. These can include imaging difficulties related to complex data processing and low spatial resolution (Tao et al., 2020). Additionally, airborne and UAV systems with low speeds and short flight ranges limit the area that can be covered (Bandopadhyay et al., 2020). Other limitations in the literature include the following facts: the calculation method for the VNAI is relatively complicated compared to that of band-operation-based chlorophyll VIs limiting the application of the VNAI (Yue et al., 2020), satellite or aircraft remote sensing systems produce coarse resolution images that are not suitable for small plot research studies (Shafian et al., 2018), satellite hyperspectral sensors cannot provide spatial distributions of crop Chl content over large areas with high temporal and spatial resolution (Yue et al., 2020).

The last group of limitations which frequently occur in RS research is related to resource availability. High costs per campaign and considerable data processing costs (including time) are disadvantages of airborne SIF measurements (Bandopadhyay et al., 2020), direct field measurements of chlorophyll content over large areas require a tremendous commitment of labor and are thereby expensive (Haboudane et al., 2008), traditional methods used in ground measurements limit the timeliness and effectiveness of crop growth monitoring (Cao et al., 2020), plant sampling and analysis used as calibration data are time consuming, labor intensive, and expensive if enough representative samples are to be collected for large fields (Miao et al., 2009), traditional manual methods for the measurement of crop chlorophyll content are inefficient, costly, and cannot provide crop chlorophyll maps over large areas (Yue et al., 2020), LiDAR photogrammetry is less cost-efficient than RGB and is complex in terms of operation and data processing (Maimaitijiang et al., 2020) (although it does provide higher penetration capability into the canopy than RGB), and satellite hyperspectral sensors are expensive and scarce (Yue et al., 2020).

It is absolutely necessary to understand and troubleshoot the limitations associated with RS research in order to reduce knowledge gaps and to improve study design, instrument performance, algorithm retrieval, and the applied models. RS research allows scientists to better understand plant physiological processes at different scales while allowing stakeholders interested in crop yield to access better methods and data for more effective management of crop cultures. Limitations require a critical overall appraisal and interpretation of their impact. Acknowledging limitations offers the opportunity to reframe the design and make suggestions for further research.

5. Challenges and prospects in RS monitoring of crop growth

Short- and long-term prospects have been outlined in studies on crop remote monitoring concerning plant systems, methodologies, optics, and hardware. In the context of forthcoming large-scale remote sensing applications, new methods and models to quantify crop growth are needed. These have the potential to be useful tools in precision agriculture and to provide reference and technical support for management decisions.

Although many different species have been subject to RS monitoring, there still exists a need to extend the number of species and to assess the performance of new cultivars. Furthermore, plant leaf features (e.g., waxy cuticle or hairy leaves) (Haboudane et al., 2008), plant density (Maimaitijiang et al., 2020), environmental stressors (e.g., drought, nutrient limitation, temperature, or disease) (Miao et al., 2009), and crop development stage should each be considered for further investigation. Moreover, additional quantitative field measurements should be conducted to investigate the feasibility of long-term canopy chlorophyll estimation (Yue et al., 2020).

Bandopadhyay et al. (2020) identified the need to enlarge the database of measurements, as satellite SIF products have a shorter amount of data (GOSAT, GOME-2, OCO-2) than traditional RS datasets (MODIS and LANDSAT). Another research area that can be improved is data analyzation and interpretation. This category includes improvements in remote signal interpretation when the leaf level fluorescence emission is modified by the structure of the canopy (Migliavaca et al., 2017, Frankenberg et al., 2014) or designing spectral indices that can reduce canopy structure effects (Yu et al., 2014). Sofonia et al. (2019) suggested further investigations into the interactions of signal parameters, such as wavelength and incident angle, with biophysical features such as texture, geometry, moisture content, and roughness.

Another subject that has been suggested as a topic of future research is the improvement of crop growth radiative transfer models (i.e., PROSPECT) to reflect a more detailed and realistic relationship between RS measurements and vegetation parameters (Haboudane et al., 2008). Other topics for future research that have been suggested in the literature include the introduction of new techniques, particularly state-of-the-art deep learning algorithms (Maimaitijiang et al., 2020), the optimization and improvement of retrieval methods and the application of these methods to various new sensors (Maimaitijiang et al., 2020), and the combination of pre-existing methods with satellite data to enlarge practical application for large agricultural areas (Fu et al., 2020).

6. Conclusions

The preceding review identifies and discusses aspects of research design that need to be addressed in order to improve RS research concerning growth monitoring of crops. It identifies theoretical assumptions, research gaps in working methodology, the advantages and drawbacks of certain methods, and prospective future research.

Biological systems are nonlinear complex systems which are by nature highly dynamic, governed by feedback loops rather than by equilibrium, and lack centralized control. Due to the complexity of RS research, there are only a few examples in which the entire protocol is designed as an experiment. In most cases, there are several stages with different designs. The designs used for RS crop monitoring are trend monitoring, effects-oriented monitoring, and predictive-oriented monitoring.

RS research studies seek to advance scientific, technical, methodological, economic, and practical questions, such as establishing the causal relationships between plants and stress factors or environmental conditions, developing new techniques, and comparing and improving existing methods, systems, approaches, and models.

Considering the goals of the research, one may use RS exploratory investigations to improve working methodology, descriptive studies focused on collection of data and correlation between variables, explanatory research where cause and effect are outlined, and predictive research where future events are anticipated.

In experimental designs, independent variables are related to spatial scales at different levels (leaf-canopy, ground-airborne-spaceborne) or to levels of temporal scale such as stages of plant growth, time of day, seasons, or different doses within an applied treatment. Dependent variables are radiance, reflectance, or apparent reflectance of the vegetation measured with different spectrometers at different wavelengths. Vegetation indices are derived from ground and airborne-based spectrometer measurements. They are continuously evolving and refined in relation to specific features of plants and/or environmental conditions to increase their estimation accuracy and prediction capability. Solar-induced chlorophyll fluorescence (SIF), representing a small fraction of the solar radiance reflected by plants, is deployed as a more comprehensive alternative to vegetation indices.

Several spectrometers and sensors with different resolutions have been developed to measure fluorescence signals from leaf to canopy levels. The florescence of the vegetation captured in images offers information on the characteristics of ecosystems. Research at a global scale is deploying satellites operated by space agencies, designed for missions dedicated to this. Among SIF retrieval methods, multispectral and hyperspectral radiance-based methods and reflectance-based methods, such as the reflectance ratio, derivative index, and infilling index, have been documented.

Some of the problems which have occurred in more than one reviewed article are: the availability of plant biophysical data in the growth season, the low number of variables which were included in the modelling of plant growth, the uncertainties and error propagation associated with data processing, and errors due to the calibration of instruments.

The limitations identified in this review are related to research design, the reductionist tendency, introduced for simplifying models, technical limitations, and the availability of resources.

It is essential to understand and troubleshoot the limitations associated with RS research to succeed in improving designs, reducing the scientific knowledge gap, and improving the performance of instruments, retrieval algorithms, and models applied in this field.

The prospects concerning the biological systems are considering the need to extend the number of species and new cultivars in relation to plant leaf features, plant density, and environmental stressors such as drought, nutrient limitation, temperature, disease, and development stages. The need to enlarge the satellite database to improve data analysis and interpretation, instrument calibration, the retrieval process, and modelling has also been identified.

In the context of the forthcoming large-scale remote sensing applications, new methods and models to quantify crop growth are needed. They can be useful tools in precision agriculture, providing reference and technical support for managerial decisions. Improvements in RS monitoring activities will ensure the successful integration of these methods in future farming practices. For these methods to be accessible to agricultural stakeholders, their utility and economic potential should be advertised through outreach activities.

Conflict of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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