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Review

Remote Sensing for Precision Agriculture: Sentinel-2 Improved Features and Applications

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Abstract: The use of satellites to monitor crops and support their management is gathering increasing attention. The improved temporal, spatial, and spectral resolution of the European Space Agency (ESA) launched Sentinel-2 A + B twin platform is paving the way to their popularization in precision agriculture. Besides the Sentinel-2 A + B constellation technical features the open-access nature of the information they generate, and the available support software are a significant improvement for agricultural monitoring. This paper was motivated by the challenges faced by researchers and agrarian institutions entering this field; it aims to frame remote sensing principles and Sentinel-2 applications in agriculture. Thus, we reviewed the features and uses of Sentinel-2 in precision agriculture, including abiotic and biotic stress detection, and agricultural management. We also compared the panoply of satellites currently in use for land remote sensing that are relevant for agriculture to the Sentinel-2 A + B constellation features. Contrasted with previous satellite image systems, the Sentinel-2 A + B twin platform has dramatically increased the capabilities for agricultural monitoring and crop management worldwide. Regarding crop stress monitoring, Sentinel-2 capacities for abiotic and biotic stresses detection represent a great step forward in many ways though not without its limitations; therefore, combinations of field data and different remote sensing techniques may still be needed. We conclude that Sentinel-2 has a wide range of useful applications in agriculture, yet still with room for further improvements. Current and future ways that Sentinel-2 can be utilized are also discussed.

Keywords: Sentinel-2; remote sensing; precision agriculture; crop monitoring

1. Introduction

In current and future climate scenarios the resilience and productivity of agricultural systems will be increasingly jeopardized [1]. Furthermore, population growth trends, expected to reach 8.7 billion by 2030 and 9.7 billion by 2050 [2], will further strain food production systems worldwide, which so far have not been able to keep pace [3]. Within this changing context, crops face a threefold obstacle: management-derived challenges as well as increased pressure from abiotic and biotic stressors. Thus, the application of all available advanced technologies towards managing crop variability and maintaining or improving yields and reducing negative impacts on environmental quality, namely advancements in precision agriculture [4], is central to approaching these issues.

The possible technological solutions for these issues are multifold within precision agriculture's paradigm. On the one hand, plant breeding and the use of phenotyping technological advances to improve breading programs [5] allow for obtaining genotypes adapted to various stressors. However, improved management scales are also a central topic to approach. The fundamental functioning of agroecosystems in food production and their role in environmental conservation calls for the development of operational global scale methodologies. In this sense, within the scope of precision agriculture, remote sensing technologies are able to provide crucial contributions to agriculture monitoring [6] and improve our understanding of the impacts of environmental variations [7]. Many of the limitations in the application of remote sensing techniques for precision agriculture of previous years [8] have been overcome with the launches of Sentinel-2 A + B. The Sentinel-2 constellation, with improved spatial, spectral, and temporal resolution was designed specifically to meet the needs of the agricultural community, both farmers and academic researchers with a focus on international agricultural development.

Management-derived challenges as well as abiotic and biotic stressors may all be confronted and their negative impacts greatly ameliorated by employing remote sensing technologies to better guide adaptive agricultural management decisions, such as variable rate applications and treatments, which can be assessed and confronted at different levels of precision using different sources of remotely sensed data. Remote sensing data has long been made freely available to help to deploy precision agriculture in crop management to optimize the use of scarce resources but requires the necessary know-how for correct implementation. The combination of imaging and spectroscopy has allowed, for the last five decades since the launch of the NASA (National Aeronautics and Space Administration) Landsat-1 or Earth Resources Technology Satellite (ERTS) and its Multispectral Scanner (MSS) in 1972, the application of satellite-based remote sensing technologies. The use of this technology has played an important role, yet with some limitations, in agriculture monitoring all around the world and will increasingly be needed to assess and confront issues related to global climate change. Remote sensing provides coverage of large areas with high precision and can be a very efficient tool for improved management across scales. In this sense, remote sensing using multispectral images is a proxy for extensive manual crop monitoring operations in the field [9] and provides potential savings in precious time and resources. Precision agriculture has grown and established itself as a central tool in agricultural management to forecast yield, monitor plant stress, and optimize fertilization, irrigation, and soil tilling activities for a more sustainable management of farming practices and improvements in yield for farmers.

The launches of Sentinel-2 A + B twin platforms by the European Space Agency (ESA) has resulted in an improvement of precision agriculture possibilities. The ESA openly and freely provides Sentinel-2 with an improved number of multispectral bands, a more frequent revisit time, and a higher spatial resolution that should be of great interest to the agricultural community and to international agricultural development researchers worldwide.

This review article focuses on the field of precision agriculture and monitoring, with a particular emphasis on the recent advances provided by the ESA Sentinel-2 constellation, as part of the European Union (EU) Copernicus Program. Our goal is to frame remote sensing principles and Sentinel-2 A + B constellation features in the context of the state-of-the-art in precision agriculture. In order to better understand the improved features of Sentinel-2, its characteristics were compared to other satellites with potential use for agricultural monitoring. We also present an updated review of scientific literature on Sentinel-2 applications and advancements in precision agriculture. Furthermore, we explore its applications in biotic and abiotic stress monitoring, as well as at different management scales for agriculture.

2. Remote Sensing for Agriculture

2.1. Plant Spectral Reflectance Properties

Plants interact with sunlight—the full spectrum of sun-emitted electromagnetic radiation—differently depending on the wavelength observed. In this sense, incident solar radiation can follow three pathways: it can be transmitted, reflected, or absorbed. The electromagnetic radiation that is reflected by plants contains information about their biophysical composition and physiological status and can be measured using satellite sensors, such as those placed in the ESA Sentinel-2. Focusing on the visible domain, the chlorophyll pigments present in green leaves strongly absorbs in the visible (VIS) region of the spectrum (400–700 nm), especially in the blue and red wavelengths, where energy is captured for photosynthesis. Meanwhile in the near-infrared (NIR), from approximately 700 to 1300 nm, leaves exhibit high reflectance values and transmission, mostly related to leaf structural properties and biomass, and absorb less radiation in this spectral region [10,11]. Furthermore, plant canopy structure and leaf area are also fundamental traits connected to canopy reflectance patterns [12,13] and are key parameters for monitoring growth. Regarding the shortwave infrared region (SWIR), from approximately 1300 to 2500 nm, the absorption of radiation is largely dominated by water, followed by other biochemical components present in leaves. Concerning agriculture, in situations where crops interact with any given aspect of their environment (seasonal climatic variations, meteorological extreme events, pests, soil properties, etc.) or as crops grow and pass through different phenological stages, the interactions between plants and light reflectance translate into changes in plant signal patterns that can be interpreted using satellite data. The use of remote sensing instruments to monitor electromagnetic radiation reflectance changes in crops is well demonstrated in the scientific literature [13–24]. For example, chlorophyll content plays a direct role in photosynthesis and it is responsive to a range of stresses, and hence is often used as a general plant health indicator [25] and interpreted along with the signals related to biomass and water content. These are examples of general potential uses of plant spectral reflectance properties for vegetation monitoring. However, often it is the temporal and spatial properties of satellites that determine if their use is appropriate for agriculture. This is a consequence of the characteristics of crops, which grow more quickly and frequently in smaller and more closely managed parcels of land compared to natural vegetation.

2.2. Satellites and Remote Sensing Scales of Observation

Over the last 50 years of digital evolution, numerous satellites with multispectral sensors have been launched to orbit around the Earth for the purpose of environmental and agricultural remote sensing. Currently, one of the most relevant Earth observation programs focused on detection and assessment of vegetation is Copernicus. The Copernicus Program, led by the ESA, is a program aimed to increase the satellite-based Earth observation capacities and within which Sentinel-2 twin platforms were launched. Besides the multispectral Sentinel-2 system, various satellites have been launched or are planned to be launched as part of this still on-going program. Regarding potential agricultural applications within the Copernicus program, it is worth mentioning Sentinel-1 (https://sentinel.esa.int/web/sentinel/missions/sentinel-1) that carries a synthetic-aperture radar on board as well as Sentinel-3 that provides thermal data at 1 km of spatial resolution (https://sentinel.esa.int/web/sentinel/missions/sentinel-3).

Framing the concepts regarding satellites features is especially relevant in order to grasp Sentinel-2 improvements compared to other orbiting satellites. In this sense, it is central to understand first satellite resolution and observation scales as they determine satellite systems' agricultural monitoring capacities.

Regarding resolution, four parameters are central to approach a better understanding of the aims and scope of these instruments. First, the spectral resolution, namely the number, width, and location on the electromagnetic spectrum of spectral bands in the sensor system. Second, the spatial resolution, which is the measure of the smallest object that can be resolved by the sensor, e.g., pixel size. Third, one must consider the temporal resolution which is a measure of the frequency with which a sensor revisits the same area of the Earth's surface; and finally, the radiometric resolution, which is determined by the number of bits into which the recorded radiation is divided [26] and determines the spectral precision of the measurements.

Following Homolová et al. [27], on the matching of ecological, agricultural, and remote sensing scales, we currently find that on the basis of individual plants, plant communities, and agroecosystems, different remote sensing technologies may provide coverage across canopy and landscape scales. Furthermore, it provides coverage across a range of plant physiological processes from evapotranspiration and photosynthesis to phenology dynamics, productivity, and even quality traits such as those of a crop's harvestable component nutritional value. The spatial, temporal, and spectral resolutions of any sensor-satellite system are central to determining the scale at which an instrument can monitor crops, and therefore the most adequate approach towards guiding agricultural monitoring and assessments and subsequently management actions.

2.3. Sentinel-2 Spatial and Temporal Resolutions Compared to Other Satellites

Sentinel-2 has had two launches, Sentinel-2A that was launched on 23 June 2015 and Sentinel-2B on 7 March 2017, forming, up from this date, the Sentinel-2 A + B constellation (https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/sentinel-2). Both have a 7.25-year lifetime, including a 3 months commissioning phase with adequate propellant for up to 12 years. Both Sentinel-2A and Sentinel-2B satellites have on board the exact same MultiSpectral Instrument (MSI) with bands from the visible to the shortwave infrared: four (4) bands at 10 m, the classical broadband visible blue (490 nm), green (560 nm), red (665 nm), and near infrared (842 nm); six bands at 20 m, four narrow bands in the vegetation red edge spectral domain (705, 740, 775, and 865 nm), and two longer SWIR bands (1610 and 2190 nm); and three (3) bands at 60 m dedicated to atmospheric correction (443 nm for aerosols and 940 nm for water vapor) and to cirrus detection (1380 nm) (Table 1). After the second launch the satellite provides higher temporal resolution with a 5-day global revisit frequency, and up to 2-day revisit in top northern and southern parts of the globe.

Satellite spatial and temporal resolutions depend on their type of orbit and their orbit altitude. Most of the satellites are two types: polar orbiting which are sun synchronous and have orbits that cross near the poles in low earth orbit (around 700 km); or are geostationary geosynchronous and orbit above the equator, located much farther distance from the earth (35,000 km). In this case Sentinel-2 is sun synchronous and has a systematic coverage of all land surfaces (including croplands) globally from −56° (Southern America) to +83° (Northern Greenland) latitude, with a swath width of 290 km [28] and an earth orbit of 786 km.

Table 1. Bands and resolutions of Sentinel-2 MultiSpectral Instrument (MSI) [28,29].

MSI Band	Spatial Resolution (m)	Central Wavelength (nm)	Bandwidth (nm)
B1: Coastal Aerosol	60	443	20
B2: Blue	10	490	65
B3: Green	10	560	35
B4: Red	10	665	30
B5: Red-Edge	20	705	15
B6: Red-Edge	20	740	15
B7: Red-Edge	20	783	20
B8: NIR	10	842	115
B8A: Vegetation RE	20	865	20
B9: Water Vapor	60	945	20
B10: SWIR Cirrus	60	1375	30
B11: SWIR	20	1610	90
B12: SWIR	20	2190	180

Focusing on spatial and temporal resolution, in Figure 1 various satellites are shown in comparison to the most recently launch satellite of interest to precision agriculture—Sentinel-2. For comparison, the MODIS (Moderate Resolution Imaging Spectroradiometer) and Proba-V, with spatial resolutions ranging from 150 to 500 m and both with a daily revisit time can monitor agricultural systems at the agroecosystem level. Meanwhile, the IRS AWiFS and Landsat 8 satellites have a spatial resolution of 30–100 m and a revisit time of 24 and 16 days, respectively. In this case, both agroecosystems and plant communities at local to regional scales, namely the crop field level, can be monitored. On the other hand, both the SPOT (Satellite Pour l'Observation de la Terre) 6/7 have similarities with Sentinel-2 A + B as both are constellations of two satellites and therefore the combined revisit time is reduced, which translates in providing global daily imagery in the case of SPOT and every 5 days in the case of Sentinel-2. Additionally, the constellation combination also helps maintain relatively detailed spatial resolution, with SPOT spatial resolution at 6 m and the Sentinel-2 maximum resolution is 10 m. Specifically in the case of Sentinel-2 resolution ranges between 10 and 60 m, but the agricultural dedicated bands are either 10 or 20 m, depending on the band width, while the other bands at 60 m are for atmospheric aerosols and water vapor observations mainly for improved image calibration. Due to their shorter revisit time and more detailed spatial resolution (compared, for example, to LandSat at every 16 days and mostly 30 m pixel size), more precision in sub-field monitoring can be performed using these paired satellite constellations, hence covering from agroecosystem to field scales more precisely and thus gaining relevance for use in agricultural contexts and even more specifically smallholder farming systems in developing countries. Finally, GeoEye-1, Worldview-3, Planet, and Quickbird are each constellations of numerous commercial satellites allowing higher temporal resolution (as high as a 24 h revisit time) and have a more detailed spatial resolution with pixels smaller than 3 m, but in comparison to Sentinel-2 they do not provide free and open-access global coverage and may, in some cases, only capture data at controlled moments when contracted, which limits their potential use.

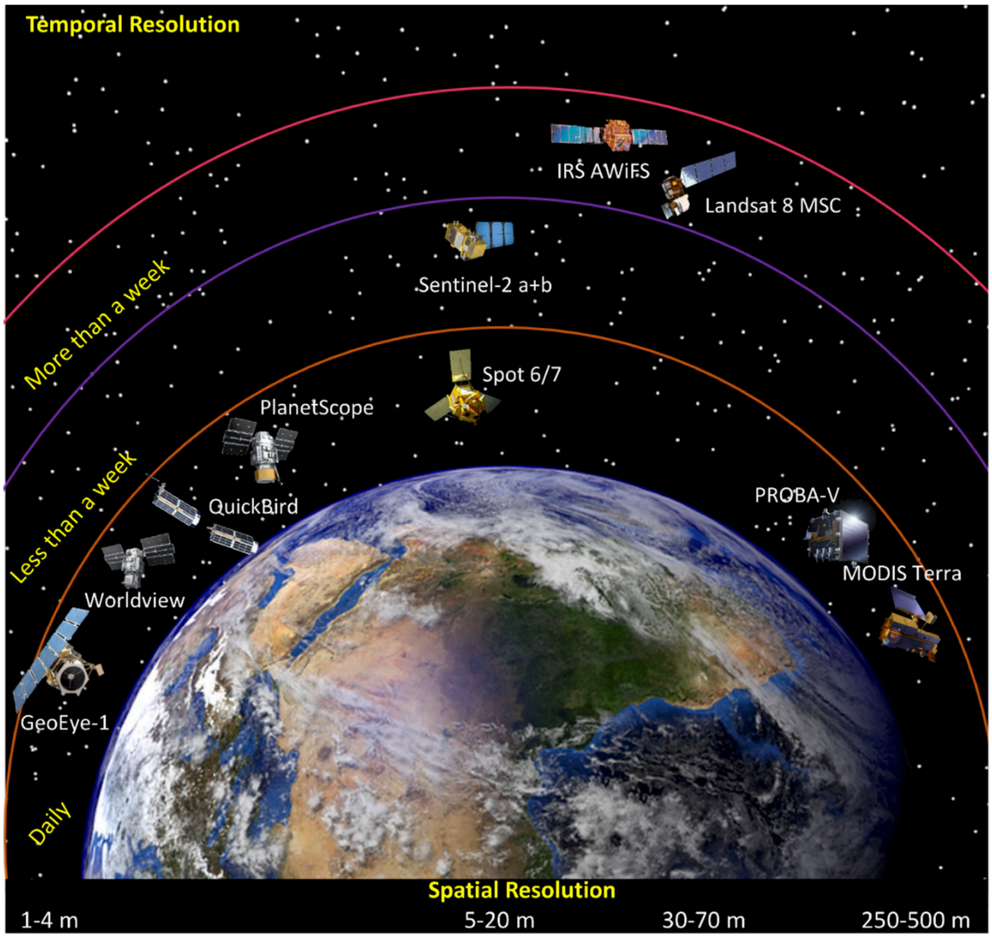

Figure 1. Current constellation of available satellites for land remote sensing that are highly relevant to crop monitoring and management, presented with their temporal and spatial resolution.

2.4. Spectral Resolutions and Useful Vegetation Indices for Sentinel-2 Features

Besides temporal and spatial resolution, spectral resolution is a central feature of satellites as it determines the plant physiological properties that may be accurately quantified. In this sense, the number of spectral bands in several sensor systems is shown together with the canopy reflectance spectrum in Figure 2, taking the examples of landscape, canopy, and plant scale sensors placed in satellites (MODIS, Landsat-8, Sentinel-2, and Planet, respectively). Comparing these satellites with Sentinel-2, we observe that all include sensors with visible, near infrared, and shortwave infrared bands; differently, Planet has only the three available bands in the visible (RGB, for red, green, and blue reflected light) and one in the near infrared (NIR). A different feature from Sentinel-2 is that it also captures four narrowband spectral regions of different wavelengths present in the Red Edge (RE) spectral region that are provided at 20 m resolution (Figure 2). The reflectance spectrum between 690 and 740 nm determines the point of maximum slope in the spectral signature of the vegetation [19], such that the RE marks the boundary between the processes of chlorophyll absorption in red wavelengths and within-leaf scattering in near-infrared wavelengths [20,21] (Figure 2), which provides unique capacities for separating crop photosynthetic activity from biomass, as indicated by some of the spectral indices that have been developed specifically for deployment by Sentinel-2 or other satellites that provide RE spectral band coverage. Moreover, the Sentinel-2 10 m spatial resolution that is achieved in the other broader spectral bands in the visible and near-infrared can provide improved details and allows for obtaining a large variety of spectral information to define crop topologies. In this sense, the big data volume of Sentinel-2 images provides novel opportunities though also challenges towards processing due to the increased complexity of interpreting additional spectral bands and the increased overall file size.

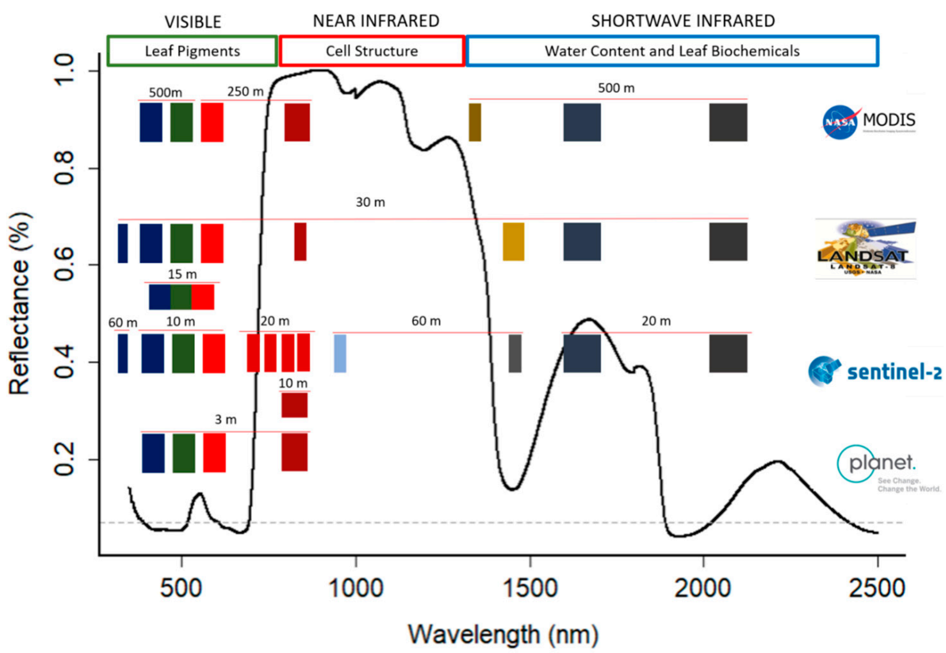

Figure 2. Crop reflectance spectral features, and representation of MODIS (Moderate Resolution Imaging Spectroradiometer), Landsat-8, Sentinel-2, and Planet multispectral bands and spatial resolution.

While many crop parameters may be estimated or indirectly inferred from their spectral light reflectance properties, some parameters, however, cannot be directly sensed but rather inferred through a combination of measurements of other plant properties. Chlorophyll spectral features are optically discernible within the visible and red-edge parts of the spectrum in a straightforward manner as these are classic plant pigments whose most basic function is the absorption of light for photosynthesis. On the other hand, plant nitrogen (N) content, for example, may not optically be discernible because N absorption features (1450–1940 nm) are obscured by water [22]. However, due to the close relationship between N concentration and chlorophyll content, chlorophyll-related indicators can be used as proxies of crop nitrogen concentration or status [23]. In this sense, the sensitivity of remote sensing data towards specific plant biophysical properties of interest can be estimated using vegetation indexes (VIs, Table 2) [24,30], which are usually fairly simple spectral wavelength (or spectral bands to indicate both the width and the central wavelength of a spectral region as captured by satellite multispectral sensors) measurement combinations. More in depth reviews and extensive databases (e.g., https://www.indexdatabase.de) on the spectral regions most useful for agricultural monitoring are suggested for a more exhaustive coverage of spectral indexes in general [31,32]. Regarding the chosen VIs relevant to Sentinel-2 imagery presented in Table 2, for the visible spectrum the Normalized Green–Red Difference Index (NGRDI) compares the differences between the green and red visible bands for vegetation, together with the well-known Normalized Difference Vegetation Index (NDVI) have shown to be able to remotely sense total crop green biomass [33], which is often indicative of general crop vigor and may be closely correlated with crop nitrogen (N) content and may provide good predictions of yield at specific growth stages. Another index that uses the visible bands of the spectrum is the Triangular Greenness Index (TGI), which has been shown to estimate correctly chlorophyll concentration at leaf and canopy level [34].

In some cases, a combination of two VIs may allow for more specific measurements, given that the sensor has enough spectral bands for both calculations. Many of these more advanced calculations were taken into account in the specific design of Sentinel-2 as part of its development specifically for precision agriculture and environmental/vegetation monitoring in general. For example, the ratio of the Transformed Chlorophyll in Reflectance Index and the Optimized Soil-Adjusted Vegetation Index (TCARI/OSAVI) has been shown to estimate chlorophyll leaf content [35], basically by providing a canopy chlorophyll measurement (TCARI) and then correcting for biomass (OSAVI). In some instances, the spectral indexes were originally developed for a prior satellite with similar spectral but coarser spatial resolution that did not make them amenable to smaller-scale agricultural applications, such as in the case of the MERIS (Medium-spectral Resolution Imaging Spectrometer) Terrestrial Chlorophyll Index (MTCI) [36]. Based on the red-edge bands, many of which are newly featured at higher spatial resolutions with the Sentinel-2 satellite, MTCI has showed that Sentinel-2 derived indexes using red-edge bands perform very precisely in estimating chlorophyll and N content [36]. It is also the case of the chlorophyll index red edge (Cl red edge) [37], effective for estimating leaf area index (LAI). The Chlorophyll Vegetation Index (CVI), a broad-band VI sensitive to leaf chlorophyll content at canopy level, has also shown good results for estimating chlorophyll content [38]. Another index of interest, in this case based on NIR and RE bands is the Inverted Red-Edge Chlorophyll Index (IRECI), which has shown good abilities to estimate chlorophyll content at the canopy level [39].

Table 2. An example of some spectral vegetation index (VIs) calculations of interest for use with European Space Agency (ESA) Sentinel-2 satellite data, where B is the spectral reflectance value of the band number of the Sentinel-2 band as detailed in Table 1.

VIs	Sentinel-2 Bands Used	Original Author
NGRDI	(B3 − B4) / (B3 + B4)	Hunt (2005)
TGI	−0.5 × [190 × (B4 − B3) − 120 × (B4 − B2)]	Hunt (2012)
NDVI	(B8 − B4) / (B8 + B4)	Tucker (1979)
TCARI/OSAVI	3 × [(B5 − B4) − 0.2 × (B5 − B3) × (B5 / B4)] / [(1 + 0.16) × (B7 − B4) × (B7 + B4 + 0.16)	Haboudane (2002)
MTCI	(B6 − B5) / (B5 − B4)	Dash and Curran (2004)
CVI	(B8 / B3)] / (B3 / B4)	Vincini (2008)
CI red-edge	(B8 / B5) − 1	Gitelson (2003)
IRECI	(B7 − B4) / (B5 / B6)	Frampton (2013)

2.5. Sentinel-2 Data Access, Secondary Products, and Support Tools

Regarding some of the highest spatial and temporal resolution satellites, such as Planet, the access to imagery is private or at least restricted, and therefore inaccessible for many institutions with limited funding, especially in developing countries. Besides that, NASA satellites, namely MODIS and LANDSAT-8 for instance, are publicly accessible and completely free, as well as ESA's entire Sentinel program, including Sentinel-2, along with the other sun-synchronous orbiting satellites that form part of the greater ESA Copernicus Program. This makes the data more readily accessible and more openly free for a more globally coordinated remote sensing of agriculture in this case.

The accessibility to this data is central. In this sense, there are several ways to freely and openly download Sentinel-2 imagery; one of them is the direct download of the imagery from ESA's website, through Copernicus (https://scihub.copernicus.eu/dhus/#/home). Furthermore, third party tools for downloading the imagery are available. For instance, there is the United States Geological Survey (USGS) (https://earthexplorer.usgs.gov/) which allows comprehensive searching and downloading of full-resolution Sentinel-2 images. On the open-source software QGIS, there are various plug-ins that take advantage of the ESA's Application Programing Interface (APIs) at the Copernicus Open Access Hub (https://scihub.copernicus.eu/apihub/), such as the free and open source Semi-Automatic Classification Plugin (SCP), developed by L. Congedo [40], which provides tools to simply download Sentinel-2 imagery or even download and immediately calibrate and apply image analyses to the data. Furthermore, the API access portals allow for download only specific bands of select images, thus reducing the storage requirements of personal computers. Moreover, Google Earth Engine has daily updated copies of all the available Sentinel-2 data and provides both access to this data repository along with high processing capacity using their image processing servers. Many other similar tools and services exist on other software applications and web portals and are being developed continuously.

Another relevant point is data itself, its plan for continuity, and its access to both raw data and pre-calibrated and pre-processed satellite images that provide value added benefits to end-users. Sentinel-2 products consist of Level-1B, which provides radiometrically corrected granulates in Top-Of-Atmosphere radiance covering (25 × 23) km^2. Sentinel-2 also offers Level-1C imagery which consists of tiles of 100 × 100 km^2 that provide geo-coded Top-Of-Atmosphere reflectance with a sub-pixel multi-spectral and multi-date registration. It additionally includes cloud masks, supplying an indication about the presence of cirrus clouds. Moreover, it provides Level-2A, a tile of 100 × 100 km^2 which provides Bottom-Of-Atmosphere reflectance in cartographic geometry [41]. Since December 2018 Level-2A products are generated globally and are ready for users to download. Level-2A can be also generated using Level-1C with Sentinel-2 Toolbox.

ESA frequently provides specific access tools, algorithms, and software in support of the use and processing of their satellites, such as the Sentinel-2 Toolbox within the Sentinel Application Platform (SNAP, https://sentinel.esa.int/web/sentinel/toolboxes/sentinel-2). On SNAP Sen2Cor is the atmospheric correction processor to generate Level-2A data; it also includes algorithms for cloud and cloud shadow detection, cirrus detection, and slope effect correction. Beyond SNAP, Sentinel-2 imagery can also be atmospherically corrected using MAJA (developed by CESBIO/CNES) or i-COR (developed by VITO), among other options. In addition, the further pre-processing chain of Level-2A products can be done on SNAP: resampling and subsetting followed by calculations using the bands. Besides vegetation indices, more deterministic biophysical parameters, such as LAI or FAPAR, can be calculated on SNAP with Sentinel-2 data following the algorithms developed by Weiss and colleagues [42]. It is relevant to point that as an experimental Sentinel-2 approach done with simulated Sentinel-2 imagery in 2015 [43], even before its launch, it already showed potential for retrieving LAI and with actual Sentinel-2 data it is currently fully operational.

3. Sentinel-2 for Precision Agriculture

The ESA Sentinel-2 satellite's potential applications in agriculture are multi-fold, as described above with regard to its specific spatial, temporal, and spectral capacities. Regarding the definition of the International Society of Precision Agriculture, precision agriculture is a management strategy that uses temporal and spatial information to support management decisions according to estimated variability for improved resource use efficiency and sustainability of agricultural production. This section gathers examples of Sentinel-2 capacity to sense variations at several levels of agricultural production and the subsequent management decisions that can be taken to address any disruption on crop development. The examples discussed are summarized in Table 3.

One very notable use of Sentinel-2 features at field monitoring is the ESA Sen2-Agri system which generates modules of time series along the growing season. These different products consist of a monthly cloud-free composite of surface reflectance at 10–20 m resolution; monthly dynamic cropland masks, delivered from the agricultural mid-season onwards; a cultivated crop type map at 10 m resolution for main crop groups; and time series of vegetation status indicators, NDVI and LAI [44]. This field monitoring tool has been successfully used not only in developed countries with homogenous and well delineated fields, but as well in challenging (in terms of farm fields boundaries) countries such as Mali, successfully differentiating crop types (80% of overall accuracy) [45]. In Europe S2-Agri is going to be used among other initiatives within the Sen4-CAP (http://esa-sen4cap.org/) to advance towards an integrated administration and control system of the Common Agriculture Policy (CAP), which will be reformulated in 2020. CAP subsidies play a central role in European Union policies as they account for around 30% of EU total budget [46]. Hence, the European Union is taking advantage of Sentinel-2 features to monitor croplands aiming to optimize resources by determining actual crop type and cropland accurate area. Following the coming 2020 CAP framework, several case studies in European regions for cropland classification using Sentinel-2, such as the one published by Campos-Taberner et al. [47] for Valencia (Spain), will provide scientific tools necessary for the upcoming policies. The precise agricultural monitoring will follow adequate fertilization or irrigation guidelines, among others.

The advantage of Sentinel-2 multi-temporal data for crop-type classification is very relevant as it reaches up to 91–95% overall accuracies in various crop classifications [48] while single-date images show limited results. Besides the revisit time, the higher spatial and spectral resolution also improves area detection and estimations as shown in small size rice fields classification in Taiwan [49]. Additionally, in complex landscapes Sentinel-2 imagery was able to map sugarcane fields in China with over 90% of accuracy [50]. Regarding classification techniques, beside pixel based, object based has showed to be an accurate classification approach using Sentinel-2 imagery [51]. In this sense, object-based dynamic time warping was demonstrated to be more efficient in classifying crops than the pixel-based approach when using multitemporal Sentinel-2 imagery [52], nonetheless random forest seems to be more efficient for crop type classification when crop spectral variability is high [53]. In general terms, the combination of Sentinel-2 imagery and various algorithmic approaches, such as random forest, k-nearest neighbor, and support vector machine have also shown optimal classification accuracy, resulting with over 90% of overall accuracy for the various approaches [54]. Understanding the context of the crop, namely crop type spectral features and surface extension, is central to accurately making classification method decisions when using Sentinel-2 imagery.

Sentinel-2-derived research has approached yield predictions in two different fashions. On the one hand empirical models using fitting techniques of the obtained data sets (VIs and climatological data correlated with actual yields) show robust results with machine learning and random forest techniques [55,56] as well as relatively high correlation, with an R^2 over 0.70, when using simple regressions with the most suitable VIs (i.e., NDVI) [57,58]. On the other hand, the radiative transfer models approach uses the calculated biophysical parameters such as LAI or FAPAR to model crop growth and predict yields [59–62]. The estimation of yields is a central issue in order to ensure food security and stabilize market demands. These performance models from Sentinel-2 imagery developed once images are available are not only aimed to provide final grain yield estimations, but they can also be used to monitor sudden changes in crop potential yields. This is especially central in taking agricultural management decisions as information is worth a little if it comes too late.

Soil is the element that facilitates the assimilation of both fertilizers and water through the roots, namely the two central factors for a proper development of crops. Studies of Sentinel-2 potential for soil monitoring have been undertaken. Soil organic carbon (SOC) can be successfully mapped in croplands using Sentinel-2 bands [63–66]. SOC prediction models were found to be overall better when formulated using the visible B4, B5, near infrared B8A, and two SWIR bands (B11, B12) [67]. Furthermore, cropland soil degradation with classification methods have also been studied [68,69].

Detecting agricultural fields affected by soil degradation or poor SOC can drive the intervention of farmers in order to prevent the failure of their fields. Thus, the decision to apply organic matter to improve soil structure or to improve field edges buffers (e.g., revegetating or reshaping them) can be driven with these Sentinel-2 data.

Irrigation and water requirements of crops are related to cultivars evapotranspiration (ET), where thermal bands are very suitable to estimate this parameter. However, in the case of Sentinel-2 only optical bands are available. In this sense, different strategies have been performed in order to determinate evapotranspiration and propose proper irrigations based on Sentinel-2 information. The combination of Senitnel-2 data with models such as FAO-56 Penman–Monteith and Aquacrop in the case of tomato have shown to be successful [70,71]. Moreover, the combination of FAO-56 Penman–Monteith with Sentinel-2 derived LAI have also shown relatively high accuracy in ET retrieval [72]. Several studies also take advantage of the red and red-edge bands to predict the crop coefficient (Kc) and thereafter use it together with ET_o [73,74]. The combination of accurate crop type mapping and ET models allows establishing regional and field-level water requirements to drive a sustainable use of water resources.

Regarding precision fertilization management, two different approaches, both fairly similar to those described above for yield, have been developed. On one hand, the use of radiative transfer models to obtain chlorophyll content [75–77], and on the other hand, using empirically correlated vegetation indexes and bands to assess the nitrogen status of the crop [78–81]. This strategy generally includes the three Sentinel-2 RE bands (705, 740, and 783 nm, Figure 2), which are very important for the retrieval of chlorophyll content [82]. The Belgian collaborative agriculture platform (http://www.belcam.info/) is taking advantage of these Sentinel-2 features to provide freely nitrogen status information at parcel level for farmers growing potato and winter wheat in Belgium. Information on the nitrogen absorbed by the crops and nitrogen nutrition index is provided; this information allows Belgian farmers to decide on precise N applications. Furthermore, geolocalized fertilizer spreaders can make applications on fields following Sentinel-2 sensed data in other to balance the applied amount of fertilizer depending on the crops needs per zone.

Regarding biotic stresses several approaches have been studied. Despite the insufficient resolution of Sentinel-2, 10 or 20 m, to analyze crops at leaf and individual plant scale, different strategies have been developed. On the one hand, the use of VIs to monitor effects of pests at canopy level in crops have been used in coffee [83] and wheat [84], as well as new VIs proposed with Sentinel-2 multispectral bands that have shown to sense wheat yellow rust using bands 4, 5, and 7, the so-called Red Edge Disease Stress Index (REDSI) [85]. On the other hand, classification algorithms using 2, 3, 4, and 8 bands have shown to correctly separate cotton rot root affected areas with 94.1% accuracy [86]. Furthermore, the combination of UAV and Sentinel-2 for western swamphen monitoring in rice crops have shown a relative high potential (57% of accuracy) for detecting infested fields [87]. The detection of biotic stresses can drive precise application of pesticides for both regional and field-level, furthermore the current drones' on-board carrying capacity has increased and there are various drone-based spraying experiences for crop protection against biotic stresses [88,89]. In this case, the application within the field could be driven by Sentinel-2-derived information on the most affected sites by the biotic stresses.

Concerning abiotic stresses, heavy metal stress in rice fields produced by cadmium (Cd), lead (Pb), and mercury (Hg) have shown to be effectively sensed using red edge features of Sentinel-2 [90–92]. In the case of salinity, Sentinel-2 bands 2 and 4 showed higher correlation (R^2 = 0.67) with the electrical conductivity of fields than Landsat-8 bands [93]. Drought monitoring at 20 cm soil-depth, using combined soil moisture models, and Sentinel-2-derived NDVI has shown to correlate strongly, with determination coefficients (R^2) ranging between 65% and 83% [94,95]. Detecting areas affected by abiotic stresses can guide determination of suitable zones for agriculture or, on the other hand, in need for phytoremediation activities or the implementation of halophyte cultivars.

Table 3. Examples of remote sensing information, derived from Sentinel-2, used for crop monitoring and management and the methodological approach used.

S2 for Agriculture		Sensed Trait	Method	Ref.
Plant stress	Biotic	Cotton rot root (*Phymatotrichopsis omnivore*)	Classification of affected areas with trained algorithms using bands 2, 3, 4, and 8	[86]
		Rice crops and Western Swamphen (*Porphyrio porphyrio*)	S2 imagery calibrated with an UAV	[87]
		Hessian fly (*Mayetiola destructor*) infestation in Wheat	NDVI decrease with increasing infestation, ground, airborne, and satellite multiplatform	[84]
		Coffee leaf rust (*Hemileia vastarix*)	Field spectral data and S2-derived VIs	[83]
		Wheat yellow rust (*Puccinia striiformis*)	Proposed index: Red Edge Disease Stress Index (REDSI), bands 4, 5, and 7	[85]
	Abiotic	Metal stress in rice	Red-edge S2 bands	[90–92]
		Drought	S2 VI and OPTRAM soil moisture monitoring	[94,95]
		Salinity	S2 visible bands, blue and red, are sensitive to soil salinity	[93]
Management scale	Fertilization	N in crops	Biophysical retrieval of canopy chlorophyll content, also with VIs within the red-edge. Assessment of the nutritional status, NNI	[75–81]
	Water	Irrigation and hydric requirements (cotton, tomato, wheat, and maize)	S2 vegetation parameters, surface albedo, and crop height for FAO-56 Penman-Monteith ET estimation; red and red-edge bands to predict crop coefficients (Kc). Irrigated and rain-fed cropland differentiation. Combination of S2 and Aquacrop.	[70–74]
	Fields monitoring	Cropland assessments	VIs for cropping practices assessment; regional and nation-scale cropland and crop type classification with S2, time series and retrieval of biophysical and vegetation radiometric indexes (sen-2Agri)	[44,45,48–54]
	Soils	Soil features	Determining soil OM with VIs, and S2 bands. The wavelength of the OM spectral feature in the visible is close to S2 red band. Classification of soils degradation.	[63–69]
	Yield prediction	Empirical models Radiative transfer models (RTM)	VIs and yields, together with climatological data to build a dataset. Fitting techniques (regressions, random forest, machine learning) to predict yields. Coupling with crop functioning models, FAPAR, LAI, SLA, and light use efficiency.	[55–58] [59–62]

4. Sentinel-2: Comparative Advantages and Future Work

The Sentinel-2 spatial resolution and number and positioning of spectral reflectance bands excel at cropland and crop type classification, as well as monitoring of crops phenology, namely by enabling the measurement of growth (biomass) and health (stress symptoms) separately. Furthermore, as reviewed, red-edge bands are also effective for monitoring nitrogen status, and therefore optimizing fertilization practices. The literature-proven VIs using the red-edge bands have proven robust indicators of plant N status that can be useful for agricultural monitoring. Due to Sentinel-2 red-edge bands characteristics, the biophysical parameters estimation obtained with these multispectral indexes have higher accuracy than other satellites [96]. Hence, the revisit time of 5 days, the red-edge band, and the higher resolution sets an improved management perspective.

The combination of available sensors also remains an excellent opportunity for improvement. For instance, Sentinel-2 has limitations towards estimating evapotranspiration and water stress due to its lack of any thermal bands, and as such data fusion with other complimentary sensors may generate opportunities to coordinate data with available thermal bands such as NASA's MODIS or Landsat-8 [97]. However, the spatial resolution of their thermal bands (1 km and 100 m, respectively) might be a downside for some agricultural applications that require more detail. Other possible approaches are the combination of optical imagery of Sentinel-2 and thermal bands from the sensors on board Sentinel-3 to obtain crop evapotranspiration, which is promising for bridging the gap and monitoring evapotranspiration with a higher resolution [98]. Besides that, the combination of Sentinel-2 optical bands and Sentinel-1 C-band Synthetic Aperture Radar has successfully been used for mapping soil moisture and irrigation demands [99].

Another challenge is pest monitoring, where pest early warning systems are useful to predict outbreaks and are generally based on weather information, and intensive and time-consuming field work. Being able to use Sentinel-2, or other remote sensing instruments, to assess pest distribution would be of great importance, considering the current globalization of invasive pests and their sudden effects. Nonetheless, a bottleneck is found here, on the one hand the pixel resolution makes it very difficult to monitor pests and generally only when damage is significant it can be sensed. On the other hand, it is a challenge to differentiate the reflectance patterns of plants due to biotic stresses and see what the exact cause of the stress is. The combination of ground, drone, and satellite sensors might be a way to go, with some regional and technical limitations that need to be overcome.

Soils are generally not considered at the expense of other parameters. However, the importance of SOC, which is gaining interest within the sustainable agriculture paradigm, can be monitored with Sentinel-2. This can help to overcome this fact and move forward into precision agriculture and soil sustainability. Regarding soils, monitoring cropland pollution due to heavy metals is important to ensure food safety. It is relevant to see that three papers reviewed in this issue had rice and China as the case study [90–92] where serious pollution problems in this sense happen [100].

Sen2-Agri has set the structure for a coordinated field monitoring platform which will likely lead to a multi-country precision agriculture initiative. In developing countries, on the other hand, this platform, and similar ones using Sentinel-2 data, can contribute to food safety and help farmers in managing their crops. Due to the small fields, intercropping practices and terrain-derived issues crop monitoring strategies need to be tuned in order to successfully manage these areas.

5. Conclusions

Several previous review papers exist on the use of remote sensing for agriculture [101–103], however, to our knowledge there has not yet been a specific review article on Sentinel-2 features for agriculture. We are convinced that may prove beneficial to researchers and agrarian institutions entering this field to understand the features and applications of Sentinel-2 in crops monitoring alone and as compared to other previous and current satellites. The comparison of the Sentinel-2 A + B constellation with other orbiting satellites with similar features highlights its improved capacities within precision agriculture. In this sense, we detail several applications on the detection and management of biotic and abiotic stresses, crop water requirements, crop type classifications, and the estimation of crop yields and nitrogen status. Furthermore, besides the promising technical features of Sentinel-2, it is worth mentioning the public availability of its imagery. By making this data accessible to all interested institutions, the potential benefits of precision agriculture are greater and may better provide the mechanisms for advising farmers towards a more productive and sustainable management, thus, contribute to economic and ecological sustainability worldwide.

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