Satellite Imagery in Precision Agriculture

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Abstract Many national and international institutions recognize that novel agriculture paradigms are needed to address the current challenges of adaptation to and mitigation of climate change. In this sense, digital agriculture and, specifically, satellite images in precision farming allow efficient monitoring of crops to ameliorate the management impacts to the environment. These data allow estimating yields or fertilization requirements, as well as water-related aspects, such as evapotranspiration and crops hydric status. In this chapter, I aim to describe satellite imagery applications in precision agriculture, and I present the nature of remotely sensed data, the types of satellites, and data access, management, and processing in the case of precision farming applications. Landsat 9, Sentinel-2, as well as other commercial satellites orbiting the Earth are described as feature relevant characteristics for agriculture monitoring, especially regarding the visible, near-infrared, and red-edge parts of the spectrum, which can be related to biomass, canopy vigor, or chlorophyll content and subsequently be matched with agronomic features. Regarding data access and coverage, openly accessible datasets and commercial satellites are discussed. Moreover, data management and processing have also been presented in regard to the limitations that processing and analyzing such large amounts of data (i.e., images from vast agricultural regions on a daily basis) has and the potential of cloud computing and processing. I conclude that in industrial agriculture settings, openly accessible satellite imagery can contribute significantly to an overview the status of crops, guide specific and timely actions, and reduce production losses and the impacts on the environment. Satellite imagery has a spatial dimension that can be used at the field to regional level. The assessment of agricultural performance can also be matched to several agroecological and environmental levels; however, satellite imagery in precision farming has several limitations and knowledge gaps in its application in heterogenous and agricultural landscapes with small-scale fields.

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1 Introduction

Since agriculture started thousands of years ago, humans have shaped the Earth by producing agricultural landscapes in most of the habitats that we live in today (Blondel 2006). Rice terraces in Asia, high-yielding maize hydroponic islands in Mexico (Chinampas), or Mediterranean agroforestry systems have traditionally articulated local agricultural landscapes. The technique and the geographic milieu simultaneously change with human's actions (Santos 2000), and so happens currently with a technique that has gone beyond using local resources and species for farming and has become a global highly technological and productive activity, such as many others in society. Since the mid-twentieth century, the "Green Revolution" transformed traditional agriculture into an industrial system by providing high yielding genotypes, fertilizers, and other chemically derived products, as well as improved machinery for sowing and harvesting. This turning point changed the agricultural paradigm in most areas of the world by improving agricultural yields and reducing the human labor force needed. Yet, the current industrial production system is recognized as a major source of global pollution, and its sustainability is discussed.

The current industrial farming practices, characterized by a generalized use of chemical fertilizers and pesticides together with fossil-fueled machinery, have caused a tremendous negative impact to the environment. Agriculture is responsible for 21.2% of global anthropogenic greenhouse gas emissions when including land-use changes (Tubiello et al. 2015). Hence, a significant contribution to climate change and temperature increases is related with agriculture, and many national and international institutions recognize that novel agriculture paradigms are needed to address the current challenges of adaptation to and mitigation of climate change (Rhodes 2016). In this sense, remote sensing data used in precision framing, such as that obtained with satellite technologies, allow an efficient monitoring of crops by acquiring satellite data. These data allow monitoring yields (Segarra et al. 2020b; Wolanin et al. 2019) or fertilization needs (Nutini et al. 2018), as well as water-related aspects, such as evapotranspiration and irrigation needs (Rozenstein et al. 2018) to ameliorate the agricultural management impacts to the environment. Many satellites orbiting the Earth have relevant characteristics for agriculture monitoring (Segarra et al. 2020a), especially regarding the visible, near-infrared, and red-edge parts of the spectrum, which can be related to biomass, canopy vigor, or chlorophyll content (Gitelson and Merzlyak 1996). These plants' physiological features can be related to agronomic characteristics of crops and drive management decisions. This information is central for crops production, irrigation planification, and yield stability. The role of remote sensing and spatial analysis in adaptation to and mitigation of climate change is certainly relevant (Yang et al. 2013); however, there are still scale and knowledge gaps which need to advance to find adequate management strategies when following these remotely sensed data in precision farming.

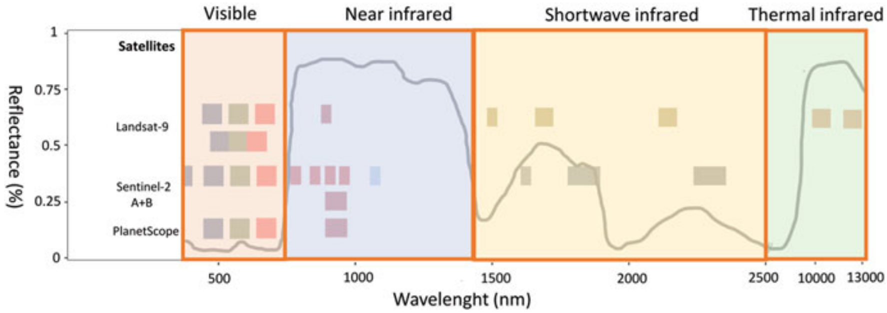
Precision farming is an agricultural management paradigm which is based on observing, measuring, and responding to crops' temporal and spatial variability with the aim to improve agricultural production sustainability (Cisternas et al. 2020; Zhang et al. 2002). Hence, this paradigm goes beyond the classical "Green Revolution" framework, and the use of agricultural inputs is optimized regarding crop demands and its impacts to the agro-environment. The multispectral sensors mounted on board of satellites have resolution features (Adams and Gillespie 2006) which can be used to determine crops' physiological and agronomic characteristics. The temporal and spatial variability of crops is central for its monitoring in precision farming, and it suits satellites resolution features. Satellites have a temporal resolution in the sense that an orbiting satellite has a specific period in which it returns to the same geographic area after orbiting the Earth, and the revisit time is central to follow the emergence of crops or features related to phenology and the evolution of the crop. Moreover, the spatial resolution of satellites is central to precision farming as agriculture fields and landscapes are generally heterogenous and meet singularities within the field that can be observed if the spatial resolution of the satellite is enough to differentiate certain objects. The spectral resolution refers to the number of bands and the width, namely, the parts of the reflected spectrum that satellite sensors can capture and the spectral resolution allows monitoring different physiological characteristics of the plant. Finally, the radiometric resolution refers to how much information the satellite sensors can capture. All these sensor features are central for understanding the corresponding plants' agronomic and physiological characteristics.

This chapter presents satellite imagery use in precision farming, namely, it is focused on understanding the nature of satellite data and match it with farming. Moreover, we present how data can be accessed and different data management approaches. Finally, we discuss the advantages and limitations of using satellite data for agriculture and the implications it has regarding global sustainability and planetary boundaries. This chapter mainly focuses on passive remote sensing, comprehending optical and thermal spheres. Active remote sensing, those sensors using radar and other active technologies are presented but do not occupy a central part of this section, reviews on the use of active sensors in agriculture can be found elsewhere (McNairn and Shang 2016). The novelty of remote sensing applications in agriculture at multiple levels (Weiss et al. 2020) or for specific satellites such as Sentinel-2 (Segarra et al. 2020a) have been addressed in the last years with increasing interest. In this chapter, I present a general overview of satellite data applications in agriculture and how these data can be accessed and managed to finally discuss the advantages and limitations of satellites application in agriculture regarding the multiscale framework of digital agriculture for a sustainable food production.

2 Satellite Data and Farming

Satellite remote sensing is a technological field which senses Earth surfaces using multispectral, hyperspectral, and other instruments mounted on satellites orbiting the Earth. These Earth observation systems are available as a diverse array of sensors and, in regard of the source of illumination used on the sensed objects, can be divided between passive and active sensors. Passive sensors, such as optical and thermal systems, rely on reflected sunlight or emitted thermal energy. Passive multispectral sensors can acquire data beyond the visible wavelengths (i.e., infrared and thermal wavelengths) across the electromagnetic spectrum (Lechner et al. 2020). Earth surfaces reflect and absorb sunlight at different wavelengths; these differences in spectral reflectance properties (i.e., spectral signatures) work as distinct fingerprints to differentiate surface types (Shaw and Burke 2003) which allow, for instance, identifying different crop types. Active sensors, meanwhile, emit a pulse and measure the backscatter reflecting to the sensor. Such sensors can penetrate clouds and operate at night. Active sensors such as SAR (synthetic aperture radar) on board of Sentinel-1 can differentiate crops features according to their surface roughness and the three-dimensional structure of the targets (d'Andrimont et al. 2021; Ndikumana et al. 2018). Other active sensors such as LiDAR (light detection and ranging or laser imaging, detection, and ranging) systems emit a pulse from lasers and measure distance to a target and the reflected light; differences in laser return times and wavelengths can then be used for making digital three-dimensional representations of the target (Lechner et al. 2020). Satellites from the European Space Agency (ESA), such as ADM-Aeolus, has a LiDAR mounted on board, although its use is not focused on agriculture. Meanwhile, NASA (National Aeronautics and Space Administration) has several satellites with LiDAR such as ICESat-2 (Ice, Cloud, and Land Elevation Satellite-2), which is used to monitor vegetation across the globe and determine vegetation structure, also with some potential applications for farming (Brown et al. 2023); in 2019, ICESat-2 data was made available (Martino et al. 2019).

Remote sensing satellite sensors feature a trade-off between the spatial, temporal, and spectral resolutions (Shen et al. 2016). Spatial resolution refers to the pixel size, which is very relevant as the spatial dimension allows differentiating objects within the Earth surface. The temporal resolution is the frequency with which satellite images of the same area are taken, that is, the time it takes for the sensor to revisit the same location on Earth. This depends on the features of the satellite and the mission itself; while some satellites are single devices, others are a constellation of them, such as Sentinel-2 A+B which is a constellation of two twin satellites (A and B) and therefore synchronically orbit the Earth increasing temporal resolution with relevant applications in precision farming (Segarra et al. 2020a). Spectral resolution is also relevant, and optical sensors vary in terms of the number of bands (and the widths of those bands) from which data are captured. The spectral resolution allows to extract more accurate information on the sensed surface as several parts of the



Target trait	Spectral Information	Applications
Field vegetation cover and greenness	Visible and near infrared	Stress detection Canopy cover Leaf area index Growth dynamics Senescence Crop greenness Agronomic and yield traits Plant emergence Phenology Leaf nitrogen content
Chlorophyll content	Visible, near infrared, and red edge	Crop greenness Stress detection Chlorophyll content Leaf nitrogen content Grain nitrogen content
Photosynthesis and yield	Visible and near infrared	Photosynthetic status Biomass and yield Senescence Chlorophyll content Stress detection
Water content	Shortwave infrared and thermal infrared	Water status Evapotranspiration Stress detection

Fig. 1 Crop reflectance signature with the bands available for the satellite sensors (Landsat 9, Sentinel-2, and PlanetScope). The spectral regions are indicated, and the agronomic and physiological traits described in relation with its application in agriculture and plant monitoring

reflected spectrum can be detected. As an example, Sentinel-1 SAR has a six-day revisit period at a high spatial resolution of about 20 m.

In Fig. 1, the spectral signature of a crop is shown together with satellites Sentinel-2, Landsat 9, and PlanetScope. The physiological characteristics of the crop vegetation cover are appreciated in the reflectance spectrum in the sense that in the visible green parts of the spectrum the electromagnetic radiation is reflected, while in the blue and red areas the reflectance is inferior as the absorption of sunlight by the chlorophylls to carry out the photosynthetic activity happens in these regions of the spectrum. Moreover, in the area between red and near infrared, the so-called red edge, the reflectance increases greatly as in wavelengths over 700 nm the energy of the photon is not sufficient to synthesize organic molecules (Taiz and Zeiger 2015), and it is hence highly reflected. The differences between photosynthetic active regions (between 400 and 700 nm) and the near infrared allows understanding the status of the vegetation cover, the biomass, and the photosynthetic activity. It is the case of the widely used vegetation index NDVI (normalized difference vegetation index) (Rouse Jr. et al. 1974) which takes advantage of the physiological characteristics of the plant and the interaction with light to calculate a biomass indicator using the red a near-infrared bands of a multispectral instrument. The visible and near-infrared parts of the spectrum are related with the leaf pigments and plant cell structure. While shortwave infrared and thermal infrared are related with leaf biochemical and plant water content (Fig. 1). As observed in Fig. 1, the three satellites presented have several bands which can sense several parts throughout the reflectance spectrum and can be related to physiological characteristics of plants. The spectral resolution allows monitoring specific characteristics of the crops.

Field vegetation cover and greenness are crop traits which can be sensed with visible and near infrared spectral information obtained from multispectral instruments (Gracia-Romero et al. 2017). In this sense, this data can be used to detect plant stress (both biotic and abiotic), to assess the canopy cover as well as to understand growth dynamics or phenology. Moreover, the chlorophyll content can be monitored with mainly green and red-edge bands, specially the red-edge band is very relevant to monitor chlorophyll content which can also be used as a proxy for the nitrogen status of the plant (Segarra et al. 2022b). The photosynthesis activity of the crop is directly linked to the yield as it is the source of organic matter for the plant (Sanchez-Bragado et al. 2014); hence, understanding this activity through satellite imagery allows developing yield estimation models which can be useful for both prediction of final yield and guiding management action to stabilize the potential final yield. The shortwave infrared and the thermal infrared are especially relevant regarding the water status of the plant (Guan et al. 2017). The water that the plant needs to grow can be monitored with the evapotranspiration which is a balance of the water transpired through the plants' stomata during photosynthesis plus the evaporation of the water in the plant and soil surfaces within the agricultural fields in this case.

Generally, as shown in Table 1, the spatial resolution of thermal bands obtained from satellites is coarse. Sentinel-3 provides 1 km spatial resolution thermal data, while Landsat 9 provides 100 m resolution thermal bands. These resolutions do not provide sufficient precise information to understand at the field level, for instance, the water status of a crop and drive the management decision of the farmer, namely, applying the precision farming framework in the case of irrigation. However, the combination of other satellite spectral information such as higher-resolution 10 to 20 m Sentinel-2 bands allows fine-scaling some thermal remotely sensed data and obtain higher-resolution evapotranspiration products such as Sen-ET (https://www.esa-sen4et.org/) which resamples 1 km pixels into 20 m by combining it with Sentinel-2 higher-resolution images. A few decades ago, estimates of crop water demand from Landsat satellite data (Allen et al. 2005) were already addressed, however, for a regional level. The combination of thermal and multispectral visible and near-infrared satellite-based imagery to empirically solve surface energy balance equations and provide estimates of crop actual evapotranspiration from fractional vegetation cover and latent heat flux is almost operational currently for precision agriculture with the 20 m evapotranspiration grids available through the Sen-ET plugin from the ESA.

Table 1 Satellite missions, data type, and characteristics

Sensor type	Satellite name	Data type	Revisit capability and spatial resolution
Passive	Sentinel-2 A+B	Visible and multispectral	Every five days, pixels of 10 to 20 m size (archives since 2015)
	Sentinel-3	Thermal	1 km of spatial resolution
	Landsat 8 and 9	Visible, thermal, and multispectral	Every 15 days pixels of 15 to 30 m size, thermal 100 m (archives since 2013)
	Landsat 1, 2, 3, 4, 5, 6, 7, 8 and 9	Visible, thermal, and multispectral	Archives available since 1972, ongoing active missions Landsat 8 and 9
	PlanetScope	Visible and multispectral	Scenes taken daily, high-resolution images below 5 m
	WorldView-3	Visible and multispectral	Scenes taken daily, spatial resolution of 0.34 to 4.1 m
	Pléiades 1A/1B	Visible and near infrared	Scenes taken daily, spatial resolution of 0.5 m
	Amazônia-1	Visible and near infra-red	Every five days, pixels of 60 m
	Cartosat	Visible	Every five days, archives available since 2005 with Cartosat-1, current Cartosat-3 has a 0.25 m spatial resolution
Active	Sentinel-1	SAR (radar)	Every six days, 20 m of spatial resolution
	ICESat-2	LiDAR	1 km spatial resolution and 90-day revisit time

For the case of grain yield or nitrogen status monitoring, the applicability of satellite data in precision farming is more advanced. In this sense, some studies have addressed the use of Sentinel-2 images to map grain yield within field variability at 10 to 20 m resolution (Cavalaris et al. 2021; Hunt et al. 2019; Segarra et al. 2022a). These products take advantage of the several elements used in the digital agriculture paradigm such as geolocated combine harvesters, which allow obtaining the harvested grain, for instance, with a geolocated reference. In contrast with obtaining single field values on the yield, or carrying out crop cuts by researchers, the combination of these technological advances allows creating high-resolution within-field performance maps. Moreover, beyond the performance maps themselves, the spectral data obtained from satellites and its relationship with physiological characteristics of the plant can determine the logic behind higher and lower yielding areas within a field. Whether the water status, the emergence of the crop, or the nitrogen status, just to mention some, are the reasons behind having lower-yielding areas in a field, they can be understood by linking the reflectance characteristics with the actual understanding of the plant physiology, either by using vegetation indices as proxies or biophysical variables obtained from more complex radiative transfer models such as those developed by (Weiss and Baret 2016) in the case of Sentinel-2 images.

Hence, the capacity of satellite data is not limited to generate within field actual agronomic grain yield or nitrogen status maps but can moreover be used to assess the physiological features of the plant hindering the specific limitation of the crop to subsequently guide specific management decisions. The vast dimension and potentialities for the use of satellite imagery for precision agriculture could be totally deployed when hyperspectral openly available satellite data can be accessed for agricultural monitoring. At UAV (unmanned aerial vehicle) and aircraft level, such hyperspectral data have been used in biotic stress monitoring in olive groves (Poblete et al. 2021) or grain nitrogen status monitoring in wheat (Zhao et al. 2019). However, these demonstrations of the potentialities of remote sensing do not represent the operationality of precision farming. Mainly due to the lack of general availability of data and the intrinsic cost of many of these devices which make it operationally unlikely for most farmers to use them. However, on the scientific basis and future application, these pathways are of pivotal interest.

Beside hyperspectral instruments, which are in the frontier regarding agricultural applications, high-resolution multispectral instruments on board of commercial satellites capture images with potential applications in precision farming. As shown in Table 1, PlanetScope, WorldView-3, or Pléiades 1A/1B provide daily high-resolution images. Pléiades 1A/1B are a constellation of two satellites which have very-high optical resolution (0.5 m resolution); the satellites have four bands: the red–green–blue (RGB) visible bands and near infrared. Meanwhile, Worldview-3 multispectral instrument collects images at 0.31 m panchromatic (RGB) and 1.24 m in the eight near infrared bands, 3.7 m in the eight shortwave near infrared bands, and a 30 m resolution in the clouds, aerosols, vapors, ice, and snow bands. WorldView-3 has bands for enhanced multispectral analysis (coastal blue, yellow, and red edge) designed to improve segmentation and classification of land features, such as agricultural production. In this sense, several authors have used WorldView high-resolution images in agriculture monitoring, such as for segmenting olive tree crowns (Solano et al. 2019) or macadamia trees (Johansen et al. 2020), which needs a resolution that Sentinel-2 and Landsat 9 do not have. PlanetScope multispectral instruments, on board of the three orbiting satellites that constitute the constellation, operate currently in eight bands: red edge, red, green (2), yellow, blue, coastal blue, and near infrared. A PlanetScope RGB scene is shown in Fig. 2 together with a Sentinel-2 RGB scene; as observed, the delineation of the agricultural fields has a higher resolution in the PlanetScope image (below 5 m spatial resolution) than in the Sentinel-2 images (10 m spatial resolution). In both cases, nonetheless, the agricultural fields can be clearly observed. Even within-field variability can be visually assessed in the case of the RGB scene, other parts of the spectrum, in the case of these two satellites shown, cannot be sensed with the current sensors or the resolution is too coarse, as discussed, for example, in the case of thermal bands before. Regarding the findings of (Skakun et al. 2021), by comparing several spatial resolution of satellite imagery, they observed that spatial resolution of below 3 m is critical to explaining 100% of the within-field yield variability for corn and soybean.

Fig. 2 RGB composites of Sentinel-2 and PlanetsScope scenes at different spatial resolution (10 m and 5 m, respectively), coordinates of the scene (N 10.215075 E -71.943003; decimal degree WGS84)

The results also showed that moving to coarser resolution data of 10 m, 20 m, and 30 m reduced the explained variability to 86%, 72%, and 59%, respectively. I continue by analyzing data accessibility, management, and processing for the case of satellite imagery for precision farming.

3 Data Access, Management, and Processing

The access to satellite data is an important aspect to consider. Some missions such as those from NASA and ESA provide accessibility to archives when logging in with a user, as well as other mission with limited satellite data availability and coverage such as Brazilian and Indian space missions. In Table 2, the accessibility to several satellites is presented. The Copernicus mission archives can be accessed through the Copernicus Open Access Hub (https://scihub.copernicus.eu/); this provides complete, free, and open access to Sentinel-1, Sentinel-2, and Sentinel-3 products. On the Copernicus Open Access Hub, a user-friendly platform allows defining the regions of interests and downloading the satellite imagery directly from the previous year and on demand from previous years as data need to be restored from the archives. Regarding NASA, on the US Geological Survey site (https://earthexplorer.usgs.gov/), Landsat archives are available since 1972 until the current ongoing active missions Landsat 8 and 9. Moreover, other satellites such as MODIS (Moderate Resolution Imaging Spectroradiometer) are available but their spatial resolution is not suitable for the case of precision farming, and it is rather used in ecosystems monitoring. Other missions from NASA such as LiDAR ICESat-2 can be accessed elsewhere (https://openaltimetry.org/data/icesat2/), albeit its processing needs more complex transformations and its use is not specifically intended to agriculture as its spatial resolution of 1 km is limiting. Commercial satellites have their own platforms where scenes can be purchased and downloaded. In Table 2, the access of several satellites is described. The European Union provides

Table 2 Access to satellite data

Satellite name	Access and coverage	References
Sentinel-2 A+B	Publicly accessible (European Commission and European Space Agency), global	https://scihub.copernicus.eu/
Sentinel-3		
Sentinel-1		
Landsat 8 and 9	Publicly accessible (NASA, USA), global	https://earthexplorer.usgs.gov/
Landsat 1, 2, 3, 4, 5, 6, 7, 8 and 9		
PlanetScope	Private, global on-demand	https://www.planet.com/nicfi/
WorldView-2,3,4	Private, global on-demand	https://www.maxar.com/worldview-legion
Amazônia-1	Publicly accessible (Brazilian Space Agency), global theoretically but on the catalog only scenes in South America are available	http://www2.dgi.inpe.br/catalogo/explore
Cartosat	Publicly accessible (Indian Space Research Organization), scenes only cover India subcontinent	https://bhuvan-app3.nrsc.gov.in/data/download/index.php

access to some scenes already purchased for European programs and to archives of PlanetScope and WorldView; however, it is only intended for research institutions and innovative projects, which need to be justified (https://earth.esa.int/eogateway/catalog/worldview-3-full-archive-and-tasking).

The accessibility to these data is central for precision farming. In this sense, besides some exceptions made in research or conservation initiatives, private satellites such as WorldView-3 or PlanetScope offer expensive services that capture high-resolution images on demand. For most farmers on Earth, cooperatives, and even small to middle companies, these data are far from their economic capacities. Hence, by understanding that precision farming involves observing, measuring, and responding to crops' temporal and spatial variability and sustainability, one recognizes the importance of open accessibility to satellite data in this agriculture paradigm. Moreover, as most research institutions cannot afford these images and the research carried out with these data is not always reproducible (due to copyrights on the data and paywalls to access it), the potentialities of high-resolution satellite imagery in precision farming cannot be fully deployed.

Meanwhile, publicly accessible satellite data, such as Sentinel-2, features many studies and applications due to the open access nature of the data. Although the spatial resolution of 10 m cannot explain all the variability within an agricultural field, the resolution of the satellite makes it almost fully operational for its use in precision farming (especially in regions with standardized agricultural managements). Regarding its access, 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), as mentioned. Furthermore, third-party tools for downloading the imagery are available. For instance, there is the US Geological Survey (USGS) (https://earthexplorer.usgs.gov/) which allows comprehensive searching and downloading of full-resolution Sentinel-2 images as well as Landsat archives. On the open-source software QGIS, there are various plug-ins that take advantage of the ESA's Application Programing Interface at the Copernicus Open Access Hub (https://scihub.copernicus.eu/apihub/). Furthermore, Google Earth Engine has daily updated copies of all the available Sentinel-2, Landsat, MODIS, and other accessible satellite 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.

National and international agencies such as ESA or NASA provide 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), which can be used for agriculture monitoring. Besides vegetation indices, more deterministic biophysical parameters, such as LAI (leaf area index) or FAPAR (fraction of absorbed photosynthetically active radiation), can be calculated on SNAP with Sentinel-2 data following the algorithms developed by (Weiss and Baret 2016). Most of these algorithms ready for the user are developed with thousands of training and validation points and follow complex inverse radiative transfer models. The availability of these models already developed improved the capacities to take most from satellite information.

Another key point is data processing. For most research teams, farmers, or local agricultural companies, the computing capacity to operate large datasets is limited, especially when requiring visual interpretation of imagery and heavy processing. In the next few years, data accessibility will likely be widespread, including images from high-resolution satellites with increasing processing capacity demands. Currently, data acquisition is no longer a major challenge with Landsat and Sentinel-2 archives; instead, it is the capacity to process and analyze such large amounts of data (i.e., images from vast agricultural regions on a daily basis) that is becoming the bottleneck. In this sense, besides the features of satellites and the data that can be obtained, the large amount of data and its potential use has generated commercial analytically oriented initiatives such as Google Earth Engine (Gorelick et al. 2017) or EarthServer (Baumann et al. 2016) that process these data on high-capacity cloud servers. In this sense, RUS (Research and User Support) virtual machines from the ESA also offer high storage and processing capacities on cloud servers (unfortunately only accessible to European-based institutions).

Besides the technological advancements in satellite remote sensing, a central aspect when working with its applications in agriculture is modelling crops development and forecasting agronomic variables (i.e., yield, quality traits). Advanced models regarding artificial intelligence and machine learning, as a general frame, have shown considerable promise in agricultural remote sensing applications

(Chlingaryan et al. 2018). These computer algorithms are particularly useful for studying complex biological systems, as they can capture complex interactions among variables and find generalizable predictive patterns (Bzdok et al. 2018), which can eventually be useful in guiding agricultural management decisions and can take the most of the data obtained from the agricultural fields. The use of machine learning to retrieve crop performance has been considered one of the most important areas to develop associated with remote sensing and agriculture (Weiss et al. 2020).

4 Advantages and Limitations of Satellites Use in Precision Farming

The advantages of using publicly available satellite data for precision farming are multiple: having up-to-date crop-related data, having an overview of the status of crops, guiding specific and timely actions, reducing production losses and the impacts to the environment, and achieving a sustainable production. An example of satellite data potentialities being deployed in precision farming is the Belgian WatchITgrow platform (Curnel 2017). This platform uses Sentinel-2 data and algorithms developed by national research institutions in partnership with other administrations and farming enterprises to monitor potato production in Belgium at the field level. The farmers using the platform can access the information collected from the satellites and the products generated (potential yield maps, nitrogen status, etc.). Moreover, the data is secured for each user, and it is intended to improve the management of fields and is not sold to other enterprises. Namely, the data of the user always remain property of the user. The public agricultural institutions of the country and research institutes together with farmers and other agricultural enterprises can lead the creation of accessible platforms to guide specific precision farming management decision, such as in Belgium and the platform WatchITgrow to monitor potato production with Sentinel-2 data.

Satellite data applications in precision farming present significant potentialities in standardized and relatively homogenous agricultural settings, such as those common in industrial agriculture. However, most farming activities in the Earth are carried out in relatively heterogenous agricultural landscapes, with polycultures, trees, and herbaceous crops being simultaneously grown within the field, and relatively small fields (Altieri and Nicholls 2017). In such agricultural settings, in contrast with middle-resolution satellites, high-resolution satellites can best capture the variability within the fields and give a significant overview of crops status to guide the management. It is true, however, that Sentinel-2 imagery has been used in assessing heterogenous and diverse agricultural landscapes, such as in the case of Mali (Lambert et al. 2018), with relatively promising results. Nonetheless, higher-resolution WorldView scenes were also used to map trees within the field and clear pixels for an improved assessment of field's main crop.

The current availability of satellite data, which has significant restrictions to high-resolution scenes, is an important limitation for heterogenous agricultural landscapes. Such landscapes are often located in low-income countries in which securing yield and optimizing the use of inputs is pivotal. Moreover, in these regions, the complexity of interactions in agricultural production makes it difficult to monitor many variables. For instance, in the case of monitoring biotic stresses at regional level and guiding specific field-level management approaches, Buchaillot et al. (2022) observed that PlanetScope high-resolution images offered greater benefits in contrast with Sentinel-2 imagery. However, the complexity on using these scenes is also presented, especially due to the polycultures and diverse management in the fields, as well as the heterogenous agricultural mosaic present in Southern and Eastern Africa. Therefore, in heterogeneous agricultural landscapes, precision farming has several limitations regarding the sensing of the actual crops in the field, the sizes of the fields, as well as the management approaches, and the resources that farmers have in order to address them. In this sense the multiscale approach of digital agriculture together with the understanding of agroecological dynamics (many retrievable with remote sensing data) together with high-resolution satellite data can support the application of precision farming in such agro-environments.

5 Conclusion

In summary, in this section, I have presented satellite imagery use in precision agriculture. After defining the nature of satellite multispectral data, I have linked it with plants physiological and agronomic characteristics for its application in precision farming. Moreover, several satellites have been presented, regarding data access and coverage, as well as their resolution features, which are pivotal to understanding the data needed for its application in precision farming. Data management and processing have also been presented in regard with the limitations that processing and analyzing such large amounts of data (i.e., images from vast agricultural regions on a daily basis) have. In this sense, high-processing capacity cloud servers, such as Google Earth Engine, have been introduced.

I conclude that paywalls to high-resolution satellite data limit the application of precision farming in heterogenous agricultural landscapes, which are especially present in low-income countries. In contrast with the potentialities that satellite imagery uses in precision farming have in standardized agricultural settings, in heterogenous agro-environments, the variability of crops within field level is not easily retrievable with current publicly accessible data. Meanwhile, I conclude that in industrial agriculture settings, openly accessible satellite imagery can contribute significantly to overview the status of crops, guide specific and timely actions, and reduce production losses and the impacts to the environment. Satellite imagery has a spatial dimension which covers field to regional levels; moreover, the assessment of agricultural performance can be matched with several agroecological and environmental levels. Hence, satellite imagery plays a pivotal role in the multiscale framework of digital agriculture for a sustainable food production.

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