DOI 10.1590/s1982-21702023000300006

ORIGINAL ARTICLE

The use of satellite for water applications in agriculture: a review

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Received in 14th September 2022.
Accepted in 23th September 2023.

Abstract:

Many efforts have been made to understand climatic and hydrological variables' variability, magnitude, and standards. In this sense, spatial data has been a fundamentally important tool in supporting the development of agriculture and environmental management research. We start this review by giving a brief overview of the use of satellites in Brazilian agriculture. Besides that, we present a couple of examples of satellite applications in managing water resources in agriculture. The second part of this review illustrates a detailed scenario concerning the orbital sensors available for water applications in agriculture. Finally, we provide a synthesis of the future of satellites in agriculture in terms of nanosatellites, artificial intelligence, and onboard processing.

Keywords: Agriculture; Irrigation; Satellite; Remote Sensing.

How to cite this article: CUNHA SR, GUIMARÃES GN. The use of satellite for water applications in agriculture: a review. *Bulletin of Geodetic Sciences*. 29(3): e2023006, 2023.

1. Introduction

Spatial data brings a more inclusive approach to the agricultural sector, ranging from the large to the small producer, offering resources and methodologies that allow the recovery of old management practices even more assertively. The variability present in the field, which today can be observed and defined through management zones located even in small cultivation areas, can be explained through the learning acquired throughout history (Molin et al. 2015). In this sense, precision agriculture is a management strategy that combines advanced sensors associated with information technology to improve the productivity and quality of modern agriculture (Singh and Singh 2020).

Nowadays, the challenges in agriculture are related to the loss of agricultural land and the decreased varieties of crops regarding climate change, soil erosion, and flora loss. Besides that, water management for agriculture is becoming increasingly complex, mainly because of climate change. This subject is already considered in the scientific community and requires government attention. Moreover, there are plenty of challenges in agriculture involving resources, according to Saad et al. (2020): water pollution monitoring, water reuse, monitoring water pipeline distribution network for irrigation, drinking water for livestock, evapotranspiration, hydrological cycle, etc. The current sustainability challenges, food security, and climate change encourage researchers to adopt and learn new technologies. One example is the field of nanotechnology as a new source of key improvements for the agricultural sector (Parisi et al. 2015). Nanotechnology has the prospective to improve agriculture with novel tools (Prasad et al. 2017). The “Internet of Things” is also an up-and-coming family of technologies capable of offering many solutions for the modernization of agriculture (Tzounis et al. 2017).

Regarding spatial data, the development and advancement of satellite constellation technology allow for more excellent connectivity in cities and the countryside and bring the possibility of more excellent monitoring and data collection capacity. The combination of these factors with computational advances, data infrastructure, analysis, and specific interpretations has increased the prospects for using and applying remote sensors in the agricultural sector (Jarman et al. 2018). This fact brings new possibilities for contributing to the provision of services, generation of products, and decision-making in the agricultural sector. However, it also presents a challenge in ensuring that the latest technological solutions are correctly linked to production capacity, thus being used to offer the gains necessary to meet sustainable development. Used as a support methodology in agricultural management based on the spatial variability of the elements that influence the productivity of crops, orbital sensors bring today greater capacity and facility in elaborating spatialized analyses to subsidize agricultural management decision-making. As a result, products originating from low spatial resolution sensors have been increasingly applied in climate studies, such as the assessment of ocean temperature on a global scale, the monitoring of events such as El Niño and La Niña and the development of meteorological and climatological forecast models (Shiratsuchi et al. 2014). Another innovation factor in the field is the inclusion of methodologies based on temporal analysis by vegetative indexes, which are increasingly used in the context of agricultural activities. This paper aims to present a review of the use of satellites for water applications in agriculture.

2. Applications in the Management of Water Resources in Agriculture

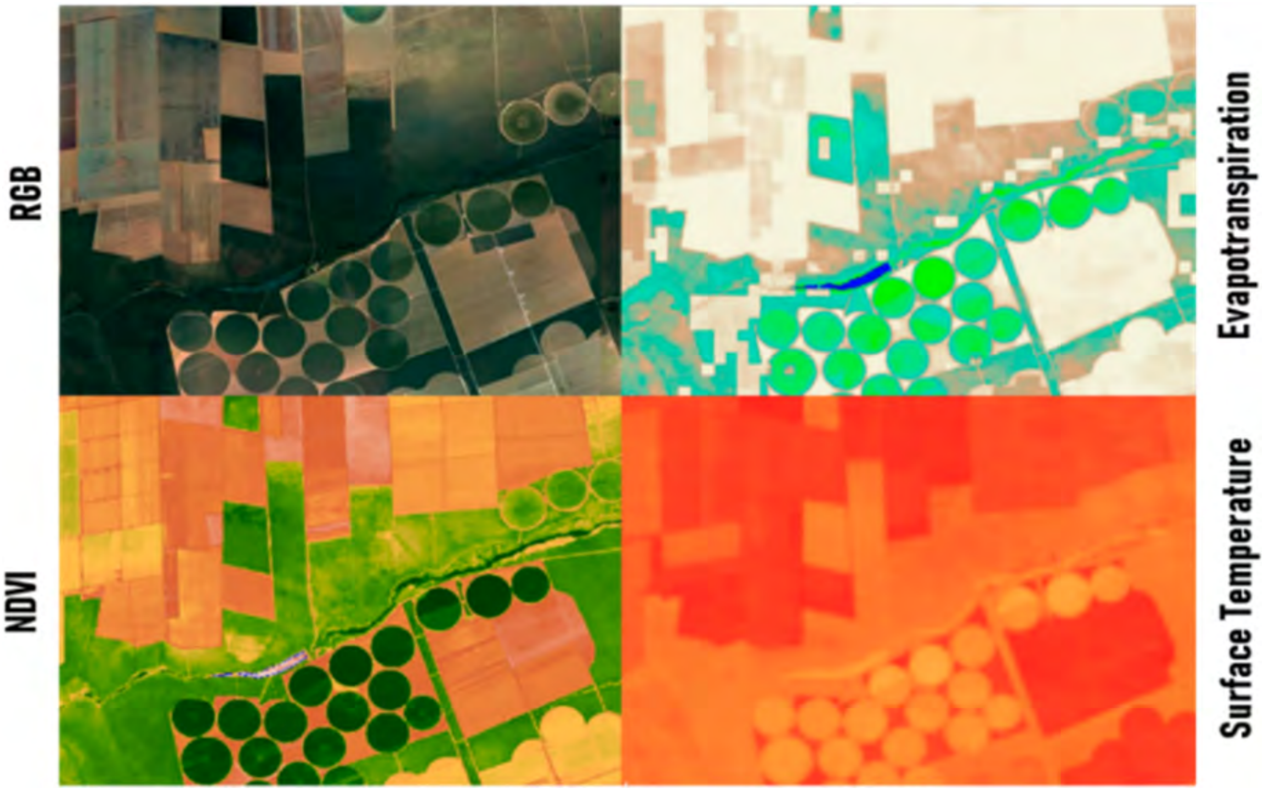
With record crop numbers, Brazil is currently on a climb to become the world’s largest producer in the coming years. According to estimates by the Brazilian Institute of Geography and Statistics (IBGE), the Brazilian harvest of grains is expected to reach a record 264.5 million tons in 2021. Thus, production should surpass by 4.1% that of 2020, which totaled 254.1 million tons (IBGE, 2021). With legally available and arable areas, a favorable climate for production throughout the year, and the expansion of the technoscientific sector in production in initially infertile soils, Brazil is today the main hope of global society in increasing food production, intending to achieve the production necessary to meet the population increase in the next 30 years (Ministry of Agriculture, 2020).

To reach its current position in the world scenario, scientific technologic advancement has been essential along with logistical and management aspects, which are fundamental today for development in a globalized and competitive trade. This fact only reiterates the need for technological updating to be continuous (Formaggio and Sanches, 2017). Thus, using satellites in agriculture directly impacted the productive sector in the regional, national, and global context. The ability to make decisions supported by maps and positional tools directly influenced the form of crop management, boosting productivity numbers, reducing production cycle costs, and minimizing environmental impacts through zoning and localized applications. However, agricultural expansion and the search for more outstanding food production bring factors that deserve to be carefully observed. What is to be monitored is a gradual increase in the scarcity of natural resources, an increase motivated by the growing search for energy and products from agriculture. Aiming at food security and support for sustainable causes, the agricultural sector has sought to optimize the production system, operating crop management with minimum input applications and greater crop productivity. This line of action makes the use of technologies in agriculture gain more and more followers, bringing technoscientific development closer to the field (Molin et al. 2015).

Examples are products from sensors with low spatial resolution, which are increasingly applied in climate studies. For example, we can cite the temperature assessment of the oceans, monitoring events such as El Niño and La Niña and developing forecast models (Shiratsuchi et al. 2014; van Oldenborgh et al. 2021). These phenomena have a high impact on the productive cycle of crops. However, a specific challenge is obtaining a more excellent food production using a lower amount of water. This is a significant paradigm and may become even more complicated if the climate changes projected for the coming decades correct it (Stocker et al. 2013). Based on this fact's limitations to the productive scenario, a new aspect of using technologies has been increasingly applied in research and the market: using satellites as a support tool in agricultural water management.

In this context, orbital sensors emerge as tools capable of generating subsidies for the rational management of water resources in areas of agricultural development in scenarios of intense climate change and variation in land use and occupation to improve. In this way, water use from precipitation and minimizing waste and water deficit problems that arise in various world regions. With the intense evolution in the sector, the need to incorporate information technology becomes essential, especially regarding the capacity to optimize and adapt existing applications and processes (Martins, 2015). It is understood that investigating trends over time and the temporal behavior of water resources stored in Brazilian hydrographic regions are relevant information to extract maximum efficiency in using this natural asset that directly impacts the supply to agriculture, society, and industrial production (Rosenhaim et al. 2018). Nowadays, temporal observations through artificial satellites further solidify a set of investigative devices ready to assist in the monitoring and study of water resources, being thus applied in different regions of the planet, in a wide variety of applications, such as in studies of the case presented by: Awange et al. (2013) and Ndehedehe et al. (2016) in Africa, Chen et al. (2016) in Australia, Molodtsova et al. (2016) in EUA and Cao, Chen and Liu (2022) in China. In Brazil, some investigations to analyze the groundwater and river stage fluctuations (Marques et al. 2020), the changes in the water resources in the Brazilian Northeast (Silva et al. 2020), and the evaluation of satellite precipitation products for hydrological modeling in the Brazilian Cerrado (Amorim et al. 2020) have been conducted in the last years.

To monitor one of the variables that directly influence the hydrological cycle, various applications are used to quantify EvapoTranspiration (ET) in large agricultural precincts (Kustas and Norman, 1996; Courault et al. 2005; Zhang et al. 2016; Wanniarachchi et al. 2022). Within these applications, algorithms such as Surface Energy Balance Algorithm for Land (SEBAL), Mapping Evapotranspiration at high resolution using Internalized Calibration (METRIC) (Allen et al. 2007) (Figure 1), and Simple Algorithm for Evapotranspiration Recovery (SAFER) (Teixeira, 2010; Teixeira et al., 2013, 2017) appear as potential tools for obtaining ET, both based on the surface energy balance, one of the most used methodologies.

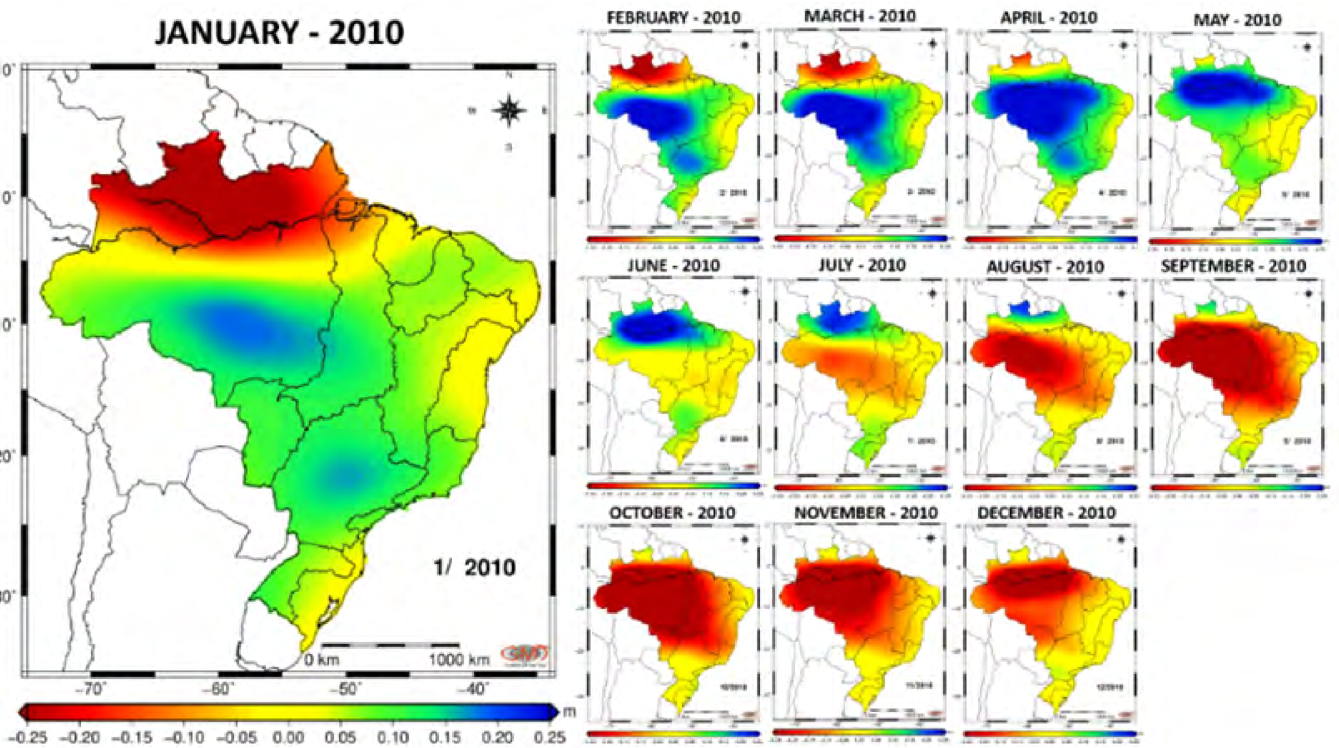


Source: The authors.

Figure 1: Products generated by Metric EEFLUX application (RGB, Evapotranspiration, NDVI, and Surface Temperature).

Operating with different objectives than conventional Remote Sensing, the GRACE (Gravity Recovery and Climate Experiment) mission emerges as an essential tool for studies related to potential water management. The task is used in research whose main objective is monitoring total water storage. Launched in 2002, it comes from a partnership between NASA (National Aeronautics and Space Administration) and the DLR (German Aerospace Center). According to Di Long et al. (2013), the analysis of signals from the GRACE satellites makes it possible to estimate the variation of water masses on the continental surface with an accuracy of 1.5 cm at a scale of 300 km, through a system composed of two satellites in the same orbit, separated at approximately 200 km.

Among other applications using the GRACE mission, we can highlight the gravity maps of the Earth, which provide information regarding the behavior of Total Water Storage (TWS), composed of the set of groundwater, surface water, and soil moisture, according to applications presented on Brazilian territory. Getirana et al. (2014) use data from the GRACE mission to identify and quantify the impacts of the prolonged drought that affected the Southeast and Northeast of Brazil from 2012 to 2015, offering estimates of impacted areas and specific water scarcity in the region (Rosenhaim et al. 2018). Figure 2 shows an example of a TWS study in Brazil.



Source: The authors.

Figure 2: TWS estimated using GRACE data, in Brazil, from January to December of 2010.

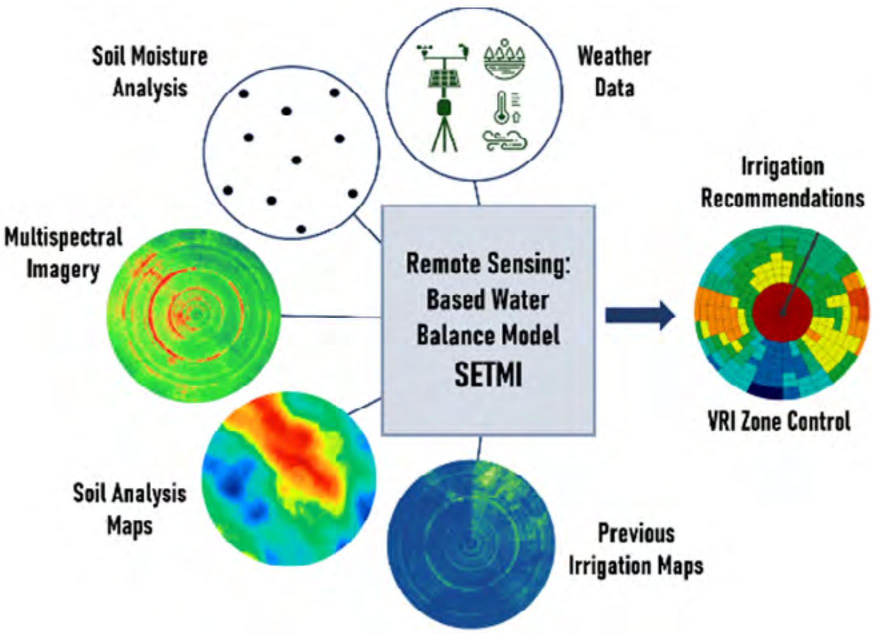
It is also essential to highlight the ability to acquire information resulting from artificial satellites, such as the precipitation provided by the TRMM (Tropical Rainfall Measuring Mission) through the rainfall product (3B43), a complement to temporal hydrographic analyses (Rosenhaim et al. 2018). The TRMM mission is the product of a partnership between the US and Japan. Launched aboard the H-II F6 spacecraft on 28 November 1997, in Tanegashima, the TRMM product is an algorithm that concatenates data from multiple orbital sensors, thus resulting in global precipitation data (Huffman et al. 2007). Analyzing the proposal of this mission in a broader way, the great advantage is the coverage of the data, acting even in places with a low density of meteorological station networks. In-situ sampling observations available at the INMET and the National Water and Basic Sanitation Agency (*Agência Nacional de Águas e Saneamento Básico* - ANA) rainfall stations are a fundamental complement to legitimizing the products obtained by satellites (Rosenhaim et al. 2018).

Another innovation factor in the field is the inclusion of methodologies based on temporal analysis by vegetative indices, which have been increasingly applied in agricultural activities. NDVI, for example, offers the possibility of identifying the dynamic behavior of vegetation at different time scales, which brings a greater understanding of phenological cycles of short and long duration and, consequently, makes it possible to interpret the dynamics of transition in land use (Bradley et al. 2007). Silveira et al. (2015) bring an application of the NDVI index aimed at leaf water potential. The authors investigated the correspondences between vegetation indices and coffee, irrigated, and dryland leaf water potential in the study. Based on statistical analysis by Pearson correlation, this study found that the NDVI showed a positive correlation with the leaf water potential of coffee trees in a dry cropping system. However, no significant correlation was found for irrigated cultivation. NDVI has known saturation problems and is unsuitable for water studies. Figure 3 shows an example between NDVI and RGB images.

Source: The authors.

Figure 3: The NDVI is one of the most used vegetative indices in studies aimed at analyzing vegetative vigor, soil moisture, and leaf water potential.

In terms of water management applications, based on imaging methodologies and vegetative index generation, SETMI (Spatial EvapoTranspiration Modeling Interface) emerges as a significant revolution in managing water resources in central pivot irrigation. The Water leads the research for Food research group at the University of Nebraska. The algorithm uses models of energy balance and soil water balance, which enables the modeling of ET and its use in the prescription of irrigation events. The main objective is the generation of VRI (Variable Rate Irrigation). In Figure 4, it is possible to observe the input products in the SETMI Model, which returns the user the VRI recommendation.



Source: Adapted from Neale, 2018.

Figure 4: SETMI Model methodology, which enables the generation of irrigation recommendations at a variable rate in the central pivot through orbital sensor products.

The possibility of bringing a heterogeneous scenario to a center pivot irrigation system, presenting the variability, and applying the absolute need for crop water compensation for each block raises expectations that the methodology will significantly reduce water use in irrigated crops. In general, applying orbital sensors in managing water resources in agriculture has become essential in planning and rationalizing water use.

3. Satellites in the Management of Water Resources in Agriculture

According to Dakir et al. (2021), some recent studies have shown the possibility of using Earth Observation Satellites (EOS) to manage the agricultural sector. The applications make it possible to detect agricultural diseases, which is likely to establish a suitable way of intervention and an adequate amount of pesticide to apply (Miranda et al. 2020; Sambasivam and Opiyo, 2020). Other applications concern the determination of soil fertility (Wu et al. 2019), yield, biomass production (Ashapure et al. 2020), and the determination of water requirement at the plant scale for precision irrigation (Tao et al. 2014; de Lara et al. 2019; Zhang et al. 2022).

In terms of EOS applications for hydro-climatological management, Table 1 presents a list of sensors and missions acting to obtain data that directly or indirectly impact the understanding hydrological cycle and, consequently, agriculture's productive capacity. They are classified as "Optical", "Meteorological", "Radar", and "Gravity" sensors or missions. It is worth noting that some applications are typical to various sensors, varying the scale. Furthermore, some sensors or missions are no longer available to perform agricultural studies since we retired, but we prefer to maintain the information.

Table 1: Orbital sensors acting in acquiring hydroclimatic data applied to agriculture.

Sensor	Measured Variables	Spatial Resolution	Temporal Resolution	Website for Information
		OPTICAL SENSORS		
Sentinel 2	Detection and delimitation of water bodies, Evapotranspiration, Surface Temperature, Aquifer Recharge, Water stress, Reservoir Water Quality Monitoring, Humidity, Central Pivot Quantification	10 m - 30 m	6 - 12 days	https://sentinel.esa.int/web
MODIS (Moderate Resolution Imaging Spectroradiometer) Aqua/Terra	Surface Water Quality, Surface Temperature, Cloud Mask Fraction, Maximum Cloud Temperature, Near-Infrared Water Vapor, Precipitable Water Vapor, Water Body Detection and Delimitation, Evapotranspiration, Water Stress, Humidity	500 m	1 - 2 days	https://modis.gsfc.nasa.gov/
Landsat 5,7,8 and 9	Evapotranspiration, Surface Temperature, Detection and Delimitation of Water Bodies, Water Stress, Quantification of Central Pivots, Humidity, Water Productivity in Basin, Water Volume Monitoring in Reservoirs, Soil Moisture	30 m	16 days	https://landsat.gsfc.nasa.gov/

Continue...

Table 1: Continuation.

Sensor	Measured Variables	Spatial Resolution	Temporal Resolution	Website for Information
		OPTICAL SENSORS		
WorldView-1,2,3 and 4	Detection and Delimitation of Water Bodies, Quantification of Central Pivots, Monitoring of Water Volume in Reservoirs, Evapotranspiration, Humidity, Surface Temperature	0.31 - 0.46 m	1 - 3 days	https://worldview.earthdata.nasa.gov/
Pleiades 1A and 2A	Detection and Delimitation of Water Bodies, Quantification of Central Pivots, Monitoring of Water Volume in Reservoirs, Validation of Water Turbidity	0.50 m	26 days	https://pleiades-cnes.fr/drupal/
KompSat-3 and 3A	Detection and Delimitation of Water Bodies, Quantification of Central Pivots, Water Volume Monitoring in Reservoirs	0.55 - 0.70 m	28 days	https://eos.com/find-satellite/kompsat-3-3a/
QuickBird	Detection and Delimitation of Water Bodies, Quantification of Central Pivots, Monitoring of Water Volume in Reservoirs, Evapotranspiration, Water Stress, Surface Temperature	0.65 m	1 - 3.5 days	https://earth.esa.int/eogateway/catalog/quickbird-full-archive
Gaofen-2	Detection and Delimitation of Water Bodies, Quantification of Central Pivots, Water Volume Monitoring in Reservoirs	0.80 m	5 days	No website
TripleSat	Detection and Delimitation of Water Bodies, Quantification of Central Pivots, Water Volume Monitoring in Reservoirs	0.80 m	Daily	https://www.21at.sg/productsservices/triplesat-constellation/
IKONOS II	Detection and Delimitation of Water Bodies, Quantification of Central Pivots, Water Volume Monitoring in Reservoirs, Humidity, Water Stress, Digital Elevation Model, Surface Temperature, Evapotranspiration,	0.82 m	1 - 3 days	https://earth.esa.int/eogateway/missions/ikonos-2
SkySat-1 and 2	Detection and Delimitation of Water Bodies, Quantification of Central Pivots, Water Volume Monitoring in Reservoirs	0.80 m	4 - 5 days	https://earth.esa.int/eogateway/missions/skysat
TerraSAR-X	Detection and Delimitation of Water Bodies, Quantification of Central Pivots, Water Volume Monitoring in Reservoirs, Digital Elevation Model	0.25 - 40 m	11 days	https://terrasar-x-archive.terrasar.com/

Continue...

Table 1: Continuation.

Sensor	Measured Variables	Spatial Resolution	Temporal Resolution	Website for Information
		OPTICAL SENSORS		
SPOT 3 to 7	Detection and Delimitation of Water Bodies, Quantification of Central Pivots, Monitoring of Water Volume in Reservoirs, Detection and Prediction of Climatological Phenomena, Water Stress, Humidity	1.5 m	1 - 3 days	https://earth.esa.int/eogateway/missions/spot/
SuperView-1	Detection and Delimitation of Water Bodies, Quantification of Central Pivots, Water Volume Monitoring in Reservoirs	0.5 m	2 days	https://eos.com/find-satellite/superview-1/
CBERS-1, 2, 2B, 3, 4 and 04A	Detection and Delimitation of Water Bodies, Quantification of Central Pivot, Monitoring of Water Volume in Reservoirs, Surface Temperature Change Phenomena	5 - 40 m	26 days	http://www.cbers.inpe.br/
		METEOROLOGICAL SENSORS		
JPSS (Joint Polar Satellite System)	Weather Monitoring, Surface Temperature, Cloud Development, Precipitation, Atmospheric Temperature, Water Vapor,	No information	Daily	https://www.jpss.noaa.gov/
METEOSAT (Meteorological Satellite)	Climate monitoring, Weather Forecasts, Water Vapor, Cloud Formation and Development, Surface Temperature	2.5 km	30 minutes	https://www.eumetsat.int/
GOES (Geostationary Operational Environmental Satellites)	Atmospheric Phenomena, Cloud Formation and Development, Surface Temperature, Water Vapor, Vertical Structure of Atmosphere, Atmosphere Contained Steam, Weather Forecasts	1 km	30 minutes	https://www.goes.noaa.gov/
MERRA Model and MERRA-2 Model	Total water vapor, Soil water profile, Cloud water conversion loss, Total precipitable water, Surface soil water layer, Open water energy flow, Soil water infiltration rate	0.5° - 0.667° (MERRA) 0.5°- 0.625° (MERRA-2)	Monthly	https://gmao.gsfc.nasa.gov/reanalysis/MERRA/
GLDAS (Global Land Data Assimilation System)	Evapotranspiration, Soil Moisture, Canopy Water Evaporation, Soil Temperature, Groundwater Runoff, Rain Precipitation, Surface Water of plant canopy, Precipitable Water Vapor	0.25° x 0.25° 1° x 1°	Monthly	https://ldas.gsfc.nasa.gov/gldas
NLDAS (North American Land Data Assimilation System)	Evapotranspiration, Soil Moisture, Surface and Subsurface Runoff	0.25° x 0.25°	Monthly	https://ldas.gsfc.nasa.gov/

Continue...

Table 1: Continuation.

Sensor	Measured Variables	Spatial Resolution	Temporal Resolution	Website for Information
METEOROLOGICAL SENSORS				
NCA-LDAS (National Climate Assessment - Land Data Assimilation System)	Evapotranspiration, Irrigated Water Rate	1.25° x 1.25°	Daily	https://ldas.gsfc.nasa.gov/nca-ldas
FLDAS (Famine Early Warning Systems Network -FEWS NET/ Land Data Assimilation System)	Total Evapotranspiration, Specific Moisture, Underground Flow, Soil Heat Flow, Surface Runoff, Latent Heat Flow, Rain Flow, Soil Temperature	0.1° x 0.1°	Monthly	https://ldas.gsfc.nasa.gov/fldas
TRMM (Tropical Rainfall Measuring Mission)	Precipitation, Liquid Water Cloud, Quantification of Water Vapor, Intensity of Precipitation in the Atmosphere, Three-Dimensional Mapping of Storm Structures	0.25° x 0.25° 0.50° x 0.50°	91 minutes	https://trmm.gsfc.nasa.gov/
ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer)	Cloud Classification, Surface Temperature,	15 m	16 days	http://asterweb.jpl.nasa.gov/
RADAR SENSORS				
AMSR-E	Water Balance Model	25 km	Daily	https://aqua.nasa.gov/
AIRS	Total Column of Water Vapor, Mass of Water Vapor on the Surface	1°	Daily	https://airs.jpl.nasa.gov/
GRAVITY SENSORS				
GRACE (Gravity Recovery and Climate Experiment) and GRACE-FO	Groundwater Storage, Drought Monitoring, Water Flow Estimates, Hydrological Modeling, Evapotranspiration	1° x 1°	Monthly	https://grace.jpl.nasa.gov/
GOCE (Gravity Field and Steady-State Ocean Circulation Explorer)	Groundwater Storage	1° x 1°	Monthly	https://www.esa.int/Applications/Observing_the_Earth/GOCE

*The spatial resolution of some sensors is expressed just in degree. Each degree corresponds to approximately 111 km.

In Table 1, it is possible to observe many optical satellites (optical sensors). On the other hand, it is often impossible to guarantee the required images because of unpredictable cloudy weather. In this sense, Synthetic Aperture Radar (SAR) data can be acquired regardless of cloudy weather conditions. In precision agriculture, for example, optical and SAR data can be used within a growth model to monitor sugar cane growth stage variations and predict potential yield across the growing season. Also, to detect the conditional canopy change (e.g., related to water stress). The use of optical or microwave sensors (passive and radar) can also identify surface water (streams, rivers, lakes, reservoirs), water quality (organic or inorganic constituents), water surface temperature, snow surface area, and water depth. Despite the fact noted above, optical sensors suffer from cloud contamination, making them difficult to use for flood detection and mapping, for which the temporal scales are small. In terms of “surface water”, High/Medium resolution multispectral sensors and SAR is suitable, which are most effective on larger water bodies such as major lakes and rivers. Regarding the “surface water quality” low resolution narrowband multispectral sensor (e.g., MODIS) can be used. Concerning the “groundwater” GRACE, GOCE and GRACE-FO gravity missions should be considered. These sensors have a gravity gradiometer. The fact of spatial resolution of these missions is about 100 km the total water storage changes with satellite observations of gravity can be combined using in-situ observations High and medium-resolution SAR can be used to detect “soil moisture”, while some atmospheric parameters such as “water vapour” can be determined using very low-resolution multispectral sensors (hundreds of meters to kilometers).

4. Looking to the Future

The food production system and modern agriculture have often been under external pressures, motivated by climate change, low water availability, and a pandemic that has recently directly impacted most sectors of society. Such conditions translate into a threat to the environmental and economic balance of production systems. Even with innovations and advances in the biotechnology and genetics sector in recent decades, a scaled assessment still had shortcomings and deficiencies that until recently were not addressed. However, the recent advances in Remote Sensing and computational tools such as Artificial Intelligence, with the possibility of quantification, zoning, and integration of systems such as big data in tools with predictive and prescriptive capacity, make the agricultural production system reach increasingly expressive results. This fact places technoscientific innovations in a position of fundamental importance in agriculture so that food production is sufficient to meet the projected increase in demand for the coming decades because population growth increasingly reinforces the need for the evolution of constant technology in the industry of remote sensors integrated into computer systems (Jung et al. 2021).

4.1 The constellation of small satellites

Until the beginning of the last decade, satellites were built to weigh tons, which required a complex organization to launch into orbit. However, this situation has changed since the emergence of nanosatellites. In 2008, the RapidEye agency launched a constellation of five identical satellites called RapidEye. One of the aims was to provide digital images focused on providing solutions for agriculture (Stoll et al. 2012). At this moment, Planet Labs Inc. (which acquired RapiedEye) is working on the development of miniature satellites called DOVES, which continuously scan the Earth’s surface and structure a constellation of satellites that provide a complete image of the Earth daily, with a spatial resolution of 3 to 5 m (Nagel et al. 2020). In total, there are more than 130 nanosatellites weighing up to 5 kilos each, which provide coverage of the entire surface of the Earth, monitoring more than 300 million square kilometers per day (Aasner et al. 2017). So far, the American company Planet is the only company to offer this daily imaging of the entire Earth’s surface with such detailed spatial resolutions. Images of the planet are made available online, and some are accessible under an open data policy. Also, the new generation of satellites has more spectral bands (PLANET, 2018). Daily images can reveal patterns and even sudden changes in water stock and availability, which is paramount for monitoring and managing resources and infrastructure and, in addition to its fundamental role in agriculture, enabling the obtaining of information relevant to the optimization of the productive sector and sustainable growth (Jarman et al. 2018).

The trend is for nanosatellites to gain more and more space in the market, given their low cost and short production cycle, characteristics that make the constellations of these small satellites accessible. Consequently, the result in the expansion of the frequency of high-resolution images aimed at Earth observation remote sensing for monitoring dynamic processes. New nanosatellite missions are being proposed to deal with specific applications, such as natural disasters, or to test improvements in these satellites' spatial, temporal, and radiometric resolutions. The unprecedented combination of high spatial and temporal resolution offered by the constellations of nanosatellites, associated with efforts to improve the quality of the sensor, is promising. It may represent a trend for space agencies, universities, and private companies to replace large satellites with smaller, cheaper ones (Nagel et al. 2020).

Another example is Spire Global's constellation, launched on 3 August 2013. Nowadays, the company has more than 90 nanosatellites. When complete, Spire plans an entire constellation of over 100 satellites simultaneously collect RO measurements. Each satellite has a tiny, low-power, Spire-built GNSS-radio occultation receiver and an upward-facing precise orbit determination antenna. The dual-frequency observations allow studies on ionospheric total electron content measurements (Forsythe et al. 2020).

4.2 Artificial Intelligence, Dual-Utility and Real-Time Satellites Performance

Agricultural Artificial Intelligence applications are becoming more and more solid. The so-called "deep learning" has now become a methodology with great potential in image processing, analysis, and elaboration of results related to field production. From weed detection to soil correction recommendations, artificial intelligence today brings the possibility of optimizing various stages of the production cycle, which makes its use essential in modern cultivation. The methodologies used in machine learning tend to make future decision-making more assertive, as it considers numerous factors and variables, such as weather conditions, soil properties, water availability, and even financial control (Fountas et al. 2020; Ayoub Shaik, Rasool and Rasheed Lone, 2022).

A big trend in the space market for the next few years is the multi-utility capability of satellites. Data from orbital sensors is potentiated when analyzed in the presence of auxiliary data sets. Missions such as NovaSAR, for example, will have complementary payloads, AIS and S-band SAR, placed on the same device to increase satellite productivity and commercial value. Other examples include the IRIDIUM communication constellation, where platforms are designed to be capable of a secondary load. Space is still an environment of opportunities in a still restricted market. However, with the trend of expansion and increasing investments in this niche of activity, especially in geostationary orbit and low-orbit satellites, companies like UrtheCast tend to invest more and more in large space assets (Jarman et al. 2018).

Greater demand for applications aimed at obtaining near real-time data, especially from the commercial and military markets, has pressured the space market for the development of geostationary data satellites, such as ESA's European Data Relay Satellite System (EDRS), the first being launched in 2016 (Calzolaio et al. 2020). These satellites will allow low-orbit observation sensors to have continuous communication with ground control stations, which will facilitate the transfer of real-time data from satellites to the ground.

4.3 Onboard Processing

Satellites today produce a great deal of data. The Sentinel 1 satellite, for example, makes approximately 1.6 TB/day of data, which is sent to a ground station and further processed. This number becomes even more expressive when analyzing situations where the end-user uses only a fraction of this data to extract the desired information. This fact has motivated the development of alterations in the computational structure aboard satellites. A great expectation has been generated with the possibility of changes related to extracting irrelevant or low-use information. The main objective would be to link the intelligence to the orbital sensors themselves, carrying out the filtering processing of the data on the satellite itself. This would reduce data exchange and consequently expand the system's responsiveness (Jarman et al. 2018).

An example of this application is the PhiSat-1 mission. The launch of the European Space Agency (ESA) mission took place on 2 September 2020, carrying this satellite, which is a CubeSat (cube-shaped nanosatellites weighing less than 1.33 kilograms) (Esposito et al. 2019). PhiSat is approximately 530 km altitude and flies at more than 27,500 km/h in a Sun-synchronized orbit. The mission aims to study the Earth, collecting many images of our planet (visible and infrared absorption bands). Then, Artificial Intelligence (AI) identifies and discards the images that appear with a high incidence of clouds, which results in savings of around 30% in bandwidth, which optimizes the process. Ubotica, an Irish startup, built and tested this technology in collaboration with Cosine, a camera maker with Intel's AI on board (Giuffrida et al. 2020).

5. Final Considerations

This paper presented satellite applications for managing water resources and others in agriculture. As outlined in this review, satellites enable and enhance water applications in agriculture in many ways, from providing positioning information and facilitating communication to delivering wide-scale observations regularly. Depending on the type of sensor or mission and the spatial and temporal resolutions, it can be used in water applications. Furthermore, combining different types of EOS for a specific application is also possible.

In addition, EOS has been used as a support methodology in agricultural management based on the spatial variability of the elements that influence crop productivity, and today bring greater capacity and facility in the preparation of specialized analyzes to support decision-making in agricultural management. Within this, the performance of professionals specialized in applying spatial data as a management tool in agriculture becomes an essential part of disseminating new practices in the agricultural management model and optimizing production systems, which raises the prospects of demand for professionals in the area.

Looking into the future, in the next years the space industry is set to play a critical role in the creation of 'smarter' and impactful agricultural solutions driven by the increasing availability of powerful EOS, as well as growing data and information expected from connected sensors. Modern agriculture is increasingly developing, driven by technological advances in remote sensing, robotic systems, and artificial intelligence, modernization in the field allows farmers to produce accurately and transparently, achieving greater productivity and quality, reducing environmental impacts, and helping to monitor and predict sudden climate change. This will generate many novel research questions and, ultimately, innovative commercial products and services.

There are several challenges regarding computational power, accuracy, and temporality of data and even resistance on the part of conservative producers. However, the search for dynamic technological development and constant modernization in the countryside bring perspectives that agriculture will no longer walk alone.

ACKNOWLEDGEMENT

The *Fundação de Amparo à Pesquisa do Estado de Minas Gerais* – FAPEMIG financed this study (Finance Code 5.313/15). The authors also thank the reviewers for their constructive comments.

AUTHOR´S CONTRIBUTION

S. R. Cunha developed the literature review, designed the research, and drafted the manuscript. G. N. Guimarães contributed with supervision, writing – revision, editing, and final approval.

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