

Advances in hyperspectral sensing in agriculture: a review

Avanços do sensoriamento hiperespectral na agricultura: uma revisão

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ABSTRACT - In view of the exponential growth in the volume of data that is considered in intelligent decision-making, hyperspectral remote sensing (HRS) has, without doubt, brought greater dominance over agricultural crops as it goes beyond the paradigm of little information being available about the targets. In this review of the state of the art of HRS, complementary views on the use of sensors and analytical techniques in agriculture over the last decade are grouped together. State-of-the-art technologies, and research trends associated with each level of data collection are cited. There is still a long way to go in the agricultural sciences; however, specialists in precision agriculture are devotees of the valuable insights offered with the increased availability of hyperspectral data. In this respect, this review is organised as follows: Section 1 helps the reader to contextualise and conceptualise the basics of remote sensing; the second section discusses the types of sensors and their resolutions; section 3 presents four subsections that show recent applications of these technologies according to their level of acquisition; finally, the fourth section offers the reader a discussion on the positive trends achieved in managing vegetation, soils and waterbodies over the last ten years, as well as the needs and challenges of the next decade.

Key words: Sensors. Monitoring. Reflectance.

RESUMO - Em virtude do crescimento exponencial no volume de dados considerados nas tomadas de decisões inteligentes, o sensoriamento remoto hiperespectral (SRH) tem indubitavelmente trazido maior domínio sobre os cultivos agrícolas porque ultrapassa o paradigma de pouca informação disponível sobre os alvos. Nesta revisão do estado da arte do SRH foram agrupadas visões complementares sobre o uso de sensores e técnicas analíticas na agricultura desta última década. Foram citadas tecnologias de ponta e as tendências de pesquisa associadas a cada nível de coleta de dados. Ainda há muito a avançar nas ciências agrárias, no entanto, os profissionais da agricultura de precisão estão devotados aos insights de aplicações valiosas com a maior disponibilidade de dados hiperespectrais. Neste sentido, esta revisão está organizada da seguinte maneira: A seção 1 contextualiza o leitor e conceitua fundamentos para o sensoriamento remoto. A segunda seção discorre sobre os tipos de sensores e suas resoluções. A seção 3 traz quatro subseções que apresentam aplicações recentes destas tecnologias segundo o nível de aquisição. Finalmente, a quarta seção oferece ao leitor a discussão sobre as tendências positivas alcançadas no manejo de vegetação, solos e corpos hídricos nos últimos dez anos, bem como as necessidades e desafios para a próxima década.

Palavras-chave: Sensores. Monitoramento. Reflectância.

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INTRODUCTION

Since the successful launch of the first experimental Sputnik satellite in 1957, mankind has experienced unprecedented advances in technology, and has applied them positively to navigation, communications and Earth observation. Notable applications of Remote Sensing (RS) include those related to meteorology, agriculture, geology, mapping, urban planning, ecological monitoring and environmental disasters. Although mainly visible electro-optical sensors have been used, more recently the application of thermal imagers, light detection and ranging (LIDAR), and hyperspectral imagers has gained more and more attention from academia and industry. Conceptually, RS can be understood as a set of techniques aimed at observing, collecting and recording signals propagated from objects over a given period of time, and necessarily requiring some distance between the sensors and the targets.

The concept of Precision Agriculture (PA) prioritises better management of such agricultural inputs as water, fertiliser, herbicides, seeds and fuel, allowing the proper kind of management to be undertaken exactly where and when it is needed. Considering that large agricultural areas under conventional management receive a uniform application of inputs, under PA these areas can be subdivided into management zones, where each receives varying inputs, based on the type of soil, altitude or history of mineral requirements. A knowledge of the physical, biological and chemical properties of the soil is especially important in designing and implementing strategies for irrigation, drainage, nutrition and health control when managing crops. As such, PA improves the productivity and profitability of a crop, together with higher environmental quality (DALE *et al.*, 2013). The axiom that guides all PA technology is to acquire information about crops, whenever, and at whatever spatial resolution is necessary for decision-making. To that end, RS is undoubtedly a valuable tool for providing this information.

More recent advances in RS have paved the way for the development of hyperspectral sensors and the processing of larger volumes of data. Researchers around the world have long recognised the need to map ground cover for the sustainable management and monitoring of natural resources, not only on a regional scale, but also from a complementary local or global perspective (WANG; MASRY, 2010). The advantage of RS is its ability to provide periodic information (YAN *et al.*, 2017) without destructive crop sampling (WALLACE *et al.*, 2017), which can be used to provide information on agricultural canopies using various agronomic parameters.

Depending on the specificity of the desired information, RS can be a competitive alternative means

of acquiring data over large geographical areas, since it can provide prompt, reliable data for a fraction of the cost of the traditional method and, as highlighted by Yu *et al.* (2020), with the collection of less field data. Combined with Geographic Information Systems, RS is highly beneficial to the creation of information layers in time and space that can be successfully applied to various agricultural challenges, including the mapping of floodplains, hydrological modelling, changes in land use, monitoring crop growth and stress detection (KINGRA *et al.*, 2016).

The principle behind reflectance spectrometry is the perception of electromagnetic radiation (EMR) to assess the characteristics of a target (JENSEN, 2011). As such, when a beam of light is directed at the target, one part interacts with the sample and is reflected from its surface, while the other part is transmitted and absorbed by the sample (DAHME; DAHM, 2013). Different objects exhibit typical spectral behaviour at given intervals and are used to distinguish between vegetation, exposed soil and waterbodies, as well as variations within the same class, such as clayey or sandy soils (ALMEIDA *et al.*, 2020), saline soils (MOREIRA *et al.*, 2015), water with sediments or undergoing eutrophication (KELLER *et al.*, 2018), and the most diverse architecture and physiological oscillations in plants (NIGAM *et al.*, 2019).

The metabolic changes that occur due to each type of stress can alter these reflectance patterns, a fact that can be detected remotely (SHANMUGAPRIYA, 2019). The growth stages of the crop and its development are influenced by a variety of factors, such as the available soil moisture, time of planting, air temperature, length of day and condition of the soil, and these in turn are responsible for productivity. Thus, monitoring the crop at regular growth intervals is necessary to discern any adverse effects of the environment on the crop (GÜRTLER *et al.*, 2018) and to predict possible losses in production due to stress factors (LU *et al.*, 2020).

A key decade for technological transition is coming to an end. Proof of this substantial incursion into modern agriculture is that 1,688 articles on hyperspectral data in agriculture, published between 2011 and 2020, can be found in the noteworthy principal Web of Science collection alone, in contrast to the 490 articles from the previous decade (2001-2010). The massive global adoption of mapping and navigation applications has accelerated the evolution of applications for the RS industry, the main factor in this transformation being the improvement in techniques of resolution (WEI *et al.*, 2019), precision (OLIVEIRA *et al.*, 2018), speed (FAN *et al.*, 2017) and analysis (ABDULRIDHA *et al.*, 2019). Within this context, scientific parameters and achievements

will be presented in this review, demonstrating that hyperspectral remote sensing (HRS), the quintessence of traditional RS, is ready to play a disruptive role in modern agriculture by offering a non-destructive and increasingly more assertive alternative for crop management.

SENSORS AND THEIR SPECIFICATIONS

The human eye is able to see only a restricted part of the electromagnetic spectrum, and can distinguish objects based on their different spectral responses in the narrow visible spectral range (VIS) between 400 and 700 nm (NOVO, 2010). To overcome these limitations, multispectral image sensors have been developed that are capable of acquiring representative data in points other than the infrared, usually between 400 and 2500 nm. The aim of obtaining the signal over a greater spectral range makes it possible to construct reflectance profiles (SHANMUGAPRIYA, 2019) and detect patterns that discriminate between the various types of targets far beyond any visible colouring. Therefore, the beyond-visible band was especially employed.

It is essential to emphasise that the sensor is more important than the platform to which it is attached. The importance of the satellite lies in its altitude. Noise in the data can be seen to a greater or lesser extent from the physical effects of the EMR interacting with gases in the atmosphere. However, the decisive factors in acquiring good-quality spectral data are the capabilities and limitations of the sensors.

Types of Sensor

Hyperspectral data are obtained using passive sensors. Essentially, there are two types of technology in RS that depend on the energy source: i) passive RS (for example, optical) and ii) active RS (for example, LiDAR and radar). The principal difference is that the former requires an electromagnetic energy source external to the sensor, such as the sun (JENSEN, 2011). There is therefore a direct dependence on the incidence of this EMR source on the area under analysis. The second type has an internal EMR source, and, in this respect, is able to acquire information about the target independently.

Nature of the data

It is worth adding that when referring to the nature of spectral data, it is understood that they can be collected by both imaging sensors (Figure 1A) or non-imaging sensors (Figure 1B). Therefore, if characterisation by spatial patterns is irrelevant, the readings can be essentially

numeric instead of expressed by pixel intensity. This considerably reduces the volume of data to be processed.

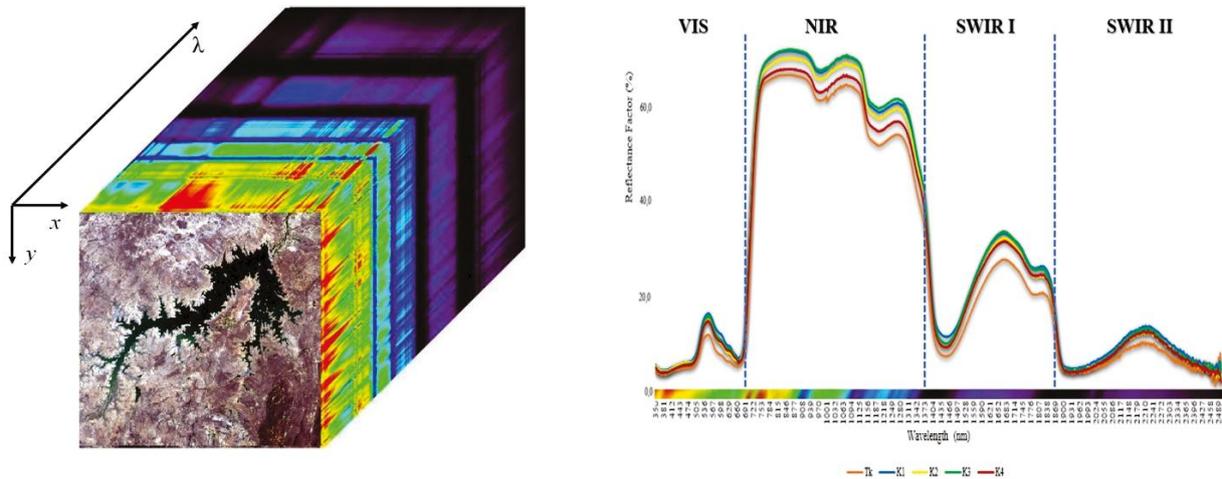
The idea of a hypercube for the three-dimensional representation of data, groups stacks of light-intensity measurements distributed in the two spatial dimensions (X and Y), while the third denotes the energy measured at each wavelength (λ) the sensor is able to capture. There is, therefore, a match for each spatial unit (pixel) of these data. Each value provides what are called spectral reflectance factors, i.e. the percentage of EMR that is received by the sensor after reflecting off the surface of the target (JENSEN, 2011). There is, therefore, a unique variation in reflectance between the matching pixels for each type of target. The concept of a spectral signature, i.e. individual behaviour by the target, only occurs in very specific cases, such as with soil minerals, e.g. mimetite (SWAMY *et al.*, 2017), which even in different landscapes, latitudes and weathering can be easily identified (TEKE *et al.*, 2013).

Data Resolution

During a remote-sensing analysis, four parameters have to be analysed: the spectral, spatial, temporal and radiometric resolutions. The sensors provide information normally categorised according to their spectral resolution, which can be: i) multispectral, ii) super-spectral or iii) hyperspectral. Multispectral data refer to sensors of less than 10 discrete bands, each covering a wide spectral range of tens to hundreds of nanometres. Super-spectral data (COLLIN *et al.*, 2019), in turn, come from sensors that express 10 to 20 bands, still representing broad portions of the spectrum, while hyperspectral sensors, the focus of this review, convey a series of continuous channels of narrow spectral bandwidth (typically less than 10 nm), hence their ability to express spectral nuances which are often imperceptible under other approaches.

In this context, multispectral data, such as those obtained by orbital sensors coupled to the Landsat (10 bands) and SPOT (4 bands) satellites, have been widely used in agricultural studies due to the prompt availability of the data. Interesting techniques are already being applied to estimate crop biomass (DONG *et al.*, 2020), land use and cover (CHAVES *et al.*, 2020), the chlorophyll content of a crop (ZHOU *et al.*, 2020), or mapping soil degradation (PHINZI; NGETAR, 2017). A quantity of even smaller bands was used by Calou *et al.* (2020) when classifying RGB (Red-Green-Blue) images in the detection of yellow sigatoka in the banana crop in Ceará, Brazil. However, due to limitations in spectral resolution, the accuracy of recovered variables is often limited, and the first signs of crop stress, such as nutrient deficiency or plant disease, are not detected early enough. Super-spectral sensors, such as those of the WorldView3 (16 bands) and

Figure 1 - A) Three-dimensional representation (hypercube) of imaged data. B) Numerical and simplified representation of vegetation hyperspectral data (OLIVEIRA *et al.*, 2020)



Sentinel2 (13 bands) satellites, have been applied in the direct detection of hydrocarbons, compounds associated with anthropogenic pollution (ASADZADE; SOUZA FILHO, 2015). In this study, the researchers used the eight bands of the visible (VIS) and near infrared (NIR), and eight bands of the short-wave infrared (SWIR) of the WorldView3 satellite for environmental monitoring in São Paulo, Brazil. Hyperspectral data - for example, from EO-1/Hyperion (242 bands), Gao-FEN-5 (330 bands) and AVIRIS (224 bands) - with hundreds of bands can capture more subtle spectral distortions of the ground cover, as in studies by Peón *et al.* (2017), predicting organic carbon in burnt areas, or the physiological state of maize (*Zea mays* L.) via the high-yield phenotyping of its biochemical characteristics (YENDREK *et al.*, 2017) and how they change over time.

It is imperative to point out that what differentiates multispectral from hyperspectral data is primarily the bandwidth (TESFAMICHAEL *et al.*, 2018) used to represent the data of the electromagnetic spectrum. As such, this parameter is more relevant than the number of wavelengths that a sensor can supply. An image sensor can cover a wide range of the electromagnetic spectrum (for example, 400 to 2500 nm) but still have a low spectral resolution if it acquires a small number of broad spectral bands. On the other hand, if a device is sensitive to a smaller range of the electromagnetic spectrum (400 to 1000 nm), but captures a large number of narrow spectral bands, it is said to have a high spectral resolution, giving it the ability to hierarchise components into elements of a similar spectral pattern.

Another important point that should be highlighted are the minimum dimensions that can be discernible on

the surface imaged by each sensor, known as its spatial resolution, and usually related to the GSD (Ground Sample Distance). This variable is fixed for orbital sensors, but can vary for other levels of collection. The smaller the size of the pixel, the more precise the boundaries and characterisation of each target. Characterisation of ground cover with hyperspectral sensors such as Hyperion (United States), CHRIS (Italy), GaoFEN-5 (China), En-MPA (Germany) or HISUI (Japan) with a GSD of approximately 30 m, expresses in a single pixel, the representative value of each element that makes up the landscape of 900 m². Assuming homogeneous and continuous coverage, such as extensive commodity-producing areas, this level of detail would be sufficient to characterise the ground cover. However, when the analysis requires a more refined level due to the excessive mixture of targets within the frame, it is necessary to reconsider the level of collection (Table 1).

The temporal resolution depends on the orbit taken by the platform that houses the sensor. This parameter is extremely relevant, as it describes the time needed to revisit the precise place of interest (PANTERAS *et al.*, 2018). In the case of Precision Agriculture, time is a crucial variable in making urgent decisions, such as monitoring the water requirements of a crop (ZHANG *et al.*, 2019). The revisit period of the EO-1/Hyperion (inactive), PROBA-1/CHRIS and GaoFEN/GF-5 is around 16, 7 and 2 days respectively. This value is generally related to the height of the developed orbit, which is stable during the working life of the satellite, and considerably limits the frequency of orbital analyses in agricultural management.

The fourth resolution to be understood is that which expresses the radiometric properties of a sensor. This parameter describes the ability to discriminate very

small differences in measured energy and, therefore, establishes a fixed interval over which the entire range of the read data can be represented. Digital systems like the airborne ProSpecTIR store VIS-NIR data in blocks of 12 bits based on 4096 (2^{12}) possible intensity values to represent a target. One important operational objective in HRS systems is the ability to adjust the amplifier controls so that a highly reflective object produces its maximum value within the available number of bits.

The greatest challenge lies in the fact that solar incidence varies considerably throughout the day and produces lower digital numbers (DN) whenever the sun is off-nadir. The need then arises to change the amplitude of the radiometric band according to the latitude, an ability already found in more-modern sensors.

Using sensors whose variations are barely discernible means that differences between similar spectra are not captured as they are easily saturated, seriously compromising the application of normalised spectral indices. A high radiometric resolution is essential for agricultural applications, especially to model crop vigour (BANDYOPADHYAY *et al.*, 2017) and phytosanitary problems accurately during the early stages (VANEGAS *et al.*, 2018), in addition to identifying subtle changes in the soil when mapping moisture (AINIWAER *et al.*, 2020) and organic carbon (GUO *et al.*, 2019).

LEVEL OF DATA COLLECTION

Applications of hyperspectral data in modern agriculture are described in this review according to the sensor system used, which includes: i) orbital, ii) airborne, iii) short-range and iv) proximal.

Orbital Systems

The Hyperion sensor aboard the EO-1 satellite was the most widely used orbital hyperspectral sensor for agriculture, collecting data in the visible (VIS), near infrared (NIR) and shortwave infrared (SWIR) bands. Even after its shutdown in 2017, significant results continue to be produced worldwide, as in the work of Moreira *et al.* (2015) and Moharana and Dutta (2019), when they established relationships between the vegetation index and leaf water content in rice based on *in situ* measurements to investigate water stress in rice fields. In the United States, Aneece and Thenkabail (2018) focused on the differences between the five main global crops (maize, soybean, wheat, rice and cotton) during different growth stages. In order to do this, using Principal Component Analysis (PCA), the authors built a spectral library containing the thirty least-redundant bands capable of carrying out this classification (Figure 2A). In this study, using only 20 narrow bands, the best overall precision remained between 75% and 95% for the various growth stages.

Table 1 - The application of hyperspectral sensors according to the level of spatial resolution

| Level of spatial resolution | Altitude | Usage | Sensor | Application |
|-----------------------------|----------|---|-----------------------------|---|
| Low | > 30 m | -Usually launched by governments to monitor the environment and the effects of global climate change on natural resources and agriculture. | Hyperspectral Imager (HySI) | Crop classification (KHOBRADE; RAGHUWANSHI, 2015) |
| Medium | 5 a 30 m | -The multiple suppliers of these sensors are at the beginning of a new frontier, where commercial startups plan to launch constellations of cheaper and more-accessible nanosatellites. | EO-1/Hyperion | Copper stress in vegetation (ZHANG <i>et al.</i> , 2019) |
| High | 1 a 5 m | -Aerial sources are being heavily used in local and regional agricultural applications. | ProSpecTIR | Soil texture (ALMEIDA <i>et al.</i> , 2020) |
| Ultra-high | < 1 m | -The advent of the miniaturisation of hyperspectral sensors enables them to be placed on board UAVs, and promises to revolutionise the detection of agricultural problems, even for smallholders. | Headwall Micro-Hyperspec | Leaf carotenoid content (ZARCO-TEJADA <i>et al.</i> , 2013) |

Measurements of electrical conductivity (EC) in the laboratory, such as those carried out by Moreira *et al.* (2015) employed different metrics in discriminating saline and non-saline soils in areas of irrigated rice. In this study, the authors found that, using the Hyperion data, NaCl resulted in no absorption bands; however, brightness was the construct that gave the best representation of the data structure. On the other hand, silviculture benefited when Lim *et al.* (2019) applied data from the same sensor to classify the trees of three species in Chinese forests using machine-learning techniques, such as Random Forest (RF) and Support Vector Machine (SVM), with an accuracy of 0.99 and 0.97 respectively. Data from the CHRIS orbital hyperspectral sensor aboard the PROBA-1 satellite are commonly used to estimate the leaf area index (LAI), as in studies by Wang *et al.* (2016), using an angular vegetation index based on *in situ* measurements.

In recent years, several hyperspectral orbital sensors have been launched or are scheduled for upcoming launches. Among recently launched but still unavailable satellites are GAOFEN-5 (2018), PRISMA (2019) and EnMPA (2020). Some researchers have simulated images and evaluated the performance of these future sensors in climate study and agricultural management: research in which Chen *et al.* (2017) and Tang *et al.* (2018) simulated data from the GaoFEN-5 satellite to model an algorithm for predicting the temperature of the soil surface and of waterbodies; Malec *et al.* (2015) simulated images from EnMPA to investigate the degree of soil erosion in Costa

Rica and Castaldi *et al.* (2015) also carried out simulations of the PRISMA sensor from spectral data in the laboratory to estimate clay content, and tried to reduce the influence of soil moisture on these estimates.

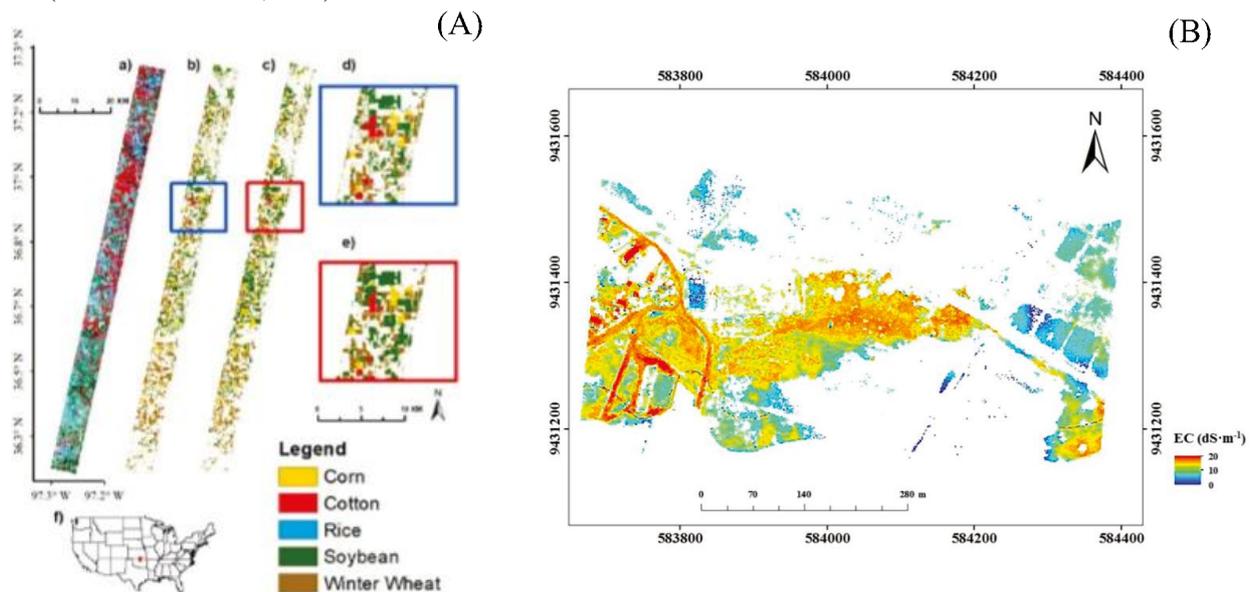
Among the scheduled launches is the SHALOM mission in 2022, a partnership between the Israeli and Italian space agencies, with a spatial resolution of 10 m in the 400–2500 spectral range (STAENZ *et al.*, 2013). Another sensor is the HypSIRI by NASA, that will cover the same spectral range with an interval of 10 nm and a spatial resolution of 60 m (LEE *et al.*, 2015).

Airborne Systems

While satellite data concentrates on more comprehensive studies, airborne sensors are commonly preferred when studying regional peculiarities. The aircraft follow the flight plan at medium to high altitude (from 1 to 4 km for CASI; 20 km for AVIRIS) with the acquired images generally having high to medium spatial resolution (Table 1), approximately 4 m for the CASI images, 5 m for HyMap and 20 m for AVIRIS. Image acquisition missions generally need to be scheduled in advance, on cloudless days, and at continuing high cost.

Serving as an example are the works of Rocha Neto *et al.* (2017) mapping salinity (Figure 2B) in the soils of Ceará, Brazil. In this study, the authors flew over the area of interest and, during the same period, revisited the area to collect soil samples. The association between the EC of the soil and the reflectance factors

Figure 2 - A) Classification of crop type using 30 narrow bands of the EO-1/Hyperion hyperspectral sensor (ANECECE; THENKABAIL, 2018), and B) Electrical conductivity (EC) of the soil estimated from images from the ProSpecTIR-VS sensor, based on the PLSR model (ROCHA NETO *et al.*, 2017)



collected by the ProSpecTIR sensor was made possible by selecting pure bands, and using PCA and PLS regression models. In a study on plant stress, Kobayashi *et al.* (2016) used the Japanese AISA Eagle sensor with spectral bands between 430 and 1,000 nm, to map rice blast, an important disease of the rice panicles.

Since Brazil gained access in 2010, when the Brazilian FotoTerra® entered into a technological partnership with the American SpecTIR®, numerous studies have been carried out in various areas using data from this sensor, considering many other approaches in vegetation, such as the mapping of invasive species with woody formations by Amaral *et al.* (2015) and geological mapping by Amaral *et al.* (2018). Sophisticated techniques such as continuum removal could also be implemented for the absorption valley at 680 nm by Sanches *et al.* (2014) when studying chlorosis in plants. Specialists in water spectra were favoured by the studies of Streher *et al.* (2014), correcting sunglint in images of flooded areas. Airborne sensor data were especially useful in studies by Almeida *et al.* (2020) to determine the texture of a Cambisol in the Chapada do Apodi, Ceará, employing 357 spectral bands (VIS, NIR, SWIR).

Short-Range Systems

The frequent acquisition of high-spatial-resolution images via commercial satellites (nadir and off-nadir) or contract flights can be expensive, especially for smallholders. Considering that the collection and processing of images in these systems can suffer a serious loss of information due to the light being obstructed by the plant canopies, short-range image sensors are generally closer to the ground and capable of carrying out strategic agricultural inspections.

These compact hyperspectral sensors (1 to 2 kg) contain hundreds of narrow bands in the NIR range and can be deployed quickly in different vehicles, both manned and unmanned. Innovative works, such as those by Van De Vijver *et al.* (2020), point to a new level in PA. In this study, the researchers built a hypercar (Figure 3A) capable of traversing a potato crop and detecting *Alternaria Solani*. Using the technique of a convolutional neural network (CNN), only damaged leaf tissue is stored and classified as to the presence of the fungus, which greatly optimises the time and performance of the processing algorithms.

In recent years, the noticeable trend towards miniaturisation of hyperspectral and more affordable sensors for commercial use, has prompted researchers to place them aboard unmanned aerial vehicles (UAVs) to acquire images of extremely high spatial resolution in routes and directions that are easily readjusted. Multirotors,

helicopters and fixed-wing aircraft have been used in studies of vegetation, among them such works as those by Kang *et al.* (2019), placing the Headwall Nano-Hyperspec sensor aboard the DJI Matrice 600 Pro UAV to inspect plant health and water quality in Ontario, Canada. PIKA is another super-light sensor, whose performance was reported by Abdulridha *et al.* (2020), when classifying tomato leaves into healthy and asymptomatic, and the early and late stages of bacterial spot and target spot. The main contribution of the work was to emphasise that incorrect or late diagnoses are followed by inappropriate management decisions or even application of the wrong chemicals. In this context, HRS becomes even more important when it is understood that field analysts may not notice metabolic changes (such as the initial stages of a bacterial infection), but can rely on a dedicated device to do so.

Fang *et al.* (2019), carrying out an environmental analysis, applied PLSR, SVM and ANN to images from the Cubert-UHD185-Firefly sensor to map iron concentrations in exposed soil. The phenotyping of high-yield (CHAWADE *et al.*, 2019) and quantitative resistance to disease in plants (MAHLEIN *et al.*, 2019) using hyperspectral sensors is already a reality. In this scenario, it is clear that although the cost of using land vehicles (FUE *et al.*, 2020) and UAVs on a commercial scale still requires high investment, small and medium producers can join together to share useful technologies in the control of pests and diseases between neighbouring areas, such as potato virus Y (POLDER *et al.*, 2019) or black sigatoka in the banana (FAJARDO *et al.*, 2020).

The possibility of obtaining hyperspectral data more than once a day makes it possible to detect early anomalies. This revolution is clearly exploited in the works of Ge *et al.* (2019) when combining machine learning with UAV images to monitor soil moisture, as well as by Tao *et al.* (2020) when estimating the parameters of wheat production. Water parameters require rigorous inspection in studies by Matsushita *et al.* (2016) and Luo *et al.* (2019) when monitoring the quality of waterbodies, in addition to the methodological adaptations cited by Kang *et al.* (2019) when mounting hyperspectral sensors aboard UAVs. Keller *et al.* (2018) innovated by combining machine learning to interpret hyperspectral responses when estimating chlorophyll-a, diatoms, green algae and turbidity in water under eutrophication.

Proximal Systems

Despite the unprecedented benefits, the main obstacles to the use of hyperspectral images in agricultural applications include the high cost of the sensors/missions, the technical challenges of the signal-to-noise ratio (atmospheric windows), and processing large volumes of data on a desktop computer. One

Figure 3 - A) Vehicle with onboard hyperspectral sensor (VAN DE VIJVER *et al.*, 2020), and B) Saline stress in rice using FieldSpec3 (MOREIRA *et al.*, 2015)



objective alternative are proximal reading devices, in which numerical measurements are obtained almost in contact with the target. Despite their limitations in representing spatial variability over large areas (LU *et al.*, 2020), these portable devices allow a more accurate and more representative numerical understanding of a given target. The reflectance factors of thousands of wavelengths can be read *in situ*, or the samples can be collected and taken to the laboratory (dark-room) equipped with a single light source (usually a halogen lamp).

Hand-held spectroradiometers, such as the FieldSpec from Analytical Spectral Devices Inc., are compact alternatives and widely used in the spectral characterisation (350-2500 nm) of vegetation, as well as estimating the nitrogen content of the canopy (WEN *et al.*, 2019) in maize, or potassium deficiency in cotton leaves (OLIVEIRA *et al.*, 2020). Soil parameters are also richly detailed, as in research by Moreira *et al.* (2015) (Figure 3B), estimating electrical conductivity in saline areas, Wei *et al.* (2020) estimating soil arsenic content, and by Almeida *et al.* (2020), investigating soil granulometry using a contact-probe.

As it is an indirect method of estimation, to obtain an efficient qualitative and quantitative analysis, the methods of reflectance spectroscopy demand a high rate of accuracy during validation with unpublished data. This technique is known as chemometrics, and uses statistical methods to measure the biochemical concentrations of objects. Studies, such as those by Sankaran *et al.* (2010) and Pourezza *et al.* (2016), on early detection of the incurable Huanglongbing (HLB) disease in citrus orchards, have shown that starch concentrations are significantly higher in infected

leaves than in healthy leaves or in those suffering from nutrient deficiency (Figure 4). It is therefore reasonable to assume that the detection of reflectance factors above a certain threshold level can infer the presence of HLB in the orchard, even before the appearance of visual symptoms.

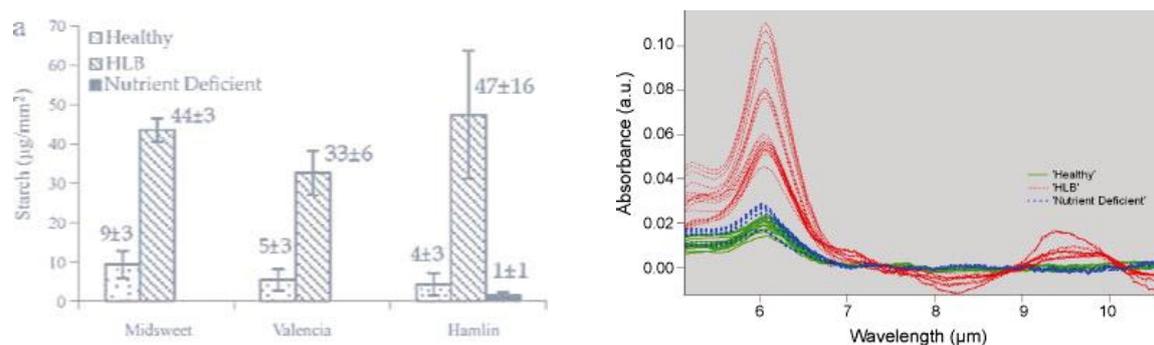
Non-imaged hyperspectral data can provide superficial information, albeit strongly related to food quality, such as the detection of anthracnose in sweet mangoes (*Mangifera indica* L.) during post-harvest (ARDILA *et al.*, 2020) or even when classifying the quality of honey (CHIEN *et al.*, 2019) and milk (KIMBAHUNE *et al.*, 2016).

CHALLENGES AND THE OUTLOOK FOR THE FUTURE

Robustness in data analysis offers more hope to the agricultural sector. In this brief review, powerful analytical methods have been explored in recent studies where HRS could be the link between the challenges and the understanding of patterns in the agricultural environment. The management of productive areas with sub-metric precision (ANGEL *et al.*, 2020), recognition of plant disease in the canopy and fruit, post-harvest classification, chemometrics in nutrients, and differentiating varieties of the same crop (SILVA JUNIOR *et al.*, 2018) are scientifically possible realities of modern agriculture.

The achievements listed here were only possible thanks to the improvement of techniques and technologies that are capable of organising RS in an

Figure 4 - Comparison of starch content (SANKARAN *et al.*, 2010) and hyperspectral absorbance (POUREZZA *et al.*, 2016) in healthy citrus leaves under nutrient deficiency and infected with HLB



objective, continuous and concrete way. The outlook for Agriculture 4.0 points to imminent global and local revolutions. In this scenario, in which the use of ultra-spectral resolutions is already beginning to be discussed (KARAS; GRISHKANICH, 2020), in which data processing and analysis software are inseparable from the professionals of agricultural science, and in which multidisciplinary information comes from domains beyond the visible, it is understood that a “new way of doing agriculture” has already arrived.

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