State of the art of Precision Agriculture

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Introduction

In the last report on world population prospects drafted by the United Nation Department [1], the global population could grow to around 8.5 billion in 2030, reaching 9.7 billion in 2050. Just now the COVID-19 pandemic has exposed the vulnerabilities of our food system, contributing to the increase in world hunger, affecting almost all low- and middle-income countries [2]. Also, currently approximately half of the world population is estimated as being subject to severe water scarcity, for at least some part of the year [3].

Sustainable development is at the heart of the global community's aspirations. In September 2015, more than 150 international leaders met at the United Nations to contribute to global development, promote human well-being and protect the environment, by setting seventeen goals (Sustainable Development Goals - SDG). Special attention should be paid to climate change, considered as one of the greatest challenges of our time and whose adverse impacts undermine the ability of all countries to achieve sustainable development [4].

Increasing in water scarcity and droughts, wildfires, and risks to food production and safety are only some of the threats due to climate change [3]. To secure the quantity and quality of food supplies to all precision agriculture in the agricultural production system can be used to decrease the input of natural resources, reduce the environmental impact and also increasing economic returns, and guarantee the best outcome in food production. Precision agriculture (PA) is a way to apply the right treatment in the right place at the right time [5] using different kinds of technologies able to monitor and implement site-specific management.

Over the years, there has been a growing scientific focus on research precision agriculture. Among the countries most interested in PA are the United States, followed by China and India. A substantial number of publications on this topic are also to be found in European countries, with Italy standing out above all others [6]. As for now, farms of an area greater than 300 hectares tend generally to invest more in new technology compared to small farmers. In fact, it is not surprising that in the United States of America are present about 90% of the yield monitors [7]. For this, the PA is moving towards the implementation of low-cost technologies.

PA finds application both in agricultural production (precision crop farming) and livestock production (precision livestock farming). The purpose of this paper is to highlight the advances in precision crop farming, so we will refer to it by the generic term precision agriculture.

Precision agriculture workflow

The steps of precision agriculture can be interpreted as a cycle of actions that is repeated several times during the growing season and over the course of years. Briefly, three are the steps necessary to take in AP: i) gather data from the field, ii) extract information from the collected data, and iii) development and implementation of management plan derived from the preceding critical analysis (Figure 1) [8-9].

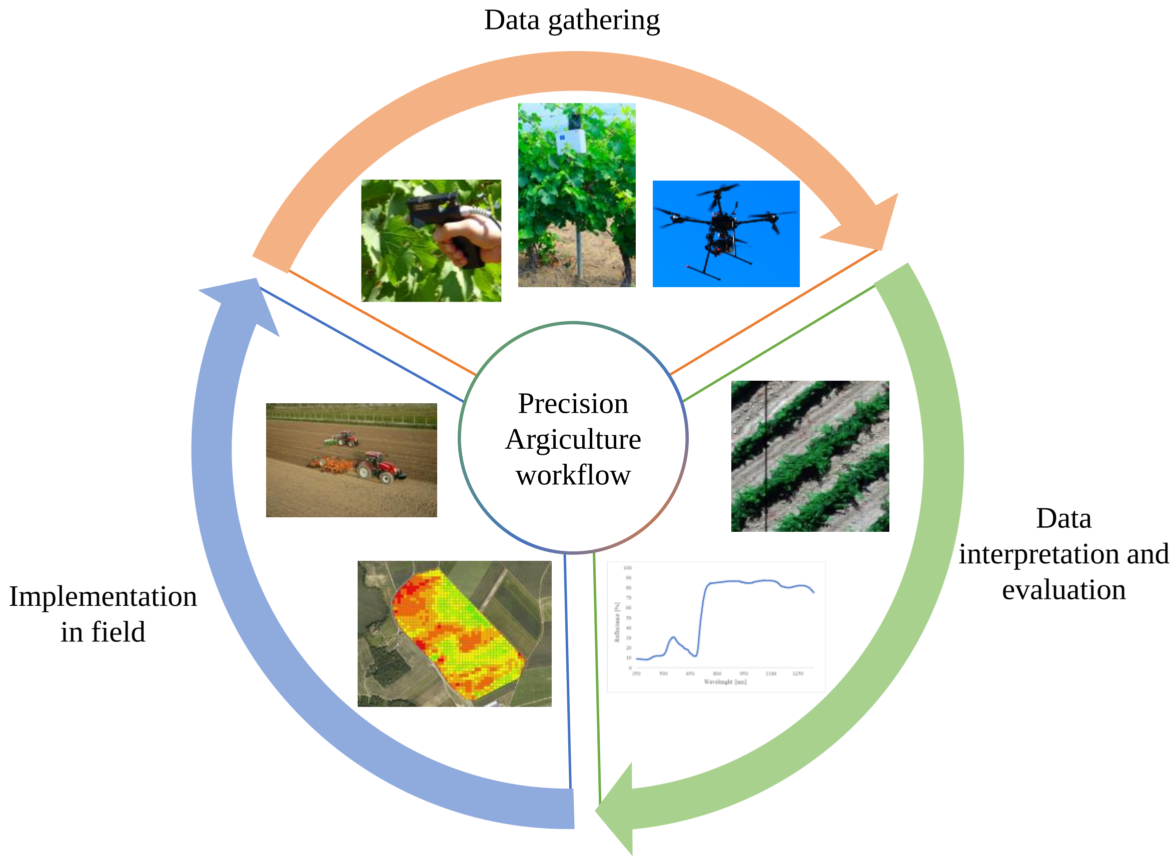

FIGURE 1:OVERRALL WORKFLOW OF PRECISION AGRICULTURE.

The application of steps in precision agriculture is considered a cycle because it involves a continuous and iterative process. The cyclical nature of precision agriculture acknowledges that it is an ongoing process that requires regular assessment, adjustment, and iteration to achieve optimal results and continually enhance agricultural practices. The cycle implies that the steps are not performed once and completed, but rather repeated over time to continually optimize agricultural practices. By continuously monitoring and evaluating the outcomes, farmers can assess the effectiveness of their actions and make necessary adjustments for further improvement.

Georeferencing and site-specific management

One of the key roles in the development of precision agriculture is given to the geolocation of information thanks to the introduction of the Global Navigation Satellite System (GNSS) for civil use in the early 90s at work of the American NAVigation Satellite Timing and Ranging Global Positioning System (NAVSTAR GPS), followed by the Russian GLONASS and, in recent years, Chinese BeiDou and European Galileo. A GNSS is a system that uses a constellation of the satellite at a global level to locate the position on the Earth.

The basic principle of operation on which GNSS systems is based on the triangulation of the position, and it involves estimating the distances from at least three satellites orbiting the around Earth along different and separated trajectories to determine the position of an object in 2-D along with the uncertainty in measurement [10]. Three segments that, interface with each other, compose the GNSS: the Space Segment, the Control Segment, and the User Segment. The first one comprises the set of satellites in space that constantly transmit signals to ground control bases and to users' receivers. The Control Segment consists of a series of ground bases that continuously monitor the orbit of the individual satellites, set the necessary course corrections, and transmit the ephemerides (messages about satellites information such as health status and position at a given time). The bases receive signals from the satellites and send them commands and data. The third segment is the User Segment which includes all the devices able only to receive the satellite signal [11].

However, normal users' technologies can estimate the position with an accuracy of meters, while, talking about precision, we need the exact position in real-time. To reduce the margin of error in the measurement and increase its accuracy, real-time kinematic (RTK) differential position is used, which uses a radio signal sent to the receiver from a base station located at a short distance away using one or more fixed base stations with known coordinates (master) and one receiver with unknown position (rover). In the case of Network RTK (NRTK), the rover receiver on site receives corrections from a GNSS permanent station via NMEA network. If the distance between the master and rover receivers is less than 5 km, a single-based RTK methodology can be exploited while if the inter-station distance increases it is better to use the NRTK positioning (Figure 2) [12].

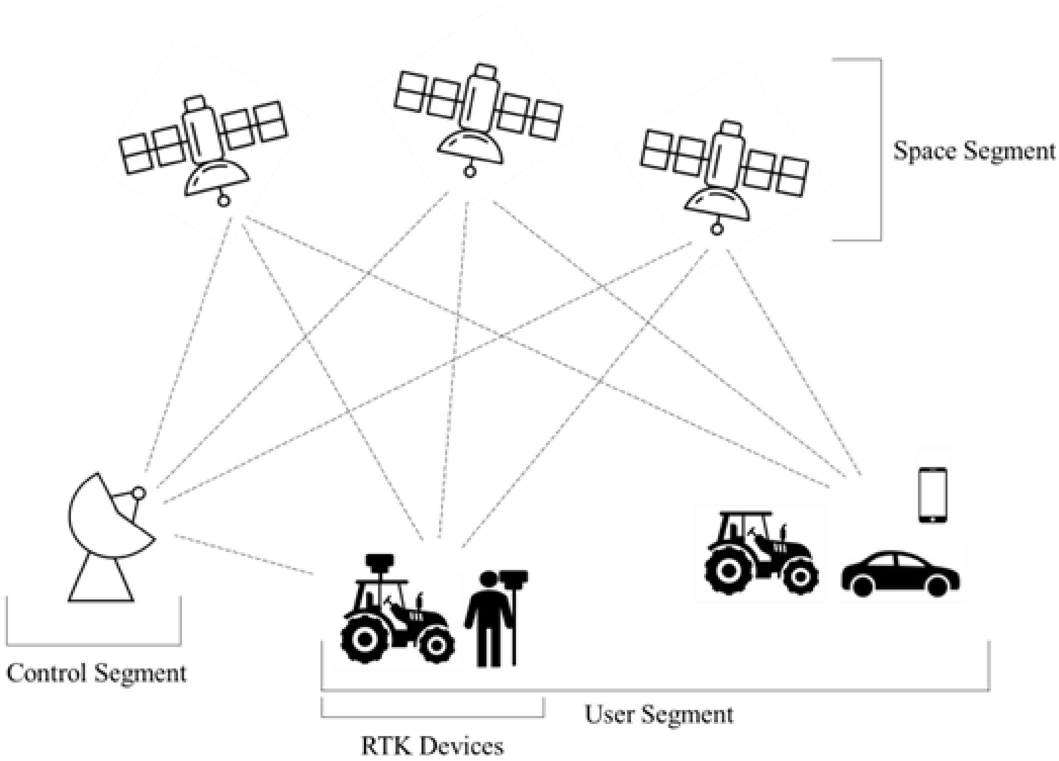

FIGURE 2: SIMPLE GLOBAL NAVIGATION SATELLITE SYSTEM (GNSS) ARCHITECTURE.

Precision positioning systems allowed the development of analysis methods able to study spatial variability, extract statistical information from locations with unknown data, use geostatistics, and also mapping systems to create prescription maps useful, for example, for reducing inputs within the field or for identifying the best time for harvesting.

Data acquisition

When the decision to use PA is taken, the first step is always data acquisition. For this task, we can categorize the used devices into three primary groups, depending on the distance of application to the object of study: continuous measurement technologies, proximal devices and remote. Continuous measurement technology involves the use of automated sensors or monitoring systems that provide continuous, real-time data acquisition. These systems are designed to capture data at regular intervals without interruption. Continuous measurement technology is often used for monitoring environmental conditions, such as temperature, humidity, soil moisture, or weather parameters. It enables a comprehensive understanding of dynamic changes and trends over time. Proximal sensing involves collecting data from sensors that are in close proximity to the target object or area of interest. In agriculture, this typically involves using handheld or mounted sensors that are physically close to the plants or soil. Lastly, remote sensing involves collecting data from sensors that are positioned at a distance from the target object or area.

Wireless sensor networks, IoT and DSS

One of the main objectives of the precision agriculture concept is to connect the farmer to the field by providing spatialized, real-time information. Wireless sensor networks (WSNs) are technologies able to provide this kind of connection, allowing the monitoring of different parameters that vary on the kind of sensors installed in the field. WSN technology is a network of multiple independent wireless nodes able to communicate to a gateway in order to transmit the collected information of the sensors via radio-frequency (such as cellular signal, ZigBee, Wi-Fi, LoRaWan etc.) to a receiver [8] (Figure 3). When the receiver is connected through the internet to transmit this data, then we can speak about the IoT (Internet of Things) platform. IoT connects the physical world to the webs and therefore performs a major role in numerous activities in the precision structure. IoT systems possess the awareness, the ability of the system to sense other entities, exchange information with each other and the capability to represent in accordance with the programming behavior [13].

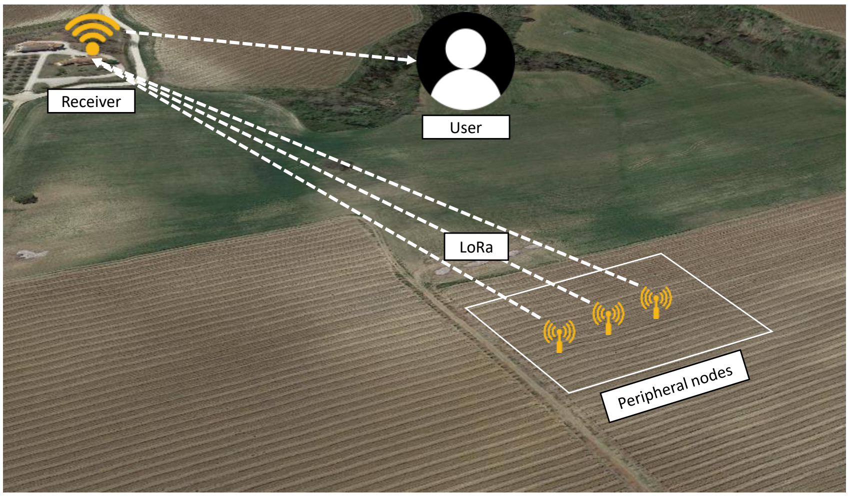

FIGURE 3: SIMPLE WIRELESS SENSOR NETWORK (WSN) ARCHITECTURE

IoT technologies can find a pivotal role in a lot of different activities concerning precision farming, such as decision making and automation of agricultural operations. The union of wireless sensors and IoT in smart farming answers many of the issues facing conventional agriculture, for example, land suitability, drought monitoring, irrigation, pest control, and yield maximization [14]. In recent years, many decision support systems (DSS) have developed from WSN and IoT systems. DSS is able to collect, organize and process raw data, interpret them and give back a graphic explanation and direct the farmer toward a choice of crop management [8].

The main challenges behind the IOT-based system are latency with minimal energy requirements, better bandwidth utilization and intermittent Internet connectivity. However, the size and the cost of WSNs have progressively decreased due to their rapid advancement, making them easily implementable technologies in the field to monitor microclimatic parameters at a site-specific level [15].

Support platform for precision agriculture

In the field of precision agriculture, particular attention must be paid to the platform capable of carrying the weight of the sensors (payload). The spatial and temporal resolution, as well as the cost of acquisition, depend on this.

Depending on the distance from the target, the platform can be divided into remote (satellite, aircrafts, and Unmanned Aerial Vehicle) and proximal (machines on-the-go) sensing (Unmanned Ground Vehicle).

Satellite

The use of satellites in precision agriculture goes back to the 70s with the launch of Landsat 1, the first civilian earth observing satellite. From those days to now, several multispectral satellites were developed and used in precision agriculture, whit a constant rising in spatial and spectral resolution. Today satellite photos are also available for free, the image from MODIS, Landsat or Sentinel [16], however, despite the different satellite availability and low cost, there is a tradeoff between cost and spatial resolution, that may affect its use in precision agriculture. In fact, generally, with free or low-cost images the spatial resolution is less than optimal. In order to achieve a higher resolution, the cost increases (as for the use of Ikonos, WorldView [16]), making the expense unsustainable, as well as often being still insufficient for plots consisting of small areas [17] or if we are talking about precision viticulture, were low spatial resolution makes rather complicated the removal of soil and inter-row pixel in the post processing of the image [8]. Also, despite the increasing temporal resolution, the availability of nadir images is too long for time-sensitive uses, also considering the possibility of cloud-corrupted images when passing over the area of interest [18].

Aircrafts

In order to obtain higher spatial and temporal resolution, aircraft can be used. They allow monitoring wider areas (bigger than 10 hectares) with multiple sensors at once, as they can carry heavy payload [19].

Contrary to satellites and Unmanned Aerial Vehicle (UAV), aircraft are manned vehicles, and a license is needed in order to fly. In each country, there are no-fly zones, whose overflight is prohibited or need to be limited to certain altitude range, hours, and days. These areas are published by Civil Aviation Authority (CAA) in detailed maps and lists [8].

Unmanned Aerial Vehicle (UAV)

UAV are aerial vehicle able to fly autonomously without carry the operator. There are different categories of UAV and can be divided generally in: Fixed-wing UA, planes with wing that produce lift power from their wings and need to be catapulted, hand-launched or require a runway to take off, with long endurance and high speed; Rotary-wing UA, that have hovering capability and high maneuverability, divided in unmanned helicopter and multi-rotor (with four or more rotors); Blimps, lighter than air, with high endurance and low speed; Flapping wing, small and flexible UAV; Parafoil-wing, using one or more propellers able to harness the air power and fly without consuming much energy [20]. The most used in precision agriculture are the multi-rotor rotary-wing, often called drones [21].

UAVs can be controlled remotely by the operator following visually, or they can fly autonomously following a set of pre-set points (waypoints), that the drone can follow thanks to a set of sensors able to detect the position of the vehicle in space as gyroscopes, compass, GPS, pressure sensor and accelerometers [8]. The operator is able to communicate via the UAVs by the Ground Control Station (GCS) that receives relevant data on the flight and also by the flight control sensors. They can also contain software required for the processing of the data acquired by the UAV [21]. The full system that includes UAV, GCS and the operator, is called Unmanned Aerial System (UAS).

The use of UAVs is subjected to the same limitation of aircraft for what it concerns the need for patents and the flight restriction by CAA.

Unmanned Ground Vehicle (UGV)

Unmanned Ground Vehicles (UGVs) are machines able to be remotely piloted on the ground without the need for a human being on board. The use of UGV can be useful in several situations that may include hazardous situations for the operator or the inability of different machines [22-23]. In precision agriculture, UGV can represent a substitute for UAV, especially in the no-fly zone.

UGV uses a similar pilot system to UAV, but, contrary to them, they need sensors (such as LiDAR, monocular camera and millimeter-wave radar) to perceive the external environment to avoid danger to the surrounding [24].

Precision agriculture sensors

The use of precision agriculture generally comprises a set of techniques that permits the analysis of the earth's surface with supports equipped with sensors, able to perceive signals coming from the target object with different resolutions (spatial, spectral and temporal). However, in one way or another, this system uses the interaction between electromagnetic radiation and the studied material.

Electromagnetic spectrum

Electromagnetic radiation (EM) is the transmission of electric and magnetic disturbances through space, traveling at the speed of light (2.998 × 10^8 m/s). EM radiation possesses both wave-like and particle-like characteristics. The wave properties of EM radiation can be described in terms of its amplitude, wavelength, and frequency. Amplitude corresponds to the height of the wave, while wavelength represents the distance between wave crests (measured in sub-multiples of meters), and frequency indicates the number of wave crests that pass a specific point within a given time (measured in Hertz). EM radiation travels in a waveform at a constant speed. As the speed is constant, an increase in frequency results in a corresponding decrease in wavelength. Thus, wavelength and frequency are inversely proportional. The particle-like behavior of EM radiation becomes evident when ionizing photons interact with matter [25]. The energy (E) carried by a photon is equal to the product of its frequency (ν) and Planck's constant (h):

$$E = \nu h$$

Photon energy is directly proportional to photon frequency (Figure 4).

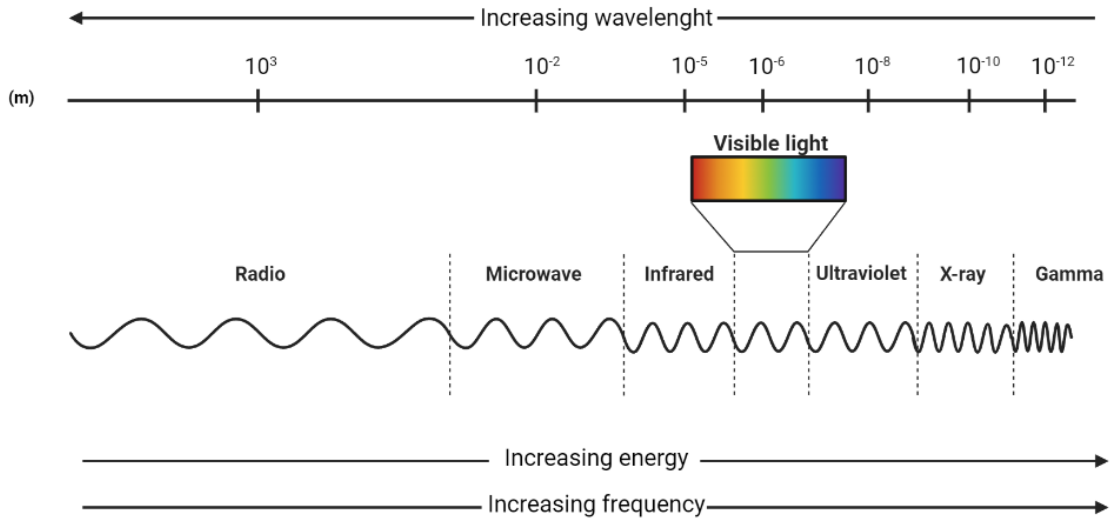

FIGURE 4: ELECTROMAGNETIC SPECTRUM.

The range of electromagnetic radiation emitted by a body in different bands is called a spectrum. A body hit by electromagnetic radiation responds differently depending on its chemical and physical characteristics, reflecting, absorbing or transmitting the radiation. The spectrum it creates is therefore called a spectral signature; variations in the physiological state of the plant correspond to variations in its signature (Figure 5). The electromagnetic spectrum can be divided into different portions according to different wavelengths. Light in the visible (VIS), that portion of the electromagnetic spectrum visible to the human eye, is between 0.4 and 0.7 µm, while above 0.7 up to 20 µm we are in the infrared range. The latter in turn is subdivided into near infrared (NIR, 0.7-0.1.3 µm), short infrared (SWIR, 1.3-2.5 µm) mid infrared (MSWIR, 3-8 µm) and thermal infrared (TIR, 7-20 µm).

The VIS portion of the spectral signature of vegetation is characterized by absorption in blue and red bands, while there is a high reflection in green. This portion of the spectrum is called Photosynthetically Active Radiation (PAR) as it is used by plants to perform photosynthesis. The main photosynthetic pigments used to capture light are chlorophylls, chlorophyll a (Chla) and chlorophyll b (Chlb). Their absorption peaks are in the blue portion (420 nm for Chla and 435 nm for Chlb), with the highest intensity, and in the red portion (660 nm for Chla and 642 nm for Chlb) of the spectrum. Another important category of pigments, with absorption peaks in the visible spectrum, are the carotenoids, whose main function is to protect the lipids of the chloroplasts (organelles within which chlorophyll photosynthesis takes place) from photooxidation caused by excessive luminous intensity. They include carotene, lycopene and xanthophylls and depending on the type have three absorption maxima at 420 - 425 nm, 440 - 450 nm and 470 - 480 nm [27].

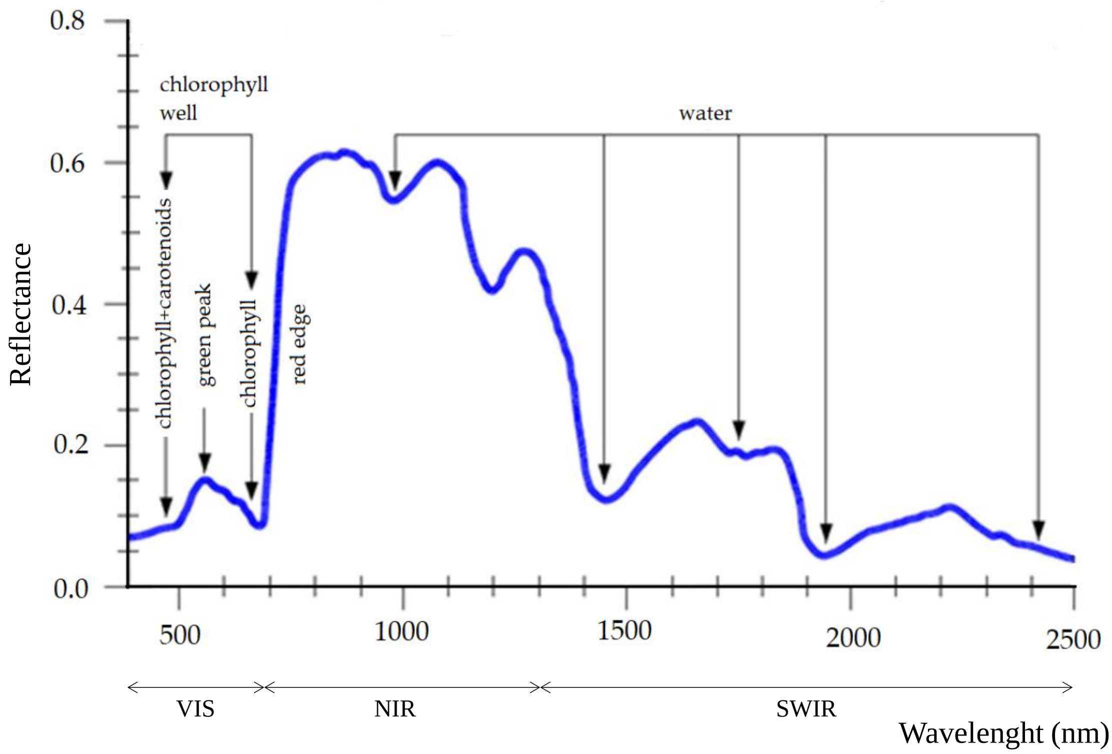

FIGURE 5: CHARACTERISTIC SPECTRAL SIGNATURE EXHIBITED BY HEALTHY PLANTS (MODIFIED FROM MORONI ET AL., 2019).

Leaf reflectance in the NIR region is affected primarily by many characteristics of leaf structure. Has been demonstrated how this reflection is influenced by the ratio of mesophyll cell surface area (Ames) exposed to intracellular air spaces expressed per unit of leaf area (A); this ratio (Ames /A) has also been strongly associated with photosynthetic performance in numerous species [28], but they can be considered separate phenomena, as the chlorophylls pigments are completely transparent to NIR wavelengths. The radiation is diffused and scattered through the cuticle and epidermis to the mesophyll cells and air cavities in the interior of the leaf. Here the radiation is further scattered as it undergoes multiple reflections and refractions where refractive index differences between air (l.0) and hydrated cellulose walls (1.4) occur [29].

A unique contrast in reflectance is given in the red-edge portion of the spectrum (670-760 nm) due to the sharp increase of reflectance from chlorophyll absorption in the red region and scattering by the plant cells in the NIR part of the electromagnetic spectrum. The red-edge can be used for phenological and health status studies for its sensibility to plant development [30]. Due to the influence of the NIR on the leaf structure, the NIR region can be also investigated to identify pathogen attacks that alter the very structure [31].

Absorption by vegetation liquid water occurs in the near-infrared (NIR) at 970 nm and 1200 nm and in the shortwave infrared (SWIR) at 1450 nm and 1950 nm, with higher absorption in the latter for its sensitivity to water content [29], [32], [33]. However, precisely this sensitivity can result in high background noise with a saturation of the value. Particular attention must therefore be paid to those measurements that are made above the atmosphere and above the canopy [33].

Sensors

Remote sensing in precision agriculture mostly uses passive sensors capable of detecting solar energy reflected (0.4-2.5 µm) and emitted from surfaces in the TIR domain (8-20 µm). Instead, passive sensors use the microwave domain to receive and measure emissions produced by constituents of the earth in the function of the surface composition, physical temperature, surface roughness, and other physical characteristics of the Earth [34]. Passive sensors can be used for estimating some parameters (like soil moisture) in big areas; therefore, they are not frequently used in the field of precision viticulture.

Depending on the type of sensor and the type of its support, we can have different resolutions of the image. We can distinguish three kinds of resolution: temporal, spatial and spectral. Temporal resolution refers to the time between captured images of the same area; spatial resolution is defined as a measure of the smallest object that the sensor can resolve or the linear dimension on the ground represented by each pixel referred to as Ground Sampling Distance (GSD) [35]; spectral resolution refers to the ability of the sensor to measure specific wavelength and how narrow the bands are.

RGB sensor

The most common sensors used in precision agriculture are RGB cameras, sensors able to acquire data in the visible spectrum. RGB sensors can be used to analyze the geometry of trees canopy and identification of missing plants [36-38], for weed detection [39] and also for plant phenotyping, although with limitations [40]. The high resolution of the image, the possibility to acquire data with different meteorological conditions and their relatively low-cost price, in comparison to other kind of sensors, has made them the most widespread sensors in circulation. The diffusion and the accessibility dictated by the low price of this kind of device led to the development of simple tools able to evaluate plant growth, like the app "VitiCanopy" [41]. On the other hand, they miss a lot of information about vegetation parameters that need to be observed within the non-visible spectrum [21]. In order to cope with their imitations, RGB cameras are commonly used in tandem with other types of sensors.

Multispectral and Hyperspectral sensors

Currently, the most widely used sensors in precision agriculture are multispectral sensors [6]. Sensitive to a limited number of specific wavelengths (typically four or six, mainly in the visible spectrum and near-infrared), they allow for calculating the main VIs with the low purchase cost [9]. Most multispectral cameras include several sensors and lenses, and each sensor is sensitive to one spectral band, but by some modifications, like adding a filter, RGB cameras can be turned into a simple multispectral [35].

Similar in operation, hyperspectral cameras have established themselves in recent years as useful technologies that can provide information in a wide range of wavelengths (from visible wavelength to SWIR (970-2500 nm)) that allow for more in-depth analysis of crop status. The limiting factor to the diffusion of this type of sensor is its high price [21]. Imaging hyperspectral sensors are able to measure the spectral bands for each pixel of the created image, thereby combining spectral and spatial resolutions. Each pixel of the image thereby has its own spectral signature, including reflectance values for all spectral bands measured by the hyperspectral sensor. This open the possibility to further investigate both abiotic and biotic stressors to which the plant is subjected.

Four main types of hyperspectral sensors can be identified: non-imaging sensors, whisk broom sensors, push broom sensors, and filter-based sensors. Non-imaging sensors provide average spectral reflectance values without spatial details. Push broom and whisk broom scanners acquire spectral information along a line or at a specific point on the object, respectively. In this case, hyperspectral images are created by scanning or rotating the object of interest.

Lastly, filter-based sensors capture the complete spatial image for each spectral band simultaneously [31].

Knowing the principles of electromagnetic spectrum and the response of the object to solar light, is possible to extract different information about its condition using different indices, mathematical ratio between the various bands of the spectrum. This indices in precision agriculture empowers farmers to employ a data-driven approach, optimizing resource allocation, reducing environmental impacts, and ultimately improving overall agricultural sustainability and productivity.

Thermal sensor

Thermal cameras allow for identification of thermal alterations of the leaf surface measuring the temperature of plant tissues. In fact, due to a reduction of the stomata opening, induced by thermal stress, there is an increase in the vegetation temperature, whose measure permits to identify the plants water stress. The physical law that allows us to describe the operation of thermal sensing is the Stefan-Boltzmann law [42]. According to this, the amount of radiation emitted by a body M (Wm-2) is equal to the product of the emissivity of the body ε, the absolute temperature of the body T (K) and the Stefan-Boltzmann constant σ (Eq. 1).

$$M = \sigma \varepsilon T4 \qquad [1]$$

So, the higher the temperature of the body, the greater the amount of radiation emitted. measuring the radiation emitted by bodies using thermal sensors, and knowing the emissivity of the body (which in the case of leaves is 0.98 [43]), it is possible to estimate the temperature of the vegetation. Knowing the temperature of the canopy allows for calculation indices, such as the Crop Water Stress Index (CWSI), that may help to estimate the magnitude of the water stress. It can be evaluated with UAS [44], [45], but can also be used as proximal sensing [46].

LiDAR sensor

The LiDAR (Light Detection and Ranging) is an active sensor capable of sending laser pulses towards a target and intercepting the return of the pulse, which is reflected from the surface by a detector. By recording the return time, the instrument is able to determine the distance to the object, thus being able to recreate a three-dimensional map. Furthermore, by precisely knowing the coordinates of the sensor in three-dimensional space, it is possible to derive the coordinates of the points where the light impulse hit the objects [35].

In the agricultural field, lidars are mostly used for the geometric characterization of plant canopies, providing extremely precise information that correlates with the leaf area index (LAI) [47]. Lidar measurements can be aimed at recording the spatial position of a target point, which requires exact georeferencing of the sensor during moving measurements.

Interpretation and implementation of data

Crucial step in precision agriculture is the interpretation of the data and their evaluation, so that the farmer can take site-specific decisions. Generally the data are represented with a geolocalized map that can display how to manage the field [48]. This are called prescription maps and can be done using GIS (Geographic Information Systems) software [49].

When confronted with numerous field parameters that require consideration, some challenges can be found in effectively managing complex information to make informed decisions. In such instances, artificial intelligence (AI) offers valuable assistance through various techniques and alghoritms. AI serves as a powerful tool to analyze and interpret the vast amount of data, enabling more accurate and efficient decision-making processes in complex scenarios [48].

Use of Artificial Intelligence in Precision Agriculture

Artificial Intelligence (AI) has gained significant traction in the agricultural industry in recent times, as this sector is encountering various obstacles that hinder yield optimization, such as inadequate soil management, pest and disease outbreaks, the need for handling large amounts of data, low productivity, and a technology knowledge gap among farmers. The core attributes of AI in agriculture are its adaptability, superior performance, precision, and cost-efficiency. Able to play significant role in different stages of the workflow of precision agriculture, being useful for data gathering, their evaluation and interpretation and also in the implementation in field.

Machine learning (ML) is a subset of AI that focuses on enabling machines to learn and improve from experience without being explicitly programmed.

The main steps for machine learning process can be reassumed as follows [9; 50]:

1. Data Collection: the initial stage is to gather relevant and representative data for the problem at hand. This data should include input features (X, independent variables), with each feature consisting of two or more variables (xi, attributes), and corresponding target values (also known as labels or dependent variables). The data should be various and cover a wide range of scenarios to ensure the model's generalizability.
2. Feature selection: his step involves identifying the most relevant characteristics or features that are crucial for addressing the problem at hand.
3. Algorithm Selection: it consists of selecting the most suitable algorithm or method to handle the specific problem.
4. Parameter Selection: certain algorithms require tuning with parameters, which may need to be experimentally determined.
5. Training: using a set of inputs, the selected algorithm and parameters, the training phase involves constructing a computational model that will be utilized to predict responses for new data.

Evaluation: the system's accuracy and performance are assessed by evaluating its ability to make accurate predictions based on the training data.

ML algorithms can be classified into three main categories [51]: supervised learning, unsupervised learning and reinforcement learning. Supervised learning are algorithms that learn from a labeled dataset, where each input is associated with corresponding outputs. By establishing an input-output relationship based on this labeled data, the algorithms can generalize and predict outputs for new, unseen inputs. When unlabeled data are used, the algorithms is called unsupervised learning. The aim is to discover unknown patterns by grouping similar objects together. Unlike supervised learning, unsupervised learning extracts hidden knowledge from the training dataset, making it a more challenging approach to implement. Lastly reinforcement learning is a different paradigm in which algorithms learn from their interaction with the environment, receiving rewards or punishments. By maximizing cumulative rewards, reinforcement learning algorithms improve their decision-making capabilities over.

A machine learning training model is a process in which a machine learning (ML) algorithm is fed with sufficient training data to learn from. In precision agriculture the most used models are listed below [50–53]:

-Regression model, a type of supervised learning algorithm that establishes a relationship between input and output based on the training data. These algorithms are used to predict numerical values for unseen inputs. Examples of regression algorithms include simple linear regression, multiple linear regression, polynomial regression, and logistic regression.

- Instance Based Models (IBM) are supervised algorithm; the most common is the K-Nearest Neighbor (KNN) that classifies new data points by comparing them to the labeled data, previously divided in classes based on the output in the training set, and assigning them to the class that the majority of their nearest neighbors belong to.

- Decision tree (DT), is a versatile algorithm that can be applied both to categorical and continuous input and output variables. It operates by recursively partitioning the data into two or more homogeneous subsets or regions based on the most significant splitter among the independent variables. Among the tree-based approaches, random forest (RM) has proven to be the most effective one.

- Support Vector Machines (SVM), both for classification and regression tasks, it builds multi-dimensional boundaries between data points in the feature space. The output of the SVM is predicted based on the classes divided using the training data.

- Neural Networks (NN) consists of an interconnected network of artificial neurons, also known as nodes or units. At each connection is assigned a weight representing its strength and signal. These weights serve as the main form of long-term storage in neural networks, and learning algorithms typically update them. Input and output nodes are the ones connected to the external world. Each node operates independently of others, performing calculations based on its input values and associated weights. Example of NN methods used in PV are: Recurrent Neural Network (RNN), Multilayer Perceptron Neural Networks (MLP NN), Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN).

- Clustering models, an unsupervised model used to find group in the data.

- Bayesian Models, an unsupervised model that use probabilistic methods and Bayesian inference to make predictions or estimate parameters. They are useful for tasks such as classification and regression.

- Ensemble Learning (EL), aim to enhance the predictive performance of a specific statistical learning or model fitting technique by creating a composite model through the combination of simpler base learners.

Artificial intelligence application in agriculture

In order to enhance crop yield and preserve soil resources, several studies have dealt with applications of ML in for predicting and identifying agricultural soil properties, including soil drying, condition, temperature, and moisture content. Traditional soil measurements are time-consuming and expensive, making ML-based computational analysis an attractive and cost-effective solution. Accurate estimation of these soil properties is crucial for understanding ecosystem dynamics and improving soil management in agriculture.

AI can also be used to automatically identify and classify plant species, reducing the reliance on human experts and minimizing classification time.

Artificial intelligence has been applied in several studies concerning the crop management. In particular, has been studied how to predict and optimize crop yield and quality, with the aim to provide growers with specific information to enhance productivity and profit while addressing market supply, with significant impact on product price, waste reduction and demand imbalances.

Other studies focused on the use of AI in order to reduce the input in field, targeting agro-chemical with time-saving detections of different plant disease, use algorithms combined with sensors able to offer a low-cost and environmentally friendly solution for weed detection, enabling the development of tools and robots to control and remove weeds without relying heavily on herbicides, or estimate evapotranspiration for management of water resources and irrigation system design.

Several information about the use of ML and the various algorithms along with the accouracy of the measure for different aims, can be found in the articles by Patrício and Rieder, 2018; Liakos et al., 2018; Eli-Chukwu, 2019; Sharma et al., 2020; Hossen, 2023.

The use of AI could therefore actually help limit the inputs given to crops, improving their quantity and quality.

Use of AI in agriculture: challenges and limitation

Despite the notable advancements of AI in the agricultural sector, its current impact on agricultural activities remains below the average compared to its vast potential and impacts in other sectors. Further efforts are required to maximize the benefits of AI in agriculture, considering the existing limitations that hinder its widespread implementation.

In precision agriculture time and accuracy is of utmost importance, while many systems fail to give one of them or both. Also, the accuracy requires big volume of data as input. Creating an agricultural expert system necessitates collaboration among specialists from various agricultural domains and active participation from the growers who will utilize these systems. Such collaborative efforts are essential for the successful development of agricultural expert systems [54]. In addition, there is a cost issue [55].

Application of Precision Agriculture

As already mentioned, the main objective of precision farming is to help increase environmental, economic and social sustainability by improving the precision of farming, allowing to save time, money and reducing of potentially polluting and harmful products. The phase following the acquisition and processing of field data, concerns the need to implement the results obtained in the field in order to achieve an effective gain. Application possibilities range from soil processing to production mapping.

In the last decades several systems have been developed to improve the efficiency of agricultural machinery used for field work and improvement for the site-specific management [56]. The first requirement of PA is to be able to guide vehicles along predefined trajectories. In order to achieve this as best as possible, GNSS-based guidance systems have been introduced into agricultural machinery, which enable enables agricultural vehicles to operate on parallel tracks or predefined paths, reducing driver stress and minimizing gaps and overlaps in operations [5].

To optimize the application of input in the field (such as fertilizers, pesticides, and water), variable rate technology (VRT) can be used. VRT allows farmers to apply inputs at varying rates across different areas of the field according to the specific needs of the crops and the soil conditions. This technology utilizes data from various sources like remote sensing, soil sampling, and yield mapping to create prescription maps that guide the application of inputs in a site-specific manner [57].

Several are the possibilities of application of AP in precision agriculture, contributing with environmental, economic, and social sustainability. The main utilizations of AP are:

- Monitoring and map of crop yields across their fields. This information helps identify spatial variations in productivity and optimize resource allocation [58].

- site-specific application of inputs such as fertilizers, pesticides, and irrigation water at variable rates based on the specific needs of different areas within a field. This targeted approach improves resource efficiency and reduces environmental impact. [59–61].

- Detailed soil mapping to assess soil characteristics such as nutrient content, pH levels, and moisture retention. This information helps in creating soil management plans tailored to specific areas within a field [62].

- Weed Management: Precision agriculture facilitates the identification and mapping of weed and pest infestations. This information aids in implementing site-specific control measures, reducing the reliance on broad-spectrum treatments and minimizing chemical inputs [63-64].

Advantages and limitation of precision agriculture

With the introduction of new technologies, starting in the 1990s with the possibility of geo-localized information, precision agriculture has become increasingly popular and, perhaps never before, so much important. Precision agriculture, if well managed at a site-specific level, is able to cover all the tree sustainable aspects: environmental, economic and sociological [65]. Adding input at the right time, with the right amount and in the right place contributes to decrease the use of harmful, polluting chemicals and natural resources, with benefits both for environment and humans. At the same time, it concurs to the reduction of costs and increase of profitability. Technologies may also help to get a rise in quality of the product and detect the best harvest time, reducing the post-harvest losses [66].

Despite its many positive aspects, PA has also drawback. First of all, the use of available technologies requires knowledge and skilled personnel. In addition, it requires high financial means to support the costs. For these reasons, the use of AP is more frequent in developed country with large size, where the farmers are able to invest in relatively expensive tools and that allows for an economy of scale to pay for the investment [67]. Furthermore, in the face of unfavorable seasons, the use of precision techniques may increase the quality of production, but it might not completely remove the negative effects, leading to greater losses due to the costs incurred in surveying and maintaining precision technology [68] (Table 1).

TABLE 1: SWOT ANALYSIS OF SMART FARMING TECHNOLOGIES (MODIFIED FROM TRIANTAFYLLOU ET AL., 2020)

Strengths	Weaknesses
- Inputs control (water, fertilizer, agro-chemicals)	- Limited sensor battery life
- Eco-friendly remote sensing	- Reliability (data loss)
- Upgrade crop quality	- Lack of initial fund
- Reducing production costs	- Lack of hardware and software
- Raise profits and productivity	- Lack of operational knowledge
- Real-time weed, disease and animal detection in the fields	- Difficulty in set up and maintenance
Opportunities	**Threats**
- Get acquainted with modern technologies	- Data security and privacy issues in modern technologies
- Management of field working hours	- Natural disasters (storms, floods, fire)
- New collaboration strategies and partnerships	- Hardware risks
- New business plans	- Experienced staff to be dismissed suddenly
- Impact of vocational guidance of urban population	

Given the challenges of diminishing arable land and the growing global population's food requirements, it is imperative to adopt intelligent and efficient approaches to crop production. It is crucial for all individuals to recognize the importance of food security and the need for sustainable agricultural practices in order to address these concerns effectively. Therefore, maximizing crop production by utilizing sustainable IoT-based sensors and communication technologies is crucial for optimizing every parcel of farmland and addressing the needs of every inch of land [14].

Conclusions

Precision agriculture holds great promise for improving agricultural practices and addressing the challenges of modern farming. The benefits it offers, such as enhanced resource management, increased crop yield, and environmental sustainability, make it a valuable approach for the agriculture factory. The industry acknowledges the existing challenges and looks to the future for potential opportunities, providing guidance to researchers and engineers. However, with ongoing advancements and efforts, precision agriculture can play a crucial role in transforming the future of agriculture and ensuring food security while minimizing environmental impact.

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