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Review

From Smart Farming towards Agriculture 5.0: A Review on Crop Data Management

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Abstract: The information that crops offer is turned into profitable decisions only when efficiently managed. Current advances in data management are making Smart Farming grow exponentially as data have become the key element in modern agriculture to help producers with critical decision-making. Valuable advantages appear with objective information acquired through sensors with the aim of maximizing productivity and sustainability. This kind of data-based managed farms rely on data that can increase efficiency by avoiding the misuse of resources and the pollution of the environment. Data-driven agriculture, with the help of robotic solutions incorporating artificial intelligent techniques, sets the grounds for the sustainable agriculture of the future. This paper reviews the current status of advanced farm management systems by revisiting each crucial step, from data acquisition in crop fields to variable rate applications, so that growers can make optimized decisions to save money while protecting the environment and transforming how food will be produced to sustainably match the forthcoming population growth.

Keywords: agriculture 4.0; big data; farm management information system (FMIS); robotics; IoT; variable-rate technology (VRT); AI

1. Introduction

The agriculture sector is undergoing a transformation driven by new technologies, which seems very promising as it will enable this primary sector to move to the next level of farm productivity and profitability [1]. Precision Agriculture, which consist of applying inputs (what is needed) when and where is needed, has become the third wave of the modern agriculture revolution (the first was mechanization and the second the green revolution with its genetic modification [2]), and nowadays, it is being enhanced with an increase of farm knowledge systems due to the availability of larger amounts of data. The United States Department of Agriculture (USDA) already reported in October 2016 that Precision Agriculture technologies increased net returns and operating profits [3]. Also, when considering the environment, new technologies are increasingly being applied in the farms to maintain the sustainability of farm production. However, the adoption of these technologies involves uncertainty and trade-offs. According to a market analysis, the factors that would facilitate the adoption of sustainable farming technologies include better education and training of farmers, sharing of information, easy availability of financial resources, and increasing consumer demand for organic food [4]. When applying these new technologies, the challenge for retrieving data from crops is to come out with something coherent and valuable, because data themselves are not useful, just numbers or images. Farms that decide to be technology-driven in some way, show valuable advantages, such us saving money and work, having an increased production or a reduction of costs with minimal effort, and producing quality food with more environmentally friendly practices [5]. However, taking these advantages to the farm will depend, not only on the willingness of producers for adopting new technologies in their fields, but also on each specific farm potential in terms of scale economies, as profit margin increases with farm size. The USDA reported that, on average, corn farm operating profit of Precision Agriculture adopters was 163 dollars per hectare higher than for non-adopters, taking into account that the highest adoption rates for three technologies (computer mapping, guidance, and variable-rate equipment) were on farms over 1500 hectares [3]. Such margins can even go up to 272 dollars depending on the crop. A greater use of Smart Farming services is vital to not only improving a farm's financial performance, but also to meet the food needs of an expanding population [6].

The final purpose of this paper is to demonstrate how making decisions with the modern data-based agriculture available today can lead to sustainable and profitable actuation to nourish people while reducing harm to the environment. In order to evaluate how modern agriculture can help in a sustainable decision-making process, this article revisits the main steps of an information-based agriculture and focuses on data management systems by reviewing recent applications related to each crucial step, from data acquisition in crop fields to the execution of tasks with variable rate equipment.

2. Data-Driven Agriculture: Agriculture 4.0

This new philosophy centered on agricultural data has been expressed with several names: *Agriculture 4.0*, *Digital Farming*, or *Smart Farming*, and was born when telematics and data management were combined to the already known concept of Precision Agriculture, improving the accuracy of operations [7]. As a result, Agriculture 4.0 is based on Precision Agriculture principles with producers using systems that generate data in their farms, which will be processed in such a way to make proper strategical and operational decisions. Traditionally, farmers have gone to the fields to check the status of their crops and make decisions based on their accumulated experience. This approach is no longer sustainable as, among other reasons, some fields are too large to be efficiently managed according to the threefold criteria that will lead the coming years: Efficiency, sustainability and availability (for people). Advanced management systems within the context of Smart Farming are providing practical solutions. Also, despite some farmers have a long-time experience gathered after many years of work in the field, technology may provide a systematic tool to detect unforeseen problems hard to notice by visual inspection on occasional checks. Regarding the willingness of adopting modern tools in agriculture, young farmers show a more positive attitude than elder ones, as the former can support their not-so-large experience in the field with new smart tools providing key information. However, the average age of farmers in the last decades has been alarmingly increasing: Around 58 years old in the USA and Europe, 60 in sub-Saharan Africa, or 63 in Japan [8,9]. Fortunately, this trend is expected to change. Several European policies, for example, are being set to support a generational renewal, facilitating access to initial investment, loans, business advice, and training [9]. A generational renewal in a rural development context goes beyond a reduction in the average age of farmers; it is also about empowering a new generation of highly qualified young farmers to bring the full benefits of technology in order to support sustainable farming practices [10]. This implies that young farmers will need to transform the existing land to more modern and competitive farms with the purpose of maintaining viable food production while improving the competitiveness of the agrifood chain, because with advanced technologies and new thinking, young people can transform the agricultural sector [8].

2.1. *Internet of Things: Collecting Information*

Internet of things (IoT) in an agricultural context refers to the use of sensors and other devices to turn every element and action involved in farming into data. It has been reported that an estimation of a 10% to 15% of US farmers are using IoT solutions on the farm across 1200 million hectares and 250,000 farms [11]. IoT drives Agriculture 4.0 [12]; in fact, IoT technologies is one of the reasons why agriculture can generate such a big amount of valuable information, and the agriculture sector is expected to be highly influenced by the advances in these technologies [13]. It is estimated that, with new techniques, the IoT has the potential to increase agricultural productivity by 70% by 2050 [14], which is positive, because according to Myklevy et al., the world needs to increase global food production by 60% by 2050 due to a population growth over nine thousand million [15]. The main advantages of the use of IoT are achieving higher crop yields and less cost. For example, studies from OnFarm found that for an average farm using IoT, yield rises by 1.75% and energy costs drop 17 to 32 dollars per hectare, while water use for irrigation falls by 8% [12].

2.2. Big Data: Analysis of Massive Data

In the current technology-based era, the concept of big data is present in many economic sectors, but is it already available to agriculture? The ever-growing amount of data available for field management makes necessary the implementation of some type of automatic process to extract operational information from bulk data. However, the volume of data currently retrieved from most commercial fields is, arguably, not yet at the level considered to be classified as big data. According to Manyica et al. [16], big data has three dimensions: *Volume*, *velocity*, and *variety*. Kunisch [17] added a fourth V for *veracity*. Finally, a fifth V was added by Chi et al. for the extra dimension *valorization* [18]. Overall, the five V (dimensions) of big data stand for:

- *Volume* refers to datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze information. This definition includes an estimate of how big a dataset needs to be in order to be considered big, and it can vary by study sector, depending on software tools that are commonly available and common sizes of datasets, typically starting in the terabyte range [16].
- *Velocity* refers to the capability to acquire, understand and interpret events as they occur. In agriculture, this would refer to applications that occur in real time, like data being processed right in the field to apply variable rates of chemicals in equipment featuring variable rate application technologies.
- *Variety* refers to the different data formats (videos, text, voice), and the diverse degrees of complexity. This situation is not strange in agriculture when different data sources are used to work in complex scenarios such as images and soil or weather probes.
- *Veracity* refers to the quality, reliability, and overall confidence of the data.
- *Valorization* is the ability to propagate knowledge, appreciation and innovation [18].

In the context of crop management, Kunisch [17] concluded that big data is applicable only in some cases in agriculture, depending on each farm and its level of technology adoption. Nevertheless, the Proagrica [19] report confirmed that big data was being increasingly applied in the agriculture sector. Kamilaris et al. [18] cited 34 works where big data was used in agricultural applications, and Wolfert et al. [20] published a review on big data applications in Smart Farming. In line with this trend, the Consortium of International Agricultural Research Centers (CGIAR, Montpellier, France) created a Platform for Big Data in Agriculture with the purpose of using big data approaches to solve agricultural development problems faster, better, and at a greater scale than before [21].

2.3. Agriculture 5.0: Robotics and Artificial Intelligence (AI) to Help in Nourishing People

Big engineering challenges typically spur big solutions through disruptive technologies, and Agriculture 5.0 is probably the one for the first half of the 21st Century. The concept Agriculture 5.0 implies that farms are following Precision Agriculture principles and using equipment that involves unmanned operations and autonomous decision support systems. Thus, Agriculture 5.0 implies the use of robots and some forms of AI [22]. By tradition, farms have needed many workers, mostly seasonal, to harvest crops and keep farms productive. However, society has moved away from being an agrarian society with large quantities of people living in farms to people living in cities now; as a result, farms are facing the challenge of a workforce shortage. One solution to help with this shortage of workers is agricultural robots integrating AI features. According to a Forbes study [23], farm robots augment the human labor workforce and can harvest crops at a higher volume and faster pace than human laborers. Although there are still many cases in which robots are not as fast as humans, agriculture is currently developing robotic systems to work in the field and help producers with tedious tasks [24–27], pushing agricultural systems to the new concept of *Agriculture 5.0*. According to Reddy et al. [28], the advent of robots in agriculture drastically increased the productivity in several countries and reduced the farm operating costs. As said before, robotic applications for agriculture are growing exponentially [27], which offers promising solutions for Smart Farming in handling labor shortage and a long-time declining profitability; however, like most innovations, there exist important limitations to cope with at the current early stages. These technologies are still too expensive for most farmers, especially those with small farms [29], because scale economics make small individual farms less profitable [30]. Nevertheless, the cost of technology decreases with time, and agricultural robots will be surely implemented in the future as the alternative to bring about higher production [4,31]. The world agricultural production and crop yields slowed down in 2015. The concept of agricultural robotics was introduced to overcome these problems and satisfy the rising demand for high yields. Robotic innovations are giving a boost to the global agriculture and crop production market, as according to the Verified Market Intelligence report, agricultural robots will be capable of completing field tasks with greater efficiency as compared to the farmers [32].

Agricultural tech startups have raised over 800 million dollars in the last five years [31]. Startups using robotics and machine learning to solve problems in agriculture started gaining momentum in 2014, in line with a rising interest in AI [33]. In fact, venture capital funding in AI has increased by 450% in the last 5 years [34]. This kind of new agriculture pretends to do more with less, because nourishing people while increasing production sustainably and taking care of the environment will be crucial in the coming years, as the Food and Agriculture Organization of the United Nations (FAO) estimates that, in 2050, there will be a world population of 9.6 billion [35]. Advanced sensing technologies in agriculture can help to meet the challenge; they provide detailed information on soil, crop status, and environmental conditions to allow precise applications of phytosanitary products, resulting in a reduced used of herbicides and pesticides, improved water use efficiency and increased crop yield and quality [2].

3. Data-Driven Management for Advanced Farming: Principal Stages

The raw measurements of key parameters from crops need to be efficiently processed so that numbers or images unambiguously turn into valuable information. Crop management based on field data already evolved when Precision Agriculture came to light thirty years ago, but it has certainly been transformed by the present digital information era. Traditionally, and in those places where technology has not arrived yet, field management consists of visually inspecting the development of crops to reach a diagnosis with which farmers make decisions and actuate giving different treatments to their crops. This approach relies on field experience and the information perceived through the eyes of farmers. Additionally, associated growers can follow the recommendations of cooperative technicians or engineers hired by the society they belong to. In farms where advanced technology has been implemented, field management varies according to the operating cycle shown in Figure 1. This management system based on objective field data and smart decision-making starts with the actual *crop* to manage, taking advantage of its inner variability, both spatial-wise and time-wise. The *platform* refers to the physical means with which information is acquired, being the sensors the specific elements through which objective data are obtained. *Data* includes the information directly retrieved from the parameters measured from the crop, soil, or ambient. Retrieving the data from the sensors can be done in multiple ways, from inserting a pen drive in a USB port to get the files [36] to retrieving data from software applications synchronized to the Internet. The nexus between the data and the *decision* stage involves filtering routines and AI algorithms for getting only the right data and helping the grower make correct decisions. Finally, *actuation* refers to the physical execution of an action commanded by the decision system, and is typically carried out by advanced equipment that can receive orders from a computerized control unit. As each action takes place over the crop, the cycle starts and closes at crop level; the response of the crop is then registered by specialized sensors and the loop continues systematically until harvesting time, which marks the end of the crop life cycle.

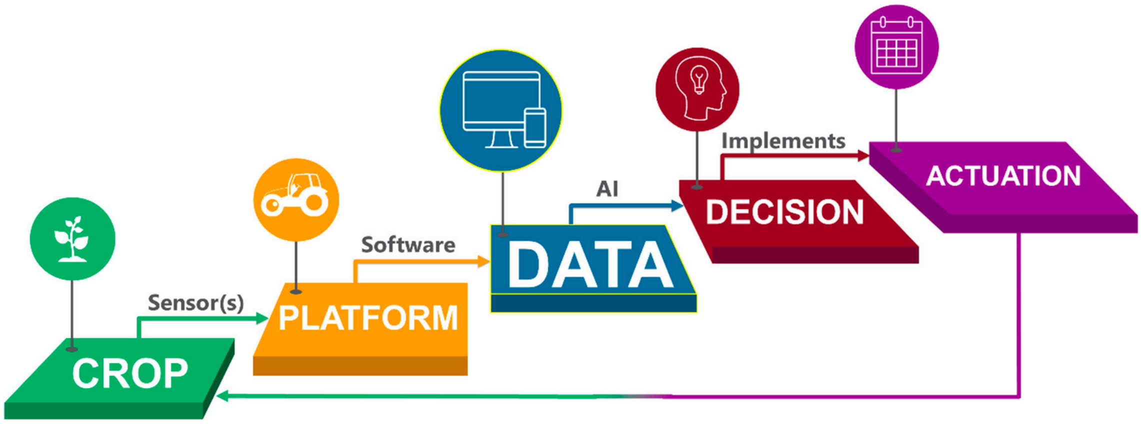


Figure 1. Information-based management cycle for advanced agriculture.

The following paragraphs and Figure 1 explain the cycle that embodies a general data-driven management system for advanced agriculture, including representative examples for each stage. Table 1 classifies the scientific works referenced in this study into the different categories of Figure 1.

Table 1. Classification of the research articles referenced in the present study.

Category	Subcategory	References
CROP	Precision and Smart Farming	[2,4,7,29,35,37–40]
	Social and economic impact	[3,5,6,8–11,31]
	Management zones	[38,41–43]
PLATFORM	Remote sensing (satellite and aircraft)	[44–46]
	Proximal sensing (ground vehicles)	[24–28,36,45–63]
DATA	Big data	[1,16–21,30,32]
	Internet of Things (IoT)	[12–14,64]
	Mapping	[42,65–69]
	Information Systems (GIS, FMIS)	[64,70–80]
DECISION	Artificial Intelligence (AI)	[22,23,33,34,81]
	Decision Support Systems (DSS)	[77,82–90]
ACTUATION	Variable Rate Applications (VRA)	[91–93]

3.1. *Stage I: The Crop as the Beginning and End of the Agricultural Management Cycle—Analyzing Variability*

Regardless how the crop will be managed, some degree of spatial variability is assumed for all fields by nature. According to Searcy [37], natural variability is influenced by weather within a growing season and from year to year; then, data from several years may be needed to determine trends in the parameters of interest, and hence, data becomes a regular input to the farm management system. Therefore, the necessity of monitoring crops comes from the existence of variability, but there is a need for the producer to manage that variability in a feasible way, and the widely accepted way to do it is by setting within-field management zones. Management zones are subfield areas that have homogeneous features, so field practices can be custom-made to each of such areas, resulting in a practical and cost-effective approach to Precision Agriculture [41]. The adoption of management zones would reduce the cost of fertilizing, improve crop yields, reduce the usage of pesticides, provide better farm records that are essential for sale, and provide better information for management decisions [4]. According to Zhang et al. [38], the number of management zones is a function of the natural variability within the field, the size of the field and certain management factors. If the variability is high, the minimum size of a zone is limited by the possibility of each farmer to differentially manage regions within a field in economic and logistics terms. In addition to decide the area of working zones, the selection of the specific parameters to be tracked within those zones must be carefully made early in the process. Rovira-Más and Saiz-Rubio [65] classified crop biometric traits in a tri-level division of crop features depending on the focus of interest being at soil level, plant level, or produce level. This division allowed the superimposition of various layers in a standardized map with the aim of determining a data-based wine quality index defined as the Quality Potential Index (QPI) for each subfield area in a vineyard. Nevertheless, there may be specific cases where the spatial variability of a field is so low that a single mapping event can be sufficient, as reported by Klassen et al. [42] when characterizing soil variability in rice fields.

3.2. Stage II: Platforms Supporting Sensors

Sensors are the universal devices to monitor crops and to obtain objective information from them. They are usually integrated in a platform, which is the general term used in Figure 1 to name the structures where sensors are placed and carried. These platforms may be attached to off-road vehicles or fixed to the ground within fields such as local weather stations. One of the most urgent challenges to cope with in the next few years will be getting a wider range of non-invasive sensors able to measure on-the-go. This approach would be closer to Agriculture 5.0, as these sensors could be attached to autonomous platforms and robots. Nowadays, not all the parameters of interest can be measured non-invasively and at a distance from the target; however, some technologies such as multispectral or hyperspectral imaging are making significant improvements.

3.2.1. Remote Sensing Platforms: Satellites

Remote sensing has played a key role in the progress of Smart Farming when field data became generally accessible from artificial satellites. Important satellites providing agricultural information are the American Landsat satellites (eight satellites take spectral data from the Earth each 16 to 18 days), the European Sentinel 2 satellite system (it provides multispectral data at 10 m pixel resolution for NDVI—Normalized Difference Vegetation Index—imagery, soil, and water cover every ten days), the RapidEye constellation (five satellites provide multispectral RGB imagery, as well as red-edge and NIR bands at 5 m resolution), the GeoEye-1 system (captures multispectral RGB data and NIR data at a 1.84 m resolution), and the WorldView-3 (collects multispectral data from the RGB bands including the red-edge, two NIR bands, and 8 SWIR bands with a resolution of 1.24 m at nadir). IKONOS and QuickBird have been already decommissioned. There exist several reviews on satellite sensing applications, having recent studies focused on the potential applications of thermal technologies using remote sensing [44] and nutritional status in commodity crops [45].

3.2.2. Aircraft Systems

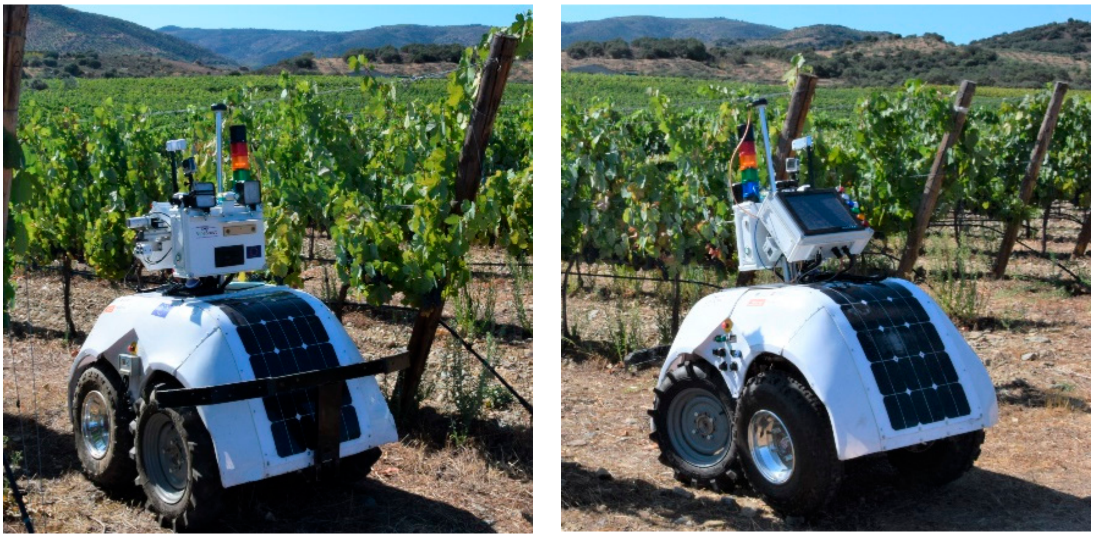
The distance between crops and satellites is considerable, typically around 700 km, and deeper insights are reachable when sensors remain closer to the targets. For aircraft systems, the distance to land can be around 100 m. For example, there is a legal limit of 120 m above the ground in Spain for unmanned flying vehicles. Unmanned aerial vehicles (UAV) and remotely-piloted aircrafts (RPA) can basically be of two kinds: Fixed-wing aircrafts and multirotor aircrafts. Rotary-wing UAVs are more stable fliers as they are capable of a vertical take-off and landing; however, they are slower and cannot cover as much area during their battery life. Fixed-wing platforms, on the other hand, can cover more area per flight and carry larger payloads, but tend to be more expensive and break more easily after multiple landings [45]. When compared to remote sensing, the advantages of UAVs for Precision Agriculture are their flexibility in frequency (revisit time of satellites) and better spatial resolutions. When compared to ground vehicles, UAVs can get data from inaccessible places where conventional equipment cannot stand; however, they require a professional planning of the flight route beforehand, and certain machine vision applications may require flying at midday to avoid vegetation shadows on the ground causing errors with imagery data. Furthermore, post processing the data and image mosaicking is often quite challenging. An important disadvantage of UAVs is the limited payload they can carry, which often limits the suite of sensors onboard, as well as the incapacity of flying with strong wind.

3.2.3. Proximal Sensing: Ground Autonomous Systems—the Great Push for Agriculture 5.0

When monitoring platforms operate from the ground, the distance from the sensors to the target crop diminishes to less than 2 m. Due to the proximity of the sensor to the plant, when data is acquired from ground-based platforms, it is called proximal sensing. Ground vehicles are polyvalent in relation to the payload of sensors. As these vehicles move near the crop, the data acquired increase in accuracy, and resolutions of one or more samples per meter are feasible, being only limited by the specifications of the particular sensors implemented. When active sensors are used, weather conditions such as strong sunlight or poor illumination are not a serious problem anymore, and, in case of on-the-fly processing, real-time applications are possible, as spraying weeds with the previous detection of the pest [47]. There has been a significant impulse in the last five years for the particular case where data is retrieved from an autonomous platform (unmanned ground vehicle or UGV) [48–52]. Aravind et al. [48] reviewed ground robots for tilling, soil analysis, seeding, transplanting, crop scouting, pest control, weed removal and harvesting, where crop scouting has been defined as the process of continuously monitoring the field to acquire information on the plant status, disease incidence, and infestations affecting crop growth. Shamshiri et al. [27] described recent achievements of UGVs for weed control, field scouting, and harvesting, highlighting that, if successfully integrated and implemented, field scouting robots can play a key role in reducing production cost, increasing productivity and quality, and enabling customized plant and crop treatments. The European Commission (EC) has recently backed the relevance of robotic technology for Smart Farming by funding four projects involving the construction of UGVs for advanced vineyard management: VineRobot, Vinbot, GRAPE, and VineScout. In 2016, the European project VineRobot [53] delivered a monitoring robot prototype at a Technology Readiness Level (TRL) status between 6 and 7 (TRL1 represents an early stage concept and TRL9 is a solution ready for production), paving the path for its conceptual termination in the VineScout project [54]. The 2019 version of VineScout is shown in Figure 2. This robot is autonomously driven when monitoring vineyards with the assistance of local perception sensors (stereo camera, lidar and ultrasound sensors) for navigation and safeguarding. It gathers data from the canopy of the vines with the goal of creating plant water status maps and nutritional status maps. In order to accomplish its mission in a reasonable timeframe, established by end-users at a rate of 6 ha per day, this robot monitors vine canopies non-invasively, which implies several challenges. Regarding hardware, fast and robust sensors were set to work non-invasively and in motion, while having a cost-efficient price for the agriculture sector. Regarding software, the challenge was the agile integration of all the crop-sensing devices and the multi-season ground-truth validation of the models developed in the field.

In addition to scouting robots, the introduction of robotics to the farm is also being led by industry on specific agricultural tasks. Naïo Technologies, for instance, has developed robot Oz for mechanical weeding [55], and the autonomous sprayer GUSS received the Davidson Prize in 2019 [56]. RowBot Systems LLC (Minneapolis, MN, USA) patented a robotic platform whose structure was configured to perform several field tasks, as selectively applying fertilizer, mapping growth zones, or seeding cover crop [57]. Over the 20th century, farm productivity has been increasing by augmenting the size of machines, which has led to heavy and oversized equipment. In order to invert this trend, researchers and growers have started to think about alternatives to tractors to avoid soil compaction.

Shamshiri et al. [27] suggested using various machines instead of one heavy machine. In the same line, Hameed [58] proposed a technology that enabled a single farmer to control a team of automated vehicles, and Ball et al. [59] used cooperative robots as a measure to control weeds. In fact, there have been several projects implementing more than one machine operating in collaborative work, as the Flourish European project that combines UAVs and UGVs to retrieve information for decision support [46], or the RHEA project where a fleet of autonomous robot units performed treatments in crops [82].

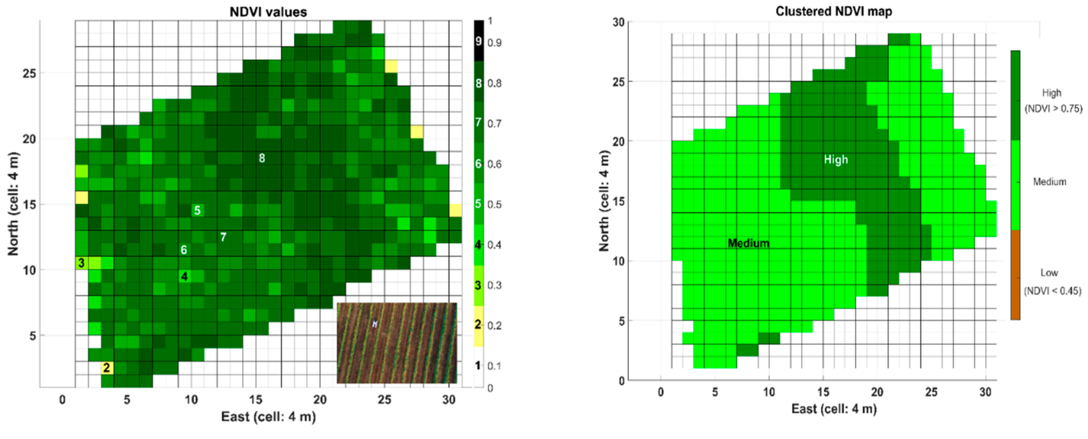


(**a**) (**b**)

Figure 2. Version II (2019) of VineScout autonomous robot: Front (**a**) and rear (**b**).

3.3. Stage III: Data

One of the fundamental differences between traditional and modern farming is, apart from the mechanization level, the data collected directly from the crops. In traditional farms where growers judge by visual assessment, decisions are relative and subjective. Modern farming offers assessment by quantitative data producing objective decisions. Sensors allow data acquisition in the field, but the special case of non-invasive technologies in combination with on-the-fly sensing from moving platforms has opened the window of massive data collection, a forerunner of big data in agriculture. However, the excess of data is also a serious challenge to cope with, as vital information may result masked by noise. The NDVI measurements collected for plotting the maps of Figure 3 [94] were collected with two sensors working simultaneously (SRS sensors, METER Group, Inc., Pullman, WA, USA) and placed in the robot of Figure 2. One of the sensors pointed to the sky and corrected NDVI estimates with the incident light from the sun, and the other sensor pointed sidewise to the canopy to collect data from the leaves at an approximate distance of 0.5 m. The zenithal photo inserted on the bottom-right corner of Figure 3a shows the VineScout autonomous robot taking data between two rows in a vineyard. The onboard algorithm averaged individual local measurements of NDVI in square cells of 16 m^2 classified into nine NDVI levels between 0 and 1 (Figure 3a). The grid map of Figure 3a, despite informative, is not operational, so a further simplification of data is necessary before a grower may find it useful. Figure 3b is the result of applying a clustering filter to Figure 3a. It shows two management zones based on vine vigor (high-medium) for the grower to make decisions, together with water status maps, about fertilization and differential harvesting.



(**a**) (**b**)

Figure 3. Grid maps of NDVI (Normalized Difference Vegetation Index) without zoning (**a**), and after applying a clustering algorithm (**b**).

3.3.1. Maps Containing Relevant Field Features

Displaying data in a coherent format is key for final users to understand what is happening in the field. The most common way to display agricultural data has been in the format of maps, as mapping is useful to define spatial trends and homogeneous zones. However, displaying agronomical information in beautiful maps should not be the goal of map generation. Maps need to be useful for making decisions, they need to be a help to answer a question, providing an interpretation of spatial information [39]. The goal of building maps is obtaining a few management zones with the parameters of interest so that a treatment can be efficiently applied. To get plausible management zones, kriging is one of the most used interpolation techniques to delimit areas of manageable sizes [43]. Taking into account the considerable amount of data that Smart Farming generates, there are many software applications to cope with interpolation, in general, or kriging in particular [66]. Also, when building a map, a coordinate system needs to be supplied along with the map. One ideal alternative for agricultural maps is brought by the Local Tangent Plane (LTP) coordinate system, which features Euclidean geometry, allows user-set origins, and employs the intuitive coordinate frame east-north. Regarding the coding and display of data in the maps, grids allow the systematic quantization of the LTP coordinate system to manage crop production information more efficiently, facilitating the exchange of information among successive seasons and the comparison of multiple parameters on the same field [67]. A practical example of grid-based maps using LTP coordinates is shown in Figure 3.

Taking into account the key role of positioning systems, a map-based approach is the method in which a Global Positioning System (GPS)—or any other Global Navigation Satellite System (GNSS)—receiver and a data logger (e.g., an onboard computer) are used to record the position of a particular measurement (georeferenced data), so several maps can be generated and processed along with other layers of spatially variable information [68]. In general, GNSS receivers are the universal position devices used to build maps; however, in some cases, for example in greenhouses or dense fields of tall trees, GNSS is not the best option to use due to the difficulty of getting signals with reliable accuracy; so, in some cases, alternative solutions such as machine vision must be implemented [69].

3.3.2. Data Management Software to Ease the Process of Decision Making

A popular way to manage field data displayed on maps and culminate with a practical solution is through the use of Geographic Information Systems (GIS). This set of computer-based tools (or data platforms) allows to store, analyze, manipulate and map any type of georeferenced information. A specific GIS system called the Field-level geographic Information System (FIS) was developed for Precision Agriculture applications [70], but it was set for old computer operative systems such as Windows 3.1×, 95, 98, or NT [71]. The updated version of FIS is the farm management information system (FMIS), which according to Burlacu et al. [72] is a management information system designed to assist farmers with various tasks, ranging from operational planning, implementation and documentation to the assessment of performed field work. The purpose of FMIS is to reduce production costs, comply with agricultural standards, and maintain high product quality and safety, guiding growers to make the best decisions possible [95]. Farm management software solutions support the automation of data acquisition and processing, monitoring, planning, decision making, documenting, and managing the farm operations [64], and include basic functions for record keeping like crop production rates (harvests and yields), profits and losses, farm tasks scheduling, weather prediction, soil nutrients tracking, and field mapping, up to more complex functionalities for automating field management accounting for farms and agribusinesses (accounting, inventory management, or labor contracts). In many cases, growers do not need to be fluid on data management because the software can build maps or decision-making models with basic information introduced by growers. Furthermore, a critical feature of these applications is that they even help in the early warning of weather-related hazards that enables farmers, policy makers, and aid agencies to mitigate their exposure to risk [83]. However, it must be taken into consideration that the efficiency of a recommendation for a particular agent will depend on the factors included in the algorithms of the software (technical, economic, safety-wise. . .). In this sense, a DSSAT (Decision Support System for Agrotechnology Transfer) provides outputs with experimental data for evaluation of crop models, allowing users to compare simulated outcomes with observed results, which is critical if real-world decisions or recommendations are based on modeled results [84]. Table 2 gathers a representative set of commercially available FMIS programs specifically configured to deal with the usual data generated in the farm. It includes the name of each application program, the company commercializing it with its headquarters location, and the main features of the program. The table is focused on programs managing crop data as the primary tool, and its purpose is not the compilation of all available FMIS software, which would be futile given the rate new applications are constantly released, but bringing a proof of the global effort realized in the last decade to deploy Smart Farming in actual farms, accelerating the move from academics to agribusiness. The examples show that some smartphone and tablet applications already include complex features so that growers can insert data directly in the field; other companies, on the contrary, prefer having a basic application for mobile devices to increase complexity in the cloud-based desktop version. In the majority of cases, it is not necessary to have wireless connection while the grower is entering data in the field, because as soon as the mobile device finds a wireless connection to the internet, it synchronizes the data previously introduced by the grower in the mobile device with the data safely stored in the cloud. Many of the programs listed below offer the option of upgrading the software depending on specific grower needs, increasing the price accordingly. The most advanced tools include features for financial and machinery management, help in the decision-making process, release warnings, or even propose management advice. In many cases, these software applications are not only addressed to the grower or producer, but also to other stakeholders in agriculture such as inputs suppliers, service suppliers, and food distributors, which makes a difference for Smart Farming, where multiple agriculture agents are connected. Regarding exploitation rights, various agricultural management systems have been patented, as the software from The Climate Corp. to generate agriculture prescriptions [85], which entered into partnership with AGCO Corporation in 2017 [4]. Decisive Farming Corp. [73,74], AgVerdict Inc. [75] or Trimble [86] have also patented their commercial solutions.

Table 2. Crop data management software applications and their main features [31,77–79,91].

Software	Company	Headquarters	Relevant Features
ADAPT	AgGatekeeper	Washington DC, USA	Input/output translator to manage data among controllers, field equipment, and farm management information system (FMIS) in an adequate format. Open-source system offered at no cost for developers to adopt into their proprietary systems.
AGERmetrix	AGERpoint	Florida, USA	Crop data and analytics platform with mapping interface. Able to scan and collect high-resolution crop data through LiDAR and other collaborative techniques. Permits taking data on mobile devices.
AgHub	GiSC	Texas, USA	Independent solution by a cooperative. Collect and securely stores data. Data can be shared with trusted advisors. Integration from IBM's Weather Operations, *Main Street Data Validator*, and *Market Vision*.
Agrivi	Agrivi	United Kingdom	Weather, field mapping, plan inventory. Crop, machinery, and personnel management (notifications and reports). Web-based and mobile versions. Upgrades and Add-ons.
Agroptima	Agroptima	Spain	Mobile App as an electronic notebook to record field activities, products applied, workers implied, working time or machinery usage. Data can be downloaded on Excel, and safely stored in the cloud. [In Spanish]
AgroSense	Corizon	Netherlands and Spain	Open source. Work done, fields data, and timetables can be shared with contractors or employees. Automate importing and interpreting performed tasks via ISOBUS. Export in several formats.
AgVerdict	AgVerdict (Wilbur-Ellis)	California, USA	Desktop and mobile app. Enables data delivery to regulatory agencies or packers, shippers, and processors. Data security, decision making, VRA [1] possibility, soil analysis and crop recommendations.
Akkerweb	(Several providers)	The Netherlands	Independent consulting platform for organizing field and crop rotation plans. Information in one central geo-platform. Several applications. [In Dutch]
APEX TM JDLink	John Deere	Illinois, USA	Online tools enabling access to farm, machines, and agronomic data. Allows collaborative decisions from the same set of information to optimize logistics, plans and direct in-field work.
CASE IH AFS software	CASE IH	Wisconsin, USA	Single, integrated software package. View, edit, manage, analyze and utilize precision farming data to generate yield or VR [1] prescription maps. Maps and reports can be shared in different formats.
Connected Farm	Trimble Agriculture	California, USA	Input, access, share records (images, reports) in real time. Integrates the whole system: crop scouting, grid sampling, fleet management, contracts. *Farm Core* connects all aspects of farm operation.
Cropio	New Science Technologies	New York, USA	Productivity management system. Remote monitoring of land. Real time updates on current field and crop conditions; harvest forecasting. Web-based service and mobile app. Training provided.
Cropwin Vintel	itk	France	Customizable tool for integrated crop management. Observation, analysis, and optimization. Vintel: Decision support tool for vineyards. Tracks water status, cover crop and nutrient management.
The Phytech Platform	PHYTECH	Israel	Plant-based app for irrigation. Monitors and provides data on crop growth. All data can be used to determine overall water needs.
ESE™ Agri solution	Source Trace	Massachusetts USA	Thought to manage group of farms and farmers. Unified and up-to-date farmer database. Record field visits with photos, notes, activities, location. Farm-to-Fork traceability of produce. Unique ID for each farmer.

Table 2. *Cont.*

Software	Company	Headquarters	Relevant Features
Farmbrite	Farmbrite	Colorado, USA	Farm schedule at-a-glance or in detail. The schedule can be shared to set up daily or recurring tasks. Weather forecast available. To-Do list, reminders, events, and appointments.
FarmCommand	FarmersEdge	Manitoba, Canada	Farm management platform. Provides both hardware (i.e., weather station) and software for in-field decision support. Available as a web-based tool and a mobile app.
Farmleap	Farmleap	France	Comparison of field performance locally and nationally. Reports time spent by operation type, yield analysis, production costs, irrigation follow-up, detailed weather, data sharing, employee management (In French).
FarmLogic/ FarmPAD	TapLogic	Kentucky, USA	Web-based ag record-keeping. Global Positioning System (GPS) field mapping to draw boundaries, mark points, measurements, etc.; personalized reports for distribution, pesticide database, maintenance records, and work orders creation.
Farm Management Pro	Smart farm software	Ireland	Mobile app for farm records, costs and expenditure accounting, tractor management, crop management, fertilizer and spray compliance, staff timesheets, document management. No desktop version available.
Farmplan (Gatekeeper)	Proagrica	United Kingdom	For crops (Gatekeeper), livestock, and business. Exchange data, workplans setup, weather data, data storage, instantaneous reports, pesticide information. Several upgrades. Compatibility with other brands.
FieldView™	The Climate Corporation	California, USA	Data connectivity and visualization, crop performance analysis, field health imagery. Offers VR [1] prescriptions and fertility management based on models.
Granular	DowDuPont	California, USA	Different software according to necessities. Combination from several sources to build decision-making models. Advisory and training services. Support for more than 230 crop subspecies. Cloud-based.
KSAS	Kubota	Japan	Cloud-based agricultural management support service integrated by Kubota machinery. For smartphones and PC. Farm management by collecting and utilizing data from supported machinery.
Mapgrower	Agropreciso	Chile	Company-oriented platform that allows automated planning, work management, traceability, online statistics, account management, or visualization on maps. Available for smartphones.
Myeasyfarm	MyEasyFarm	France	Allows to define fields and their operations, plan season work and share it with a team, see real-time progress, and analyze results.
My Farm Manager	Decisive Farming	Alberta, Canada	Mobile devices. Packages available for VRA [1], agronomy and soil testing. Advice from experts. Marketing plans. Inventory and scheduled task in Croptivity application.
Phoenix	Agdata	Queensland Australia	It is modular so farmers can build their solution. Available in the cloud or desktop. Training provided. Farmers can create maps (.shp, gpx, pdf, bmp, and jpg formats), add data, and update them.
PLM Connect	New Holland	Italy	Enables connection with field machinery. Map and analysis of crop/soil data, yield performance, VR [1] prescription, inventory and accounting records on supplies, seeds, chemicals, and fertilizer.
SST software	Proagrica	United Kingdom	Collect and manage data in the field. Statistical analysis reports, decision-making tools. PaaS [2] (agX® Platform) for the ag industry providing geospatial infrastructure.
SMS	AgLeader	Iowa, USA	Soil sampling, grids and regions. Seed with higher yield potential can be chosen based on historic performance, reports, record operations, VRA [1] maps, and prescriptions. Mobile app available.

Table 2. *Cont.*

Software	Company	Headquarters	Relevant Features
SpiderWeb GIS	Agrisat Iberia	Spain	Allows consultation, management and analysis. Satellite images and other spatial reference layers. Data corresponding to each pixel can be downloaded in the form of temporary tables and graphs.
Telematics	Claas	Germany	Collects important operational data for a self-propelled harvester and transfers it to a web platform. Unlimited access with Internet connection.
TAP TM	Topcon	Japan	Topcon and other companies' equipment compatible. Traceability and connectivity. Data management for farmers, data analysis for agronomists, multi-user data management, cloud-based data management.
Visual Green	Visual NaCert	Spain	Web platform to store farmers' data. GreenStar and MyJohnDeere compatibility, costs control, agroclimate data, official field notebook (compulsory in Spain), authorized products.
WinGIS	ProGIS Software	Austria	GIS: raster/vector maps, *krigging*, import/export in DXF or shp, fast Sentinel images. With its own development environment (SDK) allowing programmers to link their database apps to maps.

[1] VR: Variable rate (A: Application, T: Technology); [2] PaaS: Platform as a service.

The use of commercial data management systems, as the ones listed in Table 2, often implies that producers need to share their crop data with a software platform owned and run by private companies. This fact creates some controversy regarding the ownership of the data. In the Software Services Agreement (SSA), it is stated that the person or entity providing the data to the farm management software company shall own and retain all rights, title and interest in and to their data, so that the data belongs to the provider [76]. However, when data are aggregated with other growers' data, the combined data typically become property of the software company [96]. The list of applications included in Table 2 proves that there is a global interest in developing software for farm data management, and most of the features requested by end-users are similar everywhere. This table also gives an idea of the interest raised in industry by software-based management systems. However, many applications use their own proprietary formats, which complicates the share of data among data acquisition and processing systems. A standardization effort is needed among software developers and providers. The ADAPT toolkit of Table 2 [77] is an example of how to face this challenge, as it provides an open-source application that eliminates a barrier to the broad use of Precision Agriculture data by enabling interoperability between different hardware and software applications.

3.4. Stage IV: Decision-Making

In situations where many field parameters need being considered, people find practical difficulties in managing complex information to make effective decisions. In such cases, artificial intelligence (AI) can help with techniques like deep learning or neural networks, fuzzy logic, genetic algorithms, or expert systems. AI, with its modelling and reasoning capabilities, can play a key role in agriculture, helping to make sense of all the data available. Fuzzy logic, to name one example within AI, resembles human reasoning imitating the way of making decisions that involve several possibilities instead of 'true' or 'false' alternatives; this technique uses linguistic variables that fit well with the complexity of the challenges posed by the diversity of agricultural decision making. According to Dengel [20], agriculture offers a vast application area for all kinds of AI core technologies as agents operating in uncontrolled environments. Giusti and Marsili-Libellia [81] designed a fuzzy-based decision support system (DSS) taking as input variables soil moisture and rain forecast for kiwi, corn, and potato. Similarly, the DSS developed by Navarro-Hellín et al. [87] estimated weekly irrigation for citrus orchards taking into account climate and soil variables; in that work, real-time measurements from soil parameters in a closed-loop control scheme were decisive to avoid the accumulative effect due to errors in consecutive weekly estimations, as the DSS was allowed to adapt to local perturbations. In the same fashion, Lindsay Corporation (Omaha, Nebraska, USA) was awarded for its solution FieldNET Advisor™ [91] that provides irrigation management decisions for growers. DSS may be more robust and reliable when different variables are considered, but some procedures remain controversial as objectives can lead to different solutions at different times based on the priority set by decision makers or other people involved in the procedure [88].

Srivastava and Singh [80] highlighted the importance of incorporating the graphical part of GIS to DSS, which was demonstrated for water management scenarios in India. The importance of using GIS for agricultural DSS lies on using user-friendly graphical interfaces for growers. The result of a questionnaire distributed by VineScout project [36] members to the attendees of a field demonstration in Portugal (October 2019), evidenced the high value given to graphical user interfaces (GUI). Considering that the prototype is in research phase and not commercial yet, 84% of the attendees concluded that the robot GUI shown in Figure 4 was simple to understand and easy to use (unpublished research). Rupnik et al. [89] developed a cloud-based system to allow growers upload their own data, utilize several data analysis methods, and finally present their outputs as decisions to apply. This time, their use case focused on spray planning for fighting against pests in vineyards and orchards. Rose et al. [90] conducted a survey on DSS and arrived to the conclusion that 15 factors were influential in convincing UK growers and advisers to use DSS, including usability, cost-effectiveness, performance, relevance to user, and compatibility with compliance demands. In addition, they found that 49% of UK farmers used some kind of DSS, and the preferred ways of delivery were software (28%), paper-based (22%) tools, and mobile apps (10%). These results show that the use of software to manage decisions is growing, but its percentage is still low and comparable to those who preferred paper-based tools. Choosing software and mobile applications to make agricultural decisions may be considered beneficial because digital tools increase management efficiency when compared to paper-based tools; however, there is still a long way to make technology-based tools attractive enough—easy to understand, intuitive and nice—for growers to adopt. On the producer side, it is important to have access to proper training until these technologies can be comfortably managed.

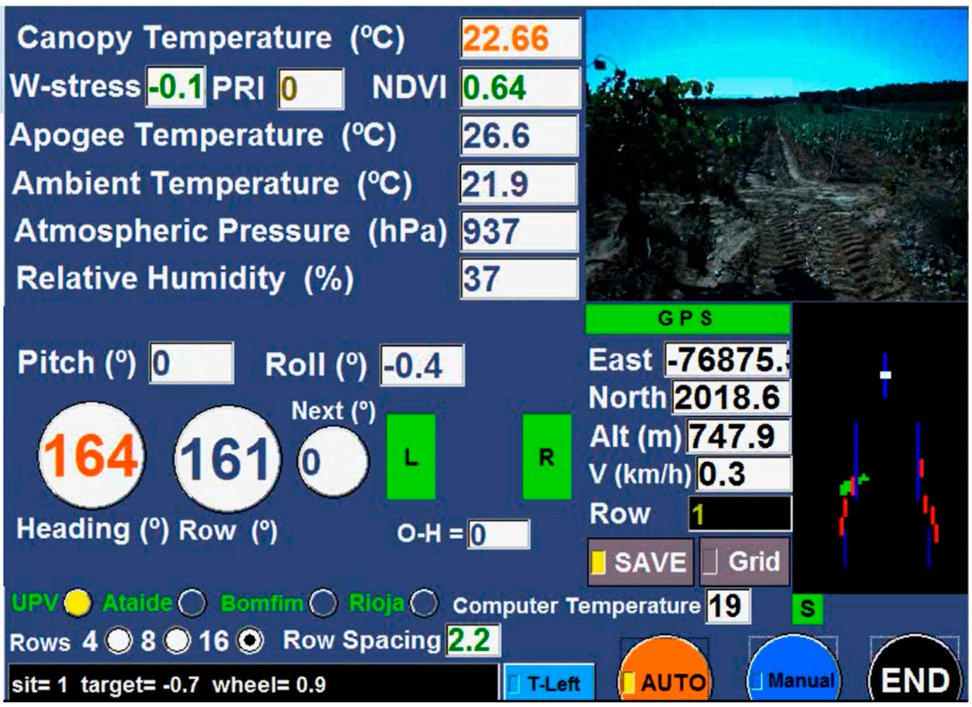


Figure 4. Graphical user interface (GUI) for the VineScout robot.

3.5. Stage V: Actuation through Variable Rate Technology

The last step for closing the loop in the complete crop management cycle of Figure 1 is the physical actuation on the crop. Actuation is understood as executing some action on the crop or related to it, and this can be done by making decisions right after obtaining information (real-time applications) or in another moment deferred in time (off-line). For farmers to execute decisions, they need advanced equipment that can receive orders from a computerized control unit. Variable rate machines can execute a number of farming tasks driven by a smart system [60]. Variable rate technology (VRT) applied on site-specific crop management (SSCM) has the potential to increase profit and decrease environmental impact [61] as only what is needed is actually applied. Colaço and Molin [92] conducted a long-term study for six years with the goal of evaluating the effects of variable rate fertilization on fertilizer consumption, soil fertility, and yield in citrus. The outcomes of comparing variable and uniform rates showed that the former achieved higher yields while using less fertilizer: using nitrogen, fruit yield (kg of oranges) respect to the amount of fertilizer resulted in a 32% yield increase in field 1, and 38% in field 2. When using potassium, the yield increase even reached 40% in field 1. In the case of phosphorus, the growth rate was approximately 20% for both fields. A recent review led by Nawar et al. [93] confirmed that, when management zone delineation techniques were used for variable-rate nutrient application, farm efficiency increased in all cases when compared to traditional uniform-rate applications, and environmental impacts were reduced. Machinery manufacturers are leading the development of commercial solutions implementing VRT. Thomasson et al. [62] described commercial VRT systems offered by major agricultural machinery manufacturers, like CLAAS, that used the ISARIA crop sensor for the variable-rate application of nitrogen-based fertilizer, or the CEBIS MOBILE ISOBUS, which, apart from having other Precision Agriculture functions, it is a compatible terminal to integrate the ISARIA sensor. Another promising type of variable actuation is automatic differential harvesting or variable rate harvesting (VRH), which attempts harvesting according to previously defined management zones. In specialty crops, Sethuramasamyraja [40] worked in differential harvesting for vineyards by using near-infrared sensors to determine grape quality in the field based on the anthocyanin content of berries. The three steps for this VRH system involved sensing the anthocyanin content of grapes, using these data to produce quality map based on a threshold anthocyanin level, and feeding the quality map to the harvester for its commanding. CLAAS was awarded for implementing VRH in combines and forage harvesters [91] by merging precision sensing technology with autonomous machine control. The goal was to maximize productivity and automatically optimize harvester performance, according to the changing conditions of the soil, plants, grain, and humidity in the harvested field. A USDA statistical analysis conducted in 2010 [3] showed that variable rate technologies had positive, but small, rate adoptions of 1% due to their difficulty of use. Apart from efficiency and utility, cost is also a critical parameter to consider for the adoption of this technology. In this sense, the ubiquitous availability of low-cost electronics will favor the introduction of such digital applications. In fact, advances in autonomous driving technology for cars, including object detection capabilities through multi-camera systems, have already reduced the cost of developing automated agricultural machines [22].

4. Discussion

After the Industrial Revolution, mainly since the advent of mechanization, and along the Green Revolution, humans and machines have been efficiently collaborating for growing crops to feed people. However, to face the population growth in the coming years, an extra effort is needed to succeed, not only in feeding people by increasing productivity, but also in doing it in the most efficient and respectful possible way, that is, producing sustainably. To face this challenge, remarkable advances in technology have been appearing over the last decades, in particular the access to reliable agricultural data and advanced computer techniques to get the optimal meaning from them, eventually obtaining maximum benefits while being respectful with the environment. This new approach driven by digital technology implies that growers must act as supervisors of their crops rather than laborers, in an attempt of avoiding repetitive, physically-demanding, and tedious field tasks. In this modern agronomical framework, DATA is the key, and the information-based management cycle described above provides the practical approach that unites concept and tasks. The following points summarize some of the specific ideas drawn from this study:

- *Precision Agriculture*, which consists of applying what is needed when and where is needed, has further improved the efficiency of managing farms with the addition of data-based digital systems that increase the knowledge of producers about their fields; this is known as *Agriculture 4.0* or *Digital Farming*. When these data-driven farms incorporate robotics with AI algorithms to their systems, the overall concept is then referred to as *Agriculture 5.0*. Some studies report that agricultural robots integrating forms of AI can do certain tasks faster than humans [23]. Despite there are other studies that contradict this statement [63], robotics is a growing economy and there exists a great potential for many applications within agriculture.
- A greater adoption of Digital Farming by professional growers is vital to not only improving a farm's financial performance, but also to meet the food needs of an expanding population [6]. Small farms will steadily incorporate basic technology whereas large fields will likely invest with sophisticated equipment, but data-less intuition-driven management will no longer represent the *modus operandi* of professional farms in the future. This should be considered a source of opportunities, especially for a new generation of young farmers used to digital technology, who are the ones with the capacity to balance an aging population in rural areas, mainly those in industrialized countries.
- After the rapid growth of UAVs, a steady-state is being reached, mostly induced by the fact that data analysis and ground-truth validation has resulted far more complex and delicate than image acquisition and platform handling. This has promoted the expansion of proximal sensing and the exploration of combining both data sources—aerial and terrestrial—for a better understanding of the physiology of plants and trees.
- Maps, as the most common way to represent agricultural data, would need to be standardized. Intensely-interpolated colored maps are output by GIS, FMIS, and other software applications, but at the time of comparing data with the precision enough to grant statistical significance, it often becomes an impossible mission without standardization. Figure 3, for example, uses the flat representation provided by the local tangent plane (LTP) and formatted in a regular grid. Other programs use UTM projections, and there are even images only given in geodetic coordinates. At the need of overlapping maps, it takes a big effort to make all data compatible. Not only the way coordinates are represented needs a standard, but also the units, intervals, and even colors in which parameters are displayed. The combination of aerial and ground data, for instance, will greatly benefit from such standardization in the way data is visually displayed for the average grower to understand.
- Table 2 provides a representative compilation of software applications for farm management. The list is not exhaustive, and yet includes companies from four continents and 14 countries, which provides evidence of the fact that agricultural digitalization is in fact a global move.
- Regarding variable rate applications, adoption rates need to augment, and to do so, farmers must find by themselves the value in this technology for their crops. Only after maintaining accurate spatial records and analyzing field data can effective variable rate prescriptions be created [39] to address particular tasks.

5. Conclusions

This analysis confirms that consistent knowledge about farms leads to optimal decisions. Agricultural management systems can handle farm data in such a way that results are orchestrated to address customized solutions for each farm. This aid for farmers in the form of digital solutions combines forces with robotics and artificial intelligence to launch the imminent idea of Agriculture

5.0. After thirty years of great expectations—and disappointments—by the application of robotics to agriculture, the timing seems right for the first time. However, in order to take the most advantages from Agriculture 5.0, deep training needs to be delivered to users, ideally young farmers eager to learn and apply modern technologies to agriculture and granting a generational renewal still to come. It seems to be the right time to move forward towards a modern and sustainable agriculture that is capable of showing the full power of data-driven management to face the challenges posed to food production in the 21st Century. The evolution to Agriculture 5.0 is in the agenda of most major farm equipment makers for the next decade, and therefore off-road equipment manufacturers will play a key role in this move if agricultural robots are considered as the next—smarter—generation of farm machines.

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