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A compilation of UAV applications for precision agriculture

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ABSTRACT

Climate change has introduced significant challenges that can affect multiple sectors, including the agricultural one. In particular, according to the Food and Agriculture Organization of the United Nations (FAO) and the International Telecommunication Union (ITU), the world population has to find new solutions to increase the food production by 70% by 2050. The answer to this crucial challenge is the suitable adoption and utilisation of the Information and Communications Technology (ICT) services, offering capabilities that can increase the productivity of the agrochemical products, such as pesticides and fertilisers and at the same time, they should minimise the functional cost. More detailed, the advent of the Internet of Things (IoT) and specifically, the rapid evolution of the Unmanned Aerial Vehicles (UAVs) and Wireless Sensor Networks (WSNs) can lead to valuable and at the same time economic Precision Agriculture (PA) applications, such as aerial crop monitoring and smart spraying tasks. In this paper, we provide a survey regarding the potential use of UAVs in PA, focusing on 20 relevant applications. More specifically, first, we provide a detailed overview of PA, by describing its various aspects and technologies, such as soil mapping and production mapping as well as the role of the Global Positioning Systems (GPS) and Geographical Information Systems (GIS). Then, we discriminate and analyse the various types of UAVs based on their technical characteristics and payload. Finally, we investigate in detail 20 UAV applications that are devoted to either aerial crop monitoring processes or spraying tasks. For each application, we examine the methodology adopted, the proposed UAV architecture, the UAV type, as well as the UAV technical characteristics and payload.

1. Introduction

Although scientific advances in genetics, chemistry and robotics have contributed significantly to the evolution of agricultural technology, agricultural products have to be increased largely due to the rapid increase of the global population. In particular, according to [1], agricultural products have to be increased by 70% by 2050, when the world population is expected to reach 9 billion people. At the same time, the agricultural sector has to address severe challenges such as the issues of climate change, the limited availability of arable lands, as well as the growing necessity for freshwater. A feasible solution for these critical challenges can come from the Information and Communications Technology (ICT) services. More specifically, the advent of the Internet of Things (IoT) and especially the accelerated development of the Unmanned Aerial Vehicle (UAV) technology combined with image data analytics can provide promising Precision Agriculture (PA) solutions to deal with the aforementioned challenges. In general, PA aims at adopting ICT services to aggregate and process information provided by multiple sources that can extract useful conclusions regarding the soil understanding, thus making it possible to manage the crops with a more efficient way [2–5].

The most common PA application is to assess the vegetation health by using Remote Sensing (RS) techniques and image analytics. One of the most applied RS techniques is aerial monitoring, by using images captured by satellites, manned aircrafts and UAVs [6–8]. In the context of PA, satellite images are very expensive for a typical farmer, and usually their resolution and quality are not satisfactory and practical due to the weather conditions. Accordingly, aerial images captured by human-crewed aircrafts present a better quality compared to the satellite images, but this method is also very expensive. Conversely to the previous cases, small UAVs, also known as drones are characterized as a more economical solution and are capable of providing high-quality images.

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In brief, UAV is an uncrewed aircraft which is controlled remotely by an operator, and it can carry various kinds of cameras such as multispectral and hyperspectral, thereby acquiring aerial images. Next, these images can be utilized to extract vegetation indices that enable farmers to monitor constantly the crop variability and stress conditions. For instance, the Normalized Difference Vegetation Index (NDVI) [9–11] can provide accurate information concerning the biomass levels. Next, the NDVI values can be interpreted, thus providing useful conclusions concerning the crop diseases, water stress, pest infestations, nutrient deficiencies and other relevant conditions affecting crop productivity.

Besides the crop monitoring process, another possible use of UAV in PA is the crop spraying [12]. This process was first introduced in the 1980s in Japan, by combining uncrewed helicopters with small pesticide tanks [1]. Today's UAVs can carry large tanks whose capacity may overcome 10 litres. Moreover, the liquid discharge rate can reach or even overcome a one-litre per minute, thereby making it possible to cover a hectare per 10 minutes. Nevertheless, it is worth mentioning that a UAV-based spraying platform should be synchronised with an aerial crop monitoring process described previously, thus providing efficient and accurate use of the agrochemical products. Such a combined approach can not only minimise the amounts of agrochemical products but also contribute to the environmental protection.

According to [1], UAV sales in Germany reached 400,000 units in 2017 and are likely to approach 1 million in 2020. Similarly, the National Purchase Diary Panel (NPD) group which is a global information provider estimates that the UAV sales in the US doubled in 2017, by recording an increase of 117% compared to the previous year [1]. Moreover, according to the Association for Unmanned Vehicle Systems International (AUVSI), 80% of UAVs will be utilised for agricultural purposes in the near future. Therefore, it is clear that UAVs are going to play a crucial role in the development of the agricultural sector. In this paper, we aim at providing a comprehensive analysis concerning the potential UAV applications in PA. In particular, we analyse in detail 20 cases, including both UAV-based crop monitoring applications and UAV-based spraying system, thereby identifying possible challenges and open issues. Furthermore, based on this study, we define the research trends and provide directions for future work.

More specifically, the rest of this paper is organised as follows: Section 2 presents the motivation and contribution of our work. Section 3 and Section 4 provide an overview of PA and UAV respectively. Section 5 analyses in detail 20 UAV applications related to PA. Section 6 discusses the previous analysis and provides the research trends concerning the use of UAVs in PA. Finally, Section 7 concludes this work.

2. Motivation and contribution

Climate change has already affected significantly multiple sectors, including food security. A characteristic example is that more than 815 million people are chronically hungry and almost 64% of them locate in Asia [1]. More specifically, based on recent studies of Food and Agriculture Organization of the United Nations (FAO) and International Telecommunication Union (ITU) [1], the world has to discover means in order to increase the food production by 2050. Therefore, food industries, farming communities and scientists linked with the agriculture sector need to deploy new processes or adapt suitably the existing ones in order to address the challenges introduced by climate change. In this context, agriculture has to adopt emerging ICT-driven services that can play a significant role, by providing reliable, accurate and timely data. More particularly, a meaningful advancement in this domain is the development of small agricultural UAVs. Despite their functional constraints such as the limited battery time, UAVs can provide valuable data concerning the vegetation and chemical attributes, thereby influencing relevant decisions and policies.

Several papers have examined the UAV applications and their capabilities for various sectors. In particular, M. Mozaffari et al. in [13] present a comprehensive survey concerning the contribution of UAVs in wireless communications, by analyzing the corresponding benefits and challenges. Based on this analysis, open problems are discussed, and potential mathematical frameworks such as optimization theory, machine learning, game theory, transport theory and stochastic geometry are investigated as possible solutions. In [14], H. Shakhatreh et al. provide a study which discusses in detail multiple civil UAV applications, like Search and Rescue (SAR), RS, infrastructure inspection, PA, monitoring of the road traffic and delivery of goods. For each application, the corresponding challenges are given and proposed solutions are examined. Similarly, Alena Otto et al. in [15] also worked on UAV civil applications by reviewing more than 200 relevant papers. Accordingly, in [16] C.F. Liew et al. provide a survey which organizes with a systematic way 1318 papers related to UAV topics, thereby summarizing important information that can assist researchers in identifying the research trends. S. Hayat et al. in [17] also focus on UAV civil applications, by examining mainly network issues such as Quality of Service (QoS) requirements, data requirements and in general network parameters related to UAV missions. T. Lagkas et al. in [18] review UAV application areas enabled by the IoT and 5th Generation (5G) technologies. On the contrary to the previous references, other papers [19–23] follow a more specific approach by examining the contribution of UAVs in regards to the agricultural domain. In [19], S. Manfreda et al. examine UAV applications devoted to agricultural ecosystem monitoring. S. Yang et al. in [20] provide an overview of UAV applications related to agricultural purposes in China. S. Khanal et al. in [21] investigate the use and potential of thermal cameras carried by UAVs for PA applications. Accordingly, B. Bansod et al. in [22] provide a comparison between the satellite-based and UAV-based RS technology. Finally, J. Gago et al. in [23] discuss UAV challenges regarding missions performed to assess the water stress.

Undoubtedly, the previous works offer a significant contribution to the relation between ICT services and agriculture, by discussing relevant applications, potential challenges, methodologies and open issues. Nevertheless, none of them provides a comprehensive study analysing in detail specific UAV applications in the domain of PA. Most of them either analyse a set of civil applications or examine issues of a specific agricultural topic, such as the water stress. Conversely, this paper aims at providing a comprehensive survey, which analyses in detail 20 UAV applications relevant to PA. In particular, we investigate two kinds of applications: a) crop monitoring and b) spraying process. Based on this analysis, we identify the research trends and provide directions for future work. Therefore, in conclusion, the contribution of our work is summarised in the following sentences:

- **Providing an up to date overview of PA and UAVs**: We describe the various aspects of PA, such as soil mapping, production mapping, etc. as well as the role of the Geographical Information Systems (GIS) and Global Positioning Systems (GPS). Also, we discriminate and analyse the various types of UAVs based on their technical characteristics and payload.
- **Providing an up to date overview of the UAV regulatory framework in Europe**: We discuss the various laws and regulations in force related to the use of UAVs in Europe. We distinguish them based on the UAV's weight and use.
- **Providing a comprehensive analysis of 20 UAV applications relevant to PA**: We provide a detailed analysis concerning the UAV applications focused on either aerial monitoring processes or spraying tasks. For each case, we describe in detail, the proposed architecture and the overall methodology utilised as well as the evaluation process.
- **Identifying open issues and research trends related to the use of UAV in the domain of PA, thereby providing directions for future work**: Finally, we present the ongoing trends in this field, by identifying possible directions and technologies for future research work.

Table 1
PA processes and means.

Process/mean	Description
GPS Systems	Provide information about the geolocation of crops and vehicles
GIS Systems	Organize agricultural information in digital maps
Production Mapping	Calculates the efficacy of a crop in each growing season
Soil Mapping	Understanding the soil variability
Mapping Soil EC	Ease with which the current passes through its mass
RS	Obtaining information utilising ICT services
VRA	Application agrochemichal products with different doses

3. PA processes

This section aims at providing a concise overview of PA, by presenting its primary characteristics and properties. The extending use of IoT technologies, such as the Wireless Sensor Networks (WSNs) and UAVs rendered it possible the deployment of PA applications that can calculate efficient vegetation indices, thereby optimising the effectiveness of crops. To this end, many studies have already examined the context and the multivariate aspects of PA. Some of them are listed in [24–30]. Specifically, in [24], F. Pierce and P. Nowak define the term of PA and present its aspects in detail. In [25] A. Mcbratney et al. investigate and discuss some open issues and challenges. Accordingly, in [26] N. Zhang et al. provide an overview of PA by presenting many common applications. Other studies follow a more precise approach by examining specific PA processes. For instance, in [27], D. Patrcio and R. Rieder provide a systematic review regarding the use of computer vision and artificial intelligence in the domain of PA. R. Sharma et al. in [28] present a survey of GIS systems, thus identifying possible research gaps. In [29], K. Liakos et al. analyse the various machine learning techniques in PA. Finally, in [30] A.-K. Mahlein et al. investigate the various hyperspectral sensors and imaging systems adopted for PA purposes.

Based on the aforementioned studies, PA constitutes a new crop management method whereby agrochemical products such as pesticides, fertilisers and irrigation water are proportionally applied based on the specific needs of crops since they can vary spatially and temporally [31]. The primary objectives of PA are: a) to increase the yield of crops, b) to improve the quality of the products, c) to make more efficient use of agrochemical products, d) to save energy and e) to protect the physical environment against pollution. A fundamental requirement for the utilisation of PA technologies is the knowledge of the spatial and temporal variability. The role of the spatial variability is to identify specific measurement features to oversee the variations of the crop characteristics such as vegetation, water status, moisture, soil composition, topography, as well as the state of the plant diseases and pests. On the other side, the temporal variability aims at identifying particular features of the time information affecting the crop yield. For instance, some soil properties are constant over time or change minimally such as organic substances and the soil composition. This information enables the producer to divide a crop into specific management subareas, in which variable amounts of inputs can be applied, thus optimising the overall performance through increasing production and reducing agrochemical inputs. To this end, PA can combine multiple analysis processes and technological means related to all stages of production from sowing to harvesting, such as: a) GPS systems, b) GIS systems, c) production mapping, d) soil mapping, e) mapping of the soil Electrical Conductivity (EC), f) RS technologies and g) Variable Rate Applications (VRA). Table 1 offers a brief description about these processes and means, while the next subsections describe them further.

3.1. Use of GPS systems in PA

The presence of GPS systems is necessary for most of the application technologies in PA, since it provides real-time information concerning the position of crops and the agricultural vehicles during their utilisation [32–36]. There are various applications of GPS systems related to the agriculture sector, such as field contouring, soil mapping, production mapping and crop monitoring. Commonly a GPS carries a GPS receiver, or Differential Global Positioning System (DGPS) placed on the vehicle moving in the field, a device for storing information and a software package responsible for generating and visualising maps. To contour an area, the farmer simply walks or drives around the field and records the data by using both GPS and a laptop or a smart device. Utilising the same equipment and during the vegetation period, the farmer can cross the field and record the data concerning the areas suffering from pests and diseases. Consequently, knowing the areas with these problems, the farmer can apply the appropriate cultivation care. Concerning the soil mapping, GPS is used to record the location of the soil samples that are captured for generating the corresponding maps. Accordingly, regarding the production mapping, GPS is used to record the position of each area whose production status has been identified via other sensors. Next, this information is used for generating the corresponding maps. Finally, GPS systems are necessary for driving the agricultural vehicles in specific areas of the field during a crop monitoring process, or when an agricultural vehicle is used to apply specific doses of agrochemicals depending on the soil and production characteristics of each area.

3.2. Use of GIS systems in PA

In PA applications, the field information is represented by numbers describing measurements of specific parameters, field observations as well as doses of agrochemical amounts. This information is accompanied by geolocation data captured by GPS systems, thus forming appropriate production maps. Accordingly, such maps possess a huge amount of data which requires the use of appropriate software for its processing. GIS systems constitute a specific category of software which organises, analyses, processes and visualises the field information as digital maps [36–40]. Moreover, they can include statistical analyses, simulation information and data provided by various database systems used for extracting useful conclusions and making decisions [41]. Particularly, a GIS system consists of the following elements: a) a spatial data input system including information from maps, satellite imagery, multispectral imagery, etc., b) a data storage system, c) a data visualisation system containing information represented as maps, tables and shapes, d) a data analysis system responsible for removing possible data errors and analysing geospatial data and finally e) a user interface system.

3.3. Production mapping

The economic benefit or damage of a farmer is related to the production efficiency of crops in each growing season. In particular, farmers aim at increasing the quality and quantity of their products and simultaneously decreasing the required production cost. The production mapping contributes to this procedure by identifying those factors of each area affecting the production process. Subsequently, these maps can be combined with terrain maps and other data, such as RS and meteorological information in order to deploy an overall and efficient PA application. More detailed, production mapping is a necessary process which has to be performed initially by a farmer interested in applying a PA system. If a crop does not present any significant spatial and temporal variation, then there is no reason for applying a PA technology. This process is usually implemented by specific systems and sensors such as impact force sensors, place displacement sensors, radiometric systems, local cell systems, volume measurement systems, moisture sensors, speed sensors and GPS systems [42].

3.4. Soil mapping

Understanding the soil variability is one of the oldest challenges faced by farmers and researchers [43–47]. In particular, the soil analysis and the regular sampling constitute the base for a variable-dose fertilisation system. Usually, the first one includes the analysis of the chemical elements required for the growth of plants. These elements are nitrogen (N), phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), sulfur (S), boron (B), chlorine (Cl), copper (Cu), iron (Fe), manganese (Mn), zinc (Zn) and molybdenum (Mo). Regarding the second process, there are two main sampling methods: a) grid sampling and b) soil type sampling. The first method divides the field into several squares or rectangular cells from which appropriate samples are received and mixed, thus representing the soil attributes of the specific cell. On the other side, the soil type sampling is made through parts of the field, presenting similar characteristics. As in the grid sampling, several samples are collected and mixed from each area with a different soil type.

3.5. Mapping soil EC

EC is defined as the ease with which the current passes through its mass. It is measured with mSiemens/m and is affected by many factors [48,49], including a) composition of the soil, b) compaction of the soil, c) water content, d) salinity, e) cation exchange capacity, f) organic substances and g) soil temperature. In the context of PA, EC is utilised for identifying homogeneous soil management zones. In general, there are two methods of EC mapping: a) electromagnetic induction and b) contact method. The first one is implemented by measuring the effect of the soil in a magnetic field. Usually, this method is difficult to implement, requires regular calibration and is susceptible to interference with metal objects. On the other side, the contact method measures the voltage drop among the electrodes on the soil. Such a process is characterised by ease, speed and low cost.

3.6. RS technologies in PA

RS technologies refer to obtaining information remotely, by using ICT services [50–54]. The most common RS technology is the processing of the images captured either from satellites or UAVs. Specifically, the key element of RS is the electromagnetic radiation, since measurements of the reflected radiation of crops render possible the aggregation of significant information concerning the water stress, the nutritional status of crops and other field characteristics. This spectral information is employed by vegetation indices, such as NDVI which enables the generation of agroclimatic models that in turn allow the identification and separation of a crop into individual subareas with particular characteristics.

3.7. VRA methods

VRA methods enable the application of agrochemical products with different doses based on the needs of each area. In general, there are two VRA methods: a) map-based and b) sensor-based. The first one requires the creation of a prescription map as well as a GPS. In this case, the device responsible for applying the agrochemical products utilises the information provided by the map and GPS in order to configure appropriately the dose for each area. On the other side, the sensor-based method does not require any map or GPS. Now the device responsible for applying the agrochemicals is equipped with sensors that measure the characteristics of each area or subarea in real-time. In particular, the information captured by the sensors is transmitted in a software package calculating the needs of the soil or plants and sends them back to the device, which in turn distributes the inputs proportionally.

4. UAVs discrimination

UAV is a type of aircraft having the ability to fly autonomously without the presence of a pilot. Commonly, the flight mission of UAV is predefined, or a pilot can control its motion and direction through remote teleoperation commands from a ground station [55]. Although this technology has evolved rapidly in the 21st century, the first attempts to deploy UAV were initiated for military purposes starting with World War I. Specifically, Dayton-Wright Airplane Company constructed a type of unmanned aerial torpedo which was able to be exploded at a predetermined time [56]. In 1917, the Hewitt-Sperry Automatic Airplane firm also built an unmanned torpedo capable of bursting at a specific time [57,58]. First remarkable deployment and utilisation of UAV were accomplished during World War II, when the Reginald Denny Industries constructed 15,000 UAVs for the US army [56]. The Cold War also assisted in the further development of UAVs. In particular, in 1955, the MQM-57 Falconer was employed for a reconnaissance mission [56]. Moreover, Israel utilises UAVs as reconnaissance tools, electronic jammers and electronic decoys in the 1982 Lebanon War [56]. Similarly, in the Balkans War, the Predator RQ-1L UAV was used [56]. Finally, UAVs were also adopted in newer military operations, such as the war in Afghanistan, Iraq and Syria [56].

Although the first UAVs concerned military operations, the rapid evolution of new technologies such as imaging sensors, Inertial Measurements Unit (IMU) [59], synthetic aperture radar [60] and Global Navigation Satellite Systems (GNSS) [61] resulted in the development of civilian UAVs capable of assisting the evolution of multiple fields, such as PA, geomatics, logistics and infrastructure monitoring. There are two primary categories of civilian UAVs: a) fixed-wing and b) rotary-wing or multirotor. Both categories will be analysed further in the following subsections. Concerning fixed-wing UAVs, the milestones were reached by the Sensefly firm, constructing powerful UAVs for PA applications [56]. On the other side, the first rotary-wing UAV was developed by Microdrones [56].

This section aims at providing a brief overview of the UAV technology, by explaining the different types of UAVs, their technical characteristics, potential payloads, as well as the regulatory context concerning their use in Europe. At this point, it should be clarified that the technical characteristics of UAV refer to those characteristics being necessary for its operation, while payloads refer to the additional equipment utilised for other applications, such as monitoring processes.

4.1. UAV types and technical characteristics

This subsection discusses the various types of UAVs based on their technical characteristics. First, we investigate the possible UAV categories based on the aerodynamic features. Next, we examine their level of autonomy as well as the potential size, weight and power resources.

4.1.1. UAV types based on aerodynamic features

Based on the aerodynamic features, UAV can be classified into three types: a) fixed-wing, b) rotary-wing and c) hybrid [62]. The first type (fixed-wing) possesses a predefined airfoil of static and fixed wings that enable lift based on the UAV forward airspeed [56]. The control of such a UAV is accomplished through elevators, ailerons and rudder that are attached to the wings. In particular, these construction characteristics enable UAV to turn around roll, pitch and yaw angles, respectively. Fig. 2 illustrates an example of a fixed-wing UAV. The airflow of the second type (rotary-wing) is composed of several rotors that generate the appropriate power necessary for lifting [56]. Based on this airflow and in contrast to the first one (fixed-wing), this type does not need a

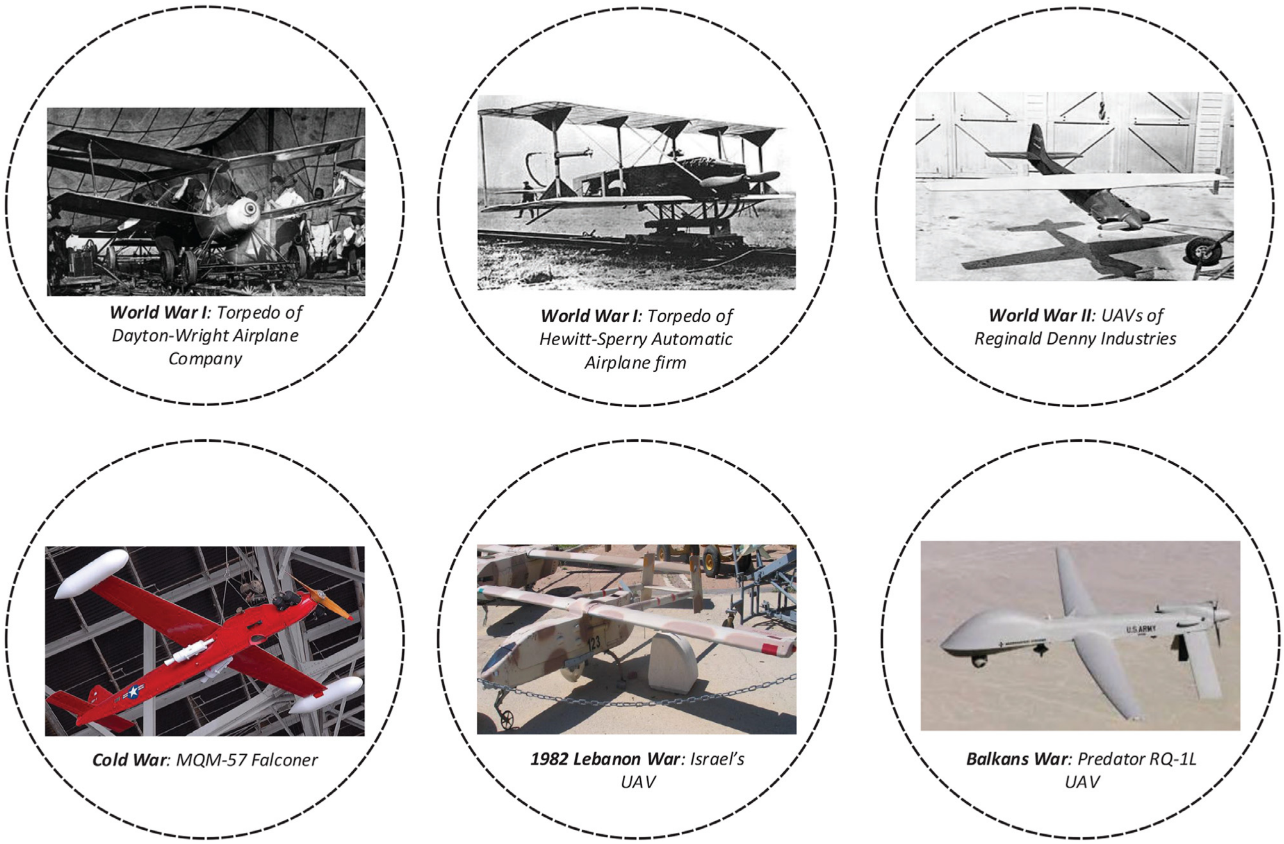

Fig. 1. UAVs history during the various wars.

forward airspeed for lifting. Accordingly, the control of such a UAV is based on the torque and thrust of the rotors. For instance, the speed of the diagonal rotors determines the yaw movement. More specifically, depending on the number of rotors, a rotary-wing UAV can be classified into the following categories depicted by Fig. 3: a) tricopters, b) quadcopters, c) hexacopters and d) octocopters. It is noteworthy that each of the types mentioned above presents the corresponding pros and cons [56]. For example, a rotary-wing UAV possesses a better and easier control and is able to carry a heavier payload compared to the fixed-wing type. On the other side, a fixed-wing UAV presents an efficient and simpler architecture facilitating the maintenance processes and is also characterised by a longer flight duration and larger coverage. Finally, there is a third type (hybrid-wing) which combines the previous ones [62]. In particular, this type possesses rotors for taking off and landing, but also includes fixed-wings utilised for covering large areas (Fig. 1).

Fig. 2. Fixed-wing UAVs.

4.1.2. UAV types based on level of autonomy

Due to the absence of the pilot, each UAV is characterised by a rate of autonomy [62]. At this point, the difference between an automatic and autonomous system has to be clarified. The functionality of an automatic system is based on the operator who has preprogrammed the system to perform a specific operation without deviating in any way [62]. On the other side, an autonomous system is characterised by the existence of specific rules that can provide a kind of adjustment in various situations. This freedom does not exist in the automatic systems [62]. Being in the IoT era, modern UAV systems are characterised by a level of autonomy. According to the United States Department of Defence [62,63], there are four types of autonomy. The first type, named human-operated system defines that the system operator is responsible for controlling all operations of the unmanned system. The second type called human deligated system is characterised by a higher level of autonomy compared to the first one, by maintaining the ability to take autonomously some restricted decisions. The third level is named human supervised system and can take various decisions based on the directions of the system operator. Specifically, in this case, both the system operator and the unmanned system can perform various actions based on the data received. Finally, the last level is named fully autonomous systems and is responsible for all its operations. In this case, the unmanned system receives data from the system operator and interpret it into specific tasks. Surely, in the case of an emergency, the system operator has the ability to intervene in the function of the unmanned system.

Fig. 3. Rotary-wing UAVs.

4.1.3. UAV types based on size and weight

Several countries and researchers have categorised UAVs based on their size and weight. For instance, the Dutch Human Environment and Transport Inspectorate distinguish UAVs as light and heavy [62]. In particular, if a UAV exceeds the weight of 150 kg, then it is characterised as heavy. Otherwise, it is specified as light. Custer et al. [64] provide a more specific separation, taking into consideration the UAV type based on its aerodynamic characteristics. In particular, they consider that the fixed-wing UAVs whose weight is between 20 kg and 150 kg can be characterised as large. On the other side, if a fixed-wing UAV does not exceed 20 kg, then it can be characterised as small. Similarly, the rotary-wing UAVs whose size ranges from 25 kg to 100 kg, are considered as large. Accordingly, if a rotary-wing UAV does not exceed 25 kg, then it is small. Moreover, they consider that the small UAVs can be distinguished further, extracting a new subcategory called mini. As mini UAVs are those whose weight ranges from some grams to several kilograms.

4.1.4. UAV types based on power source

Finally, UAVs can also be categorised based on the fuel utilised for their flight. There are four main fuels for a UAV: a) kerosene, b) battery cells, c) fuel cells and d) solar cells [62]. Kerosene is usually employed by large fixed-wing UAVs appropriate for military purposes. An example of such a UAV is Predator [65]. Conversely, the small rotary-wing UAVs incorporate battery cells, since their functional needs require less operating time. An example of such a UAV is DJI Phantom [66]. Accordingly, a fuel cell is an electric device which transforms chemical substances into electrical energy. These devices can only be integrated into fixed-wing UAVs and are usually employed to maximise the flight distance [62]. A characteristic example is the Stalker drone [67]. Finally, solar cells can be used for both fixed-wing UAVs and rotary-wing UAVs. Google and Facebook have already focused their attention on the UAVs using this technology, aiming at lifting such UAVs in the atmosphere, thus making possible the connection to the Internet more massively.

4.2. UAV payload

The kinds of payloads that can be integrated into a UAV depend on their size and weight. In general, there are two kinds of payloads: a) sensors and b) other payloads. The most used sensor integrated into UAVs is a camera [17,62,68]. There are three main technologies of cameras: a) multispectral, b) hyperspectral and c) thermal. The first one (multispectral) integrates five bands, namely red, green, blue, red-edge and near-infrared. The second (hyperspectral) includes more bands in contrast to the first case, sometimes reaching the number of 2000 [62]. Finally, the third type (thermal) employs the infrared radiation to form a heat zone image, operating at wavelengths of 14000 nm approximately. Other types of sensors that can be integrated into UAV are chemical, biological and meteorological sensors [13,62]. Particularly, chemical sensors are able to identify chemical compositions and specific organic substances. Biological sensors can identify various kinds of microorganisms, while meteorological ones possess the ability to measure various values, such as wind speed, temperature and humidity. Finally, there are many payloads that do not belong in the sensor category. For instance, a UAV can carry on a spraying system or other objects like goods that should be delivered to a specific destination.

4.3. UAV regulatory framework in europe

As UAVs constitute a kind of aircraft, they must respect the determined aviation safety regulations and rules. Since 1944, at international level, the United Nations have introduced specific civil aviation rules that clarify that UAVs must not fly in the territory of other countries without its necessary and appropriate permission. At the European level, through the European Commission (EC) Regulation No. 216/2008 [70], the European Aviation Safety Agency (EASA) is responsible for enacting particular regulations and rules for the Unmanned Aircraft Systems (UAS) and Remotely Piloted Aircraft Systems (RPAS) that are utilised for civilian applications and weighted 150 kg or more. From now on, the UAS and RPAS terms will be referred to as UAV. The UAV systems whose operating mass is less than 150 kg are excluded from the EC Regulation No. 216/2008. Nevertheless, many member states of the European Union (EU) have established National Aviation Authorities (NAAs) that have introduced a regulatory framework for UAVs that are weighted less than 150kg. In particular, as explained in Table 2, NAAs classify the currently defined regulations of UAVs based on their weight and the type of their application [71,72].

In 2015, EASA was mandated by EC to establish specific safety rules for the UAVs whose mass is less than 150 kg, taking into consideration two essential priorities: a) the need to deploy a functional and friendly environment for the UAV industry and b) the need to ensure the privacy protection of the citizens [73]. Based on this direction, EASA established a Technical Opinion [69] which takes into account both commercial and non-commercial use of UAVs. Specifically, it categorises the operation of UAVs into three classes based on their risk level. The first class, called open category specifies the operations of UAVs with low risk. This class defines a few safety rules, that should be overseen by police. Moreover, the authorisation of NAA is not required for the UAVs of this class even for commercial purposes. The second class, named specific category identifies operations with medium risk. In this case, the authorisation from NAA is required. The potential risks have to be analysed through a risk assessment process. Finally, the last category, called certified category identifies the functions that are characterised by high risk. This category comprises similar regulations and rules with the human-crewed aircraft, such as necessary certification processes and a pilot's license.

Since the final rules of EASA are not available publicly, EASA feeds the member states with interim safety rules for the operation of UAVs. Some EU member states such as Germany, France, Italy, Denmark, Sweden, Austria, Spain and Finland have adopted some rules concerning the use of UAVs with less 150 kg weight. Nonetheless, the details of these rules differ among the EU countries. Moreover, the conditions of allowing a UAV to fly among the territories of EU countries have not been determined. Therefore, in conclusion, this situation results in a complicated regulatory framework at the European level with many ambiguities and limitations [72,74].

5. UAV applications in PA

This section presents and analyses 20 UAV applications related to the agricultural domain. More specifically, these applications are

Table 2
Overview of the regulatory framework of UAVs in Europe.

UAV weight (kg)	Potential uses	Current regulations
Small ($W \leq 25$ kg)	Both Commercial and Personal Use (e.g., monitoring, photography)	1. NAA Regulations 2. EASA Technical Opinion [69]
Medium ($25kg \leq W \leq 150$ kg)	Both Commercial and Personal Use (e.g., geospatial inspection, photography)	1. NAA Regulations 2. EASA Technical Opinion [69]
Large ($W \geq 150$ kg)	Commercial Use (e.g., military processes)	(EC) Regulation No. 216/2008 [70]

divided into three categories, namely a) UAV-based Monitoring Applications, b) UAV-based Spraying Applications and c) Multi-UAV Applications. Table 3 summarises and compares these applications by listing their primary characteristics. Based on these applications, in the next section, we identify the relevant research gaps and provide directions for future research work.

5.1. UAV-Based monitoring applications

In this subsection, we investigate and analyse UAV applications that monitor crops and provide imaging data that are subsequently processed to extract particular appropriate information and vegetation indices, thereby identifying problematic areas in a crop suffering from various diseases and pests. The data received by the sensors of UAV can be spectral, spatial and temporal. The selection of the proper sensor and data depends on the application nature. For instance, the thermal data is appropriate for identifying the water status, while the spectral information constitutes a good option for identifying possible plant diseases. The papers examined utilise various kinds of sensors such as thermal, multispectral and hyperspectral cameras. Each paragraph examines a different case.

B. Allred et al. in [75] describe UAV missions concerning the detection of possible drainage pipes. Usually, farmers need to repair drain lines or construct new ones in order to remove efficiently the water from the soil. Moreover, the drainage procedures may release amounts of phosphate (PO4) and nitrate (N03), thus causing the corresponding environmental hazards [129,130]. Therefore, the location of these drain lines is required; nevertheless, usually, it is not available in many areas such as many US states like Ohio, Illinois, Minnesota and Indiana. The authors in this paper perform UAV missions in order to examine the capability of the Visible (VIS), Near-Infrared (NIR) and Thermal Infrared (TIR) imagery to identify drainage pipes under arid conditions. The farm field utilised for the missions is located in Ohio and the presence of the drainage pipes is already known. Specifically, the farm field included corn and soybean crops as well as residue from the previous year growing season. Firstly, the authors establish the appropriate equipment for measuring the rate of the rainfall, temperature and water content, thus identifying the aridity rate. More detailed, for measuring the rate of rainfall, the Tipping Bucket Rain Collector (Spectrum Technologies, Inc.) was utilised. Accordingly, WaterScout SMEC 300 Soil Moisture/Temperature Sensors (Spectrum Technologies, Inc) were used to estimate the water content and the temperature. Hence, the rainfall rate was less than 5 mm; the water content was approximately calculated at 16% while the temperature exceeded 33 Celsius. The flight missions were implemented by using a senseFly SA eBee Ag fixed-wing drone [76] with two cameras, namely a) Parrot SA Sequoia [77] and b) senseFly SA thermoMap [76]. The first one combines VIS and NIR wavelengths, while the second provides only TIR wavelength. Additionally, the senseFly SA software, eMotion3 [76] was utilised for processing the images by mainly subtracting possible overlapping. Consequently, based on the experimental results, it is clear that TIR imagery can efficiently identify drain lines under arid conditions.

In [78], M.P. Christiansen et al. provide a UAV system for monitoring the production and health state of agriculture crops. In particular, they focus their attention on winter wheat crops by employing a Light Detection and Ranging (LiDAR) sensor integrated on UAV and performing textual analysis on the data provided by UAV. LiDAR constitutes a method which lights a target point with pulsed laser light, thus measuring the distance from this point, by utilising a sensor which measures the reflected pulses [131–133]. Subsequently, a textual analysis was conducted on the data provided by the LiDAR sensor, thereby estimating the overall plant volume and the soil surface for specific crop parcels. For their experiments, the authors utilised a crop field at Aarhus University, Flakkebjerg as well as a DJI Matrice 100 UAV (DJI Enterprise) [79]. Two flight methods were implemented and evaluated. The first one focused on the borders of the crop parcels, while the second followed a different approach by monitoring the crop rows. The second method provided higher spatial resolution, but also is characterised by significant battery consumption.

In [82], J. Primicerio et al. describe a UAV application called VIPtero, which was implemented for monitoring and assessing the state of vineyard crops. Specifically, their system examines the images generated by the UAV and produces vigour maps utilising NDVI [9]. The UAV used is a Mikrokopter Hexa-II (HI Systems) [83], which is a six-rotor platform, possessing the capability of autonomously flighting based on a predefined path. More detailed, it includes GPS, integrated flight control boards, as well as a magnetic compass. The authors enhanced the capabilities of Hexa-II, thus forming the VIPtero system. In particular, they introduced a first-person view platform, named EagleTree telemetry kit, a Global System for Mobile Communication (GSM) modem, an independent power supply, a camera operated by the Flight Control board (FlightCTRL), a GPS receiver and a Navigation Control board (NaviCtTRL). Based on these components, the operator is able to receive information regarding the state of UAV as well as transmit commands concerning the flight path. The primary role of VIPtero is to monitor and record the reflectance of the vegetation canopy. The images captured by VIPtero are processed by several steps, providing the vigour maps. More detailed, firstly, the images are analysed and ortho-rectified by a digital elevation model. Next, they are geo-referenced and undergo a specific analysis, converting each pixel into spectral radiance and subsequently into reflectance. Then, NDVI is calculated and processed by a software package, thereby separating soil pixels from canopy pixels. Finally, the vigour maps are formed. Regarding the evaluation of the proposed system, the authors investigated its performance by testing its capabilities in a real vineyard of Monteboro. Specifically, they compared NDVI values of VIPtero against NDVI values of a spectroradiometer, thus evaluating the accuracy. The correlation between the two values is calculated at 0.98. Finally, it should be noted that VIPtero consumes 350 Watt on average in their experiments.

In [84], A. Ruangwiset presents a testing process regarding the power consumption [134,135] of a prototype UAV, taking into account the parameters of altitude and weight. The proposed UAV prototype was implemented for monitoring the performance of cassava crops, which constitute a commercial type of agriculture crops in Thailand. The commercial use of cassava mainly concerns food, alcohol, sweetener and animal feed. The UAV deployed is a fixed-wing type, since the author argues that the specific type is characterised by a higher performance regarding the endurance and range. In particular, its main characteristics are the following ones: a) empty weight: 2 kg, b) span: 2m, c) payload weight 1 kg, d) battery LiPro 14.8v and e) propulsion: brushless motor 1300kv, propeller 10x5. Moreover, to conduct automatic flights, the UAV prototype was equipped with Ardupilot Mega [85] which is an autopilot system composed of a) 3-axis angular velocity sensor, b)

Table 3
Summary of 20 UAV Applications in PA.

Literature work	Objective	Task	UAV Architecture	UAV Type	UAV Technical Characteristics and Payload	Crop	Testbed Products
Allred et al. [75]	Detecting drainage pipes	Monitoring Process	Single UAV	Fixed-Wing	1. VIS Camera 2. NIR Camera 3. Thermal Camera	1. Corn 2. Soybean	1. senseFly SA eBee [76] 2. Parrot SA Sequoia [77] 3. senseFly SA thermoMap [76] 4. eMotion3 [76] 5. Tipping bucket Rain Collector (Spectrum Technologies, Inc.) 6. WaterScout SMEC 300 Soil Moisture/Temperature Sensors (Spectrum Technologies, Inc) 7. Pix4Dmapper Pro-(Pix4D SA)
Christiansen et al.[78]	Monitoring vegetation state	Monitoring Process	Single UAV	Rotary-Wing	1. LiDAR 2. Multispectral camera 3. IMU 4. GNSS	Winter wheat	1. DJI Matrice 100 UAV [79] 2. TB48D battery pack 3. Odroid XU4 4. Velodyne VLP-16 LiDAR 5. Point Grey Chameleon3 3.2 MP Color camera 6. Sony imx265 sensor 7. Vectornav VN-200 IMU MAXTENA M1227HCT-A2-SMA antenna 8. Trimble BD920 GNSS 9. ROS [80,81]
Primicerio et al.[82]	Monitoring vegetation state	Monitoring Process	Single UAV	Rotary-Wing	1. Multispectral camera 2. GPS system 3. FlightCTRL 4. NaviCtTRL 5. First person view platform 6. GSM modem 7. Magnetic compass	Vineyard	1. Mikrokopter Hexa-II [83] 2. ATmega1284P microcontroller 3. ATmega8 control boards 4. ARM9 microcontroller 5. LEA-6 GPS 6. 4-cell 3300Ah 14.8 V lithium polymer battery 7. Koptertool software 8. Tetracam ADC-lite camera 9. FieldSpec Pro spectroradiometer 10. EagleTree telemetry kit
Ruangwiset [84]	Investigating computational resources during a monitoring process	Monitoring Process	Single UAV	Fixed-Wing	1. IMU 2. GPS system	Cassava	1. New UAV prototype 2. Ardupilot Mega [85]
Santesteban et al.[86]	Evaluating water stress	Monitoring Process	Single UAV	Rotary-Wing	1. FlightCtrl 2. NaviCtrl 3. 3-axis accelerometer 4.Thermal Camera 5. Storing device 6. Pressure sensor 7. Digital compass 8. GPS system	Vineyard	1. Mikrokopter Okto XL [87] 2. FLIR TAU II 320 Camera 3. Mikrokopter software 4. ATMega1284P microcontroller 5. ARM9 microcontroller 6. LEA-6 GPS module 7. ATMEGA8 control boards
Vasudevan et al.[88]	Monitoring vegetation state	Monitoring Process	Single UAV	Rotary-Wing	1. Single-board computer 2. Multispectral camera 3. IMU 4. LiDAR	Vineyard	1. Parrot SA Sequoia [77] 2. Beaglebone Black board 3. Hector UAV package [89] 4. Gazebo [90] 5. rviz software [91] 6. GY80 10DOF IMU 7. ROS [80,81]
Paredes et al.[92]	Optimizing the image acquisition system of UAV	Monitoring Process	Single UAV	Fixed-Wing	1. Multispectral camera 2. Single-board computer 3. Storing device	1. Potato 2. Grapes 3. asparagus 4. Sugar cane	1. Skywalker X8 UAV [93] 2. PCDuino v2 board [94] 3. Point Gray Chameleon Camera [95] 4. Pixhawk flight controller [96] 5. Mission Planner software [97]
Sankaran et al.[98]	Evaluating cameras performance concerning field-of-view, accuracy, resolution	Monitoring Process	Single UAV	Rotary-Wing	1. Multispectral camera 2. GPS system 3. Compass 4. Gyroscope 5. Accelerometer 6. Radio transmitter board	Citrus orchards	1. HiSystems hexacopter 2. XNiteCanon SX230 camera 2. Tetracam ADC Lite camera
Katsigiannis et al.[99]	Evaluating water stress and vegetation state	Monitoring Process	Single UAV	Rotary-Wing	1. Thermal camera 2. Multispectral camera 3. Single-board computer 4. GPS system 5. Stabilization mechanism	Pomegranate	1. Vulcan hexacopter [100] 2. Raspberry Pi 3. Agisoft PhotoScan Professional

(*continued on next page*)

Table 3 (*continued*)

Literature work	Objective	Task	UAV Architecture	UAV Type	UAV Technical Characteristics and Payload	Crop	Testbed Products
Uto et al. [101]	Estimating chlorophyll density	Monitoring Process	Single UAV	Rotary-Wing	1. Hyperspectral camera 2. Autonomous power supply 3. Storing device 4. GPS system 5. Control switches 6. LCD screen	Rice	1. MD4-1000 UAV [102] 2. GT-723F GPS receiver 3. C10988MA Mini-Spectrometer
Zheng et al. [103]	Estimating nitrogen state	Monitoring Process	Single UAV	Rotary-Wing	Hyperspectral camera	Rice	1. HiSystems's MK OktoXL 2. Cubert UHD 185 camera 3. GreenSeeker RT 100 4. ASD Field Spec Pro
Stroppiana et al.[104]	Identifying variability of rice	Monitoring Process	Single UAV	Rotary-Wing	Multispectral camera	Rice	1. DJI S1000 Octocopter [105] 2. Canon S100 camera [106] 3. Tetracam ADCMicro camera [107]
Skobelev et al.[108]	Providing a distributed flight scheduling system	Monitoring Process	Multiple UAVs	Rotary-Wing	1. Single-board computer 2. Storing device	Not identified	1. 3DR IRIS UAVs [109] 2. Raspberry Pi2 [110,111] 3. General Designer Stand tool [108]
Ju and Son [112]	Evaluating performance of single and multiple UAV systems	Monitoring Process	Multiple UAVs	Rotary-Wing	1. RGB camera 2. IMU 3. Additional battery 4. Onboard controller 5. Printed Circuit Board (PCB) 6. GPS system 7. Wireless adapter	Not identified	1. 3DR SOLO UAVs (3DR) [113] 2. ROS [80,81]
Barrientos et al.[114]	Providing a multiple UAV system for aerial imaging	Monitoring Process	Multiple UAVs	Rotary-Wing	1. Hummingbird: IMU, compass, pressure sensor, GPS system 2. AR100: servo and three-axis magnetometer, gyroscope, barometer	Vineyard	1. Hummingbird [115] 2. AR100 [116] 3. AutoPilot board 4 LPC2146 ARM high level processor 4. XBee 2.4-GHz module 5. Asctech Software Development Kit
Faical et al.[117]	Optimizing spraying process via UAV system taking into consideration climate conditions	Spraying Process	Single UAV	Not identified	Not identified	Any crop	1. OMNeT+ [118,119] 2. Mixim framework [120]
Faical et al.[121]	Optimizing spraying process via UAV system taking into consideration climate conditions	Spraying Process	Single UAV	Not identified	Not identified	Any crop	1. OMNeT+ [118,119] 2. Raspberry Pi
Dai et al. [122]	Spraying fruits and trees	Spraying Process	Single UAV	Rotary-Wing	1. Spraying Device 2 Multispectral camera 3. IMU 4. Magnetometer 5. Barometer 6. Servos	Not specific crop. The proposed application was tested in a competition environment	1. DJI Spreading Wings S1000+ 2. PixHawk controller [96] 3. MPU6000 IMU 4. MS5611 barometer 5. HMC5883 magnetometer 6. Point Grey BFS-U3 camera 7. ROS [80,81]
Li et al. [123]	Optimizing spraying process proposing an innovative path planning algorithm	Spraying Process	Multiple UAVs	Rotary-Wing	Spraying device	Any crop	Merak UAVs
Ju et al. [124]	Providing a control system for the efficient management of multiple agricultural UAVs	Monitoring Process	Multiple UAVs	Simulated environment	Not identified	Any crop	1. Novint Falcon haptic device [125,126] 2. ROS [80,81] 3. Gazebo [90,127] 4. ODE [128]

magnetometer, c) accelerometer and d) barometer. The testing process included a selection from various payloads and altitude values and was accomplished in a 400x400 rounded rectangular area in Thailand composed of 8 predefined waypoints. Based on the experimental results, the power consumption [134,135] does not present a significant value for the payloads of 0.2 kg, 0.4 kg and 0.6 kg. However, a minor increment is presented for the payload with 0.8 kg. On the other hand, concerning the altitude, the maximum power consumption is presented when a disturbance decreases the altitude or airspeed and the UAV has to compensate these values.

L.G. Santesteban et al. in [86] present a UAV application for assessing thermal imaging to estimate the seasonal and the instantaneous variability of the water status in a vineyard. The evaluation was based on the Crop Water Stress Index (CWSI) [136] values calculated from UAV images in comparison with the stomatal conductance and the stem water potential values that were measured manually from specific sites. In particular, the application was applied in a real vineyard in Spain, whose size was divided into two types of grid. The first grid constitutes an approximately rectangular area and is devoted to characterising the agronomical nature of the vineyard, consisting of 92 Sampling Points (SPs). The second one also forms an almost rectangular area, including 14 Water Status Points (WSPs). Each of the 92 SPs is characterised by the following values: a) yield, b) vegetative growth, c) berry carbon isotope ratio and d) grape composition at harvest. On the other side, each of the 14 WSPs is identified by weekly measurements of the stem water potential values. Furthermore, the values of the Plant Cell Density (PCD) and EC were available. The UAV used for the experiments was a MikrokopterOktoXL multi-rotor [87] capable of flying 15 min and carrying 2 kg weight. Specifically, it is equipped with the following features: a) FlightCtrl, b) NaviCtrl, c) 3-axis accelerometer, d) microSD card, e) pressure sensor, f) a digital compass, g) GPS module, h) universal camera and i) a FLIR TAU II 320 sensor for capturing the thermal data. The flight path was determined to provide 80% overlapping among the photos as well as among the flight lines, by using the Mikrokopter Tools software. After capturing the thermal data, the stomatal conductance and the stem water potential values were measured for each WSP, by calculating the CWSI index [136,137] and implementing a spatial analysis [138] based on Agisoft Photoscan Professional Edition 1.1.6 tool [139–141]. The experimental results demonstrate that the thermal data can provide significant and accurate information regarding the water status of a vineyard.

A. Vasudevan et al. in [88] present a combined application composed of UAV and an Unmanned Ground Vehicle (UGV) for monitoring and managing the agriculture crops. According to the authors, the primary objective of their implementation is based on the UAV functionality capable of inspecting periodically the status of crops, capturing multiple images of them and extracting various indices [9,142] that in turn identify the density, greenness and in general the vegetation health. On the other side, UGV was mainly used to provide useful information regarding the terrain composition such as the pH level and acidity. In particular, the operation of UAV is based on a Beaglebone Black board which integrates a Debian operating system. Moreover, it possesses magnetometer, accelerometer, barometer and gyroscope that are integrated into a GY80 10DOF IMU. In addition, UAV employs a Sequoia camera [77] which supports multiple wavelengths such as NIR, red, green and red-edge. On the other side, UGV similarly integrates a Beaglebone Black board and additionally incorporates a LiDAR [143] sensor and a monolithic camera. The functionality of UAV was firstly simulated utilising the Hector UAV package [89] in Gazebo [90]. The process of constructing the map of an unknown environment was conducted using the rviz software [91]. After the collection of images, the authors perform a homography methodology by applying the Harris corner detector [144], the Lucas-Kanade method [145] and the RANSAC algorithm [146]. Finally, through the ortho-mosaic image, the following indices were extracted a) NDVI, b) Optimized Soil Adjusted Vegetation Index (OSAVI) [147], c) Renormalized Difference Vegetation Index (RDVI) [148], d) Soil Adjusted Vegetation Index (SAVI) [149] and e) Enhanced NDVI (ENDVI) [142].

Based on the UAV technology, in [92], J.A. Paredes et al. introduce a multispectral imaging system for collecting and analysing images from agriculture crops in Peru. The main novelty of their implementation is the image acquisition system which identifies how the images captured by the UAV's cameras should be stored and processed. In particular, the functionality of the image acquisition system is mainly based on two threads that are responsible for storing the images. In more detail, these threads operate consecutively and are able to store till 30 images in local memory. Once a thread reaches the aforementioned threshold, it transfers these images to an SD card, while the second thread undertakes the process to store images in local memory. Moreover, there is a third thread which is responsible for informing the previous threads when an image is captured. To test their implementation, the authors utilised the following equipment: a) A Skywalker X8 UAV [93], b) PCDuino v2 board [94], c) two Point Gray Chameleon monochromatic cameras [95] and d) Pixhawk flight controller [96]. Nevertheless, they mention that a better performance is carried out utilising 6 Blackfly cameras [150] and the Jetson TK1 board [151] which supports GPU capabilities. Regarding the flight path, it was determined using the Mission Planner software [97]. The experimental actions were performed in multiple types of crop in Peru such as sweet potato, grapes, asparagus and sugar cane. The flight missions were conducted weekly. After the collection of images, an ortho-mosaic map is formed and subsequently, the NDVI index [9] is calculated. The NDVI indices demonstrate that the entire system can successfully be used for estimating the health status of various kinds of crop.

S. Sankaran et al. in [98] implemented and tested a UAV application for assessing the capabilities of two cameras in monitoring the health status of the citrus orchards. The two cameras were evaluated based on a) field-of-view, b) classification accuracy and c) image resolution. The classification accuracy refers to the rate of the correct classification regarding the healthy trees and those that have been infected from some disease. The UAV used for the experimental actions was a hexacopter consisting of the following characteristics: a) 2 kg weight, b) 6600 mAh Lithium-Ion Polymer battery, c) six propellers, d) six brushless motors, e) GPS, f) compass, g) gyroscope, h) accelerometer and finally i) radio transmitter. The first camera integrated into UAV was XNiteCanon SX230 NDVI (LDC LLC, Carlstadt, NJ) which supports green, blue and NIR bands. On the other side, the second camera was a Tetracam ADC Lite camera (Tetracam Inc., Chatsworth, CA) [152], which correspondingly includes green, red and NIR bands. The experimental actions were performed in citrus orchards, in Florida where some trees were healthy, while others had been infected either from citrus greening or huanglongbing. Multiple images were captured in three different altitudes of 90, 60 and 30 m. For each image, the following features were extracted: a) NIR and green bands, b) Green Normalized Difference Vegetation Index (GNDVI) [9] and c) histogram information of GNDVI, thus forming six labelled datasets (2 cameras x 3 altitudes). The Principal Component Analysis (PCA) [153] method was utilised to reduce the datasets' dimensionality. Finally, a Support Vector Machine (SVM) [154,155] model was deployed in order to identify the healthy and unhealthy trees. The SVM model was trained using 75% of datasets, while 25% was used for testing. Moreover, it utilised the radial basis function and was deployed on Matlab. Based on the experimental results, the first camera presents better performance for each of the criteria mentioned above.

In [99] P. Katsigiannis et al. provide a UAV application able to aggregate thermal and multispectral data, thereby calculating and assessing the water stress and the health status of pomegranate crops. More concretely, the UAV application is based on a Vulcan hexacopter (VulcanUAV) [100] model which incorporates the following characteristics: a) a thermal camera, b) a multispectral camera, c) a Raspberry Pi board (Raspberry Pi Foundation) [110,111], d) a GPS receiver and e) a stabilization mechanism. Concerning the flight path, it was determined by specific waypoints pre-specified manually by the user. The proposed

UAV system was tested in a pomegranate orchard in Greece, by flying at 100 m and aggregating images with 60% overlapping. In particular, two flights were scheduled. The height mentioned earlier corresponds to 13 cm and 4 cm ground resolution of the thermal and multispectral camera respectively. After the image capturing, the images are processed with the Agisoft PhotoScan Professional software, thus generating the corresponding ortho-mosaic map. Next, the CWSI and NDVI indices [9] were calculated from the thermal and multispectral data, respectively. For the calculation of the CWSI index, firstly the conversion of the thermal information to temperature values was required. Based on the experimental results, the CWSI values were in the range 0.4–0.9 and 0.29–0.74 for the two flights, respectively. The difference between the two ranges is due to the implementation of an irrigation system on the second day. Regarding the NDVI values, an overall increase of 25% was marked on the second day. In conclusion, according to the authors, the proposed system is appropriate for supporting the irrigation systems, accompanying maintenance procedures and discriminating zones based on water stress and vegetation.

In [101], K. Uto et al. introduce a lightweight hyperspectral imaging system which can be mounted on the MD4-1000 UAV (MIcrodrones GmbH) [102] for monitoring tasks. According to the authors, the existing hyperspectral imaging systems cannot be supported by UAVs due to their large weight. Their system consists of the following components: a) a hyperspectral sensor, b) an autonomous power supply, c) a data collector, d) a GT-723F GPS receiver (CanMore Electronics Co. LTD), e) control switches and f) a Liquid Crystal Display (LCD). The overall weight of the proposed system is 400 g. Concerning the hyperspectral sensor, it supports the spectral range of 340–763 nm and includes the following modules: a) C10988MA Mini-Spectrometer, b) a multiplexer, c) an analogue/digital converter, as well as d) lenses. The maximum data acquisition duration does not exceed 200 ms. The authors evaluated their implementation in a rice crop by comparing the chlorophyll density between the data captured by UAV and the ground truth data. To estimate the chlorophyll density, the authors used five chlorophyll indices, namely: a) CIblackburn2, b) CIblackburn1, c) CIgitelson, d) CIgreen and e) CIrededge [156–158]. The evaluation results demonstrate the high accuracy of the proposed system utilising the red and NIR bands.

H. Zheng et al. in [103] present a UAV system capable of obtaining hyperspectral data to identify the nitrogen status in rice crops. In particular, they compared the hyperspectral information received by the UAV system with the measurements captured by two ground-based spectrometers, thus demonstrating the efficiency of their system. Moreover, the Leaf Nitrogen Concentration (LNC) was identified and estimated by using the Kjeldahl digestion method and five vegetation indices, namely a) NDVI, b) R-M, c) REP-Li, d) MCARI/MTVI2 and e) Viopt. The UAV used by the authors is HiSystems's MK OktoXL which is characterised by the following features: a) 1.83 wt, b) 15 min maximum flight duration, c) 2.5 kg payload weight and d) Cubert UHD 185 hyperspectral camera. According to the authors, the primary aim of this work was to evaluate the capabilities of the aforementioned camera. The proposed system was evaluated in a rice crop, in Rugao, China. The ground-based spectrometers used for the evaluation process are: a) GreenSeeker RT 100 (NTech Industries, Ukiah, CA, USA) and b) ASD Field Spec Pro-spectrometer (Analytical Spectral Devices, Boulder, CO, USA). Based on the experimental results, the NDVI index of images taken by the UAV is lower that NDVI of the second spectrometer, but higher than the NDVI of the first spectrometer. Furthermore, in the visible spectrum, the spectral reflectance data obtained by UAV is higher in comparison with the corresponding one of the second spectrometer. On the other side, in red and NIR bands, there is only a small discrepancy between the image captured by UAV and the data of ASD. Finally, regarding the LNC identification, the REP-Li index yields the highest performance.

In [104], D. Stroppiana et al. introduced and tested a UAV application which aims at extracting and identifying the variability of rice crops with the use of multispectral information. More concretely, to evaluate the UAV applicability, their work is based on a comparison between the visible and NIR spectral data captured by UAV and the measurements that were received by a smart harvester. The UAV employed for this work is a DJI S1000 Octocopter [105] carrying on the Canon S100 camera [106] (visible band) as well as the multispectral Tetracam ADCMicro camera [107]. This UAV application was tested in a rice crop, in Northern Italy, Pavia province. The data from the two aforementioned cameras was captured from an altitude of 70m. Moreover, the data from the multispectral camera was normalised and subsequently multiplied with the digital number to provide the red, green and NIR bands. Furthermore, NDVI was calculated and subsequently compared with the ground measurements, thereby demonstrating that the UAV system is able to monitor and acquire data from rice crops. The comparison between the aerial data and the ground measurements was conducted through three regression models, namely: a) logarithmic with a bias coefficient, b) logarithmic and c) linear.

5.2. UAV-Based spraying systems

In this subsection, we investigate and study UAV systems devoted to spraying applications. In particular, most of the examined papers describe applications that are capable of spraying appropriate and accurate amounts of pesticides and fertilisers. These agrochemical commodities are utilised to increase the effectiveness of crop and mitigate the possible plant diseases and pests. Nonetheless, their extensive usage can generate various issues on the human environment, such as environmental disasters and human diseases like cancer, neurological disorders and complications in the respiratory system [159]. Most of the papers examined mount a spraying device and take into consideration various conditions that can affect this process, such as the weather status. Each of the following paragraphs examines a different case.

B. S. Faical et al. [117] present a Particle Swarm Optimization (PSO)-based [117,160–162] algorithm which optimises the spraying process of a UAV system, taking into consideration climate conditions. Based on the authors, climatic conditions can seriously affect the performance of pesticides since in many cases, they direct vast amounts of pesticides outside of the target area. The application in which the proposed algorithm was based and deployed combines the operations of WSN and UAV. The sensing devices of WSN are suitably placed in the target area and transmit data to UAV concerning the weather such as the wind direction and speed. Next, UAV receives this information and based on the algorithm deployed by the authors takes the right decisions regarding the position and velocity of UAV. More detailed, the functionality of the proposed algorithm is based on PSO and undertakes to discover a non-optimal value for a specific parameter, called routeChangingFactor which in turn determines the motion of UAV. It should be noted that the computational time of this algorithm must be lower than the time needed for the spraying process. The proposed algorithm was implemented on the OMNeT+ + [118,119] software and specifically on the Mixim framework [120]. Based on the experimental results, the proposed algorithm accomplishes a significant precision regarding the use of pesticides which is calculated around at 86%.

In [121], B.S. Faical et al. focus their attention on the problem of not using pesticide amounts appropriately. As the authors claim, many works have proposed terrestrial or aerial spraying systems for the proper management of the pesticide amounts, but they do not take into consideration the weather conditions, such as the change of the wind speed and direction, thus resulting in various damages and disasters like the environment pollution, not sprayed regions and possible economic failures due to the pesticides overlapping. To this end, they propose a collaborative spraying system, combining UAV and WSN, capable of determining and changing suitably the route and actions of UAV, based on the weather conditions. Specifically, their system called Adaptation to the Environment (AdEn) consists of two primary components: a) Collector and Actuating (CollAct) and b) OPTImization Core (OPTIC). CollAct constitutes a software package which is performed in the UAV's computing system and is mainly responsible for monitoring the weather conditions by communicating with WSN which in turn consists of multiple sensors that have been placed in many subareas forming the area of interest. More detailed, CollAct initialises the communication with the sensing nodes of a subarea by transmitting the geolocation coordinates. Next, the sensing nodes response to the message of CollAct by sending the weather conditions. Finally, CollAct extracts the average value of the weather conditions and transmit it to the OPTIC component. OPTIC is also a software package which is executed on the ground station. It receives the weather conditions and utilising four metaheuristic algorithms determine the proper actions of UAV by appropriately modifying the value of the routeChangingFactor variable. The heuristic algorithms examined and evaluated by authors are: a) Genetic Algorithm (GA) [117,163], b) Simulated Annealing (SA) [164], c) Hill Climbing with the Next Ascent strategy (NAHC) [165,166] and d) Particle Swarm Optimization (PSO) [117,160,161]. Next, this value is sent back to CollAct, which undertakes to change the UAV's actions. The experimental results demonstrated that the proposed system is able to effectively manage the pesticide spraying process of UAV, while the most efficient decisions are taken using the GA metaheuristic.

In [122], B. Dai et al. present a UAV-based spraying system specially designed for fruits in the trees. The proposed system was evaluated successfully in a related competition, gaining the first place. The primary aim of the system is to deploy a fully autonomous mechanism which will be able to spray specific areas with high accuracy and without any human intervention. In particular, the authors utilised a DJI Spreading Wings S1000+ UAV [105] which is characterised by the following features: a) a PixHawk controller [96], b) an MPU6000 IMU, c) an MS5611 barometer, d) an HMC5883 magnetometer, e) a GPS receiver, f) a Point Grey BFS-U3 camera, g) an extended magnetometer and h) the spraying device. On the other side, the ground station includes a strong computing system which carries on a) Intel Core i5-6260 Central Processing Unit (CPU), b) 8GB Random Access Memory (RAM), c) 128GB Solid State Drive (SSD) disk and d) a 5G communication interface. The main contribution of the paper is the software platform which accompanies UAV, including a) an Extended Kalman Filter (EKF)-based navigation system, b) a control system and c) a vision system. Regarding the EFK-based navigation system, the authors introduce a dual-subsample rotation vector method which estimates the velocity, the altitude and the position of UAV. The functionality of the control system is based on various Proportional (P) and Proportional Integral Derivative (PID) controllers, such as Position P/PID controller, Velocity PID controller, Attitude P/PID controller and Angular Velocity PID controller [167]. Finally, concerning the vision system, it consists of three main processes: a) preprocessing, b) target identification and c) target localisation. Specifically, the preprocessing method is utilised to aggregate the necessary data for the target identification and localisation. In turn, the target identification method adopts a machine learning classification algorithm, named K-Neighbour Nearest (KNN) [168] to identify the target area with high precision. Finally, the role of the localisation process is to optimise the precision of the previous method.

5.3. Multi-UAV applications

In this subsection, we investigate applications, usually called multi-UAV applications which consist of many UAVs for PA tasks. Currently, most of the existing works in the literature usually focus on a single UAV which performs a monitoring process. However, in some cases such as the large crops, a single UAV cannot complete itself the monitoring process because it is characterised by limited power resources (limited battery). On the contrary, a multi-UAV application is capable of addressing this challenge, by separating the area into multiple subareas corresponding to the number of UAVs [169,170]. It is noteworthy, that there is a lack of papers in the literature that examine multi-UAV applications. Each of the following paragraphs examines a different case.

X. H. Li et al. [123] propose an innovative path planning algorithm for a UAV application consisting of multiple UAVs. The use case examined by the authors includes a pesticide spraying process of two large crops in Shaanxi Province, China by numerous UAVs. According to the authors, a single UAV itself cannot cover these areas in a single flight. Therefore, they examine the scenario of a multiple UAVs application in which each UAV is responsible for monitoring a specific block. The UAV type used by the authors is a quadcopter UAV which comprises a spraying device, capable of containing 15L. The specific UAV type called "Merak" is characterised by the following features: a) 30 min maximum flight duration, b) 6 m/s average speed, c) 4000 m maximum flight altitude and d) 30 kg maximum supported weight. The algorithm deployed by the authors is called Variable Neighborhood Descend enhanced Genetic Particle Swarm Optimization (VND enhanced Genetic-PSO) and aims at optimising the flight paths of UAVs and at the same time minimising their flight duration. The traditional PSO method [162] was deployed for addressing continuous optimisation problems. Nevertheless, it presents various computational issues concerning combinatorial optimisation problems. The VND enhanced Genetic-PSO algorithm deployed by the authors utilises the discrete PSO method and integrates genetic operators for updating the position of the particle. Moreover, it adopts the VND method to speed up the convergence. Briefly, their algorithm aims at optimising the paths of UAVs by applying the smallest make-span. Regarding the evaluation process, the authors compared their method with an approach which minimises the flight distance. The target of both approaches was to minimise the flight time. Based on the experimental results, the method implemented by the authors presented better results compared to the aforementioned approach.

In [108], P. Skobelev et al. provide a distributed flight scheduling and optimising system regarding the use of multiple UAVs to monitor an agricultural area. Their architecture consists of several 3DR IRIS UAVs (3DR) [109] that carry on a Raspberry Pi2 (Raspberry Pi Foundation) [110,111] board as well as a centralised server called Global Knowledge Base. After introducing the necessary parameters for the function of the system, the agricultural area is divided into specific squares based on the features of UAVs. Each of these squares is characterised by a particular timestamp which denotes the time interval without supervising. Subsequently, each UAV undertakes to monitor a number of squares taking into consideration two criteria: a) what are the squares without monitoring for a long time and b) the complexity of the path based on the distance and the number of turns. The aforementioned criteria are combined to form an overall performance indicator of UAVs, called Key Performance Indicator (KPI). This KPI is calculated by summing the values of the previous criteria. Accordingly, the overall evaluation of the system is calculated by summing each KPI of UAVs. Concerning the optimisation process, UAVs have the ability to communicate with each other in order to exchange squares, thus minimising the flights' completion time. Regarding the evaluation process, the authors took into account a) the time needed for the scheduling and rescheduling process, b) the time for the forecasting process and c) the overall KPI. Based on the experimental results, the greater the number of UAVs involved, less time needed for the scheduling and monitoring process. Finally, it should be noted that the authors also verify these conclusions by performing many simulations with the use of the General Designers Stand tool [108].

Having as a common variable the RS operations in the agricultural domain, C. Ju and H. Son in [112] provide several comparisons by examining the use of a single UAV and multiples UAVs as well as the autonomous control state and the remote control state. During the flight time, the autonomous control refers to controlling a UAV autonomously, by firstly determining some specific features, while the remote control is carried out by the system operator utilising a teleoperation device. Therefore, the authors conducted four experimental cases, namely a) single UAV system with autonomous control (Auto-Single-UAV), b) single UAV system with remote control (Tele-Single-UAV), c) multiple UAVs system with autonomous control (Auto-Multi-UAVs) and d) multiple UAVs system with remote control (Tele-Multi-UAVs). In addition, six metrics were utilised, namely a) total time, b) flight time, c) setup time, d) landing inaccuracy, e) battery consumption and f) coverage ratio. The total time is the process completion time, including the flight time and the setup time. The flight time is calculated by subtracting the setup time from the total time. Accordingly, the setup time refers to the necessary preparation process before the flight. The landing inaccuracy denotes how far the UAV or UAVs landed from the predefined landing point. Finally, the coverage ratio signifies the performance of the RS operations. To accomplish their comparisons, the authors utilised three quadcopters and specifically, three 3DR SOLO UAVs [113]. Based on their experimental results, the multiple UAVs system requires more preparation time (setup time) for its establishment but presents significant improvements regarding the other metrics. Concerning, the autonomous or remote control, the total time and the setup time are reduced when the remote control option is used. Nevertheless, the remote control presents an increase regarding the flight time and power consumption [134,135]. Moreover, the inaccuracy landing metric is improved when the remote control is used, while the coverage ratio metric does not present any difference either utilising the remote control or the autonomous control.

In [124], C. Ju et al. propose a distributed control system, called distributed swarm control system for managing multiple agricultural UAVs remotely by a system operator. In particular, their implementation consists of two control layers, namely a) teleoperation layer and b) UAVs control layer. The first layer is responsible for interpreting the commands transmitted by the system operator, utilising a haptic device. Through the teleoperation layer, the system operator can manage the velocity of UAVs as well as receive appropriate feedback by using the haptic device. On the other hand, the UAVs control layer includes three inputs that determine the functionality of the system. These inputs are: a) the velocity of UAVs, b) the desired formation and c) collision avoidance control. More detailed, the velocity of UAVs is determined by the teleoperation layer. The desired formation is implemented, taking into consideration the distance among UAVs. Finally, the collision avoidance control is responsible for avoiding possible obstacles based on the distance between them and UAVs. In order to evaluate their system, the authors utilise the Novint Falcon haptic device (HapticsHouse) [125,126] as well as a simulated environment by combining the Robot Operating System (ROS) [80,81], the Gazebo simulator [90,127] and the Open Dynamic Engine (ODE) tool [128]. The system evaluation includes flights of several UAVs in a specific, predetermined path. The experimental results verify the functionality of the proposed system.

In [114], A. Barrientos et al. provide a multi-UAV application in which a swarm of UAVs is in charge of obtaining georeferenced images to produce a mosaic map for post-processing. In particular, their application includes three main processes: a) area subdivision, b) path planning and c) flight control. The first process divides an existing area into multiple blocks that are allocated per UAV. The functionality of this process is based on a negotiation protocol which takes into account the state and characteristics of UAVs. After the allocation of blocks, Coverage Path Planning (CPP) techniques are utilised for each block in order to compute a set of waypoints that form the path of the corresponding UAV. Finally, the last process is devoted to controlling the velocity and position of UAV, taking into consideration the weather conditions. The authors test their application in a vineyard crop utilising two UAVs: a) Hummingbird [115] and AR100 [116]. Based on the experimental procedures, the proposed scheme demonstrates its effectiveness.

6. Discussion and research trends

The challenges of climate change introduce multiple and crucial issues as well as new difficulties for the agriculture sector. The key to addressing these challenges is the proper adaption of the farming communities, by forming a resilient ecosystem which will be able to feed the world's growing population. Based on the previous literature review, ICT services play a significant role in dealing with the problems of the agricultural sector, by offering processes to optimise the financial gain of farmers and at the same time reduce the potential cost. In particular, leveraging the PA capabilities, it is possible not only to address the various difficulties, but also accelerate efforts to realise the sustainable development goals by 2030. The combined use of UAV technology and big data analytics is very promising in dealing with the most pressing problems of agriculture. Sensor networks based on the concept of IoT are increasingly adopted in the agricultural sector in order to collect meaningful information concerning the spatial and temporal characteristics of the soil composition. More specifically, regarding the use of UAVs, Goldman Sachs claims that the utilisation of UAVs for agricultural goals will be the second-largest during the next five years [1]. Predicting the problems of agriculture, the EU has funded many research projects for deploying new PA methodologies and developing new related platforms making use of UAVs and UGVs. For example, the aim of the VINEyardROBOT project [171] was to construct an agricultural robot equipped with multiple sensing technologies to monitor water stress, vegetative growth, grape yield and grape composition. Similarly, the FieldCopter project [172] aimed at combining multispectral cameras with UAVs in order to provide accurate and punctual information of the fields. The AGRIC-LASERUAV project [173] aims at analysing and combining data captured by UAVs as well as LiDAR data for identifying significant biophysical attributes. Accordingly, the primary objective of the ARcopter project [174] funded by Horizon2020 was to construct a new fully autonomous UAV that will be able to automate the vertical take-off and landing with high accuracy and operate under bad conditions. The HOMED project [175] aspires to define a set of risk assessment and mitigation processes for protecting forests and fields from pests and pathogens. The goal of the Flourish project [176] is to optimise the existing robots used for PA processes, by combining UAVs and UGVs that will be able to monitor multiple crops. Finally, AMOTH [177] aimed at producing a novel UAV which will carry on multiple chemical and visual sensors that in turn will enable the chemical composition of an environment by a) measuring the chemical concentration and b) categorising the substances.

Aiming at raising new research challenges for the use of UAVs in the domain of PA, this paper investigates 20 related UAV applications, thus extracting meaningful conclusions and research directions for future work. Table 4 summarises the results of this analysis cumulatively. Although the use of agricultural UAVs is very widespread, it should be noted that in contrast to relevant research works, this the first attempt which concentrates and analyses multiple agricultural UAV applications utilised for both monitoring and spraying procedures, thereby providing important information. In particular, after providing an overview of PA and UAV, we study these applications by dividing them into two main subsections. The first one examines those UAV applications used for monitoring processes, while the second is devoted to spraying processes. Also, since the use of multiple UAVs is a significant challenge, but at the same time can offer significant benefits, we provide a separate subsection which describes those applications utilising a multiple UAVs architecture for both previous processes (monitoring and spraying). More specifically, the cases investigated serve various purposes such as monitoring the vegetation state, evaluating the water stress, spraying fruits and trees, estimating the chlorophyll density as well as detecting drainage pipes. More detailed, from our literature review, 16 papers focus on crop monitoring, while 4 papers are devoted to spraying processes. Moreover, 15 instances utilise a single UAV, while only 5 works employ a multiple UAVs architecture. Hence, given these values, the coordinated use of many UAVs in agriculture remains a crucial challenge. In many cases, where there are big crops, the use of a single UAV is not feasible. Concerning the works devoted to crop monitoring, most of them use a multispectral camera. The thermal type is used by 3 papers, while the hyperspectral one is used only by 2 works. RGB, VIS and NIR camera types are found only in one case. It should be clarified that the papers examined can apply more than one type of cameras. Undoubtedly, all types of cameras can provide significant data. Usually, multispectral cameras are utilised for estimating the vegetation state, while the hyperspectral type for calculating chemical attributes, such as the calculation of the nitrogen state and chlorophyll density.

Table 4
Cumulative Results of the Literature Review.

Characteristics	Value
Number of UAV applications used for monitoring processes	16
Number of UAV applications using multispectral camera for monitoring processes	8
Number of UAV applications using hyperspectral camera for monitoring processes	2
Number of UAV applications using thermal camera for monitoring processes	3
Number of UAV applications using VIS camera for monitoring processes	1
Number of UAV applications using NIR camera for monitoring processes	1
Number of UAV applications using RGB camera for monitoring processes	1
Number of UAV applications using LiDAR for monitoring processes	1
Number of UAV applications used for spraying processes	4
Number of UAV applications using a single-UAV architecture	15
Number of UAV applications using a multiple UAVs architecture	5
Number of UAV applications using fixed-wing UAVs	3
Number of UAV applications using rotary-wing UAVs	14
Number of UAV applications using hybrid-wing UAVs	0
Number of UAV applications using only simulation software	1
Crops	1. Corn 2. Soybean 3. Winter wheat 4. Vineyard 5. Cassava 6. Potato 7. Asparagus 8. Sugar cane 9. Pomegranate 10. Rice

Finally, the thermal type is commonly employed for evaluating water stress.

As mentioned previously, most of the papers investigated focus on aerial monitoring processes that utilise either image processing or machine learning techniques. This fact demonstrates how active is the specific research field. On the one side, image processing extracts some vegetation indices such as NDVI, GNDVI, SAVI and Enhanced Vegetation Index (EVI) that analyse the agricultural characteristics and generate vigour maps, thus calculating the possible yield and detecting potential diseases. On the other side, similarly, machine learning techniques are able to forecast the yield and detect potential diseases, but with different means. Typically a machine learning model is trained by relevant data, thus providing to the model a suitable experience to make the right choices concerning a decision problem. SVM models, decision trees and Artificial Neural Networks (ANN) have demonstrated their efficiency regarding PA decision problems. Nevertheless, in order to use efficiently both aforementioned processes, many challenges should be addressed. Image overlapping, variable orientation and variable scale are some characteristic examples. In addition, a more significant challenge is the limited battery time of UAVs, especially for large crops. The establishment of additional solar-powered mechanisms may solve this severe issue.

In contrast to the previous category of aerial crop monitoring systems, only a few papers focus on UAV applications devoted to spraying processes. Typically, such processes are utilised to apply specific amounts of pesticides and fertilisers in order to prevent possible pests and create the ideal conditions to maximise the crop yield. However, according to Pimentel [178], although approximately 3 million metric tons of these products are employed, 40% of the respective crops are destroyed. The main reason for this destructive state is the improper use of the agrochemical products, since large amounts drift outside of the targeted area. The spraying processes for this task can be divided into two categories: a) terrestrial and b) aerial. The first one is more accurate, requires more time and most importantly, they can cause human diseases such as cancer and neurological disorders. Concerning the second category, the aircrafts adopted for such a process are usually human-crewed. However, this solution is very expensive as well as dangerous, since if there is a failure, the pilot may be in danger. It is worth highlighting that the aircrafts used for this process operate close to the soil, which increases the risk probability. Therefore, the appropriate use of UAVs is a more safe and economical option. A significant issue for this task is the stabilisation of the spraying device and its autonomous management by UAV. Also, the UAV adaption based on the weather conditions is an essential requirement. In particular, the UAV has to change appropriately their functional characteristics such as velocity and altitude according to the weather. Furthermore, a remarkable challenge is the deployment of UAV prototype, which will be capable of combining both aerial crop monitoring and spraying processes.

Although the use of a single UAV has been demonstrated as a very promising means to enhance and optimise the PA processes, its application in large areas is not very effective, since due to the limited energy resources, it is not capable of covering the whole targeted area [13,179]. In particular, the maximum area that a single UAV can cover depends on its technical characteristics and payload [13]. Hence, for large-scale applications such as big farms and forests, a collaborative group of UAVs called swarm can be adopted, thus forming research directions in a field named Flying Ad hoc [180–183] Network (FANET) [184–186]. An Ad-hoc network consists of several nodes that can communicate with each other directly, without requiring any existing infrastructure or a centralised access point. Accordingly, FANET is an Ad-hoc network where the nodes are UAVs. Typically, a UAV from the FANET is connected with a ground-based station, while the other UAVs form a multi-hop communication where each node operates as a hop count or relay [187]. The quality of this communication can depend on many factors such as UAV mobility, bandwidth availability, environmental and geographical constraints, as well as the synchronisation complexity among UAVs. According to [188], in order to deploy a FANET, the following parameters should be taken into account: a) UAV mobility, b) localisation, c) energy resources, d) radio propagation model, e) topographical attributes and changes, f) UAV density, g) Paparazzi mobility model, h) pheromone-based model, i) random waypoint mobility model and j) mobility models. Although FANET can provide multiple benefits concerning large-scale PA applications, this field is characterised by certain issues. First, most of the existing software applications are designed to manage and control only a single UAV. Moreover, even if there are some applications that can handle a FANET, their functionality is limited, since they cannot handle efficiently the failure of a UAV or the addition of a new target area. Finally, a new set of regulations and rules, especially devoted to FNET has to be determined.

7. Conclusions

The role of ICT services has evolved significantly and rapidly in both scope and scale. By extending broadband connectivity, deploying IoT applications and taking full advantage of big data analytics, innovative applications and devices underpin what we now call digital society. This momentum offers great capabilities to enhance and optimise the procedures of the agriculture sector, by adapting and applying these technologies as PA solutions. PA becomes more crucial, as we look for means to solve the challenges faced by agriculture such as the restricted availability of arable lands, the increasing need for freshwater and the disastrous consequences of climate change. The use of UAVs for enhancing the cultivation processes is auspicious since they can perform monitoring and spraying missions, thereby optimising the efficiency of the pesticides and fertilisers, detecting timely possible pests and diseases as well as facilitating the spraying procedure.

Therefore, having as a motivating factor the challenges existed in the domain of agriculture as well as the great capabilities offered by UAV, in this paper, we aim at providing a comprehensive analysis regarding the UAV applications in the context of PA. In particular, after introducing an overview of PA and UAV by describing their main characteristics and properties, we analyse in detail 20 UAV applications devoted either to crop monitoring or spraying processes. More detailed, we analyse the UAV architecture, i.e., single UAV or multiple UAVs, the corresponding methodology adopted, the UAV type employed for each case, the corresponding UAV technical characteristics and payload, as well as the kind of crops utilised for the testing procedure. Based on this analysis, we draw the research trends and provide directions for future work.

Based on the research trends we discuss in this paper, in our future work we aim at developing a Decision Support System (DSS) which will be able to manage a FANET and a ground-based WSN for both crop monitoring and spraying processes. More specifically, concerning the crop monitoring process, DSS will take from fixed-wing UAVs many images and will utilise deep learning models in order to estimate the vegetation health. At the same time, terrestrial sensors will feed DSS with valuable chemical data, such as the rate of humidity. Based on this data, DSS will extract useful and accurate information regarding the use of agrochemical products. On the other side, regarding the spraying process, FANET will consist of rotary-wing UAVs that will be equipped with a spraying device. Each UAV will be responsible for the spraying process of a specific subarea. Finally, the WSN, in this case, will feed DSS with weather information and subsequently DSS will be able to take the right decisions regarding the motion of UAVs, by adapting properly their motion characteristics, such as direction and velocity.

Declaration of Competing Interest

None.

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Supplementary material

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