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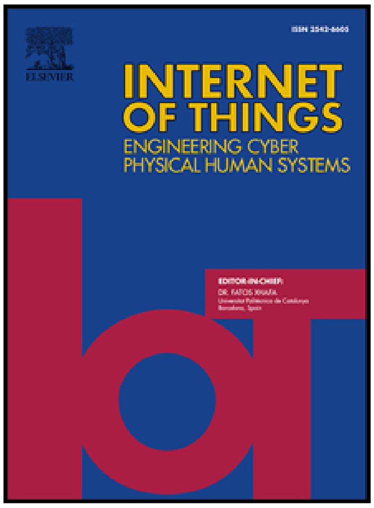

Internet of Things (IoT) and Agricultural Unmanned Aerial Vehicles (UAVs) in Smart Farming: A Comprehensive Review

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Internet of Things (IoT) and Agricultural Unmanned Aerial Vehicles (UAVs) in Smart Farming: A Comprehensive Review

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Abstract

Internet of Things (IoT) and Unmanned Aerial Vehicles (UAVs) are two hot technologies utilized in cultivation fields, which transform traditional farming practices into a new era of precision agriculture. In this paper, we perform a survey of the last research on IoT and UAV technology applied in agriculture. We describe the main principles of IoT technology, including intelligent sensors, IoT sensor types, networks and protocols used in agriculture, as well as IoT applications and solutions in smart farming. Moreover, we present the role of UAV technology in smart agriculture, by analyzing the applications of UAVs in various scenarios, including irrigation, fertilization, use of pesticides, weed management, plant growth monitoring, crop disease management, and field-level phenotyping. Furthermore, the utilization of UAV systems in complex agricultural environments is also analyzed. Our conclusion is that IoT and UAV are two of the most important technologies that transform traditional cultivation practices into a new perspective of intelligence in precision

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agriculture.

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1. Introduction

During the last few years, agriculture is undergoing a fourth revolution (Farming 4.0) by integrating Information and Communications Technologies (ICT) in traditional farming practices [1]. Technologies, like Remote Sensing, Internet of Things (IoT), Unmanned Aerial Vehicles (UAVs), Big Data Analytics (BDA) and Machine Learning (ML) are particularly promising and they can give a new breakthrough in agricultural practices [2], [3]. In smart farming, a wide range of agricultural parameters can be monitored to improve crop yields, to reduce costs and optimize process inputs, such as environmental conditions, growth status, soil status, irrigation water, pest and fertilizers, weed management, and greenhouse production environment [4]. Smart farming is a green technology approach, since it reduces the ecological footprint of traditional farming [3]. In precision agriculture, smart irrigation and the minimal use of fertilizers and pesticides in agricultural crops can further reduce leaching problems and emissions, as well as the impact of climate change [3], [5].

IoT is one of the most revolutionary technologies in modern wireless communications [6]. The basic concept is the interaction between a variety of physical things or objects using specific addressing schemes to being connected to the Internet. IoT technology can be applied in various vertical markets including industry, transportation, healthcare, vehicles, smart home, and agriculture [7]. In an agricultural environment, IoT devices provide useful information on a wide range of physical parameters to enhance cultivation practices [4]. The role of Wireless Sensor Networks (WSNs) in IoT technology is of paramount importance since the vast majority of IoT applications in various markets is based on wireless data transmission.

The use of unmanned aerial systems (UAS) as sensing and/or communication platforms is also a breakthrough technology with tremendous potential in precision agriculture [8]. It was introduced as a low-cost alternative technique in environmental monitoring, in high spatial and temporal resolution, and in imagery acquisition. Nowadays, the use of UAVs in agriculture is expanding to assist cultivators with monitoring and decision support on the farm [9]. UAS are utilized in various agricultural practices, such as irrigation, fertilization, pesticides, weed management, etc. Moreover, the combination of UAS technology with novel 3D reconstruction modeling techniques has allowed to monitoring growth parameters of the crop on a plant-level basis.

The agricultural sector is evolving by integrating several key emerging technologies towards a new and well promising era of agriculture-food production, so-called “Agri-Food 4.0” [10]. IoT technology, smart sensors, remote sensing, UAV technology, Low Power Wide Area Networks (LPWAN), Long Range Wide Area Access Networks (LoRaWAN) and Wireless Sensor Networks (WSN), etc. are included among all. These smart farming technologies can be categorized in data acquisition, data analysis, and evaluation and precision application technologies [11]. Various combinations of the aforementioned emerging technologies in smart agriculture have been successfully applied in the continents of Europe, United States of America, and Australia [12], [13], as well as in individual countries, like Brazil [14], India [15], Italy [16], and Ireland [17].

The rest of this paper is organized as follows. Section 2 includes the main objectives that motivated the authors for introducing this paper as well as the contributions of this work. Section 3 briefly outlines sensor types and wireless sensor networks commonly used in agriculture. The IoT technology application in smart farming is discussed in Section 4. Section 5 describes the basic IoT communication protocols in physical and link layers as well as cloud computing service basics used in smart farming. The applications of UAV technology in smart farming is thoroughly discussed in Section 6. Moreover, the use-case of AREThOU5A project is briefly outlined (Section 7). Finally, Section 8 includes the discussion of the paper and gives future trends and challenges for IoT and UAV technology, whereas Section 9 concludes the paper.

2. Motivation and Contribution

The motivation for preparing this comprehensive review issues from the fact that IoT and UAV are the two key enabling technologies in smart farming. Undoubtedly, IoT and UAV will be the leaders of the fourth revolution in smart agriculture for the upcoming years. The bibliographic analysis of the review involved a keyword-based search for conference and/or journal articles. The scientific research databases of IEEE Xplore and ScienceDirect, as well as the scientific web search engine of Google Scholar were selected to

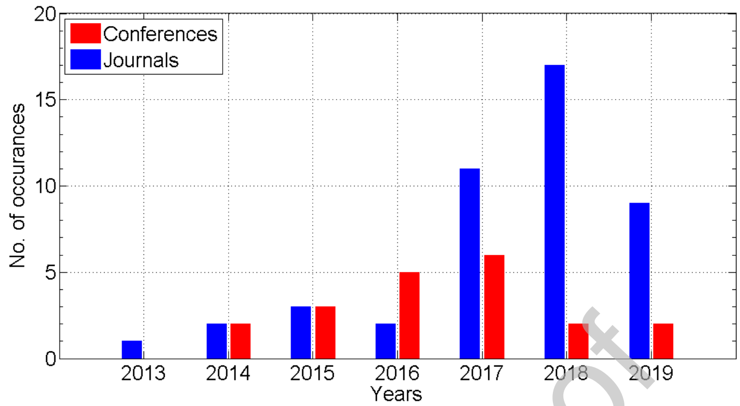

Figure 1: Distribution of journal articles and conference papers that were analyzed.

perform this review. A total of 65 papers were analyzed. Fig. 1 illustrates the distribution of journal articles and conference papers that were analyzed in this paper review.

The main contributions of this research are summarized in the following. In this work, we combine two key enabling technologies in a single paper review, as these technologies play (now and in the future) a pivotal role in the agricultural industry. It is expected that the agricultural industry, and in general the agricultural economy, will be undoubtedly transformed by the adoption of these two enabling technologies on a large-scale cultivation basis. Also, we outline enabling techniques incorporated with IoT technology, we describe the main application of these techniques in Agriculture, and we point out the benefits that derive by their utilization. Moreover, we perform a detailed analysis of applications that using UAV technology in smart farming. This approach is applied not only from the technological point of view, which is actually significant, yet of interest and usefulness only to workers in the field, but from the agricultural point of view as well, notating all the key aspects in this research field. To the best of the authors' knowledge, this is the first time that this approach is taking place in a review article. Finally, the ARETh0U5A project framework, as a use case of combined state-of-the-art technologies, is briefly described. The use case is included in this review work to exploit the importance of the incorporation of various emerging technologies, such as IoT technology, to promote rational use of irrigation water in Agriculture.

3. Sensors and Sensor Networks In Smart Farming

This section provides a brief overview of sensor types and sensor networks used in smart farming.

3.1. Basic and Intelligent Sensors

A sensor is a device that detects as input several types of physical or environmental quantities, such as pressure, heat, light, pollution levels, humidity, wind, and so on. The output of the sensor is in most of the cases an electrical signal that is transmitted to a microcontroller and, consequently, to a network for further processing. The evolution of basic to intelligent electronic sensors is creating a revolution in how we collect data from the environment, analyze them, make decisions for further investigation, and connect vast intelligence systems to enable new solutions and to accomplish tasks that we have never been able to perform before [18], [19].

It is estimated that the first intelligent sensor was proposed in 1980 [20]. The authors described the development of silicon micro-sensors that can fit on the same chip with a microcontroller. They presented various sensor types and indicated their possible applications. However, Microelectromechanical systems (MEMs) and Complementary MetalOxideSemiconductor (CMOS) technology was not able at that time to create this integrated device. Nowadays, the technology is mature and intelligent sensors are the key factor for the development of innovative IoT systems. Fig. 2 illustrates the basic components of a sensor in IoT technology. As depicted in Fig. 2b, an intelligent sensor usually consists of:

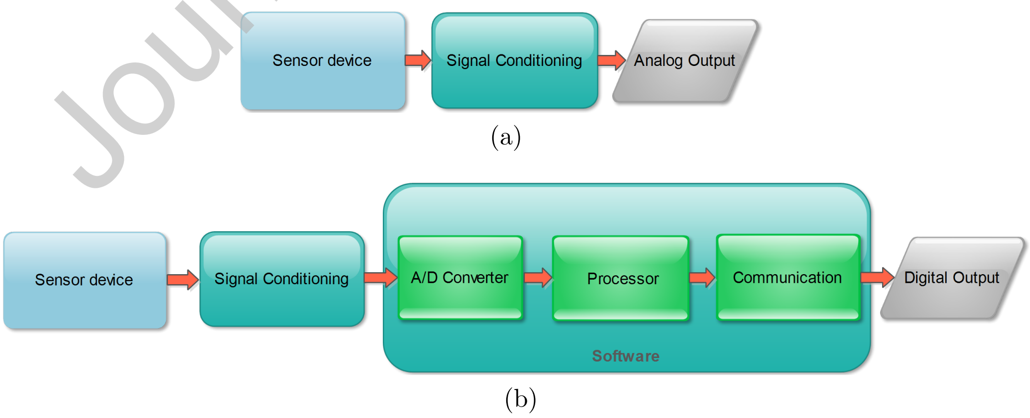

Figure 2: Block diagram of (a) Basic sensor and (b) Intelligent sensor.

1. A sensing device that measures specific physical parameters from real-world (temperature, humidity, pollution levels, etc.).
2. A signal conditioning to transform the signal into data that the intelligent sensor can use.
3. A computational block, such as a processor or Digital Signal Processor (DSP), that analyses and pre-process the measurements.
4. A communication block, such as a wireless transmitter, that exchanges information with the gateway sensor node.

3.2. Sensor Types in Agriculture

Nowadays, technological innovations are reforming the traditional farming practices. Unmanned aerial systems, satellite imagery and sensor technology are remarkably transforming the agricultural industry. Smart farming is the application of information and data technologies for optimizing complex and multi-factorial farming systems [21]. Smart farming is not oriented to perform precise measurements, but rather to access data and the application of these data [22]. The main objective is to identify how the collected information can be used in an "intelligent" way [23]. Smart farming is also a concept that involves all farm operations [24]. Farmers can use smart mobile devices, such as smartphones and tablets, to access real-time agricultural data (soil and plant condition, irrigation, fertilization, weeds, climate, weather, etc). As a result, farmers can act based on solid data and intervene when necessary, rather than their traditional intuition.

There are various types of sensors that can be used to measure and calculate the parameters of an agricultural field. The basic principles of these sensors and their related specifications are briefly outlined below.

Soil water content sensor

Soil water content sensor is used in a wide range of scientific areas. Soil water content is the ratio of the amount of water presents in the test soil to the total amount of the test soil. It is expressed by the change in capacitance value, which depends on the dielectric constant of the soil. It can range from 0 (completely dry) to the value of the materials' porosity at saturation [25]. The measurements are soil type dependent; therefore the sensor must be calibrated for each location.

Soil Moisture Content Sensor

Soil moisture content sensor (sometimes referred to as soil volumetric water content sensor) measures the water content of soil [26]. This sensor evaluates the soil water tension or suction, which is a denotation of the plant root system effort while extracting water from the soil. It can be used to estimate the amount of stored water in the soil or how much irrigation is required to reach a desired amount of water in the soil.

Soil Electrical Conductivity Sensor
The electrical conductivity (EC) of soil is used to measure the soil solute concentration while assessing the soil salinity hazard [27]. Irrigation water contains at least some salt. If salts build up around the root zone of a crop, they injure plants, reduce yields and can cause long-term damage to the land itself. The salt content of a soil is measured by using a soil electrical conductivity sensor, which is based on Faradays law.

pH Sensor
pH is a measure of acidity and alkalinity in a given solution. In agriculture, soil pH value $\notin [5.5, 6.5]$ are considered as non-optimum as it indicates lack of availability in soil nutrients. Farmers must regulate pH value by the utilization of alkaline or acidic fertilizers, which also improves also farming production [28]. If we consider that soil pH value varies within the field, one of the best practices is to spatially apply the fertilizer according to the soil pH variation.

Weed Seeker Sensor
Weed seeker is a self-contained unit, which is usually equipped with optical and electronic components for weed detection and spraying. The unit consists of an active light source and a chlorophyll identifying selective spray sensor. The optical system allows the unit to detect and spray only weeds in the field. The systematic use of the system can significantly reduce herbicide usage. As a result, very limited use of chemicals is required, which consecutively decreases application cost [29].

Temperature Sensor
In agriculture, soil temperature specifies the crop type that can be cultivated in a field. Temperature controls plant development processes such as photosynthesis, transpiration, absorption, etc. Each crop has a different temperature range in which it can grow. Outside this range, enzymes essential for growth become inactive. The temperature sensor provides alerts if the

temperature goes above or below a certain threshold. The sensor is a p-n junction diode of CMOS technology [30].

Wind Speed Sensor
The wind speed sensor designates the surface wind speed. In a field, it is usually necessary to observe phenomena, such as modifications in wind speed and direction. The wind speed sensor must be mounted at a suitable height, depending on the crop [31].

Generally speaking, sensors can be classified into the following types: i) optical, ii) mechanical, iii) electrochemical, iv) dielectric soil moisture, v) airflow, and vi) location sensors [32]. Table 1 provides the most commonly used sensor types and their application in agriculture.

3.3. Wireless Sensor Networks in Agriculture

Wireless sensor network (WSN) can be defined as a group of spatially and dedicated sensors for monitoring the physical conditions of the environment, temporarily storing the collected data, and transmitting the gathered information at a central location [33]. In recent years an efficient Wireless Sensor Network designed for smart farming is a point of interest for most of the researchers. A WSN for smart farming consists of several nodes with wireless communication capabilities. Fig. 3 illustrates a general WSN node architecture. Each sensor node comprises of sensors, microcontrollers, converters and power sources [34]. A node can support one or more sensors to monitor and measure different variables. In agricultural applications, it is essential to measure several physical quantities related to soil, such as soil moisture content, soil water content, soil temperature, soil electrical conductivity, as well as weather condition parameters.

Nowadays, wireless sensor networks can be self-organized, self-configured and self-diagnosed. WSNs are developed and installed to cope with problems or to enable applications that traditional technologies cannot address. The most obvious advantage in WSNs is the considerable reduction and simplification of wiring, which results in a more simplified final system. Typical wiring cost in industrial applications has been estimated to US$ 130650 per meter and the adoption of wireless technology could reduce this cost up to 80% [35].

Wireless sensors enable monitoring practices in dangerous, hazardous, non-wired or remote areas. This technology provides practically unlimited

Table 1: Summary of IoT sensor types used in Agriculture.

Sensor Type	**Sensor**	**Function**	**Application in agriculture**
Optical	Photodiode	Use of light to measure soil properties	Determines clay, organic matter and moisture content of the soil
Mechanical	Tensiometer	Use of probes to measure soil compaction	Detects the force used by the roots in water absorption
Electro-mechanical	Ion-Selective Electrodes (ISE) and Ion-Selective Field Effect Transistor sensors (ISFET)	Use of electrodes to detect specific ions in the soil	Detects Nitrogen Phosphorus Potassium (NPK) in soils
Dielectric soil Moisture	Electrodes for Frequency Domain (FDR) or Time Domain Reflectometry (TDR)	Use of electrodes to assess moisture levels	Measures soil water content
Airflow	Measurements can be made at fixed or dynamic locations	Measures soil air permeability	Classifies various soil types, moisture levels, and soil structure/compaction
Location	Global positioning system (GPS)	Provides information about the latitude, longitude, and altitude	The GPS provides precise positioning

installation flexibility for sensors and increased network robustness. Moreover, wireless technology simplifies the maintenance of these networks and reduces installation costs. One of the primary advantages of wireless sensors is their portability. These sensors can be placed on a farm machinery, as in a tractor, or on animals. As a result, farmers can measure critical parameters

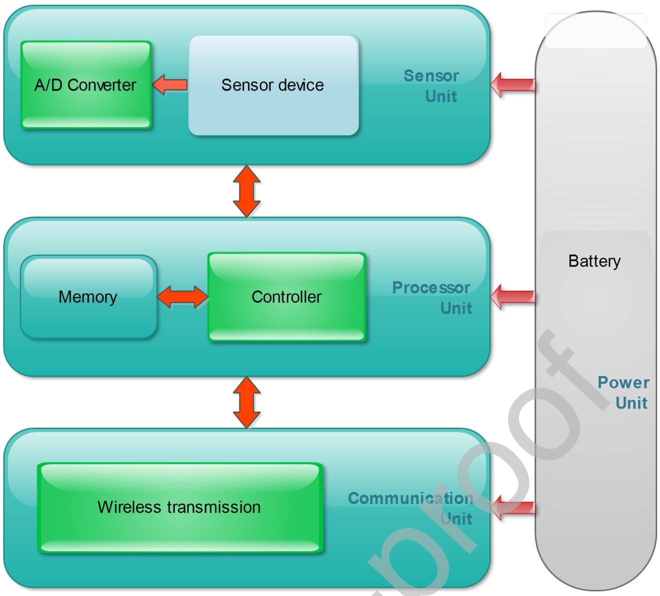

Figure 3: General WSN node architecture [34].

and monitor the entire field at any time. On the contrary, wired communication and sensors are rather expensive, require regular maintenance, and deliver with a high failure rate in their connectors. To overwhelm the drawbacks of wired sensors, the farm industry must develop new measures to improve production performance, while further reducing costs and extending the operational life cycle of new and used equipment [36].

4. Applications of IoT Technology in Smart Farming

Internet of Things (IoT) [6] refers to devices having unique identities and capabilities to perform remote sensing, monitoring and temporarily storing certain blocks of data. IoT is a cross-platform where devices are getting smarter, the processing is becoming intelligent, and communication is resulting in informative [37]. IoT devices are also capable of having a real-time exchange of data with other devices and applications, either directly or indirectly. Any IoT based device consists of the following components:

- Input/ Output interface for Sensors
- Interface for connecting to the Internet

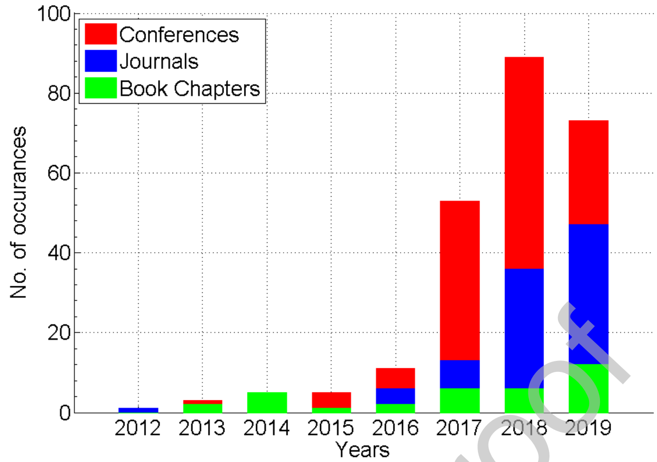

Figure 4: Stack diagram of papers from Scopus database with topic "IoT and Smart Farming".

- Interface for Memory and Storage
- Interface for Audio/ Video

A search in the Scopus database about IoT and Smart Farming reveals a total number of 231 papers starting from the year 2012. The current research trend towards IoT applications in Smart Farming is depicted in Fig. 4. It is noteworthy that there is a growing research interest over recent years.

Smart Agriculture has the capability to provide a profitable and sustainable agricultural production [38], which will be based on a combination of innovative solutions of new ICTs, such as IoT [39]. All the technologies used in smart agriculture are complex, resulting from the complexity of the activities performed by the farmers. Sensor-based irrigation systems provide a promising solution to the farmers. IoT technologies can reduce the cost and increase the scale of sensor-based irrigation systems through data collection from sensor networks. IoT is a worldwide network based on standard communication protocols. It utilizes several technologies for data collection from physical measured quantities to IoT applications [40].

Internet of Things adopts various enabling techniques, such as wireless sensor networks, cloud computing, big data, embedded systems, security protocols and architectures, communication protocols, and web services. Table 2

Table 2: IoT Technologies in Smart Agriculture.

IoT Technology	**Application in Agriculture**	**Benefits in Agriculture**
WSNs: Sensor nodes with radio communication capabilities	Sensors integrated together to monitor various physical parameters	Easy collection and management of data gathered from sensors
Cloud Computing (on-demand computing): A type of Internet based computing	Provides shared processing resources and data to computers and other devices on demand	Easy collection and management of data gathered from cloud computing services like agriculture fields maps, cloud storage, etc.
Big Data Analytics: The process of examining and analyzing large data sets	Access to various forms of data types	Uncover patterns, correlations, market trends, customer preferences, and other useful information
Embedded Systems: A computer system that consists of both hardware and software	System performs specific tasks, such as monitoring, controlling and efficient management of various activities	Productions costs can be reduced to a remarkable level which will increase profitability and sustainability
Communication Protocols: The backbone of IoT systems to enable connectivity	These protocols facilitate exchange of data over the network in various data exchange formats	Easy collection and management of tons of data gathered from sensors and cloud computing services, cloud storage, etc.

depicts the main applications and benefits of each IoT technology in smart agriculture.

There are several IoT systems in smart farming that reveal the great role and the necessity of IoT-based technology and applications. In [41] the authors proposed a Decision-Support System (DSS) based on the integration of wireless sensors and actuation network (WSAN) technology. The suggested actions were oriented to reduce water waste and to improve cultivation yield following the weather conditions. In [42] the researchers presented a framework, which was called AgriTech, to optimize several farming resources (water, fertilizers, insecticides, and manual labor) in agriculture using IoT. The farmers could monitor the crops and farmland from a distance using a mobile terminal device. In [43], a model of a smart greenhouse was proposed, which helped the farmers to carry out automatically the work on a farm. The proper amount of nitrogen, phosphorus, potassium, and other minerals were applied based on data from soil health cards by using drip fertigation techniques. In [44], the authors proposed a mobile device system to remotely monitor various soil characteristics. They utilized the inverse relation between soil resistance and soil moisture to estimate soil moisture content.

Many IoT technology systems have been successfully applied to irrigation and water quality monitoring in agricultural crops. In [45], an automated irrigation system was designed and implemented. The system used a smartphone to capture and process imagery of the soil near the root zone of the crop and estimated the water contents optically. In [46], the authors presented an autonomous drip irrigation system that was operated and monitored by an ARM9 processor. The system informed the user about any abnormal conditions, like lack of moisture, temperature rise, and concentration of CO_2. A real-time feedback control module was developed to monitor and control all the activities of a drip irrigation system. In [47], a fully automated and wireless controlled irrigation system was developed that mitigates subjective decisions about irrigation volumes and timing. In [48], the authors investigated an integrated system of IoT-based wetting front detector (IoT-WFD). The implemented system was divided in two sub-systems, a sensor node, and a web application server. In [49], the researchers developed an automated system that uses the IoT technology to monitor and gather the data related to the growth of crops in real time. The central unit extracted the recorded data to establish the crop growth model, predicted the requirement of crops in water for different growth periods, and applied the decision of irrigation.

Open Platform Communications (OPC) have been studied for agricultural machinery telemetry in smart farming. In [50], the suitability of Open Platform Communications Unified Architecture (OPC UA), which is the latest version of OPC technology for agricultural machinery telemetry applications, was studied. The authors presented both the server-side system, which was responsible for the combine harvester and the client system, which was utilized for remote monitoring. Moreover, they reported that the subscription latency was less than 250 ms when both the server and the client were located in the same region.

IoT technology systems have been also used in various aspects of agricultural crops in smart farming. In [51], the authors developed an intelligent IoT system to monitor wheat diseases, pests, and weeds. The system could diagnose and forecast wheat diseases, pests, and weeds, but also could provide recommendations to the farmers. In [52], an IoT system was designed to restrict the use of insecticides and fungicides. The system provided disease and pest data by utilizing prediction models based on correlation information, so that farmers could quickly handle them. In [53], the authors applied IoT humidity sensors to record the moisture in a Lingzhi mushroom farm. The average humidity was reached up to 90-95%. The functional status of sprinkler and fog pumps were monitored using a CCTV (Closed-Circuit Television) system, while a microcontroller was used to control switching on and off operations.

IoT applications have been utilized in livestock, too. In [54] the health status of dairy cows was investigated using IoT and Wireless Body Area Networks (WBANs). The Long Range (LoRa) off-body wireless channel has been characterized at 868 MHz. Results demonstrated that large-scale fading could be sufficiently described by a log-normal path loss model. In [55], authors introduced a WSN for snail detection in the field. The proposed network could be used both to trigger an alarm in case of snail tracking or to further incorporate statistical models of snail detection with environmental variables as temperature or humidity.

Nowadays, many platforms for IoT solutions in agriculture are commercially available. These platforms provide data storage, data management and data analytics. Table 3 summarizes the most popular IoT solutions for smart agriculture. These IoT platforms have a common goal; to simplify the input and utilize of data from all kinds of sources, using a common Application Programming Interface (API). Such platforms usually implement functions of data filtering and aggregation. The benefits of these IoT platforms in smart agriculture are not clearly clarified [56]. Currently, there are some challenges to overcome that still prevent the widespread use of IoT for smart irrigation, such as the advanced IoT software platforms, the integration of advanced sensors, etc. [57]. Furthermore, emerging IoT technologies can be used to collate a vast amount of data. Such data can then be analyzed to

Table 3: IoT Solutions in Smart Agriculture.

IoT Platform	Services
OnFarm	View critical information in the office or on the go in a user-friendly dashboard
Phytech	Plant-based application for optimized irrigation
Semios	A powerful tool in yield improvement (insect assessment and respond, disease and plant health conditions in real-time)
EZFarm	IBM Research team uses the Internet of Things to help local farmers in Kenya optimize crop growth
KAA	An open IoT cloud platform, fully customizable, based on flexible microservices, provides a set of most wanted IoT features out of the box
MbeguChoice	The result of a collaboration between the Kenya Agriculture and Livestock Research Organization (KALRO), the Kenya Plant Health Inspectorate Service (KEPHIS), Kenyas crop seed companies, Agri Experience, Ltd., and Kenya Markets Trust
Farmlogs	Farm management software for automatic activity recording
Cropx	Provides an integrated hardware and software system for measuring soil moisture, temperature and electrical conductivity
Farmx	Provides ground-truth sensing from the soil. Adds canopy growth and water content imaging to see the impact of your management on canopy health
Easyfarm	Tracks crops, crop rotations, field histories, livestock, machinery, fuel, seed, and inventory

filter and calculate personalized crop suggestions for any agricultural farm.

5. IoT Protocols in Smart Farming

According to [58], the basic components of a smart farming architecture are the network sensors, the gateways, the server, and, of course, the network. The network sensors, which are a collection of sensors placed in farm swathe, i.e., an area of 1×1 or 2×2 meters of farmland, communicate with the gateway [58], which stores the data locally and sends data to the internet according to predefined scheduling. The data from the gateway are sent to the server via Remote Terminal Unit (RTU), which is responsible for capturing data from sensors. For the communication between the gateway and the server, the selection of the utilized radio access technology depends on the application. The server can be implemented by using a cloud computing infrastructure, which offers the advantages of low-cost implementation and scalability. For the connection between the network sensor and the server (and consequentially the users), the Transmission Control Protocol/ Internet (TCP/IP) protocol can be used, which is compatible with the majority of the network hardware components. It should be noted that the integration of heterogeneous data from different sensors used in smart farming systems is particularly challenging, due to software and hardware compatibility issues.

5.1. Wireless Communication Protocols for physical and link layer

The most relevant communication protocols that can be used are IEEE 802.11 (Wireless Fidelity - Wi-Fi), IEEE 802.16 (Worldwide Interoperability Microwave Access - WiMax), IEEE 802.15.4 (Low-rate Wireless Personal Area Networks - LR-WPAN), $2^{\text{nd}}/3^{\text{rd}}/4^{\text{th}}$ generation of cellular networks (2G/3G/4G), IEEE 802.15.1 (Bluetooth), LoRaWAN R1.0 (LoRA) [59], SigFox, and Narrowband Internet of Things (NB-IoT) [60]. Among them, LoRA and NB-IoT are the two promising technologies, which comprise several technical differences. The selection of the communication protocol depends on the desired achievable rate, the energy consumption, the range, the implementation cost, etc. NB-IoT is a Low Power Wide Area Network (LPWAN) radio technology standard developed by 3GPP to enable a wide range of cellular devices and services. It focuses specifically on indoor coverage, low cost, long battery life, and high connection density. NB-IoT uses a subset of the LTE (Long Terminal Evolution) standard but limits the bandwidth to a single narrow-band of 200kHz. On the other hand, LoRaWAN offers a very high range (20 miles) and very low energy consumption, but very limited data rates, i.e., 0.3-50 kbps. In fact, this is satisfactory for transmitting measurement data from the most typical agriculture sensors. A comparison of these protocols is provided in Table 4. Indicatively, for the communication between the sensor nodes and the gateway, the IEEE 802.15.4 protocol has been proposed by [58]. In the same work, the use of General Packet Radio Service (GPRS) or Enhanced Data Rates for Global System for Mobile Communication (GSM) Evolution (EDGE) has been proposed for the communication between the RTU and the server.

Table 4: Comparison of relevant wireless communication protocols.

	Frequency band	**Data rate**	**Range**	**Energy consumption**	**Cost**
WiFi	5 - 60 GHz	High	Medium	High	High
WiMAX	2 - 66 GHz	High	High	Medium	High
LR-WPAN	868/915 MHz, 2.4 GHz	Low	Low	Low	Low
Cellular	865 MHz, 2.4 GHz	Flexible	High	Medium	Medium
Bluetooth	2.4 GHz	Medium	Low	Very low	Low
LoRa	868/900 MHz	Low	High	Very low	High
SigFox	868/902/920 MHz	Low	High	Very low	Medium
NB-IoT	800/900/1800 MHz (EU)	Low	High	Low	High

5.2. Cloud Computing Service

Cloud computing can be used for a twofold purpose in smart farming applications, i.e., i) to gather and store information that is transmitted from the remote client and ii) to process the data and display the results to the users. Data processing includes visualization, data analytics, decision making, etc. The cloud service models can be categorized into three connected layers, namely Infrastructure as a Service, Platform as a Service, and Software as a Service, which correspond to the physical resources, the tools to implement a wide range of applications, and the Internet-based applications accessed by the end-users, respectively [61]. When developing and/or using

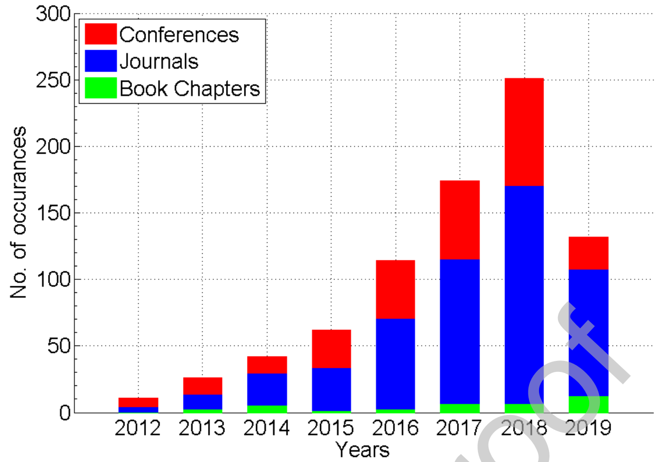

Figure 5: Stack diagram of papers from Scopus database with topic "UAV and Smart Farming".

a smart farming system, there are several issues that need to be considered, such as the corresponding charges and the security protocols.

6. Applications of UAV Technology in Smart Farming

The use of UAV technology for gathering information that helps farmers to taken decisions is currently a major research trend. The obtained results from the Scopus database with keywords "UAV and Smart Farming" show 865 total papers from 2004 to the present day. Fig. 5 shows the distribution of papers versus time. It is worth noting that the growth in the number of papers over the last seven years is almost exponential.

One of the key emerging technologies in smart farming is remote sensing [62]. The use of UAVs in agriculture along with extremely small MEMS sensors makes agricultural drones very attractive. In 2014, the Massachusetts Institute of Technology described agricultural UAVs as a green-tech tool in smart farming [63]. Undoubtedly, UAVs have played an important role during the last years in agricultural crops; moreover, it is expected that the development of UAV technology will continue expanding its application in smart agriculture [64]. In the following paragraphs, a systematic review of the role of UAVs in smart farming is performed, thus highlighting the importance and the dynamics of this green technology in precision agriculture.

UAVs in agriculture have been deployed to address various issues in farm production. In [65], the authors introduced a new method for registering images of agricultural crops taken by UAV. Based on their proposed model, they presented a technique to align three-dimensional point clouds on the field, thus reconstructing 3D models of the crop to monitor growth parameters on a plant-level basis. A similar technique was applied in [66] to determine the crop height of maize and sorghum plants in the field. A novel method to monitor crop height of Sorghum plants using UAV and 3D model reconstruction was also utilized in [67]. The authors reported that the Root Mean Square Error (RMSE) of average individual sorghum height with hand-sampling field data was 0.33 m. A rather dissimilar problem was addressed by the authors in [68]. In their work, they used UAV and 3D model reconstruction to extract leaf area index (LAI) in Soybean plants. Measured LAI predicted accuracy corresponded with the one of a handheld device ($R^2 = 0.92$) and correlated with destructive LAI measurements ($R^2 = 0.89$). The researchers in [69] mounted a multi-spectral camera on a multi-rotor micro-UAV to simultaneously collect multi-spectral imagery and SoilPlant Analysis Development (SPAD) values of maize. The derived results indicated that UAV multi-spectral remote sensing technology is instructive for precision agriculture. The authors in [70] used a UAV with an RGB digital camera to extract vegetation indices based on visible reflectance for evaluating crop biomass. An acquisition platform to manipulate the farmland crop information collected by UAV was presented in [71]. Moreover, the potential of UAV-based remote sensing for aiding precision agriculture was examined in Indonesia [72]. The proposed system produced Orthophoto images and Digital Elevation models with accuracy up to 3 pixels or sub-meter discrimination.

The introduction of multiple-UAV systems in smart farming can provide a new breakthrough in cultivation. Although there are still many technological issues to be solved, there is a noticeable increase in the multiple-UAV systems in smart agriculture. The authors in [73] developed a multi-UAV system for agricultural fields using the distributed swarm algorithm. They analyzed the performance of the proposed system and they compared the derived results with a single-UAV system. Experimental results indicated that the multi-UAV system performed better than the single-UAV one. The researchers in [74] developed and presented an autonomous system for precision agriculture based on the use of multiple-UAVs. In [75], the authors combined Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) to address the problem of mission planning of multiple-UAV systems, which is actually a multi-objective optimization problem. They proposed a precision farming system consisted of several components/agents/drones to accomplish composite agricultural missions cooperatively. The objective of this work was to utilize limited resources of machinery equipment in smart farming. Finally, the combination of UAVs and unmanned ground vehicles (UGVs) was tested in various agricultural fields [76].

Smart sensors in precision agriculture have also been integrated using UAVs. The authors in [77] developed a smart flying sensor using UAVs and mapped the volume of grain inside a trailer during forage harvesting. A set of various sensors (Gas sensor, RGB-D sensor, Adafruit AMG8833 IR thermal camera, Raspberry Pi model 3B) has been combined to produce a comprehensive solution for the improvement of agricultural drones in [78]. This solution has been tested in the plowing process. Moreover, a supervised learning model based on the Support Vector Machine (SVM) was used to analyze and classify the data. In [79], the authors performed a feasibility study of a harmless tiltrotor for specific smart farming applications using Remotely Piloted Aircraft Systems (RPAS). An innovative approach of real-time processing using UAVs in smart agriculture has been utilized in [80]. The researchers developed and presented a hyper-spectral flying platform in detail with advanced processing capabilities in order to manage the data acquisition and allow onboard processing of various vegetation indices. The proposed system has been tested in a vineyard field.

One of the most important and useful applications of UAV technology in smart farming is weed detection and management. A new method was introduced in [81] to fuse low resolution multi-spectral and high-resolution RGB images for weed detection in rice fields. The researchers reported, by utilizing three different Neural Networks (NNs), that NN with the best weed detection performance was the one having M/M_{GT}[1] index between 80 and 108% and MP[2] between 70 and 85%. In [82], the authors proposed a system that detects vegetation, extracts features, and classifies results using Random Forest (RF) technique to obtain an estimation of the crops and weeds distribution in the field of sugar beet plants. Experimental results demonstrated that the system can identify crops and weeds in the field individually. The authors in [83] applied the same as in [82] machine learning technique to UAV imagery

[1]The M/M_{GT} index indicates the percentage of pixels found to be weed

[2]The MP index shows the percentage of correct weed pixel detection

from sunflower and cotton fields by developing an automatic object-based image analysis algorithm. The field of sugar beet plants was selected by the researchers in [84], [85] to address the problem of selective weed treatment in autonomous crop management. Their approach was based on semantic weed classification with multi-spectral imagery obtained by a micro aerial vehicle (MAV). Derived results reported performance of 0.8 F1-score[3] for weed detection. A new classification system for weed detection in vegetable fields, such as spinach, beet, and bean, by applying Convolutional Neural Networks (CNN) was introduced in [86], [87]. In these two studies, the authors incorporated deep learning techniques with line detection to enhance the classification procedure. They reported that the overall precision for the bean, spinach, and beet was 69%, 81%, and 93%, respectively. Finally, a new weed detection approach from RGB images acquired by low-cost UAV imagery system was presented in [88], [89], [90].

UAV technology in smart farming has been tested and applied in agricultural crops by extracting various vegetation indices. The authors in [91] utilized single state vegetation indices (VIs) and multi-temporal VIs to predict the grain yield based on multi-spectral and digital images obtained by UAV. In [92], they used imagery acquired with a UAV and a multi-spectral sensor to test the correlation between reflectance and vegetation indices. Several key parameters have been estimated using UAV technology in agronomic wheat crops. Among all, vegetation indices and normalized difference vegetation index (NDVI), as well as spectral vegetation index (SVI), green area index (GAI) and high-resolution imagery have been evaluated to predict grain yield [93], to monitor wheat breeding in a large trial [94], to monitor key development stages of winter wheat [95], to detect plant stress caused by yellow rust disease in winter wheat [96], to support decision making systems for wheat and rapeseed crops [97], and to quantify plant density in wheat crop [98].

UAV technology has been utilized also in various agricultural crops of smart farming to manage yield. In [99], the authors applied UAV-based smart agriculture technology to address various issues of palm oil plantations, such as disease detection, yield prediction, pest monitoring, virtual plantations creation, etc. The researchers in [100] integrated a WSN with a

[3]F1-score is a measure of a test's accuracy in the statistical analysis of binary classification

smart UAV platform to perform real-time measurements that influence grape yield and quality. The objective of this work was to optimize the production efficiency in a cost-effective way. An innovative approach to support farmers with automation tools and strategies for the analysis of fertilization techniques in barley was introduced in [101]. In this work, the authors used a UAV-based solution to capture aerial RGB images in order to estimate nitrogen fertilization and barley yield. To achieve their objective, they developed a deep convolutional neural network to extract key features from the images automatically. They reported an accuracy of 83% for the estimation of nitrogen fertilization, and high correlation with low RMSE for yield estimation. Finally, a deep convolutional neural network was developed for the prediction of crop yield in [102].

Field-level phenotyping is considered in the literature as the main bottleneck to improve efficiency in breeding programs [103]. The evolution of IoT and UAV technology is expecting to mitigate this bottleneck in breeding techniques of precision farming and precision phenotyping. To this end, the authors in [104] examined the combination of UAV technology and image analysis as a high-throughput phenotyping technique. For their experiments, they planted four different maize cultivars. A similar research approach was also applied in [105]. This work aimed to evaluate the use of multispectral imagery obtained by UAVs as phenotyping tools. The authors in [103] proposed an unmanned aerial system (UAS) high throughput phenotyping framework for the selection of cotton genotype. The researchers in [106] estimated UAS-based phenotyping (chlorophyll content, nitrogen concentration, and LAI) of soybean combining multi-sensor data fusion, such as high spatial resolution RGB, multispectral and thermal data, and extreme learning machine (Partial Least Squares Regression (PLSR), Support Vector Regression (SVR), and Extreme Learning Machine based Regression (ELR)). A dual-camera high throughput phenotyping (HTP) platform on a UAV was developed by the authors in [107] to collect multispectral images for large scale soybean breeding fields. They applied a machine learning model based on the Random Forest technique to measure crop geometric features and they reported a 93% accuracy in classifying soybean maturity.

The application of UAV technology in smart farming has also been tested in more complex problems. The researchers in [108] hypothesized that UAV technology can be applied to estimate the number of existing flowers, the quantity of nectar, and habitat potential for honeybees. Generally speaking, flowers is a sensitive ecosystem, which is difficult to analyze. To overcome

Table 5: Summary of key innovations and UAV utilization endeavors in smart farming.

Key innovation / UAV utilization endeavor	**References**
3D crop modeling	[65], [66], [67], [68]
Multi-spectral imagery	[69], [70], [71], [72]
Multiple-UAV systems	[73], [74], [75], [76]
Smart sensors integration	[77], [78], [79], [80]
Weed detection and management	[81], [82], [83], [84], [85], [86], [87], [88], [89], [90]
Vegetation indices extraction	[91], [92], [93], [94], [96], [97], [98], [95]
Yield management	[99], [100], [101], [102]
Field-level phenotyping	[104], [105], [103], [106], [107]
Complex agricultural issues	[108], [109], [110], [111], [112]

this, the authors proposed a methodology to analyze flowers in tree plantations and they reported an estimation of 5.3 million flowers in a one-hectare plantation. Irrigation management is also a complex issue in smart agriculture. In [109], the authors acquired images from a thermal imaging camera mounted on a UAV to evaluate the soil properties of sugar beet plants in water. The use of pesticides in agriculture is also essential for crop yields, as well as for the environment. The researchers in [110] developed and evaluated an algorithm to self-adjust UAV routes during the chemical spraying procedure in a crop field in order to reduce the waste of pesticides and fertilizers. An extension of the previously mentioned algorithm was performed in [111], by utilizing meta-heuristics (Genetic Algorithms, Particle Swarm Optimization, Simulated Annealing, and Heal Climbing) in route adaptation of UAV. Finally, the authors in [112] introduced an alternative approach to address the problem of birds invasion in rice fields. They presented a UAV-based system to detect and chase birds from cultivated fields by producing various sounds, such as birds distress call or predators call.

Table 5 summarizes the related work that has been published in the literature grouped by the key innovations and UAV utilization endeavors in smart farming.

7. Use case: The ARETHOU5A Project description

In this section, the main concepts of ARETHOU5A[4] project are briefly outlined. ARETHOU5A Project will exploit the state-of-the-art technologies and, in particular, the emerging developments in the field of Internet of Things (IoT), low-power wide-access radio technologies, energy harvesting, and machine learning, as a means to promote rational use of water resources in agriculture. ARETHOU5A will contribute to the acceleration of the Smart Agriculture concept through a series of research and innovation actions focusing on the design, development, operation, and commercial exploitation of relevant hardware/software and IoT applications. These activities will eventually lead to a prototype end-to-end smart irrigation system deployed and demonstrated in the field.

The aim of ARETHOU5A project is to design and develop the rational management of irrigation water in two agricultural farms using 5G-IoT capabilities; one in a vineyard field and the other in a perennial olive field. In particular, the project provides a detailed description of an actual complete integrated IoT-5G network. Its flexibility allows meeting completely different performance requirements of real services for water irrigation. The project describes the design of an IoT-based platform that can automate the collection of environmental, soil and irrigation data.

The project framework is divided generally into three main layers, as illustrated in Fig. 6.

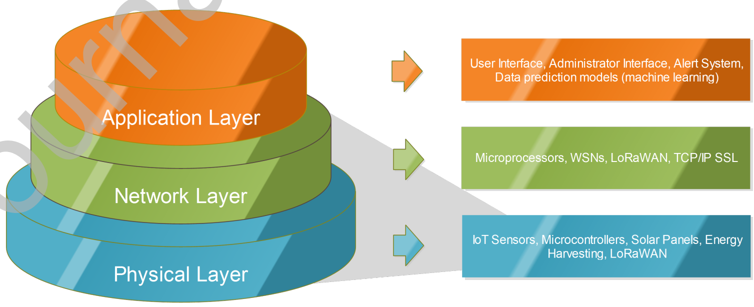

Figure 6: The main layers of ARETHOU5A project framework.

In the physical layer, all the requested information from the sensors installed on the field are gathered through WSNs and LoRaWAN networks,

[4]https://arethousa.dataverse.gr

incorporating IoT and 5G key technologies. The network layer is responsible for routing the collected data to the cloud. The application layer is fetching all the available data to the end-users (as well as to the administrators of the platform), providing various useful alerts or prediction values about irrigation. The framework of the project AREThOU5A is designed based on the capability of exploiting irrigation water in two farms (with grapes and olives) using 5G-IoT smart sensor technology. The physical quantities that will be primarily measured are the air temperature, relative humidity, and soil moisture. The weather forecast will also be recorded in these two farms for feeding the machine learning models.

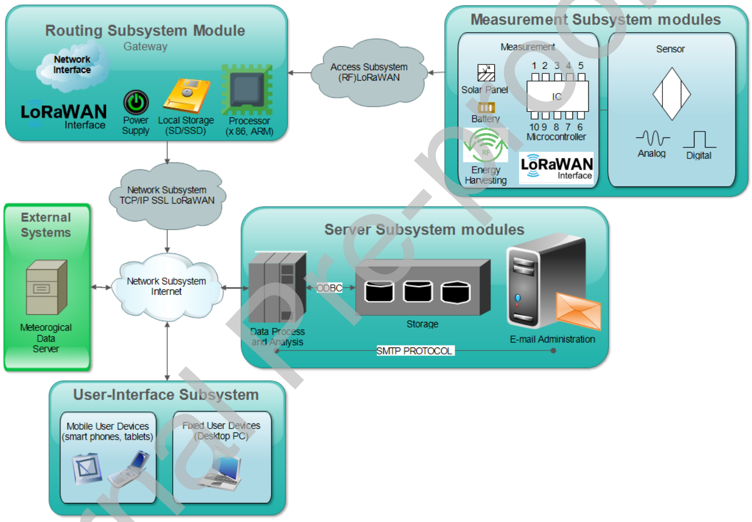

Figure 7: The system architecture of AREThOU5A project framework.

Based on the design requirements of the system as defined above, the system architecture of the AREThOU5A project is depicted in Fig. 7. It consists of seven discrete subsystems with integrated functions and operations: i) The measurement subsystem comprises of the sensor and the measurement modules. The sensor module is responsible for capturing and recording the environmental and plant-specific conditions, e.g. soil temperature, humidity and, salinity, while the measurement module processes the derived data. More particularly, the micro-controller is the heart of the module which controls all the procedures. The radio module forwards the collected data to a gateway using an unlicensed low-power and wide-area LoRa interface. The subsystem is powered by an autonomous battery that is charging by a solar panel and/or a novel RF energy harvesting circuit, ii) The routing subsystem gathers the measurement data from the remotely deployed sensors (measurement subsystem) and routes them to the next subsystem, operating as a gateway by interconnecting the field deployment with the main system back-end, iii) The server subsystem is deployed in the cloud and is responsible for storing the raw measurement data, performing data processing routines and, administrating the e-mail notification functionality, iv) The user-interface subsystem is responsible for the user interaction of different operating levels of the system through various input forms, such as web-based applications, v) The access subsystem is liable to interconnect the remotely deployed nodes in the field (measurement subsystem) with the gateway (routing subsystem) using the LoRa radio technology, vi) The network subsystem interconnects the gateway with the main system back-end using the LoRaWAN protocol and, finally vii) The internet-based network subsystem provides end-to-end connectivity among overall system and external subsystems.

8. Current Trends and Future Challenges

If we would like to clarify the current state, we would recognize that a new type of transformation is occurring in the agricultural industry. Agriculture has moved on from the legacy decision support systems equipped with a predefined time scheduling function in most of the cases, to a new era of cultivation systems that include various innovative technologies, like IoT, UAV, artificial intelligence, machine learning, and so on. Most of these systems are in a prototype form (not commercial) and they usually address to a specific (or a set of) cultivation process. To the best of our knowledge, none of these systems is integrating a group of cultivation processes or even the processes of the whole cultivation period (from sowing to harvest). As also expected, some of the key enabling technologies exhibit more benefits in various cultivation processes than others; yet all of them are difficult to be adopted by the end-users (farmers).

The introduction of IoT technology in various farming practices has improved the overall metrics in cultivation with respect to the yield, the quality and quantity of the cultivated products, and the profit increase. IoT has started to reveal its potential benefits to the end-users, since it can support and assist in their decision making. On the contrary, IoT has to overcome many barriers regarding technological complexity, parameterization, user-friendliness, installation, performance, and system efficiency. Ultimately, the key issue for the penetration on a large scale of IoT technology in agriculture will be the addressing of improving cultivation practices that limit the specific goals of the farmers.

UAV technology was firstly introduced in agriculture for remote monitoring and observation. Although UAV has several limitations, mostly regarding to the power autonomy and communication efficiency, which are still to be addressed, the benefits of utilizing this technology have early emerged. Moreover, researchers, technology workers, but farmers as well, realize the multiple advantages of applying UAV technology in various aspects of the agricultural economy. Firstly, UAV plays (and will continue to play) an important role in weed detection and management. The nature of this agriculture problem in conjunction with the aerial capabilities of unmanned vehicles gives the option to end-users effectively manage weeds in cultivation. The introduction of machine learning techniques to multi-spectral imagery data collected by UAS, exploit even further the capabilities of UAV technology. Secondly, the potential of features extraction of various vegetation indices by utilizing UAV technology and multi-spectral imagery revealed the comparative advantage of such a technology in cultivation practices. Another important characteristic of the agricultural industry, that UAV technology contributes effectively, is field-level phenotyping. With the employment of UAV systems, field-level phenotyping will allow cultivators to estimate the overall plant growth and predict the final yield in a more efficient way. Once again, UAV technology has revealed the comparative advantage of such a technology in the field against the use of static cameras. Finally, several complex agriculture issues are managed to address (in an early stage) by the utilization of UAV technology in the field.

Undoubtedly, the agricultural industry, and consequently agricultural economy, is a highly challenging ecosystem of the global economy with high potential. Therefore, it is expected that key emerging technologies, like IoT and UAV will play a pivotal role in the future. Still, there are several agricultural/cultivation issues to be addressed, such as weed intervention and management, field-level phenotyping and multi- as well as hyper-spectral imagery to manage diseases, irrigation water, fertilizers, pesticides, growth, and yield on a plant-basis, 3D plant mapping and management, quality and quantity improvement of the crop, and various complex agricultural issues. In this challenging environment, key enabling technologies, such as IoT and UAV, will efficiently and effectively contribute to smart farming practices by meeting the following constraints: system simplicity and scalability, user-friendliness, easy installation, and profit increase. As a result, these technologies will ultimately transform traditional farming practices into an evolutionary agricultural ecosystem, by satisfying human needs in both urban and rural environments.

9. Conclusion

It is apparent that the agriculture industry is undergoing an important turning point during the last few years. The traditional practices in agriculture are transforming into a new "intelligent" perspective in the process of cultivation. The so-called "Agri-Food 4.0" is bringing a revolution in traditional farming by introducing ICT technologies to the field. The use of WSNs, IoT sensors, UAS, along with optimization techniques and machine learning algorithms can introduce a novel approach in precision farming leveraging the potential of agricultural crops. These key emerging technologies can further improve crop yield, quality, reduce cost, and mitigate the ecological footprint of traditional farming. Undoubtedly, smart farming technology has lead cultivators to modern and novel practices by monitoring crops even at a per plant level.

Irrigation is an essential process that influences crop production by supplying water to the field. The ARETHOU5A project will have to address several challenges of precise water irrigation in two different farms, thus contributing to the smart farming concept. The utilize of 5G-IoT technology incorporated with energy harvesting and machine learning techniques will deliver a prototype end-to-end smart irrigation system.

Smart farming has still several agronomic aspects to be properly addressed. These, among all, include precise irrigation with salts minimization, efficient and rational fertilization and pesticide utilization by drastically reducing pollution aquifer, adequate weed management, thus improving crop yield, and efficient management of crop diseases in the field. Furthermore, the monitoring of crop growth on a plant basis by constructing efficient and precise 3D modeling algorithms, the efficiency of the nutrients from roots to plants using non-intrusive techniques, the food traceability with modern approaches (e.g. blockchain technology), thus delivering quality certified products to the consumers, and the accurate yield prediction in farms will bring a novel aspect in future agricultural industry. It is expected that the IoT technology, the UAV systems and the machine learning algorithms will significantly contribute to the new era of the agri-food industry.

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