A Survey on LoRa for Smart Agriculture: Current Trends and Future Perspectives

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***Abstract*—This article provides a survey on the adoption of LoRa in the agricultural field and reviews state-of-the-art solutions for smart agriculture, analyzing the potential of this technology in different infield applications. In particular, we consider four reference scenarios, namely, irrigation systems, plantation and crop monitoring, tree monitoring, and livestock monitoring, which exhibit heterogeneous requirements in terms of network bandwidth, density, sensors' complexity, and energy demand, as well as latency in the decision process. We discuss how LoRa-based solutions can work in these scenarios, analyzing their scalability, interoperability, network architecture, and energy efficiency. Finally, we present possible future research directions and point out some open issues which might become the main research trends for the next years.**

***Index Terms*—Internet of Things (IoT), LoRa, LoRaWAN, low-power wide-area network (LPWAN), precision agriculture, smart agriculture, smart farming, wireless sensor networks (WSNs).**

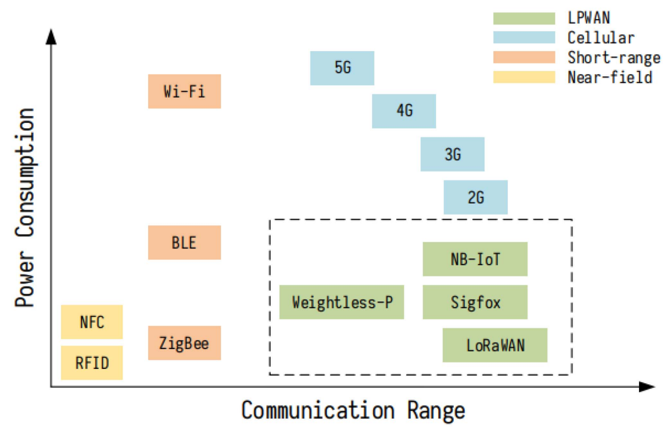

Fig. 1. Classification of wireless technologies: power consumption versus communication range [11].

I. Introduction

In THE near future, the agricultural sector is called to face a significant challenge due to increasingly scarce resources, extreme weather conditions, a growing population, and a reduction in arable land [1]. Indeed, according to the FAO, by 2050, the world's population will reach about 10 billion and, to be able to feed everyone, we will have to produce 70% more food [2], [3]. A practical and feasible solution is to move from the old farming concept to smart agriculture, with the adoption of information and communications technologies (ICTs) that help farmers to monitor, manage, and optimize their operations more effectively [4].

In particular, the introduction of the Internet of Things (IoT) applications, every single step of agricultural production can be improved: from soil management to minimizing water consumption, from plant protection to animal health and farm automation [5], [6]. Smart devices located infields are able to collect information and control the evolution of the different processes at various production stages. Besides, the miniaturization of electronic components allows to implement IoT sensors with reduced form factor and energy consumption, monitoring many variables of interest, such as temperature, humidity, wind speed and direction, soil conditions, chemical concentrations, crop growth, and solar exposure, as well as possible damages caused by drought, hail, or flooding. IoT systems integrate all this and other data and turn it into useful statistics: for example, predictive analysis allows farmers to use the strictly necessary resources (water, pesticides, fertilizers, etc.) and only where there is a real need, e.g., for poorly irrigated areas of the field, weak or sick plants, etc. [7], [8].

Despite such potential benefits, the deployment of smart agriculture systems is still in its infancy. Indeed, an obstacle to the digitization of agriculture is the lack or limitations of Internet connectivity in many areas. In the literature, several communication protocols have been proposed, with different characteristics related to cost, coverage, power consumption, and reliability [9]. Among the available technologies (summarized in Fig. 1 in terms of power consumption and coverage range), low-power wide-area networks (LPWANs), enlightened in a dashed box in Fig. 1 represent the best solution for supporting smart agriculture requirements. One of the most adopted LPWAN technology is LoRaWAN, which offers wide network coverage, built-in security, low cost, and limited power consumption during operation [10].

Indeed, LoRaWAN is an open system based on a very robust modulation (called LoRa), which provides several interesting features for covering rural areas with simple devices [9]. For

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such reasons, LoRa has been widely employed and tested in the agricultural field, connecting environmental sensors measuring temperature, air/soil moisture, etc., or to control different kinds of actuators (e.g., irrigation valves), and in applications, such as tractor communications, livestock monitoring, and location tracing [12], [13], [14].

Differently from existing surveys, which either treat LoRa together with all other IoT solutions or consider very specific technological aspects, we consider the adoption of these systems from an holistic perspective. For example, LoRa is cited in [5] in the general framework of IoT; [7] cites LoRa among the most promising technologies for agricultural IoT, and the same plan is followed by [8] which dedicated a section to LoRa in Enabling Communication Technologies; similarly [15] includes LoRa in IoT communication protocols suitable for smart agriculture. On the other hand, [16] is specific to LoRa but is focused only on the protocol performance, [13] takes into consideration only the energy consumption of LoRa, [17] discusses the application of the technologies of industry 4.0 in the context of smart agriculture. Papers [18] and [19] deal with specific issues meaning the decision support system (DSS) and robotics in agriculture, respectively. Instead, in this article, we strive to provide a thorough and focused analysis on LoRa/LoRaWAN application in smart agriculture, offering a comprehensive view of the advancements and in-field applications of this IoT technology.

LoRaWAN relies on LoRa modulation, a robust chirp-based modulation scheme, patented by Semtech [20]. It supports wireless connectivity with limited data rates over large areas and without the need of an operator. LoRaWAN is widely used in smart industry, smart home, smart city and, increasingly, in the smart agriculture environment. In the view of the authors of this article, LoRaWAN possesses five main strengths (low-cost, long-range, low-power, no-operator, and unlicensed spectrum) that can bridge the gap between smart agriculture and smart cities or industries. Moreover, several recent improvements on the resource allocation, channel access protocol, and network planning can enhance the efficiency of LoRaWAN networks, reducing capital and operational costs [21]. In rural areas, several experiments have demonstrated good coverage of LoRa [12], [22], [23]. Coverage ranges of up to 5 and 47 km have been obtained in the non-line-of-sight (NLOS) and line-of-sight (LOS) propagation conditions, respectively. In addition, in the case of NLOS propagation, the coverage range can be increased by using an unmanned aerial vehicle (UAV) [24], [25]. In terms of power consumption, LoRa offers up to 15 years of battery life to its devices. The low power consumption is a key feature of LoRa that makes it an ideal choice for smart agriculture applications. It was demonstrated experimentally that the estimated battery lifetime of a LoRa device may be six times that of a Wi-Fi device and two times that of a ZigBee device [26].

In this article, we provide a broad survey of LoRa-based smart agriculture systems, analyzing the state-of-the-art and highlighting for each solution the possible adoption of Machine Learning, control automation techniques, and energy autonomy features. We classify these works in four main categories: 1) irrigation systems; 2) plantation and crop monitoring; 3) tree monitoring; and 4) livestock monitoring. These LoRa systems are analyzed in terms of scalability, interoperability, network architecture, energy efficiency, and point out some open issues which traverse most of the current smart agriculture systems. References have been selected based on recent papers dealing with smart agriculture; however, some contributions in different fields useful as a benchmark are cited as well. Finally, we present the lessons learned and draw future research directions which we think crucial for the success and widespread of such technologies.

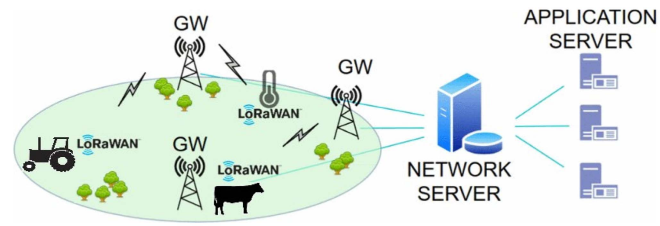

Fig. 2. LoRaWAN typical architecture.

The remainder of this article is structured as follows. Section II provides an overview of LoRa technology and its perspectives in agriculture, while section III offers a brief summary on smart agriculture applications and their main challenges. Section IV reports on general purpose LoRa-based IoT platforms applied to smart agriculture. Section V, instead, discusses specific vertical solutions for smart agriculture, according to the four above-mentioned categories. Lessons learned and future research directions are proposed in Section VI. Finally, conclusions are drawn in Section VII.

II. LoRa and Its Perspectives in Agriculture

LoRa technology is a proprietary physical layer technology patented by Semtech, which is revealing as a promising solution for large-scale low-power IoT deployments, including smart agriculture applications. Indeed, by operating in the unlicensed industrial, scientific, and medical (ISM) radio bands and with a robust chirp-based modulation scheme, LoRa provides a cheap solution for supporting wireless connectivity with limited data rates (from 0.3 to 27 kb/s) in large areas and without the need of an operator. Moreover, LoRa transmissions are regulated by having a maximum transmission power of 25 mW (14 dBm) in the uplink, a configurable bandwidth of 125, 250, or 500 kHz, and a duty cycle of 0.1%, 1.0%, and 10%, which permit low energy consumption. In some scenarios, the battery of LoRa devices can last up to 15 years.

Although LoRa technology is limited to the physical layer, different network solutions can be built on top of it, by exploiting its transmission interfaces. Among these, the most consolidated one is the open-source solution promoted by the LoRa Alliance, which is called LoRaWAN [27]. LoRaWAN networks are based on a simple star of star topology (Fig. 2): end-devices (EDs), such as sensors or actuators deployed infield, transmit packets on the wireless medium to fixed nodes called gateways (GWs), which, in turn, forward the collected packets to a central network server (NS) interacting with several application servers (ASs) [28]. The network infrastructure

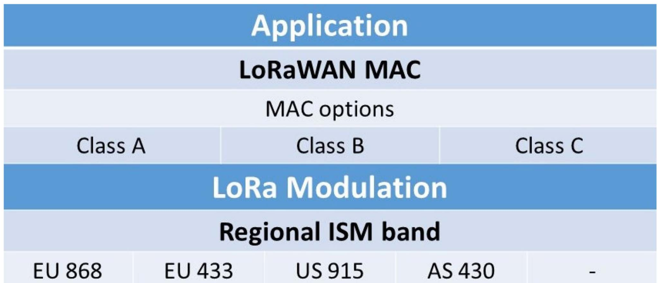

Fig. 3. LoRaWAN technology stack.

between GWs, NS, and ASs is typically based on a wired Internet technology, while EDs are not associated to a specific GW, which greatly simplifies implementation (e.g., in case of mobility [29]): in case a duplicate packet is simultaneously received by multiple GWs, the NS is responsible of filtering these packets and performs other simple decisions on network configuration.

To minimize the protocol complexity and the energy consumption, LoRaWAN employs a simple Aloha MAC protocol and defines three classes of devices (Fig. 3). Device classes represent different ways of managing the reception operations performed by the EDs. Class A devices, corresponding to the lowest energy profile, can receive downlink packets only in two time windows following the transmission of their own packet to the GW. In other words, devices can sleep all the time and downlink transmissions are triggered only after an uplink one. Class B devices add to this possibility a periodic scheduling of reception windows, by keeping a time synchronization with the GW. Finally, class C devices are constantly listening to the channel for downlink packets. Any time that a new packet is ready for transmission, devices attempt to transmit by randomly selecting one of the available channels in the ISM bands (e.g., in the 868 MHz there are 16 channels in Europe), together with a modulation parameter called spreading factor (SF). More into details, six different SFs are used in LoRa (from SF7 to SF12), which result in different symbol times and in almost orthogonal transmissions: when two signals modulated at different SFs overlap, the GW is able to decode both transmissions in a wide range of power ratios among the signals [30]. Unlike many other IoT technologies, the LoRaWAN specification offers dedicated end-to-end encryption to application providers, together with network-level security primitives, which allow sharing the same network among multitenant applications [31].

Summarizing, the ease of deployment with excellent coverage, the availability of devices with very low energy demand, and intrinsic security mechanisms make these systems very suitable for innovative agriculture applications. Indeed, several state-of-the-art IoT applications in smart agriculture are based on LoRa/LoRaWAN networks. For example, LoRa is used to connect sensor nodes measuring environmental parameters or to control different kinds of actuators (e.g., solenoid valve for irrigation purposes), and in applications such as livestock monitoring and location tracing [10], [13], [14]. These applications are not critical for data rates and latency, but often require to work in large rural areas, with limited access to energy grids and the Internet, and with decision mechanisms which benefit from data-driven learning.

III. Smart Agriculture Applications and Challenges

While industrial production processes have already become smarter and autonomous thanks to the implementation of the so called Industry 4.0 concept, the integration of technologies such as IoT, artificial intelligence (AI), robotics, and big data is more recent in agriculture. The availability of IoT technologies for supporting wireless connectivity in rural areas and controlling infields smart objects shows a great potential for improving the agricultural sector, toward the so called smart agriculture [17], [18], [19]. Indeed, farm monitoring and automation can make production more efficient and sustainable [7], by promptly detecting and reacting to water or moisture stress, wastes of raw materials, crops' diseases, pests, and nutrient deficiencies, as well as problems related to the wellbeing of farm animals. The interest on the development of smart agriculture applications has been demonstrated by the recent commercialization of agricultural sensors and robots (called Agribots), specifically designed for reducing the intense physical labor traditionally required in agriculture [15].

Apart from the availability of smart devices for interacting with the farm in the physical world, smart agriculture applications require to build a digital representation of the farm status and a decision logic based on the collected data. Different protocols can be envisioned both for providing the wireless connectivity to heterogeneous devices (from simple low-cost temperature sensors, to complex remote-controlled robots) and exporting data for analysis and decisions [32], [33].

Since a large amount of data can be produced by agricultural sensors, big data analysis can provide efficient monitoring and processing methods [34]. Data processing may involve various features such as data loading, validation, aggregation, prediction, classification, image or video processing, and data mining. Thus, based on the acquired data, DSSs can optimize the productivity and reduce the ecological footprint of the farm.

Researchers recognize that digitization of farming processes and activities is an important challenge for the adoption of smart agriculture technologies [32], [35]. In particular, the major challenges to digitization in agriculture can be categorized as follows.

1) *Communication Issues:* As we will detail later, large-scale implementations of IoT solutions require robust and secure network architectures. The reliability of communicating information still represents a challenge to be addressed in the agricultural context and justifies the adoption of LoRa/LoRaWAN technologies.
2) *Energy Management:* The power supply in devices for smart agriculture is a significant challenge and energy harvesting systems are a relevant area of research. The main issue concerns the sensor's power supply and how to optimize efficiently the power consumption. Moreover, distributed nodes can execute some

computations (Edge computing) which consumes more energy, while sensor batteries have a limited capacity. Consequently, smart devices require efficient energy storage and supply.

3) *Data/Device Heterogeneity:* In general, the agricultural data is produced by heterogeneous sensors (soil sensors, weather sensors, trunk sensors, leaf sensors, etc.). In addition, IoT devices generally use different network protocols and platforms. Thus, in addition to sensors heterogeneity, network and protocol heterogeneity should be considered as well. Getting these technologies to work together is often an issue, especially for unskilled farmers.
4) *Physical Deployments:* Spatial deployment of devices on farms proves to be a significant challenge, especially when the entire farm needs to be monitored across a large area and with different application scenarios (soil, plants, trees, animals, etc.).
5) *Data Management:* The difficulty of interpreting the data can be a huge barrier: indeed, numerous sensors are necessary and big data analysis could be required to better understand and forecast the unpredictability of agricultural ecosystems.
6) *Generic Platform:* To promote the adoption of smart agriculture technologies is often required to develop user friendly software platforms. The challenge here is to build a universal platform that can be easily modified to support different types of monitoring ranging from specific crop to livestock.

These challenges, together with the cost of infrastructure investment, the complexity of technologies, lack of farmers' education and training, data ownership, and privacy and security concerns, has motivated the research and development of innovative platforms, specific network technologies, and new architectures for smart agriculture [32], [35].

IV. Generic LoRa-Based Platforms

Since agricultural applications are widely different, varying from soil and air monitoring, to irrigation automation and livestock breeding, several general purpose IoT platforms have been adapted for farmers to accommodate all these applications together under a unified, easy to understand and simple to use interface. Therefore, in this section, we will discuss some of these LoRa-based platforms horizontally designed for smart agriculture, while in the next one, we will dig into more vertical and application-specific systems, focusing on the four reference scenarios depicted in Fig. 4.

Generic and open IoT platforms can indeed help to digitize farms by integrating numerous agriculture applications, harmonizing specific sensing devices, actuators, and decision logics, which exhibit heterogeneous requirements in terms of network bandwidth, latency, sensors' complexity, and energy requirements. A clear example is constituted by FIWARE [36], a powerful open-source platform, sponsored by the European Commission, that provides standardized interfaces for many different IoT sectors including agriculture. The FIWARE platform includes several parts called generic enablers (GEs),

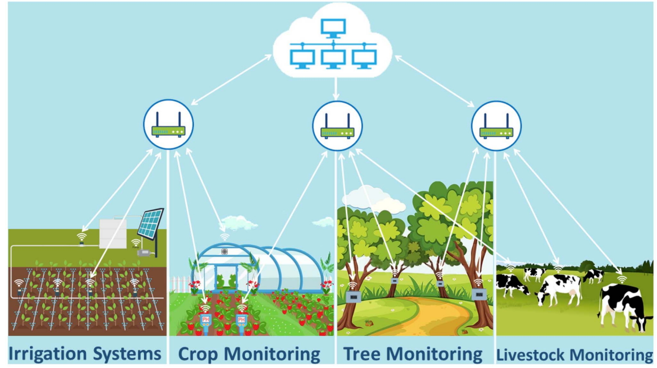

Fig. 4. Four reference applications in smart agriculture.

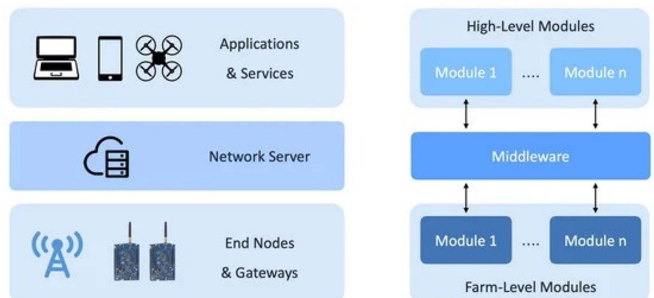

Fig. 5. LoRaFarM platform: levels and parallelism with LoRaWAN [42].

which provide components and reference implementations that support specific APIs, and can integrate data collected from heterogeneous sensors using different communication technologies, to create custom applications [37], [38]. Several GEs are available making it easier to interface with IoT systems, and the IoT Agent for LoRaWAN offers a bridge between LoRaWAN and the FIWARE Context Broker (the core component of the "Powered by FIWARE" platforms). Moreover, FIWARE can be combined with other third-party platforms to provide accessible tools to worldwide farmers and consumers too [39]. Another example is the work in [40] where low-cost, LoRa-based devices are used for soil temperature and humidity monitoring, and the data is processed and sent to the Cayenne IoT Platform for storage and visualization [41]. This platform is a drag and drop project builder for developers and engineers that can be used in different IoT applications. It encompasses cloud-based web applications as well as mobile apps for Android and IOS devices. Cayenne can integrate any tool into the library with a wide variety of IoT ready-to-use devices and connectivity options.

Other LoRaWAN-based IoT platforms are more specific to the agricultural world, aiming at improving the management of generic farms in a highly customizable way. For example, the LoRaFarM platform [42] has a generally applicable "core" infrastructure, which can be completed with specialized ad-hoc modules depending on the farm's characteristics and requirements. The LoRaFarM platform derives its topological structure from the LoRaWAN architecture, since low-level communication patterns are built around the LoRaWAN technology (see Fig. 5). Hence, expansion modules can be added at farm level (or low level), if they include physical hardware to be installed in the deployment (sensors or actuators), as well as a high level, in case data processing is needed. The middleware, in the LoRaFarM domain, refers to the set of entities and technologies by which data coming from farm-level modules are collected, stored, and exposed to high-level modules. This middleware can be defined as a sort of "connecting layer" between the farm and the back-end domain.

One of the main advantages of the LoRaFarM platform is that heterogeneous subnetworks, in terms of capabilities (transmission range, data throughput, and energy consumption), can be incorporated without altering the platform structure and, thus, making it highly scalable, flexible, and suitable for a wide range of scenarios. Indeed, this gives the freedom to choose the most suitable communication protocols and traffic policy to monitor and control the farm different areas, such as greenhouses and fields. Messages between nodes employing different protocols are translated by a multiprotocol GateWay (mpGW), enabling communications between non-LoRaWAN-enabled nodes and the LoRaFarM middleware, in a seamless way. Its protocol translation functionality, the mpGW can be enriched with edge computing features, to process and aggregate sensor data. Moreover, LoRaFarM can be extended with new functionalities like data analysis and prediction of the evolution of environmental parameters to prevent plant diseases, relying on AI and Machine Learning techniques.

Finally, the mySense environment proposed by Silva et al. [58] is a sensor data integration framework aimed to systematize data acquisition procedures to address common smart agriculture issues. It facilitates the use of low cost platforms such as Arduino and Raspberry Pi, making available a set of free tools based on the do it yourself (DIY) concept. The mySense platform builds over a 4-layer technological structure (sensor nodes, crop field and sensor networks, cloud services and front-end applications) and is accordingly divided into four levels of operation: Level 1, for data collection using common data transfer technologies (ZigBee, GSM/GPRS, LoRa, etc.); Level 2, for GWs (possibly) running local tasks according to the fog or edge computing paradigms; Level 3 for storing data in the cloud; and Level 4 for high-level applications. Data can arrive from any device provided that complies with the data formats allowed by the platform.

Summary and Insights: This section discussed LoRa-based platforms which can be exploited to unify different applications into one simple and easy-to-use platform. Platforms such as Fiware, Cayenne, LoRaFarM, and mySense provide standardized interfaces to integrate different agricultural applications with each other. These platforms provide ready-to-use solutions and connectivity between heterogeneous networks. With these platforms, LoRa can integrate and complement existing systems based on other network technologies (ZigBee, Bluetooth, etc.), making them highly scalable.

V. Application-Specific LoRa Platforms

In this section, we provide an in-depth review focusing four reference scenarios: 1) irrigation systems; 2) plantation and crop monitoring; 3) tree monitoring; and 4) livestock monitoring, which broadly cover most of smart agriculture applications.

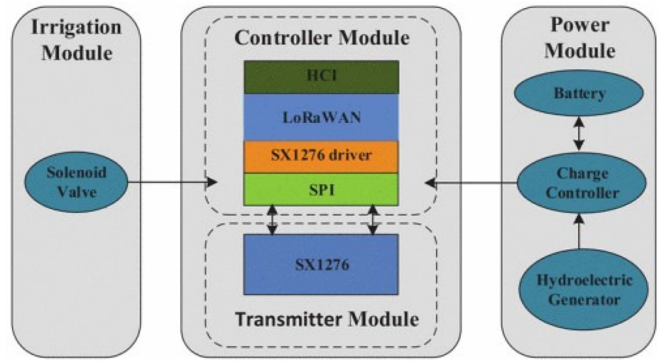

Fig. 6. Energy-neutral irrigation node described in [51].

A. Irrigation Systems

Accurate monitoring of the soil water status allows to achieve seasonal water savings of up to 90% compared to traditional management, increasing productivity and introducing significant savings in energy costs for the water pumps management [59]. To improve water management in agriculture, it is necessary to analyze and monitor the complex water interactions that occur in field, following the concept of soil-plant-atmosphere (SPA) continuum systems [60]. Indeed, the knowledge of the water status of the SPA system plays a significant role for understanding the crop water stress and implement water saving mechanisms with a minimal effect on the production [59].

Measuring the evapotranspiration (ET), which refers to the amount of water that passes from the soil into the air due to the combined effect of plant transpiration and evaporation, is another complex task. Examples of these sensors are the lysimeters or sophisticated micro-meteorological sensors (e.g., Eddy covariance), whose cost and complexity limit their application to research studies [61]. Cheaper systems are the time domain reflectometry (TDR) technique or gravimetric methods [62], whose main limit is the difficulty in calibration and automation.

Some LoRa-based irrigation systems are implemented using development boards such as Arduino, ESP32, Pycom, or STM32, e.g., [43], [44], [46], [47], [48], and [51]. Few of them also include energy harvesting modules, such as an hydroelectric generator, allowing them to operate for decades. For example, the LoRaWAN-based irrigation system in [51] comprises an energy-neutral irrigation node (Fig. 6) with the following modules: controller module, power module, irrigation module, and transmitter module.

Exploiting AI and data coming from different sensor, such as air temperature and humidity, soil temperature and humidity, light intensity, etc. makes possible to develop and train specific irrigation models to calculate the exact amount of water to be distributed. For example, the works [54], [55], [56] provide machine-learning-based smart irrigation systems, all employing LoRa technology. In particular, in [55], a random

TABLE I
LoRa-Based Irrigation System Comparison

Reference	Features			Sensors						
	Machine Learning	Energy harvesting	Automatic Control	Temperature	Humidity	Soil Moisture	Soil Water Potential	Solar radiation	Water flow	Others
Boursianis et al. [43]	✓	✓	x	✓	x	✓	x	x	x	x
Kodali et al. [44]	x	x	✓	✓	x	✓	x	x	✓	x
Nisa et al.[45]	x	x	✓	✓	✓	✓	x	x	x	x
Ali et al. [46]	x	x	x	x	x	x	x	x	x	Pump current
Jiang et al. [47]	x	✓	x	✓	✓	✓	✓	x	x	x
Zhang et al. [48]	x	✓	✓	x	x	✓	✓	x	x	Pressure
Emharraf et al. [49]	x	✓	✓	✓	✓	✓	x	✓	x	Battery level
Yuan et al. [50]	x	✓	✓	✓	✓	✓	x	x	✓	x
Zhao et al. [51]	x	✓	x	x	x	x	x	x	x	x
Usmonov et al [52]	x	x	x	x	x	x	x	x	x	x
Vu et al. [53]	✓	x	✓	✓	✓	✓	x	x	x	x
Chang et al. [54]	✓	✓	✓	✓	✓	✓	x	✓	x	x
Henna et al. [55]	✓	x	✓	✓	✓	✓	x	x	x	Pressure
Loganathan et al. [56]	✓	x	✓	✓	x	✓	x	x	x	x
Froiz-Mìguez et al. [57]	x	x	✓	✓	✓	✓	x	x	x	x

forest classifier predicts the soil moisture and, thus, irrigation is planned accordingly. In [54], instead, multiple linear regression algorithm is employed to train the model using two highest correlation coefficient features: 1) light intensity and 2) soil humidity. Data is collected with a LoRa P2P network, which uses a master–slave and TDMA-based MAC protocol. Each slave node has a unique address and can transmit a packet in each of the reserved TDMA time slots.

Alternatively, a Penman-Monteith-based irrigation model allows for an optimal irrigation strategy for different crop growth periods and uses the ET parameter to estimate the amount of water [63]. This solution requires an integration of actuators, sensors and a meteorological station in a LoRa network [49], [50]. In addition, third-party services such as weather information or fog computing may be needed to decide on irrigation schedules [57].

Since in LoRaWAN, the latency of downlink communication from GW to Class-A nodes (sensors or actuators) is relatively long (must first wait for an uplink transmission), few systems employ alternative Master/Slave protocols [52], [53], [54]. These protocols increase the stability of the LoRa irrigation system, avoiding packet collisions and, thus, can save water during the close command of the solenoid valve.

Finally, AREThOU5A [43] is an example of a water management system that combines data collected from wireless sensor networks (WSNs) in the field and satellite data provided by international weather forecast services, to achieve efficient water usage strategies for farmers. It employs a WSN with two different sensors for measuring the temperature and the soil moisture in field. A routing subsystem controls and routes the data and information through LoRaWAN and TCP/IP with SSL network interfaces. The LoRa network is used to collect data from the EDs and perform administration processes, while the TCP/IP SSL works as a bridge to the rest of the network architecture.

Summary and Insights: Comparing the characteristics of different irrigation systems, summarized in Table I, it is relevant to note that most of these LoRa-based irrigation systems adopt temperature, humidity, and soil moisture sensors. However, albeit all cited papers are recently published, ML is used only in 1/3 of the applications.

Furthermore, only 13% of these irrigation systems used an evapotranspiration-based methodology. This strategy, which is often expensive, may be accomplished by combining inexpensive sensors and AI (with a more comprehensive approach integrating meteorological variables measured by a weather station with variables measured by soil sensors into the system), significantly lowering the cost of direct evapotraspiration measurements. Such improvements could lead to more effective water management, with the simultaneous impact of decreasing water usage and increase crop output. Finally, LoRaWAN communications can be tuned to adapt the duty cycle and manage the system optimally: for example, when the irrigation system is not in use, sensor data could be collected every hour or even less, while when irrigation is taking place the measurements could be increased to every 5–10 min. This way, the use of water and energy could be further reduced [71].

B. Plantation and Crop Monitoring

Plantation and crop monitoring requires a large number of sensors to obtain an effective control and, thus, increase productivity, especially when agricultural fields are very heterogeneous. For example, in order to optimize the production while minimizing the ecological footprint, it is necessary to control the injection of pesticides and fertilizers [72], [73], increasing yields up to 10% and saving fertilizers up to 37% [74]. Such control can be performed by varying the pesticides and fertilizer application rate over time and space. Crops do not

TABLE II
LoRa-Based Plantation and Crop Monitoring System Comparison

Reference	Features			Sensor					
	Plantation	Energy harvesting	Automatic Control	Temperature	Humidity	Soil moisture	Carbon dioxide	Solar Radiation	Others
Valente et al. [64]	Vineyard	✓	x	✓	✓	✓	x	x	12 weather sensors
Shamshiri et al. [65]	Berry orchard	✓	x	✓	✓	✓	x	✓	Leaf sensor
Rachmani et al. [66]	Starfruit	x	x	x	x	✓	x	x	pH sensor
Ibrahim et al. [67]	Mushroom	x	✓	✓	✓	x	✓	x	x
Singh et al.[68]	Tomato	x	x	✓	✓	x	✓	✓	Electrical conductiv.
Sacaleanu et al. [69]	Walnut	x	x	✓	✓	✓	x	✓	Pressure
Silva et al. [58]	Vineyard	✓	✓	✓	✓	x	x	✓	Pluviometers
Codeluppi et al. [42]	Vineyard	✓	✓	✓	✓	x	x	x	x
Brunelli et al. [70]	Apples	✓	x	x	x	x	x	x	Camera

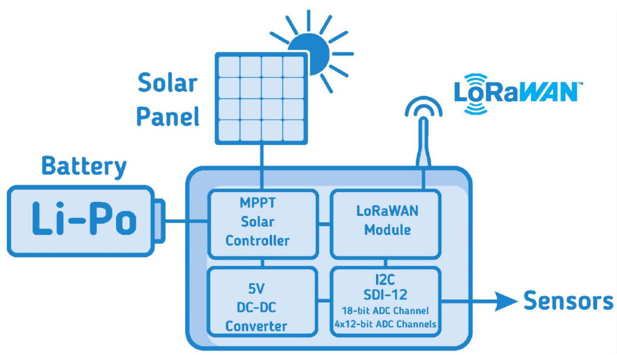

Fig. 7. Block diagram of the sensor nodes taken from [64].

always need a uniform application, as some areas have different requirements due to their location (sunlight, soil features, etc). Over-fertilization can deteriorate water quality, favor weed growth, and reduce profit. Vice-versa under-fertilization restricts yield or reduces crop quality [75]. The application rate can be modified based on weather impacts, nutrient availability, and seasonal cycles [73], [75]. Some optical or ultrasonic sensors indirectly assess the nutrient request (nitrogen, phosphorus, potassium, etc.) of the crop at the time of application [72]. In addition, to reduce the loss of productivity in crops, surveillance systems can be adopted [76]. Providing visual monitoring to growers can prevent crops from getting damaged by intruders, ensure the field conditions or enable the detection of pests attacks remotely. Although there are plenty of devices which can be exploited for building a real-time visual monitoring system, deploying them in a wide area and over wireless channels can be challenging [77], [78], [79].

Table II summarizes the main characteristics of several plantation and crop monitoring systems, based on LoRa technology. The nodes used in these systems should be of small dimensions, self-sufficient in terms of energy, relatively cheap, and often able to acquire a large variety of parameters. For example, three different sensor nodes have been developed by Valente et al. [64] and tested in a vineyard field: node 1, with an ultrasonic anemometer (that measures the direction and speed of the wind) and a sensor that monitors bulk electrical conductivity, in addition to volumetric water content (by measuring soil permittivity) and soil and air temperature; node 2, an irrometer watermark soil water tension sensor; and node 3, an all-in-one weather station with 12 sensors to measure air temperature, relative humidity, vapor pressure, barometric pressure, wind speed, gust and direction, solar radiation, precipitation, lightning strike counter, and distance. It should be remarked that each node contains sensors which differ for the sampling rate, accuracy, and supplied energy. The nodes send data using LoRaWAN to a GW that is connected to a the things network (TTN) server. In the TTN server, data is decoded and sent to the ThingSpeak [80] platform for visualization and possible analysis and aggregation. Fig. 7 summarizes the different blocks composing the nodes: 1) a maximum power point tracker (MPPT) applied to a photovoltaic source and connected with a storage system; 2) a dc/dc switching converter to interface the source with the storage system and loads; 3) the LoRaWAN module for communication; and 4) the analog-to-digital converter (ADC) module to convert the signals available from sensors.

In [66] a LoRa-based IoT monitoring system for starfruit plantation is presented. The LoRa network implemented includes three nodes and one master, and it can cover a range of 700 m. For optimal growth, starfruit plants need soil pH conditions between 5.5–7.5. Thus, thanks to the proposed LoRa system, the farmers can make important and precise decisions about how to grow the crop. Similarly, works [58], [65], [67], [68], [69] present solutions to increase production and fruit quality, with optimal use of resources through LoRa-based networks.

The Smart Mushroom Cultivation is a system used to automatize the production of expensive mushrooms [67]. The smart system includes devices to monitor and control humidity and CO_2 levels through sensors and actuators all connected using LoRaWAN. The sensor nodes measure the ambient condition inside Mushroom House (humidity, temperature, and CO_2), and data is sent to the remote server for monitoring and analysis. An automatic control maintains the ambient conditions between the required levels.

TABLE III
LoRa-Based Sensors Applications in Tree Farms

Reference	Temperature	Humidity	Soil moisture	Solar Radiation	Others
Valentini et al. [81]	✓	✓	x	✓	Sap flow
Amaro et al. [82]	x	x	x	x	Impedance Spectroscopy
He et al. [83]	✓	✓	x	✓	Carbon dioxide
Klaina et al. [84]	✓	✓	✓	✓	x
Yim et al. [85]	✓	✓	✓	✓	x
Park et al. [86]	✓	✓	x	✓	x

Finally, there are cases where anomaly detection near the sensor is required to allow decisions and actions as soon as possible. In this direction, Brunelli et al. [70] proposed a new paradigm of monitoring and pest detection to improve the performance of an apple orchard. They add intelligence to the LoRa nodes, shifting the detection of anomalies near the sensor. The application is developed on a low-energy platform powered by a solar panel, realizing an energy-autonomous system capable of operating unattended continuously over LoRa networks.

Summary and Insights: Plantation and crop monitoring requires the control of numerous parameters, captured by different heterogeneous sensors deployed in the agricultural fields. Some of the sensors used in the cited papers are specific to the type of crop, while others (e.g., temperature, humidity, etc.) are deployed in almost all of the literature works. In addition, the use of AI is not yet widely adopted, and only three out of nine papers adopt automatic control for the implementation of DSSs. An innovative approach in this context would be to add intelligence to the LoRa nodes, while moving the DSS closer to the sensor. Finally, note that the maximum size of the LoRa payload is 250 bytes; this allows a wide variety of parameters to be monitored and transferred in a single packet. For example, Sacaleanu and Kiss [69] send eight agri-meteorological measurements in a single LoRa packet of only 16 bytes.

C. Tree Monitoring

Trees are essential in modern society and are widely applied in a great number of scenarios including soil erosion prevention, air purification, wood or fruit production. For supporting the managers of urban/rural green infrastructures and forests, it is important to constantly monitor the tree conditions, in terms of growth rate and failure risk, as well as micro-climate parameters in the tree surrounding areas. The analysis of this data allows the characterization of the trees functional responses to their environment and a prompt action in case of problems. Tree monitoring also requires reliable long-range communications in the presence of foliage, large sensor densification (i.e., one sensor per tree), and measurements of various physiological/biological parameters from specific locations (at the root, the trunk, or the branch) as a function of vegetation type to obtain accurate readings [83]. In these systems, it is also important to measure changes in position over time or instantaneous trunk accelerations. Table III summarizes the main characteristics of relevant Monitoring systems.

One of the main properties to be measured is the water transport in the xylem of the trunk (called the sap flow). A possible measurement method is the Heat Balance Method, developed by Granier [91], [92], which is based on analyzing the temperature difference among two probes inserted into the stem wood at a 10 cm distance along the vertical trunk axis. The probe in the higher position is heated, while the lower one provides the stem wood reference temperature. The temperature difference generated between the probes represents an index of the transpiration activity of the plant, expressed as a variation of the flux density. This method can be used for accurate measurements of sap flow in plants, providing a reliable calibration procedure to relate the temperature difference to the actual sap flow [93]. For example, the TreeTalker (TT) [81] is a device that measures sapflow (water transport in the trunk), wood temperature and humidity, multispectral signature of light transmitted through the canopy, tree trunk radial growth, accelerations along a 3-D coordinate system used to detect tree movements, air temperature, and relative humidity, which can be additionally complemented by soil temperature and volumetric water content. A TT node is connected via LoRa wireless connection to a GW, that manages up to 48 devices in one cluster. The GW is, in turn, connected to the Internet via GPRS and sends data to a computer server. This technology can be applied to monitor the root plate tilt, as well as the flexion and the accelerations that tree trunks receive under the force of the wind for the evaluation of tree failure risk.

Another solution to analyze the health condition of a tree consists on the electrical impedance spectroscopy (EIS), it is a well-known technique with a wide range of applications. EIS has been applied to characterize solids, liquids, both in the laboratory and industrial environments. Moreover, assessment of physiological states of some trees (pinus, chestnut, etc.) has also been studied. The method based on bioimpedance indexes allows determining three distinct physiological states: healthy and watered plants, plants with a high level of hydric stress, and plants with disease [94], [95], [96]. For example, Amaro et al. [82] integrated an EIS system in a sensor node to analyze the health condition of the tree and transfer the results through the LoRaWAN protocol.

Finally, tree monitoring systems are often influenced by the presence of foliage which can severely impact wireless

TABLE IV
LoRa-Based Sensor Applications in Livestock Monitoring

Reference	Gyroscope	Accelerometer	Temperature	Humidity	GPS	Carbon dioxide	Illuminance	Others
Dos Reis et al. [87]	✓	✓	✓	x	✓	x	x	Magnetometer
Li et al. [88]	x	✓	x	x	✓	x	x	x
Germani et al. [89]	x	x	✓	✓	x	✓	✓	Ammonia
Ikhsan et al. [90]	x	x	✓	✓	x	x	x	Heartbeat

communication systems performance. This generally leads to node densification to increase coverage levels, especially in large areas, resulting in additional costs and constraining the design of LoRa systems in nonhomogeneous vegetation environments [84], [85], [97]. For such reasons, a small drone with a GW is sometimes required for collecting data from nodes and solving the Fresnel zone radio propagation issues encountered in tree farms [86], [98].

Summary and Insights: In this section, some methodologies for monitoring tree health have been discussed. It is important to highlight how LoRa can be easily integrated into these systems, e.g., to measure the lymph flow or bio-impedance of trees. In case the parameter to be monitored involves roots, it has been shown that LoRa can be used for under-ground or near-ground communications too [12], [99]. Finally, the use of drones for data collection has been exploited to solve the problem of foliage scattering.

D. Livestock Monitoring System

Smart livestock practices aim at improving the productive and reproductive parameters, feeding and handling of feces, producing a direct effect on the increment of the farmers' income, and also better milk and meat production [100]. The implementation of these practices requires to monitor the general health conditions of the animals, by tracking some biological signals to be associated to symptoms of disease, estrus and calving [101]. Wearable sensor technologies provide the possibility of remotely managing individual animals facilitating urgent interventions, responding to time and labor-intensive concerns in a more efficient way [87]. In extensive livestock production systems, the absence of access to networking and animal contact presents a barrier to the effective use of these technologies. Wearable sensors, to be more practical for extensive management settings, must: 1) network over longer distances; 2) have reliable power supplies (preferably renewable); 3) be low-cost so that damaged and lost sensors are less economically impactful; and 4) transmit data in real time.

For these reasons, LoRaWAN technology is indicated for above described applications, some of which are summarized in Table IV. Primarily, these systems are used to monitor the animal health, but by integrating LoRa technology with a GPS, remote grazing systems can be implemented [87], [88].

Animal monitoring can involve completely different scenarios; as a consequence, the LoRa network architecture could require a more specific design effort to work either in indoor or outdoor settings. For example, the work in [89] proposes two different versions of GWs: an indoor GW, designed for installation in sheltered areas such as barns and cowsheds and oriented toward dairy cattle livestock scenarios, and an outdoor version, more specific for open areas such as paddocks and pasture lands, and designed for beef cattle livestock scenarios. The indoor GW is conceived for monitoring several important physical parameters typical of the shed environment, such as temperature, relative humidity, illuminance, carbon dioxide (CO_2), and ammonia (NH_3) concentration, while the main purpose of the outdoor GW is to manage nodes in remote areas, far from the shed, directly on the pasture land. In the open field scenario, weather parameters (temperature and humidity) are collected, for purposes of correlation with the animal health status.

Moreover, in the presence of large herds, the high node density could cause an increase in collisions between sent packets. In such scenarios, a MAC layer that includes a listen-before-talk (LBT) mechanism could prevent as much as possible packet collisions among nodes. Indeed, LBT-based carrier-sense multiple access with collision avoidance (CSMA/CA) can be incorporated with the physical layer of LoRa [89]. The CA mechanism is based on a random retransmission time that randomizes the access of the nodes to the wireless medium.

The size of the pasture area is another factor to consider in deploying the LoRaWAN network. In particular, it has been shown that in large areas of pasture, the use of a mobile GW that moves along the track is a better solution than the use of one or more static GWs [90]. Contrarily, when the livestock area is not too large, using only one static GW is preferable because the data extraction rate value is high enough and the energy consumption is lower compared to multiple static GWs or one mobile GW.

The instance of cattle monitoring in New Mexico, as described by Actility [102], is one of the successful illustrations of a large-scale LoRaWAN-enabled deployment. Due to the large size of these desert ranches (10 000–20 000 hectares) and the large number of cows to track (up to 7000), monitoring and obtaining information regarding cattle wellbeing can be time consuming and expensive. Indeed, while the cattle were previously followed using traditional GPS devices, the absence of reliable cellular connection throughout the whole grazing region made this method ineffective. These issues were solved with an off-the-shelf LoRaWAN solution because of its extensive range and good coverage. Finally, LoRa technology can be used for sharing the short text messages and voice messages in the absence of cellular coverage. For example, COWShED [103] is used for supporting livestock transhumance in Senegal.

Summary and Insights: In this section, we showed how LoRa is used to collect information about the movements and health of livestock, as well as on the conditions of grassland. LoRa can also aid herders in achieving remote grazing by combining data with electronic fences, to identify whether animals have crossed it. In addition, LoRa has been used to monitor environmental parameters of barns, demonstrating how this technology can be adopted in both outdoor and indoor scenarios. Additionally, innovative MAC schemes, such as LBT method could be implemented to minimize packet collisions when big herds present, and to mitigate the limits on the effective duty cycle of channel occupation. Finally, in the absence of cellular coverage, LoRa/LoRaWAN solutions have been used for large-scale cattle monitoring or even supporting livestock transhumance for text/voice messages.

VI. Lessons Learned and Open Issues

This section discusses the lessons learned and the open research challenges for using LoRa technology in smart agriculture. According to the aim of this article, it was learned that, given the wide variety of sensors used in smart farming systems, different communication protocols need to be integrated, particularly when different platforms/vendors coexist and data must be collected from the various subsystems. In addition, since power supplies are frequently unavailable in a large agricultural area, nodes should be as energy self-sufficient as possible. Using local or edge data processing could mitigate this problem, optimizing the energy consumption. Moreover, keeping the logic on the Edge of the network could alleviate the hurdle on LoRa's centralized communications (especially on the downlink). The development of interoperability in smart agriculture systems can also be accelerated by platforms such as FIWARE and Cayenne, while machine learning can be used to model and analyze technical problems, improving scalability of LoRa networks and predicting network congestion.

The experience gained in Industry 4.0 can be transferred to agriculture, considering some peculiarities, including the need to cover large spaces that cannot be manned. In addition, there is the need to provide device power supply and data security (partially solved by leveraging on LoRaWAN built-in security schemes). Another significant factor is the initial cost of the system, which must be as low as possible since the pay-back time also depends on elements that cannot be predicted during the year, such as weather. Finally, it has been recognized that although ICT has long-term sustainability issues to be solved, they show great potential for improving the usage of natural resources, especially when cyber–physical systems (CPSs) are combined with IoT, AI, machine learning, and neuromorphic computing techniques [104].

Through the study carried out in this article, it is also possible to understand in which area LoRa has been applied and is emerging in recent years. In particular, among the application areas discussed in Section V, Fig. 8 shows in a pie chart that more than 40% of the analyzed studies focus on water management, while almost 25% are dedicated on crop monitoring, followed by tree monitoring. This result is in line with recent

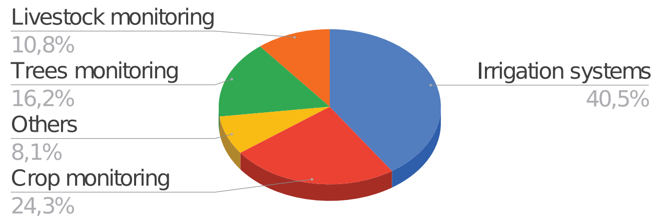

Fig. 8. Distribution of the LoRa papers according to smart agriculture application areas.

market surveys on LPWANs (e.g., [105]), and other general studies on communications protocols for smart agriculture [9].

All this confirms the great potential of implementing smart agriculture solutions using IoT, and LoRa technology in particular. However, there are still some open issues that need to be faced: for example, LoRaWAN works quite well in uplink when it needs to collect data from sensors, while downlink connections might suffer high latency. In what follows, we briefly discuss future research directions related to downlink latency, energy management, device heterogeneity and interoperability, data management, and scalability. These open issues must be solved for LoRa systems to be widely adopted in smart agriculture. We conclude the section with an eye on other wireless technologies, different from LoRa/LoRaWAN.

A. LoRa Downlink Performance

The downlink performance of LPWAN systems still represents a challenge since it is related to the energy consumption. In particular, LoRaWAN allows different tradeoffs between communication latency on the downlink channel and energy consumption. Nodes are classified by classes: they can receive only after an uplink transmission (Class A), or at regular time intervals (Class B), or at any time (Class C). The modern trend is to optimize energy efficiency, hence, data are transmitted only when necessary or periodically. According to the authors' opinion, a further optimization could be retrieved by local data processing. As a matter of fact, even if nodes remain asleep most of the time, as in [57], or with scheduling intervals of reception windows of 10–20 min as in [48] and [50] or a few hours [58], local processing always lowers the data to be transmitted decreasing the transmission time; it has been successfully tested in [42] where edge processing on the GW allows a more effective control of the actuator nodes. This last approach improves also reliability since it allows farms to work even if the Internet connection of the LoRa GW is absent for a few hours. Reliability can also be improved by a Master/Slave access control method for the LoRa network [52], [53], [54].

Alternatively, for short-range communication, a Wake-up Radio (WuR) can be adopted. WuR technology is an ultralow-power receiver that is continuously listening to the channel while spending a few nanowatts or microwatts depending on the circuit's design. WuRs work in parallel to the main LoRa transceiver and allow asynchronous wake-up of the nodes with low latency. With the LoRa-WuR scheme, the downlink latency can be reduced by almost 90% compared to the traditional LoRa protocol for a ten nodes cluster [106], [107].

B. Energy Efficiency Considerations

In addition to downlink communication performance just explained, the energy consumption in an agricultural ED can include turning on booster pumps or solenoid valves, activating sensors over a long period, use of GPS and data transmission, etc. Nodes should be autonomous as much as possible since usually power supplies are not available in a wide agricultural area. Besides, the use of batteries needs to minimize disposal costs and pollution. Providing solutions to avoid the use of batteries by harvesting energy from the environment would encourage the deployment of wireless devices in smart agriculture. The use of different energy sources, such as solar energy, piezoelectricity, thermal, wind, water, and radiofrequency is consolidated [108]. However, making a device completely energy-neutral requires a thorough analysis of power consumption in different working states [109]. One facilitation is the availability of a renewable energy source as in [51]; on the other hand, a high energy consumption due to the heating of one probe as in [91] requires a different design or the remote monitoring of the energy available or harvested as in [110]. It is evident that there are many factors that influence the analysis of offering-demanding energy, it varies on a case-by-case basis and does not lend itself to systematic analysis; on the other hand, in this context, machine learning algorithms can give a significant contribution. Infact, the ML approach has been already successfully applied in different contexts allowing to implement an efficient renewable energy selection based on the geographic location [111], or to retrieve a good energy prediction [112]. An application example is given by the energy-neutral system for pest detection [70] which takes advantage of ML algorithms.

C. Heterogeneity and Interoperability

Smart agriculture systems are quite heterogeneous in terms of sensors and, in some cases, it is also required to integrate different communication technologies, e.g., when multiple platforms coexist and data arrives from different subsystems. LoRa platforms are used with ZigBee to implement hybrid communications managing different sensors clusters or with the IEEE 802.11s-based system to build a mesh networking architecture. The path for the integration of different technologies, such as cloud, IoT, and software-defined networking, with AI is proposed in [113] with the related challenges and opportunities.

Assuring communications in heterogeneous smart agriculture systems is a critical issue that has been studied for example in [114], where LoRa and ZigBee hybrid communications are implemented. Precisely, two LoRa sensor clusters and two ZigBee sensor clusters are used and combined with two ZigBee-to-LoRa converters to communicate in a network managed by a LoRa GW. The token ring protocol in the ZigBee network and polling mechanism in the LoRa network is used. The system can work with a packet loss rate of less than 0.5% when the communication distance is 630 m for the ZigBee network and 3.7 km for the LoRa network.

An hybrid LoRa/IEEE 802.11s-based mesh networking architecture is proposed in [115], where an effective network protocol selection mechanism is developed to choose the right interface. Protocol selection is based on multiple parameters, including network communication interface type, GNSS position of the APs, RSSI of nearby nodes, type and amount of data to be transmitted. Large data to be transferred in a short time can rely on the IEEE 802.11s-based network while small data can be transmitted through a LoRa-based mesh network.

Platforms such as FIWARE [116], Cayenne [41] and mySense [58], discussed in Section IV, can also give a push to achieve interoperability in the smart agriculture systems. The above described solutions can benefit of an "industry 4.0"-based approach where the integration of different protocols cooperate to address the needs of automating computing and technology processes [18], [113].

D. Machine Learning and Big Data Management

The integration of big data analysis with machine learning can provide predictions about future outcomes, such as fruit quality or detect crops' diseases using historical data, analytical techniques, and statistical modeling [117]. The benefits of ML in the agriculture are relevant [118]. However, the deployment of models is the most challenging step to bring the ML algorithms in the production fields, and thanks to its advantages, LoRa technology could make a big contribution to taking this step. Collected data can be used to implement an intelligent system capable of supporting the identification of varieties and predicting the quality of the final product [64]. In fact, exploiting ML, the data can be used by the biologists to develop crop models and perform disease prediction [68].

The agricultural industry produces a large amount of data collected by heterogeneous sensors, so best practices should include the mechanisms to reduce the memory and time for data analysis. Thus, to pursue such objectives, edge computing models are also applied [119]. Distributed data process, such as MapReduce [120], may avoid bottlenecks when transferring all data to a single server, as in [121] where the proposed method adopts smart sensors to measure the soil quality indicators, while the preelaborated data is transmitted using the LoRaWAN protocol. The Apache Spark environment is then used to implement a parallel algorithm for statistical models based on the soil indicator data obtained from the experimental field.

E. LoRa Scalability and Network Improvement

As concerns scalability, some open points, shared with general applications, are recognized. For this reason, most of the reference literature does not directly address issues related to agriculture. Indeed, scalability is a key feature in LoRa networks due to its long-range and large number of devices can concurrently reach a given GW. The network scales quite well if dynamic transmission parameters are used, in combination with multiple sinks. However, the correct behavior of the NS is not easy to be evaluated [122]. In fact, the NS presents some challenges from the point of view of its optimization, such as processing duplicate packets or packets from other networks, or bringing down the entire network in case of Internet connection loss.

LoRa networks are bound by strict legal requirements, particularly where no LBT schemes are utilized. The transmission duty cycle (TDC) regulates the ISM bands to determine the maximum time that the band can be occupied, typically bounded to 1%. This implies that devices may not occupy the ISM band for more than 36 s per hour, forbidding the transmission of new packets when this limit is attained [123]. Machine learning can be applied to model and analyze technical problems, improving the scalability of LoRa networks and predicting network congestion [124]. Further developments could include enhanced ADR mechanisms, optimization of GW locations, and interference cancelation techniques [125].

Finally, some challenges remain such as the widespread adoption of multihop communications in LoRaWAN. Literature has shown that multihop or mesh topologies can extend the coverage of LoRaWAN networks and improve energy efficiency in certain scenarios [126]. These solutions propose intermediate nodes to forward messages to other EDs to extend the coverage. Other open points include the use of GWs as intermediate nodes, GW-to-GW communications, and practical large-scale deployment of LoRaWAN mesh networks.

F. Other Communication Technologies

The choice of a specific communication technology is central to the performance of IoT-based agricultural applications. Other than LoRa, many standards for wireless communications can be employed, including Bluetooth, ZigBee, Z-Wave, RFID, Sigfox, and NB-IoT. Some of them work well in the short-range (within 100 m), while others are more useful to cover long distances (up to tens of kilometers). Examples of the former are Bluetooth, ZigBee, Z-Wave, and passive and active RFID systems, while in the latter, standards are Sigfox and NB-IoT (and LoRa of course). As discussed previously, the deployment of a massive number of IoT devices might cause interference problems especially for technologies using the unlicensed spectrum, such as ZigBee, Wi-Fi, Sigfox, and LoRa. On the other hand, IoT devices operating with a licensed spectrum eliminate interference problems but might increase costs significantly.

Several papers have analyzed different aspects of wireless communication protocols for smart agriculture, studying possible applications and comparing their performance. For example, ZigBee-based smart agriculture systems are described in [127], [128], [129], [130], and [131]. The biggest challenges for ZigBee networks are the limited range and increased power consumption (compared to LPWANs) and relatively low data rate (e.g., compared to BLE or WiFi). Therefore, ZigBee is better suited for small-scale scenarios [130], while the use of this protocol is not suitable when the agricultural area is vast and the distance between sensor nodes is large. On the other hand, the works [132], [133], [134], [135] represent successful examples of NB-IoT applications in smart agriculture. Indeed, extensive coverage, adaptable power consumption (depending on the mode of operation), and low interference among nodes, are features that make NB-IoT an interesting protocol for various agricultural systems [136]. However, NB-IoT employs licensed frequency channels, which results in higher subscription prices for the associated system even if it offers a higher data throughput than LoRa. Moreover, when there is an existing LTE infrastructure already in place, the need for hardware update may be another source of expense for such a system. This might be a drawback in the context of smart agriculture if the projected return on investment is not high enough to cover these costs [137].

Overall, the choice of the communication technology in smart agriculture needs to consider many factors and requirements, such as support for roaming, suitability of technology to small-scale, medium-scale, and large-scale deployments, geographical location, costs, etc. For example, it has been shown that Sigfox and LoRaWAN excel on network capacity, battery lifetime, and cost, whereas NB-IoT achieves higher quality of service and lower latency [27]. Finally, while LoRaWAN has been considered the most suitable communication network for IoT in smart agriculture [16], it is still difficult to tell which technology will dominate the market, or if several technologies will coexist, perhaps specializing on different application domains.

VII. Conclusion

Although the expected transition to smart agriculture has already begun, researchers around the world are still looking for new solutions to improve agricultural productivity through IoT architectures. Indeed, albeit applications in agriculture can benefit from the experience gained in Industry 4.0, they require specific knowledge regarding sensor management, energy optimization, and data processing. LoRa technology is widely adopted, as it allows building an autonomous network that meets some of the requirements of the smart agriculture, such as low-power and long-range communication. The adoption of LoRa-based systems in agriculture results in an effective way to improve the connectivity of farms, encourage the deployment of DSSs and consequently improve their management, leading the agricultural sector toward smart agriculture. In order to provide a more focused and comprehensive view of the applications in the field, in this article, we restricted our focus to LoRa/LoRaWAN technology and its uses in the context of smart agriculture. We presented many LoRa applications in the field, and we discussed some open issues and research areas for future improvements. The main challenges analyzed using LoRa Technology in smart agriculture, are: latency on the downlink channel, energy management, heterogeneity and interoperability of the devices, data management, and scalability. All of these can benefit from the use of machine learning algorithms. Indeed, AI and edge computing are still scarcely used but related algorithms and technologies are now mature and may be successfully applied in this field. Finally, the optimization of multiple GW locations and multihop topologies to extend the coverage of LoRa networks have been recently tested to further improve the performance and coverage.

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