Chapter 14
Digital Farming and Field Robotics: Internet of Things, Cloud Computing, and Big Data

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14.1 Introduction

The demand for agricultural production is increasing, due to the 60–70% expected increase in food demand by 2050 (Porter et al. 2014). The increased production will have to face the challenge of sustainable farm management through optimized use of the available natural resources with a limited environmental impact, to meet the societal challenges of Sustainable Development Goals (United Nations 2015), such as food security and resource use efficiency. Advances in many disciplines of technology could provide their service toward giving solutions to this challenge.

Widely used precision agriculture (PA) techniques and tools, combined with technological developments in the Internet of Things (IoT), cloud computing, and big data analytics, are expected to bring the fourth revolution in farming and food production. This agricultural revolution, which in many cases is being referred to as "Agriculture 4.0" or "Digital Farming," follows the previous three revolutions. The first agricultural revolution took place around 10,000 BC and was characterized by the domestication of plants and animals. The second agricultural revolution was prompted by the industrial revolution during the nineteenth century when farming became mechanized and commercial with the development of new inventions and technologies. The third revolution or "Green" Revolution was a period when the productivity increased drastically as a result of new advances. During this period, high-yield crops were developed and introduced, and also new chemical fertilizers, synthetic herbicides, and pesticides were created.

The digital transformation of agriculture is being facilitated by the emergence of technologies focused on data acquisition and data management, which are expected to have a profound impact. The IoT is in the core (Fig. 14.1) as it is the connection

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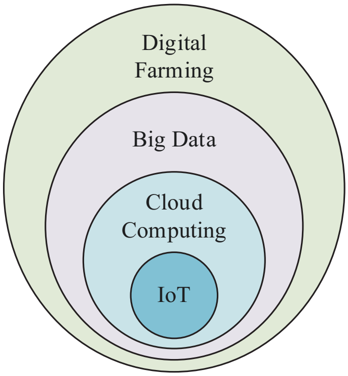

Fig. 14.1 General architecture of digital technologies in agriculture

with the physical world where various sensors and devices continuously monitor and control environmental variables related to atmospheric conditions, soil state, and biomass of biological organisms. As IoT devices are not always reachable in real time, due to energy-saving issues, the recorded timestamped information is transferred to the cloud through network gateways, in order for the data to be available for cloud-based IoT applications. Cloud computing technologies offer new possibilities in terms of storage and computation. Big data analytics are one level higher where data mining is being performed to detect trends, patterns, and associations, but also possible deviations. Digital farming, as was described above, requires this entire architecture in order to be able to support the farmer in everyday decision-making. An indispensable aspect of digital farming is field robotics as the latter act as the implementing component of the decision-making process. Agricultural robots, together with intelligent and highly automated agricultural implements, are responsible for the precise execution of agricultural operations (spraying, pruning, harvesting, etc.).

Since digital farming is being formulated as a highly cognitive system, it is necessary to have the layered architecture presented in Fig. 14.1, in order to acknowledge the increased complexity from one level to the other. The lower level of IoT can potentially operate as a stand-alone procedure in a reactive manner as closed loops can perform deterministic actions based on sensed data. Cloud computing techniques enhance manipulation of the acquired data, while big data technologies (including deep learning) introduce an associative formulation by linking sensory inputs with well-established patterns (Strube 1998). Digital farming being at the higher level of cognition requires knowledge, experience, and sensing and, thus, includes all previous technologies in order to achieve its mission.

The aim of this chapter is to give an overview of the offered technologies related to IoT, cloud computing, and big data from an agriculture-related perspective. The basic principles of each technology but also the emerging trends that could potentially have a profound impact in the agricultural domain will be also presented. One specific objective is to define a conceptual architecture that integrates all mentioned technologies and how these will interconnect in the future toward making Agriculture 4.0 a reality.

14.2 Internet of Things (IoT)

It is difficult to provide a unified definition of IoT as many exist due to the rapid penetration of the related technologies into our everyday life. Irrespective of all ambiguous definitions, everyone agrees that the IoT is an emerging technological paradigm where smart devices (Things) are equipped with sensors but can also act in order to control the physical world. The devices are assigned unique identifiers and can connect to the Internet but also interact with each other (Borgia 2014) forming a wireless sensor network (WSN). Based on the latest technology advances, it is becoming clear that the IoT is moving gradually to the cloud. In order to save energy, the IoT devices are unreachable most of the time. Nevertheless, the information should be always available for the application. Thus, a mirrored entity is being created in the cloud which holds all the information acquired from the physical entity (Atzori et al. 2017). By forming this cyber-physical ecosystem, the real and the digital world are in continuous interaction offering the user the capability to have a deeper and detailed view into the physical world.

14.2.1 IoT Architecture

A four-stage IoT architecture (Fuller 2016) is presented in Fig. 14.2. Stage 1 consists of all the "Things," typically sensors that collect environmental data such as temperature, humidity, soil properties, etc. In many cases, the Things can also be actuators with the purpose to vary the physical conditions based on the decision that is taken in situ or at a higher cognition level. At Stage 2, the data are being aggregated and converted into digital streams. Data preprocessing before entering the cloud and the data center takes place at Stage 3 by edge processing systems. Finally, at Stage 4, the data are stored on back-end cloud systems, and a thorough in-depth analysis is being performed. At this stage, advanced cloud-based systems and sophisticated big data techniques are being utilized (Popović et al. 2017).

14.2.2 IoT Hardware and Platforms

The last years the number of vendors offering IoT hardware platforms is increasing rapidly (Ray 2016). In Table 14.1, five widely used platforms are presented and are classified according to key parameters such as processor, memory, communication, logic level voltage, I/O connectivity, flash memory, operating temperature, power supply, and dimensions. The cost varies among offered platforms and at the moment this comparison was performed was from \$30 up to \$200 based on the offered hardware capabilities and programming interfaces.

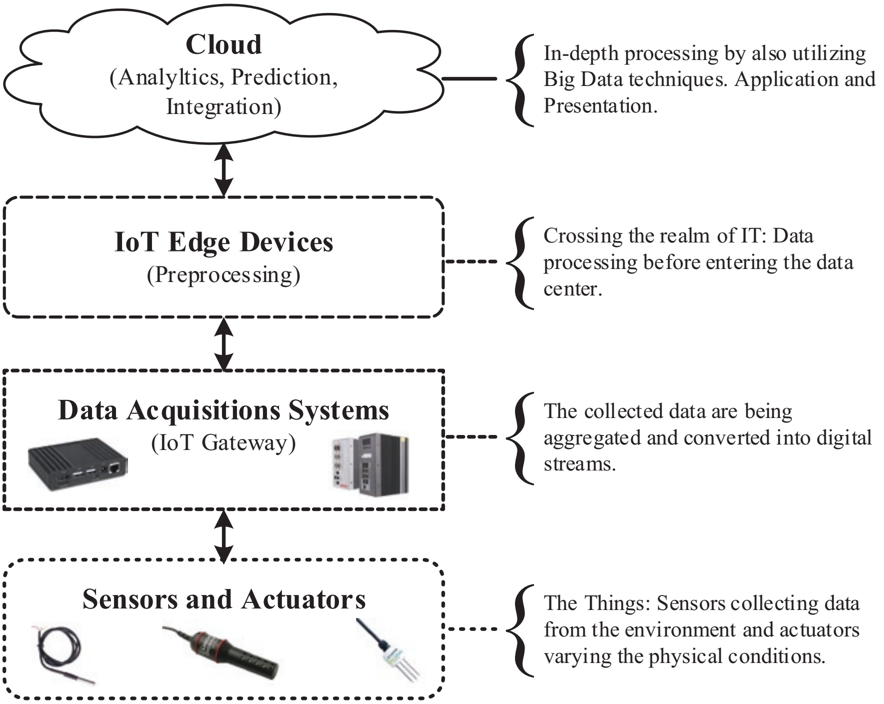

Fig. 14.2 A four-stage IoT architecture

14.2.3 Applications in Agriculture

The IoT has found wide implementation in agriculture with numerous applications. In order to categorize the various applications, three main domains have been identified: open-field farming, livestock farming, and protected agriculture. More details related to each category are presented in the following subsections.

14.2.3.1 Open-Field Farming

In open-field farming, the focus is on monitoring soil conditions such as temperature, moisture, pH, etc. Climate conditions and air monitoring are also examined by measuring temperature, humidity, and radiation (Talavera et al. 2017). Crop plant monitoring is being investigated by the detection of weeds, pests, and animal intrusion into the field, while crop growth is also being examined using IoT (Sreekantha and Kavya 2017). Irrigation control is of high importance as the proper amount and timing can minimize crop water stress and lead to water waste reduction. In this direction and toward developing an autonomous precision irrigation system through the integration of a center pivot irrigation system, an underground WSN was

Table 14.1 Basic characteristics of some of the widely used IoT hardware platforms

	Raspberry Pi 3 Model B+	BeagleBone Black	MinnowBoard Turbot Quad Core	Arduino Yún Rev 2	Qualcomm® DragonBoard™ 410c
Processor	Quad-Core Broadcom BCM2837B0, Cortex-A53 64-bit SoC at 1.4 GHz	AM335x 1 GHz ARM® Cortex-A8	Quad-Core Intel® Atom™ E3845 at 1.91 GHz	ATmega32u4 and Atheros AR9331	Quad-Core ARM® Cortex® A53 64-bit 1.2 GHz per core
Memory	1 GB LPDDR2 SDRAM	512 MB DDR3 RAM, 4 GB 8-bit eMMC on-board flash storage	2 GB DDR3L 1067MT/s DRAM	64 MB of DDR2 RAM	1 GB LPDDR3 533 MHz/8 GB eMMC 4.5/ SD 3.0 (UHS-I)
Communication	2.4 GHz and 5GHz IEEE, 802.11.b/g/n/ac wireless LAN, Bluetooth 4.2, BLE, Gigabit Ethernet over USB 2.0 (300Mbps), 4 × USB 2.0 ports	10/100 Ethernet, mini-USB 2.0 client port, USB 2.0 host port, 4 × UART, 8 × PWM/Timers, LCD, GPMC, MMC1, 2 × SPI, 2 × I2C, A/D converter, 2 × CAN bus (w/o PHY)	1 × USB 2.0, 1 × USB 3.0, microHDMI port, 1 × 1Gb Ethernet RJ45, SPI, I2C, I2S Audio, 2 × UARTs (TTL-level)	Ethernet: IEEE 802.3 10/100Mbit/s, Wi-Fi: IEEE 802.11b/g/n, 2.4GHz, 7 × PWM, BLE 4.0	Wi-Fi 802.11 b/g/n, 2.4 GHz, Bluetooth 4.1, Qualcomm® IZat™ location technology Gen8C, Wi-Fi, BT and GPS antenna, (expansion) UART, SPI, I2S, I2C x2
Logic level voltage	5 V	3.3 V	5 V	5 V	5 V
I/O connectivity	Extended 40-pin GPIO header	65 digital pins and 7 analog inputs	8 × GPIO (2 × supporting PWM)	20 digital I/O pins, 12 analog I/O pins	GPIO × 12
SD support/flash memory	MicroSD format for loading operating system and data storage	A single microSD (uSD) connector	1 × M.2 slot, with microSIM, 1x microSD	16 MB flash memory, microSD	MicroSD card slot, eMMC 4.5, 8 GB
Operating temperature	0–50 °C	0–60 °C (support for an industrial temperature range of −40 °C to +85 °C)	0–40 °C (wider range possible with a larger heat sink than provided with standard boards)	−40 to 85 °C	0–70 °C

(continued)

Table 14.1 (continued)

	Raspberry Pi 3 Model B+	BeagleBone Black	MinnowBoard Turbot Quad Core	Arduino Yún Rev 2	Qualcomm® DragonBoard™ 410c
Power supply	5 V/2.5 A DC via micro USB connector, 5 V DC via GPIO header, Power over Ethernet (PoE)-enabled (requires separate PoE HAT)	Mini-USB or 2.1 mm × 5.5 mm 5 V jack	5 VDC input via 2.5 mm center pin positive power jack	Micro-USB connection with 5 V, DC current per I/O pin: 40 mA on I/O pins; 50 mA on 3,3 pin	6.5 V to +18 V
Dimensions	85 × 56 mm	86 × 53 mm	99 × 74 mm	73 × 53 mm	54 × 85 mm

examined by Dong et al. (2013). The last years the tractor and implement communication data are also collected and analyzed. Paraforos et al. (2017b) connected an IoT device to the CAN bus diagnostics interface of the tractor, to inform the farmer regarding the performed agricultural operations.

14.2.3.2 Livestock Farming

An important contribution of IoT in livestock farming is related to animal tracking and behavioral analysis. Parameters such as animal health, proper insemination time, and reproductive health problems are monitored (Vannieuwenborg et al. 2017). Automated detection of lame animals, which produce less milk and have other problems, is being performed by collecting data from inertial measurement units. Analysis of these data reveals impaired movement or deviation from normal gait or posture (Haladjian et al. 2018). Other parameters include extreme climate condition detection that has an important impact on animal welfare, environmental conditions of a beehive, but also odor and hazardous gas monitoring.

14.2.3.3 Protected Agriculture

Greenhouses are highly intensive production systems that justify the use of advanced technologies such as IoT. High-precision monitoring and control systems are being implemented including micro-climate and crop sensing, valves and controllers for fertigation, and integrated pest management (Tzounis et al. 2017). The last years a novel farming system has emerged called "Vertical Farming" in which the crops are being cultivated inside buildings and in layers above one another, under a fully controlled and closed environment. In these systems, IoT devices are used to sense but also control various physical variables such as moisture, nutrients, light, and oxygen. Artificial lighting is offered by rows of LED grow lights, while plants are usually irrigated with recycled water by spraying the exposed hanging roots, suspended, from the crops.

14.2.3.4 Challenges in Applying IoT in Agriculture

One of the biggest challenges of applying IoT in agriculture is that the devices are exposed to harsh environmental conditions. Factors like extreme temperatures with a high variation, high humidity and intensive rainfall, strong wind, solar radiation, machine operation, and animal movement causing displacement and vibration are introducing problems to the proper functionality of the sensors and the electronic circuits. Since most of the IoT applications are based on wireless communication (e.g., WSN), the batteries that are used for power consumption offer a limited flexibility in functioning without surveillance for a longer period (Jawad et al. 2017). Except device-related problems, the harsh conditions are responsible for network issues as well. A low wireless link quality affects the transceivers and the quality of the transmitted data (Villa-Henriksen et al. 2020), while the calculation of the signal strength in that case can be highly beneficial in assessing signal quality (Reiser et al. 2017). Another component has to do with security challenges. Authentication, confidentiality, and data privacy need to be secured against all possible external threats providing that only authorized users will have access to the collected data (Tzounis et al. 2017).

14.3 Cloud Computing

Cloud computing is on-demand computing services (e.g., databases, storage, networking, servers, software, analytics, etc.) over the Internet where the provider charges the user based on usage. The creation of virtual machines, by leveraging a distributed system consisting of a collection of interconnected and virtualized computers, enables the user to utilize elastic resources based on their current needs. The shift to cloud computing significantly reduces the cost of buying new hardware and software but also increases speed as IT resources can be provisioned in some minutes. Furthermore, factors as the high level of performance and reliability, especially when connected with IoT (Stergiou et al. 2018), contribute to the wide expansion of cloud computing technologies.

14.3.1 Cloud Services

The three main types of cloud computing service models are:

- Infrastructure as a service (IaaS): a vendor provides users access to preconfigured computing resources such as storage and networking, servers, and virtual machines. Popular IaaS offerings are Amazon EC2, IBM SoftLayer, Microsoft Azure VM, and Google Compute Engine (GCE).
- Platform as a service (PaaS): the cloud is used to deliver an on-demand environment to users for developing, testing, delivering, and managing software applications. Widely used PaaS products are Google App Engine, IBM Bluemix, and Apache Stratos.
- Software as a service (SaaS): it is a method for delivering software applications over the Internet, on-demand and typically on a subscription basis. SaaS offerings are the most widely visible of all the cloud computing service models. Two of the most popular SaaS applications include Microsoft Office 365 and Adobe Creative Cloud.

14.3.2 Emerging Architectures of Cloud Computing

New cloud computing technologies are emerging due to the development of large-scale applications. They move closer to a virtualized infrastructure and deal with factors such as scalability, flexibility, and privacy. In a review by Varghese and Buyya (2018), four new computing models are identified:

- Volunteer computing: Public participants share their idle computing resources to create an ad hoc cloud. It is expected to have an important implementation on projects with a societal or scientific focus.
- Fog and edge computing: Computational resources on edge nodes are being leveraged. This technology is strongly connected with the use of IoT as it was described in the previous section.
- Serverless computing: This doesn't mean there aren't any servers, but instead the applications are being executed only when it is necessary and not all the time. Function as a service (FaaS) is a form of serverless computing.
- Software-defined computing: Using virtualization technologies, the infrastructure can be broken up into resources that can be allocated on demand. This applies not only to networking but also to computation and storage.

14.3.3 Cloud Computing Implementation in Agriculture

One of the most important implementations of cloud computing in agriculture is the farm management systems (FMSs). The use of FMSs has widely expanded the last years which nowadays are regarded as important tools for managing the agricultural business and for implementing precision agriculture principles (Fountas et al. 2015). In order for a farmer to receive valuable information, all details related to the performed agricultural operations should be carefully recorded and imported into the FMS. This is why the combination of a cloud-based FMS with IoT sensor data is very promising for future systems. Furthermore, a cloud-based FMS can be interconnected with open agriculture-related databases (e.g., weather forecasting) or even an interface for receiving online agriculture consultation from advisors (Symeonaki et al. 2017).

As the level of communication of the infield autonomous systems with the cloud-based infrastructure is expected to increase in the next years, issues related to operational safety and resilience will need to be addressed. Challenging aspects, including unplanned cloud failures or hardware malfunctions that are highly possible to occur due to various reasons such as natural disasters or even targeted attacks, should be taken under consideration. Another important topic that could hinder farmers to adopt cloud computing tools is that reliable and broadband Internet access in rural areas, which are less densely populated, has not yet been achieved resulting in a digital divide compared to urban areas.

14.3.4 The Future Internet Ecosystem

An important example of innovative ICT tools that have emerged in the last years based on cloud computing is the Future Internet Public-Private Partnership Program (FI-PPP 2011), which was launched by the European Commission in 2011. The overarching aim of the FI-PPP is to create a library of software components that are called Generic Enablers (GEs). The GEs should be public and open-source and allow developers to create mash-up applications by implementing innovative FI functionalities such as IoT connectivity and big data analytics. All GEs are developed and described in detail as a set of application programming interfaces (APIs) in the FIWARE platform (FIWARE 2020). The FIWARE architectural chapters are provided in Fig. 14.3. The usability of FI technologies in the context of environmental applications has been thoroughly examined by Granell et al. (2016), while Paraforos et al. (2016) described an FMS architecture that utilizes advanced FI characteristics.

14.3.5 Fog and Edge Computing

One of the emerging technologies that were mentioned above, which is expected to have a substantial impact in agriculture, is fog and edge computing, where cloud services are extended to the edge of the network to decrease the latency and network congestion (Ferrández-Pastor et al. 2018; O'Grady et al. 2019). Both these technologies offer similar functionalities, and their main purpose is pushing both data and computational intelligence to platforms with data analytic capabilities that are located either on the IoT device or near to the source of origination of the data. The term fog computing was first used by Bonomi et al. (2012), while its main feature is to extend cloud computing services at the edge of the network (Moysiadis et al. 2018). The primary difference between fog and edge computing is the location where data processing occurs. For edge computing, the computation takes place

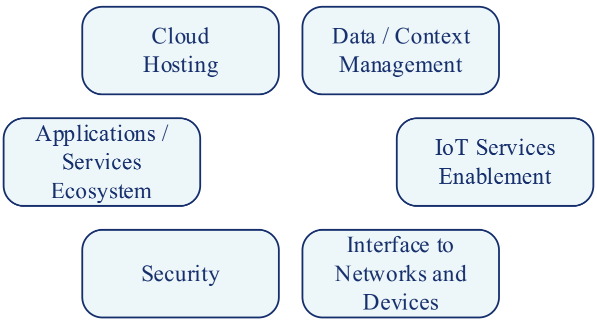

Fig. 14.3 Architectural chapters of the FIWARE platform

mainly on the devices with the IoT-connected sensors, while fog computing exists between the two layers (i.e., edge and cloud computing) and can be distributed in different locations serving a higher number of edge devices.

14.4 Big Data

Agriculture-related data are approaching the dimension of the 3 + 1 "Vs" that characterize big data: Volume, Velocity, Variety, and Veracity (Zhang et al. 2018) – Volume due to the produced amount of terabytes of data; Velocity for the increased pace that these data are becoming available to the user; Variety due to the heterogeneity of data sources, e.g., combination of structured and (semi-)structured data; and Veracity that deals with the quality and validity of the data (Lokers et al. 2016). Other studies add two more Vs in the definition: Visualization for facilitating the human interpretation of analyzed data and Visibility on efficiently processing geospatial data based on cloud computing technologies (Li et al. 2016). Big data analytics on the combination of machine data sets, with the sensor and unmanned aerial vehicle (UAV) data, could reveal hidden patterns, correlations, and other insights that are not detectable when using conventional methods for data analysis (Karmas et al. 2016).

14.4.1 Agricultural Geospatial Big Data

Geospatial data have the form of (a) raster data (images, 3D objects), (b) vector data (points, lines, polygons), and (c) graph data (nodes, edges paths). The term "geo" implies that the data correspond to a global coordinate reference system. Geospatial data have always been big data due to the vast amount of location-specific data that is being generated every day (Lee and Kang 2015). Sources of spatial data are airborne data coming from drones or satellites but also infield sensors such as IoT or mobile devices, cameras, etc. A necessary tool to store, integrate, analyze, and present geospatial data is a geographical information system (GIS).

One important source of agriculture-related data is the agricultural machines' subsystems. Different sensors and electronic control units (ECUs) that are installed on the tractors or agricultural implements produce data and communicate through control area network (CAN) bus by utilizing the ISO 11783 (commonly designated as ISOBUS) and J1939 communication protocols. Although the use of these data is intended for the correct operation as well as for the real-time inter-machine communication (Kortenbruck et al. 2017), the analysis of these data, when combined with positioning information from a global navigation satellite system (GNSS), could reveal valuable information about the performed agricultural operations but also the cultivated crop (Paraforos et al. 2017b). Details regarding the analytics of these data will be presented at one of the following sections.

14.4.2 Big Data Technologies

Conventional data analysis tools and techniques are not sophisticated enough to cope with big data and handle the vast and complex amount of data streaming from various sources. Thus, new technologies have been developed in the last years that are specialized in big data analytics by leveraging cloud-based resources. A characteristic example of an architecture that deals with geospatial big data is being developed in the frame of the BigGIS project (BigGIS 2020). This architecture (Fig. 14.4) includes most of the widely used toolboxes in big data analytics. The data sources vary and span from sensor data up to citizen sensing. In the specific architecture, StreamPipes works as an IoT platform which allows to integrate, process, and analyze big data streams by minimizing at the same time the programming effort as it uses graphical modeling. Although Apache Flink is specialized in analyzing IoT sensor data, Apache Spark featuring GeoTrellis could be incorporated when processing geographical data (e.g., raster or vector data). An important tool in the big data analysis layer is the concept of deep learning. The latter uses supervised and unsupervised techniques for data classification and data extrapolation (forecasting). Two common deep architectures of deep learning that are being implemented in big data analytics are the deep belief networks (DBF) and the convolutional neural networks (CNN) (Jan et al. 2017).

In order to handle the communication between the data processing elements, i.e., nodes, within the analytics pipelines, the Apache Kafka and the ActiveMQ could be utilized as message brokers. The Apache Hadoop software library and Exasol, CouchDB, and RDF4J are some of the offered storage back ends for the distributed processing of large data sets. The middleware is also responsible for the connection

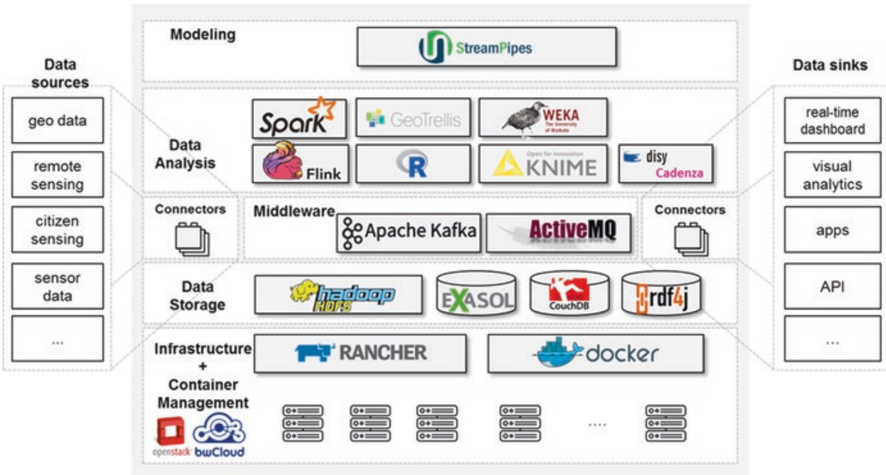

Fig. 14.4 Overview of offered big data technologies (Adapted from Abecker and Kutterer (2018), with permission)

with every possible data sink. The most important is to offer an API (application programming interface) to allow third-party software to communicate with the developed software ecosystem. The “Container Management” solutions like Rancher/Kubernetes support the whole software production chain, from software development up to testing and deployment in order to make the use of a container tool as efficient and effective as possible. Finally, the entire infrastructure is based on cloud computing technologies such as the Amazon EC2 (bwCloud in the specific example of Fig. 14.4).

14.4.3 Data Privacy and Ownership

Although the gradual shift to big data analytics and smart farming appears as an economic opportunity, it also raises important questions related to data privacy (Whitacre et al. 2014) and the balance that should exist between private and public open data as this is the core issue of the adoption decision for many hesitant farmers. Such questions are:

- Who owns the data generated on and around the farm?
- Who has control over the data?
- Who has access to the data?
- Who is entitled to the value of the data?

Mostly, “the farmer” is the answer to the first question. It is the farmer who decides (and thus gives permission) to share or sell his/her data. Still, it is not always so clear. What if the activity in which the data is generated is performed by an external person or third-party software? Does the application of particular software mean that a service provider becomes a data owner? There are actors who create data (farmers), those who collect (brokers) and those who analyze (analysts). Currently, the last ones shape the rules deciding how the data will be used and who is provided access, but farmers should be assured that their knowledge and decision-making capacities will not be replaced by algorithms, as they should always be the ones taking the last decision.

14.4.4 Open Agricultural Data

In the discussion regarding data related to agriculture and nutrition, open data concept plays an important role; that is data that anyone can access, use, or share to shape solutions by enabling more efficient and effective decision-making. According to Kunisch (2016), big data technologies offer new opportunities in giving answers to complex issues; thus, a public-private partnership framework, in terms of open source and open access, would be an appropriate platform for agricultural production and research data storage and exchange. This is also witnessed by open data initiatives, such as the global open data for agriculture and nutrition (GODAN), which aims to make agricultural and nutritionally relevant data available, accessible, and usable for unrestricted use worldwide. By leveraging open agriculture-related data, the outcome of big data analytics, except the high importance for the farmer, by providing decision support on sustainable land management, would also be beneficial for farmer advisors, public authorities, and policy-makers (Carolan 2015) toward making decisions for giving solutions to societal challenges.

14.5 Digital Farming

Although the technical capabilities of precision agriculture are already well developed, the precision and the efficiency of the application could be further enhanced shifting toward smart agriculture adapted to the new digital era. The greatest potential lies in leveraging multisource data and all previously described technologies to enhance already existing agronomical algorithms. The overarching aim is to minimize yield gaps in order to allow farms to be more efficient but also more profitable, safe, and environmentally friendly.

14.5.1 Automated Robotic Farming

One of the main components of digital farming is the utilization of autonomous agricultural vehicles. This component is responsible for closing the loop that starts with infield sensing, continues with cloud-based data analysis, and ends up again in the field where the necessary actions need to be taken with the highest possible accuracy. Recent technologies that are discussed in this chapter, in combination with artificial intelligence progress, will lead to the new agricultural era (Saiz-Rubio and Rovira-Más 2020). Nowadays field robotics are dominating agriculture performing all kinds of agricultural operations with a proliferating number of commercial products (e.g., Naïo Technologies, Saga Robotics, Robotti Agrointelli) but also research efforts such as weed control (Wu et al. 2020), apple harvesting (Silwal et al. 2017), and robot-human collaboration (Vasconez et al. 2019), just to name a few. A future trend is to use collaborative and cooperative behavior in a fleet of robots that will offer the opportunity to spread tasks over multiple platforms. This will reduce the damage caused by heavy conventional agricultural platforms on the soil or existing crops (Duckett et al. 2018).

14.5.2 Increased Accuracy

As digital farming will be using in the future sophisticated technologies such as robots and autonomous vehicles for implementing precision agriculture principles, high infield position accuracy is at a high priority. Innovative instrumentation should be considered toward reaching this higher level of accuracy. A device offering an accuracy at the millimeter level is a total station (TS). Commonly, this device is used in the domain of civil engineering and provides a higher accuracy compared to satellite-based positioning systems. Paraforos et al. (2017a) utilized a highly accurate industrial robotic manipulator to examine if a robotic TS can offer millimeter accuracy for demanding agricultural operations. The obtained results validated that this device would play an important role in the future in agricultural operations related to individual plant treatment. Afterward, the TS was used to examine the seeding depth for each individual seed in cereal no-till sowing (Sharipov et al. 2017, 2018) but also to produce a three-dimensional reconstruction of maize crop plants (Vázquez-Arellano et al. 2018a, b).

14.5.3 Automated Farm Management Systems

A common problem in farm management is that the agricultural tasks are not recorded properly; additionally, a farmer often neglects to gather all necessary data and import them into an FMS (Paraforos et al. 2016). A solution that appears promising is to utilize agricultural machinery communication data (Paraforos et al. 2019). The connection of ISOBUS with an FMS has been described in detail in Part 10 of the standard (ISO 2015). Software architecture was developed by Paraforos et al. (2017c) to automate a commercial FMS, named ifarma (Agrostis 2017). The data flow of this architecture is presented in Fig. 14.5. Machine data from ISOBUS communication were collected, analyzed, and aggregated into agricultural tasks. A stand-alone application was developed using MATLAB and was installed at the remote cloud-based server. The ISOBUS service was calling the MATLAB App by passing the acquired ISOBUS data. Initially, in this App, the data were filtered using the information from the rear hitch positions (SPN 1873) and the ground-based machine speed (SPN 1859), to extract only the infield data from the complete data set. The ISOBUS service generated the performed tasks with all related data, and this information was forwarded to the ifarma service that was responsible for storing this information in the FMS database and for presenting it to the user using the App's graphical user interface.

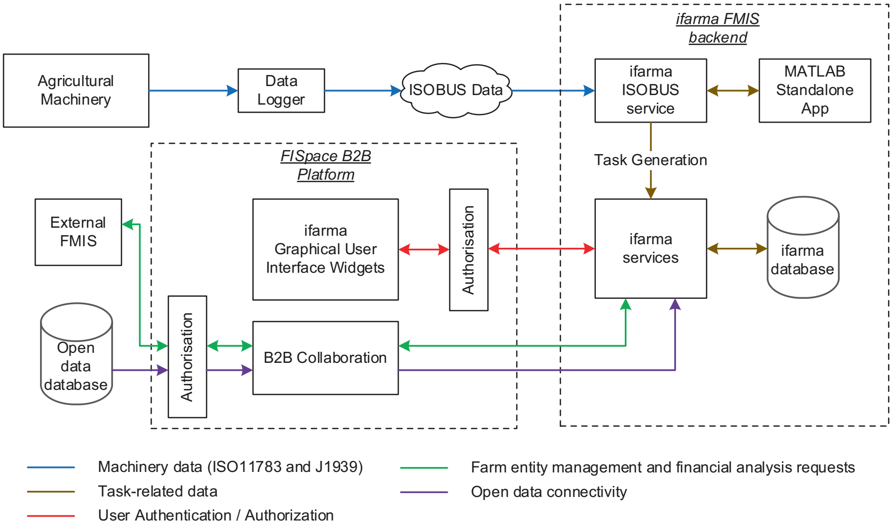

Fig. 14.5 Architecture of information flow in an automated FMS (Paraforos et al. 2017c)

14.5.4 Data-Driven Digital Agriculture

Figure 14.6 presents a scientific-technological approach and the software architecture for data-driven agricultural applications where all previously described technologies are utilized. The architecture is based on the fusion, management, and intelligent analysis of manifold kinds of agricultural data based on IoT technologies (and recently IoS – Internet of Services), especially (i) data from agricultural machinery, connected through the ISOBUS; (ii) open data as provided, for instance, by public administrations or other providers of open data for agriculture (like KTBL in Germany); (iii) sensor data originating from WSN in the field; and (iv) remote-sensing data generated by UAVs and satellites.

Such domain- and goal-specific analysis, reporting, and visualization functions will produce (a) precise inputs for innovative algorithms to support daily as well as strategic agro-technical and agro-economic decisions, as well as (b) the prerequisite for innovative agricultural data products and data services. Such data products can become the starting point for an agricultural data economy, for instance, helping agricultural advisors to improve their services or helping farm inputs suppliers to improve their products and to optimize their marketing and logistics processes. As a “side-product,” the overall data infrastructure can also facilitate all reporting and data communication processes between farmers and public authorities or even from farmers to the general public (“Agricultural Open Data”), thus increasing farm management efficiency and supporting policy-making, nature protection, food production transparency, etc. This leads to a holistic FMS which, based on formerly underexploited data sources, data connectivity, and intelligent analyses, can deliver completely new levels of insights and decision support regarding farm operations

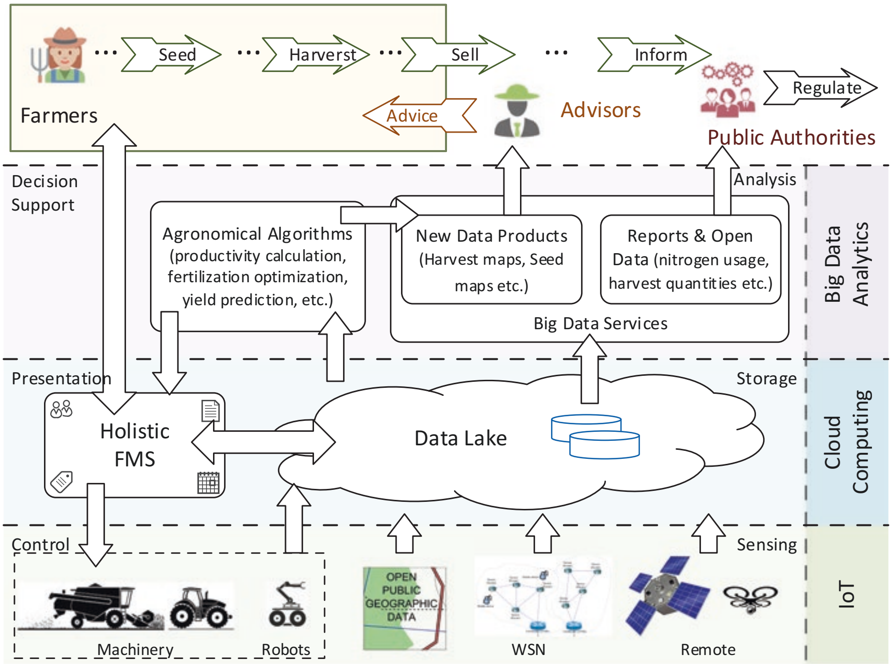

Fig. 14.6 Structural ecosystem for data-driven agricultural applications (Courtesy: Wassilios Kazakos, disy Informationssysteme GmbH, modified)

and management, especially with the ability of better spatially enabled and longer-term analyses.

14.6 Summary and Concluding Thoughts

It becomes clear that the farm of the future will be highly connected. Various sensors installed in the field but also agricultural machinery performing operations will constantly record, process, and transmit information to the cloud-based infrastructure for storage and in-depth analysis. Actuators and autonomous vehicles will be responsible for implementing the farmer's strategy, which will be supported by the results of the aforementioned analysis. The entire architecture will be based on a multilevel automation ecosystem, starting from simple closed-loop systems, i.e., irrigation, up to more complex systems with a higher level of cognition such as machine coordination.

A cutting-edge future technology that is expected to have a profound impact on agriculture in the next years is the concept of digital twins. The latter are already becoming available in other scientific disciplines, such as automotive and industrial informatics (Schluse et al. 2018). The digital twins are virtual, digital equivalents to physical objects that provide a thorough representation of the object and the context that this object is working in. The main focus of the digital twins is to combine IoT sensor data with historical data and human expertise, by utilizing machine learning techniques to improve the outcome of prognostics. This technology could provide decision support to farmers and other stakeholders by enabling them to act immediately and efficiently in the presence of a predicted deviation.

The wide implementation of Digital Farming faces many challenges like security in digital transactions. Blockchain, which is the distributed ledger technology behind many cryptocurrencies, promises smallholder farmers' highly secure access to digital technologies. Other important challenging issues that were discussed related to operational safety of cloud computing technologies should be taken under consideration when designing a digital farming system. Consequently, resilience should be incorporated into the proposed data-driven agricultural ecosystem by developing decentralized systems that leverage multi-cloud and multi-region architectures (Varghese and Buyya 2018). Although this requires significant use of human and financial resources, it will decrease the overall vulnerability of the system.

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