

Review

Crop Management with the IoT: An Interdisciplinary Survey

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Abstract: In this study, we analyze how crop management will benefit from the Internet of Things (IoT) by providing an overview of its architecture and components from agronomic and technological perspectives. The present analysis highlights that IoT is a mature enabling technology with articulated hardware and software components. Cheap networked devices can sense crop fields at a finer grain to give timeliness warnings on the presence of stress conditions and diseases to a wider range of farmers. Cloud computing allows reliable storage, access to heterogeneous data, and machine-learning techniques for developing and deploying farm services. From this study, it emerges that the Internet of Things will draw attention to sensor quality and placement protocols, while machine learning should be oriented to produce understandable knowledge, which is also useful to enhance cropping system simulation systems.

Keywords: Internet of Things; sensors; cloud computing; crop management; smart farming

JEL Classification: Q16; O13; O31



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1. Introduction

Though agriculture is recognized as a fundamental activity for all activities of mankind [1], it has had difficulties in accessing technology until the Green Revolution (GR), which led it to a (irreversible) new concept of agriculture. Machinery and chemicals were brought to agriculture to face environmental and sustainability problems, and other injections of technology have been claimed to solve them. Advances in remote sensing and Information and Communication Technologies (ICT) fostered Precision Agriculture (PA), relying on satellite-based geo-referencing, remote sensing, and imagery for surfaces survey and variable-rate applications, recently operated by autonomous vehicles [2,3]. Computers began to appear in farmers' everyday lives to host Farm Management Information Systems (FMIS) [4,5] formerly entailing administrative, accountancy, and warehouse management tools. FMISs of the last generation include the Geographical Information System [6] and Decision Support Tools (DST [7,8]). The latter is often based on Cropping System Simulators (CSS), born for learning purposes and later used for irrigation scheduling [9], hydrologic watershed management [10], and pest [11] and disease prediction [12]. The Internet, whose impacts on agriculture was envisaged more than twenty years ago [13], allowed FMISs to become outsourced services (e.g., for irrigation service managed by farmers associations) that profited from the growing amount of networked information (e.g., weather networks). The diffusion of Wireless Networks led to a number of applications recollected under the name of Smart Farming (SF) [3], centered on distributed Wireless Sensor Networks (WSNs) of sensors and actuators [14]. Major applications of SF are in high-value cropping systems such as greenhouse crops and vineyards [15]. Smart Agriculture (SA) extended the concepts behind SF to every actor of the agri-food supply-chain and their stakeholders [16]. Cloud Computing raised former problems of data ownership and employed leading software producers to follow different policies. Recently, the awareness of

the added value of data redundancy and data-exchange in problem solving has grown [17]. Cloud Computing already signed the beginning of a new age [18] and of the birth of the Internet of Things (IoT).

The first definition of IoT can be credited to Ashton et al. [19], who defined it as “an open and comprehensive network of intelligent objects that have the capacity to auto-organize, share information, data and resources, reacting and acting in face of situations and changes in the environment”. Such “intelligent objects”, later called “things”, refer to every physical and/or software devices that are identifiable and connected to a network with processing, sensing, and acting capabilities [20,21]. During the last two decades, IoT has become a consolidated reality consisting of a collection network of devices connected in a dynamic (and commonly asynchronous) environment, enabling the possibility to provide a massive amount of information to feed machine learning algorithms and may also react *proactively* to environmental stimuli operating on actuators aimed at minimizing human involvement [22]. IoT is invading every sector of everyday life and, despite the belief that it is just at the beginning of Gartner’s IT development curve [23], IoT has already been adopted by a considerable number of USA farms [5]. A recent analysis [24] estimated that in 2027, the sector will be worth 34 billion USD, with an expected increase in productivity of up to 70% by 2050 [25]. IoT is the technology characterizing Agriculture 5.0 (Figure 1).

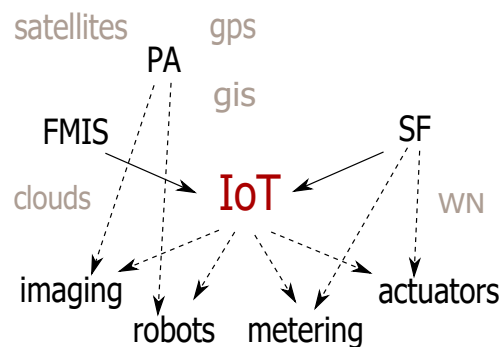


Figure 1. Major recent technologies involved in Agriculture 5.0. IoT—Internet of Things; PA—Precision Agriculture; FMIS—Farm Management Information Systems; WN—Wireless Networks; SF—Smart Farming; gis—geographic information systems; GPS—Global Positioning System.

The objective of this work is to draw a big picture of IoT and current solutions adopted in crop management from an interdisciplinary perspective, with the aim to reveal gaps and future directions. Two main questions are addressed: how is IoT going to improve crop management? Is IoT offering new solutions to crop management problems?

In this analysis, an overview of the architecture of IoT systems is given in Section 2, a synthesis of crop management practices with references to IoT is presented in Section 3; we discuss solution designs to highlight the benefits and weaknesses of IoT technology in crop management, together with open directions in Section 4. Finally, we draw the conclusions in Section 5.

2. Architecture of an IoT system

Since its introduction, the term IoT has been often misused. Some refers to IoT as its application in Industry 4.0 [26], others to its enabling factors: *physical devices*, *internet*, and *cloud computing*.

IoT has witnessed many independent conceptualizations and architectures. We refer to the well-known architecture discussed in [27] (Figure 2) that consists of four independent layers (i.e., groups of functionalities) *perception*, *network*, *service*, and *application*. In this section, we introduce the main functionalities of the first three levels, while actual applications in crop production (e.g., smart fertilization and watering) are detailed in Section 3.

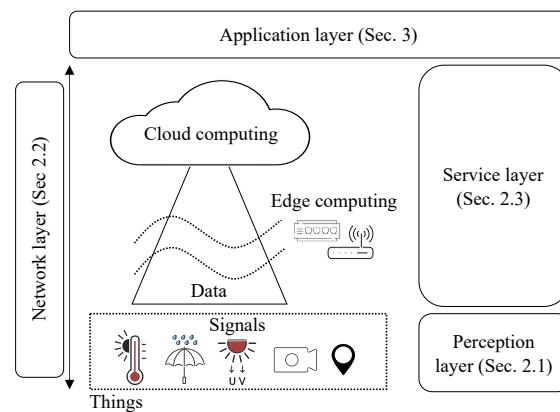


Figure 2. Architecture of an Internet of Things system (inspired by [27]); this also reflects the structure of the survey.

2.1. Perception Layer

The perception layer is oriented to connect “things” to the “CC” system, and acquires and processes physical signals into data that will be transmitted by the network layer.

Though IoT is a construction of Information Technology, its backbone is represented by hardware devices used to monitor and control the environment remotely (e.g., home automation) [28]. All of these cases are characterized by a core technology, made of internet-connected microcontrollers, whose major differences are given hereafter.

- **Power**—When far from power infrastructures (inside a building or engine vehicle), IoT devices need to be self-powered, which often means that they should host few sensors and stay awake for a short time: Low-Power IoT devices [29] are designed to be in a sleeping state for most of the time, and recently, there has been a growing interest in batteryless devices [30].
- **Connectivity**—An aspect related to power features and the amount of data to be communicated (payload); more diffused IoT-boards integrate/support radio modules for most diffuse networks (see Table 1). A relevant interest exists in Low-Power Networks whose IoT-oriented standards involve several organizations [31]. A point not to be forgotten when choosing the board to be used for a given solution is the purpose of observation and the need for bidirectional communication.

Table 1. More diffused radio networks used for IoT applications, with typical coverage and frequency (from Farooq et al. [32]). GSM—Global System for Mobile Communication.

Technology	Range	Frequency
Bluetooth	50–150 m	2.4 GHz
Wifi	50 m	2.4 GHz
ZigBee	10–100 m	2.4 GHz
LoRaWAN	2–5 km	country dep.
Sigfox	3–50 km	900 MHz
Neul	10 m	country dep.
GSM	35 km	0.9, 1.8, 1.9, 2.1 GHz

- **Modules**—A major aspect affecting power management is related to the need of hosting power electronics as actuators (e.g., valves) or cameras. IoT devices comprise a main board and several shield/interfaces (GPS, SDcard, I2C, CAN) to connect external sensors.
- **Physicality**—A non-negligible aspect of a device relating to its external design [33], which includes that of the envelope/box; in the open air, devices are directly exposed to rain, freezing and high temperatures, hard winds, and other possible dangers which destroy electronic circuits and mechanical parts.

The way design aspects and choices affect one another is presented in Figure 3.

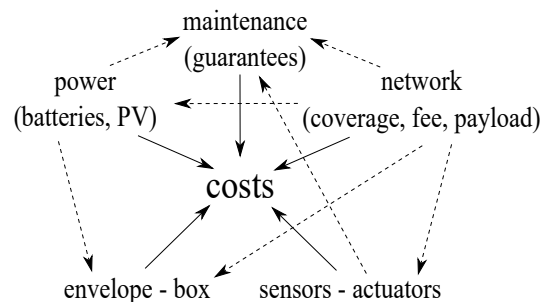


Figure 3. Major aspects to account for in IoT device design—dashed are the impacts of design choices, while continuous lines are their impact on costs.

The number of possible combinations of elements is so wide, and the technology so fluid that many applications are based on prototype-oriented development boards (e.g., Arduino, ESP, ST), and recipes for device assembling are continuously coined (e.g., Gerber and Romeo [33]). Quasi-industrial scale ready-to-use boards also exist, which are quite common for metering and localization purposes.

2.2. Network Layer

The network layer is responsible for the transmission of data through the IoT system; it routes raw data from/to the perception layer to/from the service layer. This layer moves data using communication technologies and protocols from the internet, which can connect any thing at any time from any place [34]. While the internet involves a plethora of protocols, we only mention those involved in IoT systems. According to AlFuqaha et al. [35], IoT protocols can be categorized into *application*, *service discovery*, and *infrastructure*.

- Infrastructure protocols The radio networks mentioned above, besides an electric interface, also have a logic interface corresponding to the code of signal transmitted/received. Their standards, namely, IEEE 802.15.4 (WiFi), BLE (Bluetooth Low Energy), LTE-A, Z-Wave, etc. [35], include details about frequency range and modulation, the coding of data (packets, frames, datagrams), and features affecting the velocity of a network (see Table 2).

Table 2. More diffused radio networks used for IoT applications.

Technology	Data Rate	Technology	Data Rate
Bluetooth	1 Mbps	GMS	35–170 kbps
Wifi	600 Mbps	EDGE	120–384 kbps
ZigBee	250 kbps	UMTS	384 Kbps–2 Mbps
LoRaWAN	0.3–50 kbps	HSPA	600 kbps–10 Mbps
Sigfox	10–1000 bps	LTE	3–10 Mbps
Neul	1–100 kbps	LTE-M1	10 kbps
		NB-IoT	100 kbps

The greatest difference in such sense is the connection procedure: in a traditional mobile network (such as GSM—Global System for Mobile communication) the device could take a (relatively) long time to access a radio network, and usually send long data packets (expensive handshakes, headers, etc.). LoRa, and especially Sigfox, on the other hand, allow Low-Power devices to wake-up, send a message, and sleep again in less than 1 s.

- Application protocols—They allow the exchange of chunks of data [35,36]. The most known of them is the Hypertext Transfer Protocol (HTTP), a foundation of communication for the World Wide Web. Though not specific for IoT applications, it is still used

for traditional approaches. On the other hand, one of the most popular IoT protocols is represented by Message Queuing Telemetry Transport (MQTT). The Constrained Application Protocol (CoAP) is a web-based protocol that is used in constrained nodes and constrained networks. Extensible Messaging and Presence Protocol (XMPP) is based on exchanges of XML (eXtensible Markup Language) messages in real-time that are defined to connect devices to servers. Advanced Message Queuing Protocol (AMQP) is a queuing system designed to connect servers. Data Distribution Service (DDS) is a fast data bus for integrating devices and systems optimized for direct device communication (noncentralized). The main differences between them can be identified on the basis of publish and subscribe mechanisms, request/response interaction, security level, supported quality of services (QoS) mechanisms, and payload size [35]. Other characteristics of network transport protocols are reported in Table 3.

Table 3. Most relevant characteristics of network transport protocols [36] as UDP (User Datagram Protocol) and TCP (Transmission Control Protocol), including the latency level (real-time), the adoption of publish/submit or request/reply patterns, and acknowledgment (broker or bus-based). MQTT—Message Queuing Telemetry Transport; AMQP—Advanced Message Queuing Protocol; XMPP—Extensible Messaging and Presence Protocol; DDS—Data Distribution Service; CoAP—Constrained Application Protocol.

Characteristics	MQTT	AMQP	XMPP	DDS	CoAP
Transport	TCP	TCP	TCP	TCP/UDP	UDP
Real-Time	no	no	near RT	yes	no
Pattern	pub/sub	pub/sub	pub/sub	pub/sub	req/reply
Broker/bus	broker	broker	bus	bus	broker

Other popular protocols oriented to low-power devices as LoRa (Long Range) and Sigfox, are optimized for specific connection requirements (e.g., uni-directional) and topologies and (e.g., decentralized).

- Service discovery—This class of protocols is used to detect devices and services offered through a network, reducing the effort to manage dynamic IoT systems without the need for human intervention. A well-known discovery architecture is the Domain Name System (DNS, which maps an IP address to a human-friendly name), which is extended by multicast DNS (mDNS) and DNS Service Directory (DNS-SD) to discover services by type and properties [37] in *zero-configuration* networks. In mDNS, resolution information is stored locally on each device, and each device directly answers incoming name resolution queries (each device acts both as a server and a client). DNS-SD defines how a client queries DNS servers to discover services within a domain using the service type as a selection criterion; a client gathers the descriptions of all services and selects the most appropriate. This reduces the scalability of the protocol in large networks [38].

2.3. Service Layer

The service layer ensures the functionalities necessary to route data produced from heterogeneous devices to clouds [39–41], shared pools of on-demand network resources [42] including storage, applications, and services at a large scale that are provisioned without humans in the loop [43].

Cloud computing complements the limits of “things”—that are widely distributed and have limited reliability, performance, and security [44]. The synergy of IoT and cloud computing also lies in elasticity, i.e., the degree to which a system can adapt to workload changes. This is of essential importance in a scenario in which things can be attached to the IoT system at any time from any place.

IoT prevents the need to build hardware and software solutions on-premises with high costs of installation, maintenance, and scalability.

To make it easier, clouds host IoT “frameworks” providing data structures, interfaces, and functionalities with the purpose of standardizing the design, implementation, and deployment of applications, relieving users from management and technological complexities, and enabling them to focus on the functional aspects. Well-known IoT frameworks are Amazon IoT [39], Google IoT [40], and Azure IoT [41]. A recent comparison of the three providers has been proposed in [44]. Examples of open-source IoT frameworks are SiteWhere [45], OpenIoT [46]. A comparison between some open source and proprietary frameworks has been proposed in [47]. FIWARE [48] is a framework specification supported by the European Commission that standardizes the development of IoT applications and has an open-source implementation from ORION [49]. FIWARE introduces a “Context Broker” component, surrounded by additional (third-party) components, which can supply, process, and visualize context data through common interfaces. All the frameworks above cover the following services, today included in most IoT applications.

- Device management—In IoT, device management plays a fundamental role: IoT systems could consist of fleets (from hundreds to millions of devices) of devices, to be securely accessed, and kept up-to-date. In FIWARE [48], each device type is interfaced by a specific agent, whose goal is to translate IoT-specific protocols into data exchange or information necessary to control the device. Device discoverability, together with most of the meta-data information on sensors, are increasingly maintained by ontology-based systems [50].
- Data ingestion—This refers to the gathering of raw data from things (devices) to a repository. This process can be either performed periodically, by *pulling* data from sources into the repository, or continuously, by letting sources *pushing* data streams into the repository. Examples of data ingestion technologies are Kaf [51] and AWS [52].
- Data storage—Data are collected into *databases*, structured and persistent repositories organized atop a single conceptual model [53], classically represented by a relational database (e.g., W3School [54]). However, the volume, variety, and complexity of data demand for distributed and elastic storage systems increased the usage of OORDBs (Object Oriented Relational Data Bases, e.g., [55,56]), recently further generalized to *data lakes* (e.g., examples of data lake implementations are Ama [57] and Azu [58]), that is, central repositories where raw data are organized in zones depending on the elaboration to which they are devoted. Data lakes store raw data, *as is*, into their original format, therefore, they eliminate the up-front costs of transforming data into a format suitable for a database, opening data access to every thing/user in the IoT ecosystem [59].
- Data processing—Such a functional process is aimed at extracting meaningful information from raw data. Processing may start during data ingestion, for instance when extract, transform, and load (ETL) procedures are applied before data storage (e.g., transforming raw data before copying them into a relational database). Depending on both the responsiveness and the data necessary to back the decision-making process, data processing takes different places. We distinguish processing at *embedded*, *edge*, and *cloud* computing levels (Figure 4). Indeed, processing can be carried out on a single board (embedded computing), on network devices (edge computing), and on remote data servers (cloud computing). Cloud computing allows highly scalable processing at the cost of moving data from IoT devices to data centers spread worldwide; processing can be based on data from the whole system at the cost of higher latency that is not negligible for real-time applications. “Edge” computing brings processing closer to the IoT devices by allowing data processing on internet access points (e.g., routers). This reduces the overall network latency and allows the processing of smaller data aggregates [35]. “Embedded” computing moves processing to the “thing” itself, eliminating network latency at the cost of lower processing resources (to overcome these limits, technologies such as FPGA are developed). Well-known processing models are *streaming*, *minibatch*, and *batch*. Streaming allows the processing of single data items as soon as they are pushed into the data stream. Minibatch allows

the processing of a window (e.g., a time window) of data items pushed into the stream. Batch processing supports the processing of large volumes of data items at once. While the latency of stream or minibatch processing is in the order of seconds or minutes, batch processing has latency measured in hours. Examples of frameworks supporting distributed processing at the cloud computing level are Spark [60] and MapReduce [61], while Google recently introduced the Global Mobile Edge Cloud [62] to enable edge computing on 5G networks. At the embedded level, processing can be implemented by directly programming the “things”.

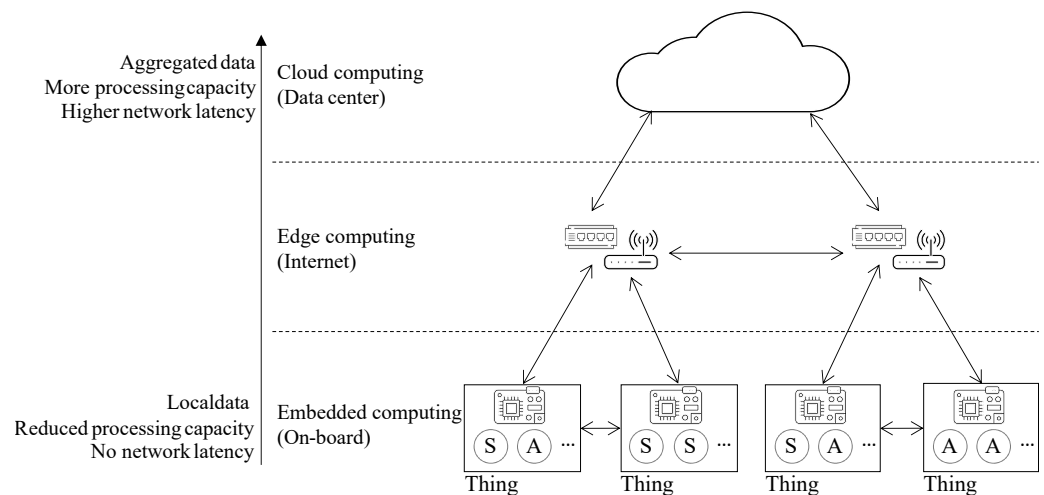


Figure 4. Data processing at embedded, edge, and cloud computing levels; moving from on-board to data center processing allows higher processing capability, broader data aggregates, and higher network latency. Things are composed of sensors, actuators, and processing capability.

3. IoT in Crop Management

Cropping systems are characterized by ecological, economic, and social aspects, and a farmer needs to keep all of them under control. Though recently policies, labor, and market are relevant aspects, ecological control represents the dominant tasks of a farmer, and it is pursued in different stages. In the setup phase of a production system, control means choosing a cropping technology, a long-term decision determined from landscape (e.g., terrace cultivation), climate (e.g., rain-fed crops), social aspects, resource availability, and market organization, the combination of which generated a multitude of different scenarios [3].

In the management practices of everyday cropping systems, adopted technologies determine relevant differences in the ability to control the environment. The main difference in cropping systems can be identified between indoor and outdoor, investigated by Navarro et al. [63]. In indoor systems, almost all production factors are under control: relevant environmental variables are regulated by hydro-electro-mechanical systems that timely supply the proper lighting, openings, fans, water, and nutrients. Only partial control can be performed in tunnels (temperature and humidity are conditioned by openings) and nets (used to prevent the spreading of insects, bird flights, and hail). In field crops, chances to control environmental factors are less available. Farmers are often unarmed in front of weather, pests, and diseases.

All of the actions mentioned—planning, scheduling, decision, and control—are based on direct and indirect continuous observations [64] of each factor affecting production. Here, we recall the most important ones.

- Weather—Stations are present even in many non-experimental farms. The classical outfit is that of a climatic station: rain-gauge, temperature, and relative humidity. In the 1970s, pan evaporimeter was also added in agro-weather stations, while radiation, wind velocity/direction, and leaf wetness became more frequent from the

1980s with the diffusion of electronic stations. Less frequent is the availability of soil temperature.

- **Water availability**—Water is recognized as the most important production factor (e.g., GRIDA [65]); in dry-summer regions (Mediterranean areas) rainfall trends determine huge risks in growing a crop, as prolonged drought in conjunction with high temperatures in a sensitive period (e.g., seedling, flowering) have dramatic effects on yield. As water availability is not always an option, it has a main role in crop choice (e.g., irrigated vs. rain-fed) and checking soil availability in terms of water content (e.g., [66]) or soil water potential (e.g., [67]), or directly by direct observation of plant status (IR sensors); water excess scenarios are no less dangerous to a crop: rainfall of long duration or high intensity, as much as an unexpected hail can do no less damage to a crop (as they do to humans); drainage systems, relevant to hydrological network management, together with channel, storage, and distribution systems, become really important for water supply.
- **Fertility**—Nutritive substances are essential for plant growth, and in many cases fertilizer is applied along the growing season (e.g., foliage fertilizer); soil water sensors often include electric conductivity, used to deduct information on soil nutrient contents. More reliable information on the nutritional state of a crop can be obtained from multispectral and hyperspectral camera sensors set on field cameras.
- **Pests and diseases**—Detecting the presence and development stage of pests and disease, spreading of insects and weeds is fundamental in growing a single species. A main activity of every farmer is maintaining an artificial ecosystem and preventing its shift toward a community of species that deteriorate the quality and quantity of expected yield. Specific sensors are available to the purpose and are already used in agro-weather networks as leaf wetness.
- **Other production-related aspects**—Detectors for carbon dioxide and other gases (IRGA) are used (mostly for research purposes) to monitor plant and soil respiration rates, including GHG emissions; IR sensors are also used for detecting heat anomalies (we already mentioned water stress) as the presence of flames and intrusions (PIR) from hot blood animals, eventually integrated with cameras. Increasing is the interest in canopy monitoring by multipurpose cameras with sensors of variable sensitivity.
- **Transponders**—Machines have a particular role in control. They are a part of technology and a production factor; they need to be controlled to be in a good working state, and under constant survey in the case of autonomous vehicles because of dangers and damages that failures may represent for human beings, crops, and the environment. Moreover, vehicles may host sensors for self-monitoring [68], and fields from varying distances (UAVs), allowing the increase of spatial detail and time resolution of most sensing tasks listed above.

3.1. Using Observations

Observations are used in production systems following the expected model and known application schemes.

Scientific knowledge has been used to build Cropping System Simulators (CSS) based on physical and empirical modules, with a different conceptualization and operational level [69]. Those with a hydrological component are also used to simulate floods, erosion, and chemical leaching. Several of these models are already embedded in automatic control (e.g., irrigation) operating as a common “home-thermostat”, and the same is also true for crop growth, and pest and disease forecast, this time using growing degree day and cardinal temperatures as thresholds for growth rate of populations during each phenology stage. CSSs are used for planning land-use, selecting crop rotations, or to forecast the spreading of pests and diseases, to produce bulletins/alerts of extension services. However, they often require a lot of parameters from expensive calibrations to be applied to a specific context, and require additional modules and algorithm refinement. Further, to be used as DSTs, simulators produce indicators and indices to be interpreted as criteria around the

objectives with strong subjective (stakeholder dependent) weights, while the final decision always includes a risk component even more difficult to be estimated [70].

That is the reason why empirical knowledge is still largely used. Adopted cropping systems are mostly based on recipes refined from experience. A proof is given from the interest in “Crowd sourcing” which has been recognized as one of the most effective sources of knowledge, e.g., to collect and make growing techniques available to other farmers [71].

Machine learning (ML) methodologies are expected to accelerate the production of DSTs, by means of a class of methods recollected in the “prescriptive-analytics” [72]. ML processes data in the same way humans do in knowledge enhancement, a process abstracted in the “knowledge pyramid” (Figure 5), a metaphor that represents—starting from a large amount of raw data that individually have a limited information value—the synthesis of insights with a progressively higher value.

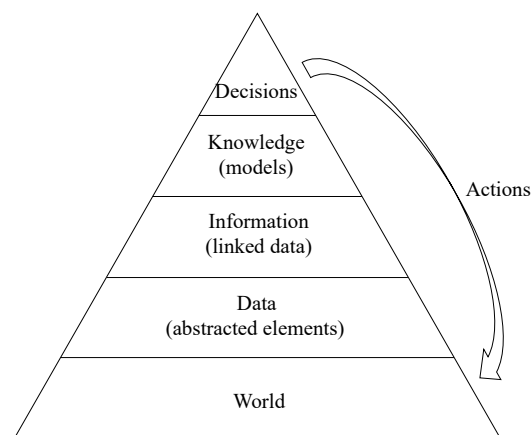


Figure 5. The “knowledge pyramid” (adapted from [73]). Actions affect the “World” level.

Machine learning (ML), relying on many families of algorithms among which (deep) neural networks [74] have recently become the most hyped, can simulate such a climbing process. Of wide interest in PA applications (e.g., for species recognition [75]), ML is based on a training phase, whose effectiveness can depend on the amount of data at hand. For instance, deep neural networks tune millions (or more) parameters (i.e., the weight of each neural connection); as a consequence, the bigger the data set, the better the networks learn. This is why the terms big data and ML are often confused; big data and huge computational capability—which can be accessed on-demand through cloud computing—are the *enabling factors* for ML. However, there are trade-offs between quality and quantity of data; high-quality small data can produce better inferences than low-quality big data [76]. Big data can have poor informative content, this is the reason why the correct design of a data warehouse, a repository that integrates data to make them accessible for successive stages [77], is a fundamental step.

At present, most of the knowledge produced by ML is “hidden” in a matrix of empirical values and cannot be expressed in terms of a physical (dynamical) model. Nonetheless, XAI (eXplainable Artificial Intelligence), aimed at producing explainable and comprehensible models, is becoming of increasing interest also in the domain of Machine Learning [78], proving that extracting “something coherent and valuable” from numbers or images is still the main task [5]. Figure 6 represents a decision tree, an explainable model made of human-friendly rules [79], which emerged from an ML analysis of features of soybean seeds related to different diseases (data set from [80]).

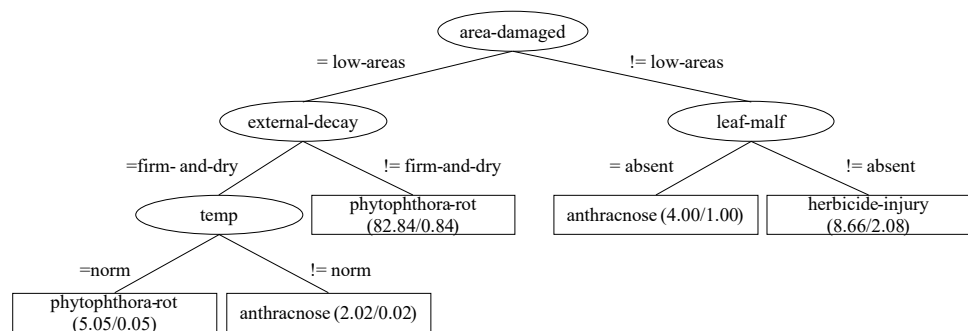


Figure 6. Excerpt of a decision tree for soybean seed disease identification.

3.2. Existing Applications

From the literature, IoT technology appears to be applied in a number of pilot applications [36,81,82] or dealing with research projects bearing on prototypes designed from developer-oriented boards [81] and using public cloud computing services [83].

In some cases, Smart Farming and Robotization are already part of IoT systems. Greenhouse control systems are integrated with the Internet and control actuated by Cloud-based Intelligent Systems [3]. Robots and other UVs adopt communication protocols typical of IoT systems such as ROS (derived from DDS) and allow them to be part of the IoT ecosystem [84].

Sensor data can be accessed from everywhere, including those aboard field machinery to trace their activities [36,85], adding details to crop management and yield [86] to produce data useful to cropping system simulators and produce accurate costing and financial reports; for instance, allowing for an appropriate allocation of indirect and general cost to a specific crop or activity [87].

The IoT produces information to be used beyond the boundaries of farms, to help farmers manage the relationships with the downstream tiers of the supply chain, allowing them to fit the harvesting period to market demand.

Crop management details are of high interest for many stakeholders, including agricultural cooperatives and quality certification bodies. Arena et al. [88] describe how IoT data from interconnected sensors may rely upon a blockchain-based application for traceability and certification.

Social aspects are expected to have benefits too, from the development of an informed and connected rural community [89] useful for problem solving: disease alert, pest identification, labor demand/offer.

A methodological survey [89] identifies 4 mayor areas of applications of IoT in agriculture:

- Monitoring environment (air, soil, water), crops (plant), and animals—62%;
- Remote control in irrigation, fertilization, pesticides, lighting, intrusions—25% of papers;
- Prediction of environmental conditions, production, growth—6% of papers;
- Logistics—7% of papers.

Table 4 reports a list of IoT applications affecting cropping systems.

To produce a closer view of the impact of IoT technology in cropping systems, one of the most important applications is illustrated.

Table 4. Major activities involving IoT technology.

Task		
Services	Know-how support/education	[80,90]
	DSS/Crop Models	[91–95]
	FMIS/accountability	[4,5,87]
	FMIS/PA/machine activity/resource usage	[85,86]
Market	quality/certification/traceability	[7,87,90]
	seeds/products/machinery/labour	[82,90]
Crop monitoring	environmental sensing	[3,36,63,81,89]
	detect crop stress/diseases/pests/weeds/ripening	[82,91,96,97]
Crop practices	smart farming/remote control/automation	[2,32,36,84,98–100]
	precision practices/prescription maps	[5,36,85]

3.3. Case Study—Irrigation Scheduling

Irrigation scheduling is based on three estimates: “When”, “How-much”, and “Flow Intensity” and three main approaches can be used.

- Direct estimate of “crop stress”, based on remote/proximal canopy sensing. Satellite sensing [97], recently integrated with those of drone images [101]. Proximal measurement of canopy temperature by IR sensors (e.g., Jones et al. [102]) and field IR cameras integrated with an IoT system are also adopted [98] to the purpose.
- Water availability in soil, based on direct “soil moisture” observation, then use the lower and upper thresholds criteria as in the previous method, to get advice on a possible water stress condition [103].
- Water availability by “water budget”, based on the estimate of water loss of a canopy (Evapotranspiration—ET [104]), from observed temperature, relative humidity, wind speed, and solar radiation. ET is used as a boundary condition to a soil water redistribution model to estimate soil water status. Logical (if-then) rules are finally used to produce irrigation advice [92].

Irrigation scheduling is implemented by a number of Smart Irrigation applications [81] and currently deployed as a WEB-service or embedded in a local controller [3]. A general framework of the architectures of these systems—describing their major elements and actors—is depicted in Figure 7.

The framework (Figure 7) hosts each of the strategy listed above, as much as their integration, which proved to be able to offer a considerable enhancement [93]. Together, it shows the actual role of IoT, and how different data are collected and managed. Moreover, ML is getting a role to solve important flows of the mention approaches.

- Direct observation of stress can be guessed from cameras that substitute direct farmer monitoring of surfaces: those from satellite, air-crafts, and UAVs (Visible or IR) can also help (by indices as NDVI) by identifying anomalous conditions in the cropped surface, which is supposed to be homogeneous, and made available to an assistance service. However, imagery needs interpretation and lacks subsurface information.
- Soil water content can give more information on the water status of a rooted zone. Nonetheless, identification of threshold values for water supply is still based on empirical knowledge based on soil and plant type, therefore with a local validity. Moreover, sampling a surface requires a number of sensors with prohibitive maintenance costs.
- For water budget potential, ET has to be complemented by empirical correction coefficients to obtain the real crop water requirement. Moreover, soil dynamics coefficients are required to estimate “Flow Intensity”, whose general physical law is well-known while parameters are subject to high spatial heterogeneity and temporal variations [94].

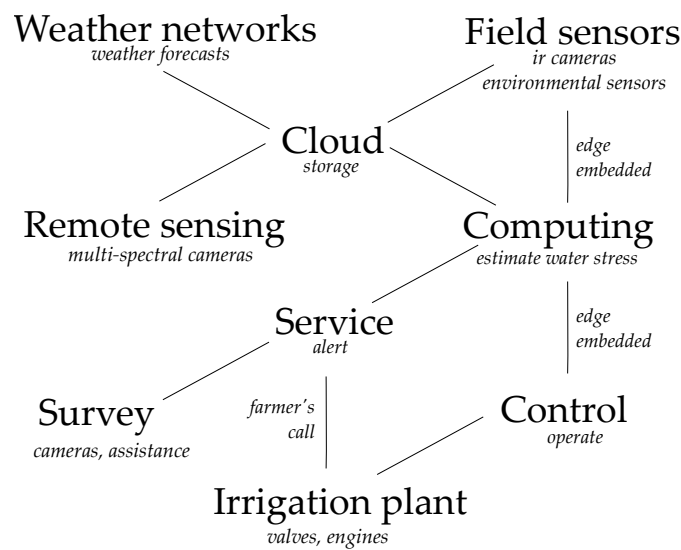


Figure 7. General framework of a field irrigation scheduling system.

4. Discussion

The main applications of IoT in cropping systems do not fall far from those of Smart Farming and Precision Agriculture, and are aimed toward their integration (e.g., [91]).

In such a framework, devices assume a primary role and, in particular, two typologies can be recognized.

- Devices for field monitoring, of the soil–plant–atmosphere system. In the majority of cases, continuous monitoring is not required, therefore, the “perception layer” is conceived as a network of low-power devices that sleep for most of the time, supported by a radio network with an easy connection protocol. Additionally, they would mainly be for metering purposes and bi-directional communication, though facilitating reconfiguration, could prove unnecessary. The payload is expected to be reduced and messages are allowed to have a high-latency, though with a high QoS (quality of service). Low-power networks such as Sigfox and LoRa could be a good choice, though most recent networks (WiFi-halow, NB-IoT, CAT-M1) reduce constraints and allows both usage of protocols to be managed (MQTT) and messages to be digested (FIWARE) more easily. Such solutions can be adopted by almost every board of class “Arduino” that, together with deep-sleep mode, includes easily configurable electrical interfaces (e.g., I2C), together with a wide availability of shields (e.g., Real-Time Clock and SD card).
- Power devices, such as actuators and cameras require a different approach, and devices with embedded computing could be required, based on nano- or single-board computers (e.g., Raspberry Pi), already adopted in the “wired” agriculture (e.g., hydroponics). They allow for continuous monitoring (and surveillance) of plants, actuators, and intrusions (including animals) and need low-latency/real-time response/alerts to be sent to a supervisor (farmer). In these cases, a reliable wireless connection is required, which, if properly optimized, can profit from networking technologies mentioned in the previous point. Nanocomputers include LAN connectors and common wireless connection interfaces and are robust enough to be set in the outer environment, but need to be adequately power supplied (Photovoltaic systems and high-duration batteries). Their use in UV/AV enhances the spectrum of application of IoT for decision support [99] allowing the collection of vehicle data, failure events, and actions performed by tools.

On the cloud-computing side, two major aspects are to be put in evidence.

- Storage—Most of the cases reported in the literature are pilot projects that use a limited number of devices, showing reduced exploitation of cloud computing potential. Major needs seem to be represented by data security, service outsourcing, and No-SQL

data storage due to information heterogeneity (inventories, satellite images, mobile platform mission data, etc.). However, the number of IoT devices/solutions is growing and, though at present such storage systems are mostly for research purposes and country-level surveys, the increase of detail of information in space and time would soon require data-lake storage and big data.

- Processing—As already put in evidence, though UV-oriented protocols (e.g., AVI-Link and ROSlink protocol) are currently used also in UAV guidance. Most IoT applications do not require real-time performances (latency < 1 s). Data collected from mobile platforms and field monitoring stations are mostly batch-processed and delivered to end-users by APP dashboards. Decision-oriented information and supervised actuation are also provided (switching irrigation valves, heaters, vents, etc.) by the processing framework. Direct commands operated by an artificial intelligence system are still bounded to industrialized cropping systems (hydroponics and greenhouses).

Figure 8 reports the most relevant application types as a combination of technology both for hardware devices (left) and data processing (right). As to the latter, the dotted line divides the processing on cloud (batch, minibatch, and stream) from edge and embedded computing.

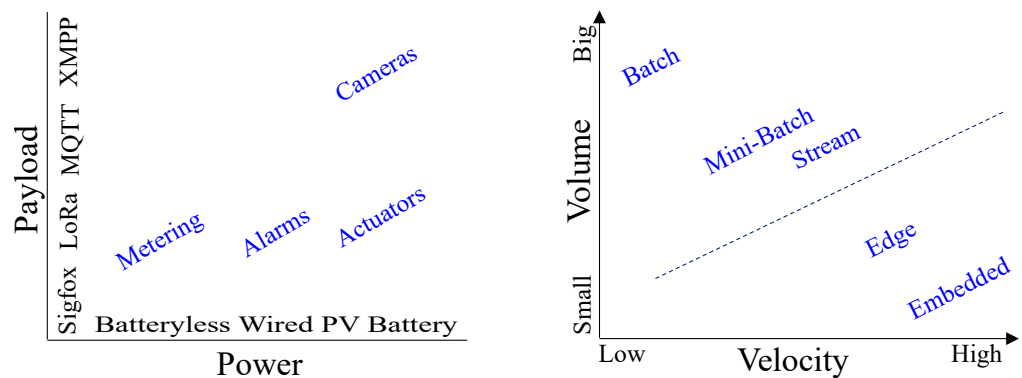


Figure 8. Device and cloud solutions in technological coordinates.

5. Conclusions

We finally may answer the foremost questions set above. IoT is going to improve crop management in terms of accessibility due to the reduction of costs and efficiency due to the timeliness of interventions, and IoT is increasingly offering solutions to crop management problems, most of which are yet unsolved, by the means of AI-driven “prescriptive analytics” implemented in CC systems.

In fact, from the literature analysis, IoT appears as a set of enabling technologies, allowing for a vast combination of architectures (e.g., [36]) and acting as a glue between FMISs, Smart Farming, and Precision Farming.

IoT has yet a little role in the choice and design of a cropping system, which is limited to experienced reliable recipes and farmers’ focus on control.

IoT technology is making crop monitoring, crop data analysis, and automated control more accessible than ever, and wide adoption of IoT is expected where there is a requirement for refinement of observations, prescriptions, timeliness of intervention, and optimization of resources (machinery, pesticides, water, etc.).

At present, the following points can be emphasized.

- IoT is an enabling and mature technology, proven to be able to accelerate the adoption of SF.
- Relying on IoT, many solutions to Smart Farming and Farm Management Systems are going to be accessible even to small farm holders.
- IoT allows increasing access to crop monitoring and significantly enhances the availability of information and early warnings which, in turn, provide more reliable predictions and decision-making support to farmers, managers, and policymakers.

- IoT is based on easy-access technology, facilitating its adoption, which is limited from financial resources [105]. Furthermore, IoT will influence the market and accelerating the development of low-cost next-generation Precision Farming [100].

Critical steps in the IoT adoption should also be evidenced.

- Excitement in IoT is pumping the belief that a large number of cheap sensors could increase data granularity in space and time with an acceptable decrease in data quality. However, data (sensor) reliability remains a fundamental aspect of any technology.
- ML is, to date, too focused on solving problems, underestimating the data requirement for learning stage and the need for explainable knowledge oriented to enhance models for simulation of bio-agro-ecological, soil-plant-atmosphere, and value-chain systems.
- Ethical aspects also emerge. Industrialization and spreading of micro-IoT-devices, envisaging fleets of “artificial insects”, could require strong regulations, [106] including a protocol for placement, location, and recollection.

Finally, the digital divide is still observed to be a concern [95,107], which also affects cropping system technology and production efficiency. IoT can facilitate both exogenous barriers, encouraging the spread of infrastructure [108], and endogenous ones. IoT may help to change the mindset of many farmers, allowing them to easily access the available solutions [109] and share knowledge on cropping systems [110].

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