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Review

Ag-IoT for crop and environment monitoring: Past, present, and future

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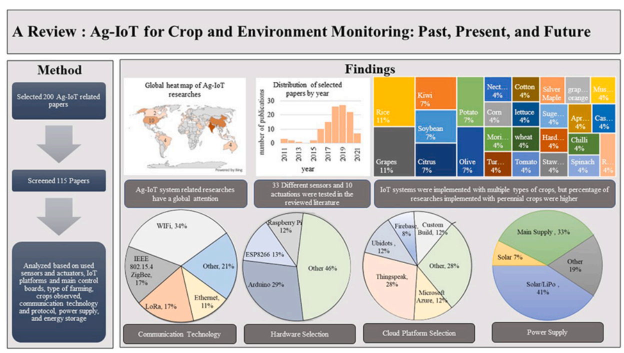
HIGHLIGHTS

- We searched and reviewed the most relevant 115 papers on Ag-IoT published between 2011 and 2021.
- The papers were analyzed focusing on sensors, actuators, main boards, crops, communication protocols, and power supplies.
- Ag-IoT components, challenges, potential solutions, and supporting technologies were presented and discussed.
- The benefits of Ag-IoT for farming systems analyses and management were discussed.
- We concluded with the future direction of designing an Ag-IoT system with completeness, robustness, and compatibility.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Automated monitoring of the soil-plant-atmospheric continuum at a high spatiotemporal resolution is a key to transform the labor-intensive, experience-based decision making to an automatic, data-driven approach in agricultural production. Growers could make better management decisions by leveraging the real-time field data while researchers could utilize these data to answer key scientific questions. Traditionally, data collection in agricultural fields, which largely relies on human labor, can only generate limited numbers of data points with low resolution and accuracy. During the last two decades, crop monitoring has drastically evolved with the advancement of modern sensing technologies. Most importantly, the introduction of IoT (Internet of Things) into crop, soil, and microclimate sensing has transformed crop monitoring into a quantitative and data-driven work from a qualitative and experience-based task.
OBJECTIVE: Ag-IoT systems enable a data pipeline for modern agriculture that includes data collection, transmission, storage, visualization, analysis, and decision-making. This review serves as a technical guide for Ag-IoT system design and development for crop, soil, and microclimate monitoring.
METHODS: It highlighted Ag-IoT platforms presented in 115 academic publications between 2011 and 2021 worldwide. These publications were analyzed based on the types of sensors and actuators used, main control boards, types of farming, crops observed, communication technologies and protocols, power supplies, and energy storage used in Ag-IoT platforms.

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RESULTS AND CONCLUSION: The result showed that 33 variables measured by various sensors were demonstrated in these studies while 10 actuations were successfully integrated with Ag-IoT platforms. Perennial crops, which introduced less disturbance to Ag-IoT platforms than annual crops, were selected by 64% of researchers. Furthermore, studies in Ag-IoT system development were more focused on outdoor than indoor environments. Ag-IoT systems based on Arduino were most common among the studies while commercial platforms were least adopted, likely due to their inflexibility in customized developments. More researchers focused on agricultural applications than the IoT technology itself. Soil water content-based irrigation scheduling and controlled environment monitoring and controlling were the main applications. Other application areas included soil nutrient estimation, crop monitoring based on multiple vegetation indices, pest identification, and chemigation.
SIGNIFICANCE: Several potential future research directions were identified at the end of the review, including integration of satellite-based internet connectivity to improve the IoT networks in non-connected farms, development of mobile IoT platforms (drones and autonomous ground vehicles) with continuous connectivity, and the use of edge-computing and machine-learning/deep-learning to enhance the capability of the Ag-IoT systems.

1. Introduction

Crops are essential for human life because they provide food, animal feed, fuel, and raw materials for clothing and shelter. Crop yield has to be doubled in 2050 compared to 2009 in order to meet the demand of a growing population while increasing the food quality and reducing production inputs (Fukase and Martin, 2020). Potential solutions to enhance global food security include closing crop yield gaps, reducing food waste, changing dietary habits, and reducing inefficiencies in resource use (Foley et al., 2011). Reducing inefficiencies in input resources (such as water and nitrogen) can be achieved by continuously monitoring crops, soil, and microclimate, and then properly controlling inputs without sacrificing the yield and quality of the crop. Internet of Things (IoT) becomes a key technology that enables continuous monitoring and control in this scenario. The ability to generate (near) real-time quantitative data with high spatiotemporal resolution is a major advantage of IoT systems (Liao et al., 2017). IoTs are considered big data systems due to volumes, velocities, and varieties of data they generate. These data are mined and modeled to elucidate the relationships between inputs and outputs (Tsai et al., 2014). Correlation, trend analysis, classification, and numerical prediction are implemented on the data to reach meaningful control decisions. Compared with the conventional wireless sensor networks, the holistic approach of IoT technology allows users to incorporate data analytics on the big data collected by IoT sensor devices. Generally, connected actuators are enabled to control the inputs to achieve desired application rates. For example, an internet-connected soil water content (SWC) sensor network measures the plant water deficit and uploads data to a cloud-based data analysis platform. The analysis will find the trend of soil water deficit to determine the best time and quantity to apply irrigation water.

There has been a boom in IoT application development in agriculture (Ag-IoT) in the last two decades, particularly around crop, soil, and microclimate monitoring. However, the application of Ag-IoT at the commercial scale is still at its early stages. A deeper and more holistic understanding of the existing IoT system development is important for various stakeholders to sketch the future landscape of Ag-IoT. Therefore, the main objective of this paper is to review the key components of Ag-IoT including sensors, actuators, data processing, and data transmission, summarize its usage in crop, soil, and microclimate monitoring, and identify the research needs for successful IoT implementation in the future. Though Ag-IoT is proliferating in both crop and animal monitoring and management, Ag-IoT for crop production is the focus of this paper. IoT platforms for livestock production, as well as other sectors of agriculture (such as postharvest) are not included.

IoT can be found in the manufacturing industry, consumers products, retail, finance and marketing, healthcare, transportation and logistics, smart city, military applications and supply chains (Islam et al., 2022). Fig. 1 shows the three main layers of a generic IoT architecture: the perception layer, network layer, and application layer (Jabraeil Jamali et al., 2020). The perception layer consists of gateways, mobile devices, sensors, actuators, power, and energy storage components. Activities in the perception layer include sensing, controlling, actuation, energy harvesting, energy storage, data transmission, and power management. The perception layer of the Ag-IoT faces challenges including harsh environmental conditions, heterogeneity of the applications, nonavailability of communication infrastructure, and lack of continuous power supplies, to just mention a few. This review therefore emphasizes the perception layer of Ag-IoT. The network layer consists of network devices and data transmission and processing functions. The application layer is responsible for user-specific applications such as data visualization, actuator control dashboards, as well as data storage, analysis, and decision making. This three-layer architecture of IoT can be expanded to five layers by including transport layer after network layer and adding business layer after the application layer (Banu, 2018). The transport layer is responsible for data transmission while the business layer manages the whole IoT system according to the user's business model.

The rest of the paper is organized as follows. The method of the literature review is presented in Section two. Section three details the major elements of Ag-IoT technology. Section four describes the challenges that Ag-IoT systems face with emerging solutions. In Section five, supporting technologies for Ag-IoT are discussed. How the information from Ag-IoT can benefit farm systems analysis and management is discussed in Section six. The final section concludes the review article with future research directions.

2. Review methodology

We have come up with a list of eleven research questions to guide the literature review and analysis in Ag-IoT. These questions, along with the motivation to ask these questions and our initial hypotheses, are listed in Table 1.

To find the answers to questions in Table 1, a thorough literature review was conducted. The main approach was to find the answers based on the recent research carried out in the field of Ag-IoT. We have searched for the recent Ag-IoT research published in scientific journals and conference proceedings between 2011 and 2021, using keywords

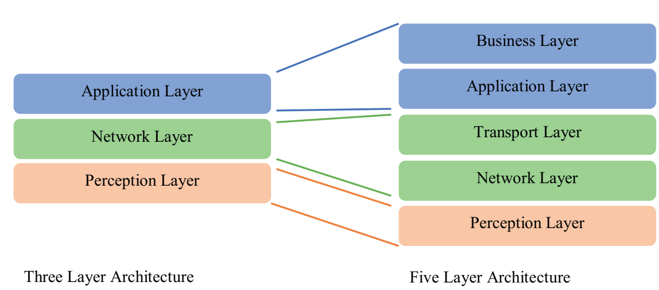

Fig. 1. Three- and five-layer architectures of generic IoT systems.

Table 1
Research questions, motivations, and hypotheses to guide the literature review and the analysis of Ag-IoT.

	Research Question	Motivation	Hypothesis
1	Has the Ag-IoT technology been receiving global attention?	To understand the global presence/importance of IoT in the crop, soil, and microclimate monitoring	>20 countries actively engaged in Ag-IoT application development
2	What types of IoT sensors have been used in agriculture?	To find the role of IoT sensors on the crop, soil, and microclimate monitoring	All types of sensors receive similar attention
3	What are the most popular IoT platforms in crop, soil, and microclimate monitoring research?	To identify the best platforms suitable for Ag-IoT system development	DIY IoT platforms are used by researchers more frequently than commercial IoT platforms
4	What IoT connectivity technologies are used in Ag-IoT?	To understand how to select a connectivity technology for Ag-IoT	Long-range low throughput wireless connectivity technology are common with Ag-IoT
5	Which IoT network/ communication protocols are used in agriculture?	To understand how to select a communication technology in Ag-IoT	IoT protocol does not affect significantly on Ag-IoT system development
6	What cloud platform have been used widely in Ag-IoT systems?	To identify the most widely used cloud service for IoT	Commercial platforms have been widely used compared to custom built platforms
7	What are the main power sources used by Ag-IoT systems?	To understand the power and energy management in Ag-IoT platforms	Solar power is prevalent with Ag-IoT systems
8	What types of IoT actuators have been used in agriculture?	To find the role of IoT actuators on crop input control	Irrigation controlling IoT actuators are most popular
9	What are the most feasible energy storage methods suitable for Ag-IoT systems?	To identify the best energy storage units for Ag-IoT devices	Lithium polymer battery is the dominant battery used with IoT system
10	Are Ag-IoT platforms more popular for indoor or outdoor farming?	To find the dominant market share of IoT for indoor and outdoor crop production	Ag-IoT systems are more popular for indoor agriculture
11	Do Ag-IoT systems have more focus on a specific type of crop?	To understand the crop type preference of Ag-IoT researchers when it comes to practical implementation	Ag-IoT systems are more popular with perennial crops

through Google Scholar and Scopus web search. Keywords used in the search were Internet of Things, IoT, Crop Monitoring, Wireless Sensor Network, Smart Agriculture, and Crop Sensing. This search resulted in 200 peer-reviewed journal articles and conference proceedings papers. After reading the abstracts, 115 papers were determined to be relevant to the topic of Ag-IoT. The selected articles are listed in the Appendix, and they were used for in-depth analysis.

Research papers selected covered countries in all six continents (except for Antarctica, Fig. 2a). Asia presented the largest number of papers (Scotford and Miller, 2004), whereas Australia had the smallest number of papers. In terms of countries, India (Coleman et al., 2022) and China (Chen et al., 2014) had the highest numbers of research outcomes. Fig. 2b presented the yearly distribution of the research papers. The number of research papers published related to the topic increased over time, with the highest in 2019. Demographics of the collected data set provided the answer to question 1 in Table 1, that Ag-IoT has received global attention. More Ag-IoT research has been completed in countries with smallholder farmers such as India and China. The selected papers were read carefully and analyzed for the technical specification of the IoT systems, including the sensors and actuators in each study, communication technologies used, environment the system implemented, and the IoT service provider used.

3. Technical review of the state-of-the-art in Ag-IoT

In Section 3, we have thoroughly reviewed the major components of Ag-IoT. To conduct this review systematically, we have divided this section into multiple subsections. These subsections are sensors, IoT platforms/main control board, wireless communication technology, IoT protocols, cloud platforms, power and energy management, and actuators.

3.1. Sensors

Sensors play a major role in Ag-IoT systems because they serve as the converter between real-world signals and their digital representations. This section begins with an introduction and categorization of sensors used to measure crop, soil, and microclimate parameters. General purpose sensors such as temperature sensor, light intensity sensor, accelerometers, soil moisture sensor, etc., can be integrated into Ag-IoT systems (White, 1987). Table 2 gives sensor categories along with sensor measurands and provides some examples found in the literature.

Proper selection of sensors to an application is essential for IoT systems developers as well as for users to best use the sensors. The advancement of sensor technologies has a major impact on the popularity of IoT. Low energy consumption, compatibility in data transmission between the microcontroller and the sensor, accuracy, repeatability, sensitivity, and robustness are major considerations to select a sensor for IoT system development. To address research question 2 in Table 1, we marked and counted the sensors in the 115 research papers reviewed, with the total count of each sensor given in Fig. 3. Soil moisture sensors were used for the largest number of applications (Ivanova et al., 2016) followed by humidity sensors (Hurst et al., 2021) and then air temperature sensors (Haque et al., 2021). The reason these sensors were integrated most in Ag-IoT so far is likely because of the need for continuous in-situ soil moisture monitoring for decision making in irrigated agricultural production. Water scarcity is a global issue, and the amount of arable land can be expanded significantly if growers can apply water efficiently (Aroca et al., 2018). On the contrary, soil water tension measured via soil water potential sensors only appeared in three papers. This lower interest in soil water potential sensors is likely due to (1) less understanding of the relationship between soil water tension and crop growth, (2) less availability of low-cost soil water potential sensors, and (3) the difficulty in interfacing the available soil water potential sensors to the IoT platforms. Next, we will discuss the Ag-IoT sensors found in the literature according to the measurand category it belongs to.

3.1.1. Acoustic sensors

Ultrasound distance measurement sensors and microphones are the most common acoustic property measuring sensors. Direct use of acoustic measurements is limited in Ag-IoT. Hardwood borer identification IoT sensor network is a direct application of microphone used in pest detection in forestry (Potamitis et al., 2019). Ultrasonic wind speed and direction sensor is an important meteorological sensor used in agriculture to estimate evapotranspiration (Kameoka et al., 2017). Compared with the mechanical anemometer, an ultrasonic anemometer requires less maintenance due to fewer mechanical parts involved. Furthermore, an ultrasonic anemometer can capture sudden changes in wind speed and direction very accurately. Acoustic sensors were used indirectly to measure biological measurands. Crop canopy height estimation by ultrasound sensor is an indirect approach to measure biological parameters (Yuan et al., 2018; Elci et al., 2018). IoT-enabled ultrasound distance sensors are widely used in irrigation systems to estimate the water volume in tanks, wells and reservoirs, and it is an essential sensor for irrigation scheduling in automated irrigation

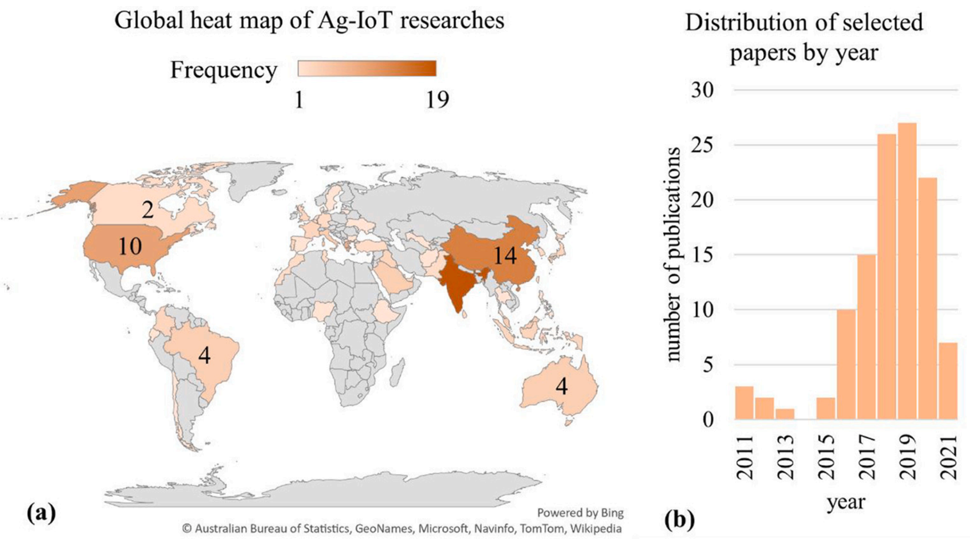

Fig. 2. (a) The heat map of Ag-IoT research around the world; (b) Distribution of the selected papers by year.

systems. Recently ultrasound flow meters replaced the mechanical flow meters due to their high accuracy in flow rate measurement with less maintenance. Underwater ultrasound scanning is possible for aquatic plant growth monitoring purposes such as lotas and seaweed and has a huge potential to determine the harvest stage and growth rate monitoring (Kool and Bernard, 2019). Fruit ripeness estimation is an interesting example of the indirect use of acoustics in agriculture. Daosawang et al. (2020) demonstrated that watermelon ripeness could be estimated by a sound generator and receiver. In summary, acoustic sensors advanced in recent years while replacing some traditional mechanical Ag-sensors and introducing new applications in agriculture.

3.1.2. Biological sensors

Above-ground biomass of plant, plant height, plant density, leaf angle, leaf area index (LAI), count of plant organs (leaf, fruit, flower), chlorophyll concentration, sap flow, and stomata conductance are useful biological parameters in crop monitoring.

Crop yield and the growth stage can be estimated from the plant's mass (biomass). Loadcells are used in indoor farming pots to measure the plant weight directly (Long and McCallum, 2015). Almost all the field crop biomass estimations have been measured by indirect sensing techniques such as biomass-sensitive vegetation indices (VI) or by image processing-based techniques. However, both techniques require time-consuming ground truth data collection for model calibration. The accuracy of these techniques is subject to lighting conditions, sensor type, crop type, model parameters, and training data set. Just like crop biomass, many other biological measurands are also estimated indirectly. For example, stomata conductance can be quantified through optical measurands, and plant height through acoustic sensors. Therefore, most of the biological measurands will be discussed as indirect applications under other measurands.

3.1.3. Chemical sensors

Chemical sensors can be categorized into two main types: photochemical and electrochemical. Photochemical sensors measure chemical reactions or chemicals by their spectral signature, and electrochemical sensors measure the electrical properties due to chemical reactions or the presence of chemicals (Angkawinitwong and Williams, 2021). Soil pH, soil salinity, soil nutrients, oxygen (O_2), carbon dioxide (CO_2), methane (CH_4), pH and conductivity of irrigation water, and photosynthesis are the parameters that often measured by chemical sensors.

Knowing the pH of water and soil is important because pH affects the solubility of nutrients and therefore plant nutrient uptake and growth. Soil and irrigation water pH measurements with IoT-enabled sensors were demonstrated in the literature in nine studies. Spatial variability and the dependency of sensor accuracy on soil condition are the issues to address to promote them in agriculture (Chen et al., 2019; Li et al., 2020). The soil salinity sensor and custom-made nitrate sensor were counted only once, which highlighted the difficulty of measuring soil chemical properties continuously and in a non-destructive manner. The measurement of the real-time nutrient content in the soil, especially nitrogen (N), phosphorus (P), and potassium (K) are essential for fertigation. These sensors are still at the rudimentary stage (Burton et al., 2018) of development. Real-time soil nutrient sensing has a huge potential in future agriculture as nutrient leaching and groundwater pollution are serious issues people are facing now. Nitrate sensors can be fixed to groundwater pumps to monitor the nitrate status of groundwater, or installed in leaching water collectors in fields to get reasonable estimation about nitrate leaching (Hooper et al., 2019). Soil salinity can be derived from the soil's electrical conductivity (EC), and it was demonstrated three times in the literature. This is a very important parameter to measure as soil salinity is one of the main soil degrading factors in irrigated agriculture. None of the research in the literature highlighted the importance of using EC sensors in soil or irrigation systems to ameliorate the soil salinity build-up due to irrigation.

CO_2 and CH_4 are greenhouse gases attributed to climate change and agriculture is considered a major source of their emission. Accounting for the sourcing and sinking of CO_2 and CH_4 from soil and crops is important to understand the budget of greenhouse gases in agriculture. Research suggested that elevation of CO_2 can increase crop yield as well as improve water use efficiency (Hatfield et al., 2011). Therefore, it is essential to measure CO_2 and CH_4.

There are two types of gas sensors available. Metal oxide gas sensors increase the electric resistance of the sensor when it contacts certain gas. Optical gas sensors measure the absorption spectra to detect spectral signatures unique to the gas. O_2 sensors can be used to monitor the crop respiration rate. Electrochemical sensors can be used to estimate dissolved oxygen as the increased dissolved oxygen in water can improve the quality and the yield of the aquatic plants (Shi et al., 2018; Ouyang et al., 2020). Another interesting parameter to measure is stomatal conductance. Plant stomatal openings regulate the exchange of water vapor and CO_2 between a leaf and the surrounding atmosphere. So far, no IoT-enabled sensor has been developed to measure this parameter even though handheld sensors are available (Lamour et al., 2022). Chemical sensors can be used to monitor the quality of fruits during harvesting. As an example, IoT-enabled Ethelene gas sensors have a

Table 2
The classification of sensors, measurands, and examples of each sensor class used in Ag-IoT.

Physical Parameter Category	Sensor Measurand	Sensors used to measure the measurand	Crop, soil, and microclimatic monitoring applications found in the literature
Acoustic	Wave amplitude, phase, polarization, spectrum, wave velocity	Microphone, ultrasound distance sensor	Hardwood borer identification (Potamitis et al., 2019), crop canopy height estimation (Yuan et al., 2018) (Elci et al., 2018), wind speed (Kameoka et al., 2017)
Biological	Biomass, species type, count, density, chlorophyll concentration	Multispectral sensors, RGB camera, Load cell	Plant wet weight, estimate above-ground biomass (Chamara, 2021), Continuous plant weight measurement (Chen et al., 2016)
Chemical	pH, electrical conductivity, gas type, air quality	Volatile organic compounds (VOC)	Indoor air quality (Bagley et al., 2020), soil pH (Chen et al., 2019), irrigation water pH, soil conductivity, irrigation water conductivity, soil gas flux, plant house CO_2, O_2 concentration (Chen et al., 2019)
Electric	Charge, current, potential difference, electric field, resistance, (amplitude, phase, polarization, spectrum), conductivity, permittivity	Soil moisture sensor, (capacitive, or resistive type) humidity sensor	Soil water content (Chamara et al., 2021), air humidity (Bagley et al., 2020), soil nutrient estimation, stomata conductance, sap flow estimation, evapotranspiration estimation (ET), soil electrical conductivity (EC) (Chen et al., 2019)
Magnetic	Magnetic field (amplitude, phase, polarization, spectrum), magnetic flux, permeability	Anemometer	Wind speed and direction measurement (indirect) (Chen et al., 2019)
Mechanical	Position, velocity, acceleration, force, stress, pressure, strain, mass, density, momentum, torque, speed of flow, rate of mass transport, shape, roughness, orientation, stiffness, compliance, viscosity, crystallinity, structural integrity	Pressure sensor, strain gauge load cell sensors	Air pressure measurement (Bagley et al., 2020), stem growth measurement, wind speed measurement, fruit growth measurement, Continuous plant weight measurement (Chen et al., 2016)
Optical	Wave amplitude, phase, polarization, spectrum, wave velocity, intensity, energy	Illuminance sensor, imaging sensors, thermal imaging camera	Light intensity variation over the crop canopy (Yoshino et al., 2021), object detection (ex: leaves, fruit, flowers) (Chamara et al., 2021), plant dimension extraction, chlorophyll type, concentration estimation, plant water stress estimation, leaf disease detection (Thorat et al., 2017), Canopy temperature (Bagley et al., 2020),
Radiation	Type, intensity, energy	Neutron probe	soil water content estimation (Barker et al., 2017)
Thermal	Temperature, flux, specific heat, thermal conductivity	Temperature sensor	evapotranspiration, irrigation, variety breeding and yield forecasting based on leaf temperature (Yu et al., 2016), sap flow rate estimation (Villalba et al., 2017)

huge potential to use in fruit production to identify the best time to initiate harvesting (Esser et al., 2012). Although chemical sensors improved rapidly in the past decade, applications developed based on them in agriculture are still at an early stage. More research is needed to incorporate these sensors with Ag-IoT.

3.1.4. *Electric sensors*

Electric sensors play a key role in Ag-IoT as they have been used in many industries for a long period. The main principle is to measure the change of electrical properties due to physical or chemical changes in plants, soil, and the environment. Some electrical parameters are charge, current, potential difference, electric field, resistance (or conductance), capacitance, and inductance. Soil moisture sensors via IoT systems were the most tested sensor in the literature. As most of the agricultural lands face water shortages and climate change has heavily affected the water availability, most of the studies attempted to address this requirement. We found that electrical resistance, capacitance, and permittivity of bulk soils were used to estimate soil volumetric water content (VWC). Furthermore, soil water tension was measured by the electrical resistance of gypsum blocks. For better irrigation scheduling, both VWC and soil water tension are important: VWC quantifies the amount of water in the soil whereas soil water tension is a better indicator of how difficult plant roots can extract water from the soil matrix.

Air temperature and humidity sensors are the other two dominant sensors researchers have tested. There are three types of humidity sensors: capacitive, resistive, and thermal. Crop ET and pest or disease forecasting are the potential applications of the air temperature and humidity sensing requirements. But 90% of the research just demonstrated the capability of plug play these sensors; only 10% of IoT researchers demonstrate the capability of using those sensors for a meaningful task like disease forecasting. Humidity is an important environmental parameter directly related to ET calculation, crop quality, and pest growth forecasting. Sensors can be deployed to measure absolute, relative, and specific humidity. For example, the best time to start grain harvesting is highly dependent on grain moisture content and if harvested without considering the optimal moisture level it may cause extensive post-harvesting damage and economic loss (Zoerb et al., 1993). IoT-based ET modeling and irrigation scheduling enable low water usage and low irrigation energy consumption. IoT also opened the path for non-conventional VWC measurement. Aroca et al. (2018) presented the use of RFID to estimate VWC with a received signal strength of the tag with $R^2 > 0.9$. A rain sensor based on the electrical conductivity principle was demonstrated as an IoT sensor that could detect the start and end of the rain (Andrey Rivas-Sánchez et al., 2019). Based on these literature outcomes it can be concluded that electric sensors are mature compared to acoustic and chemical sensors and have been used in the industry for a long time and have a wide range of applications in Ag-IoT.

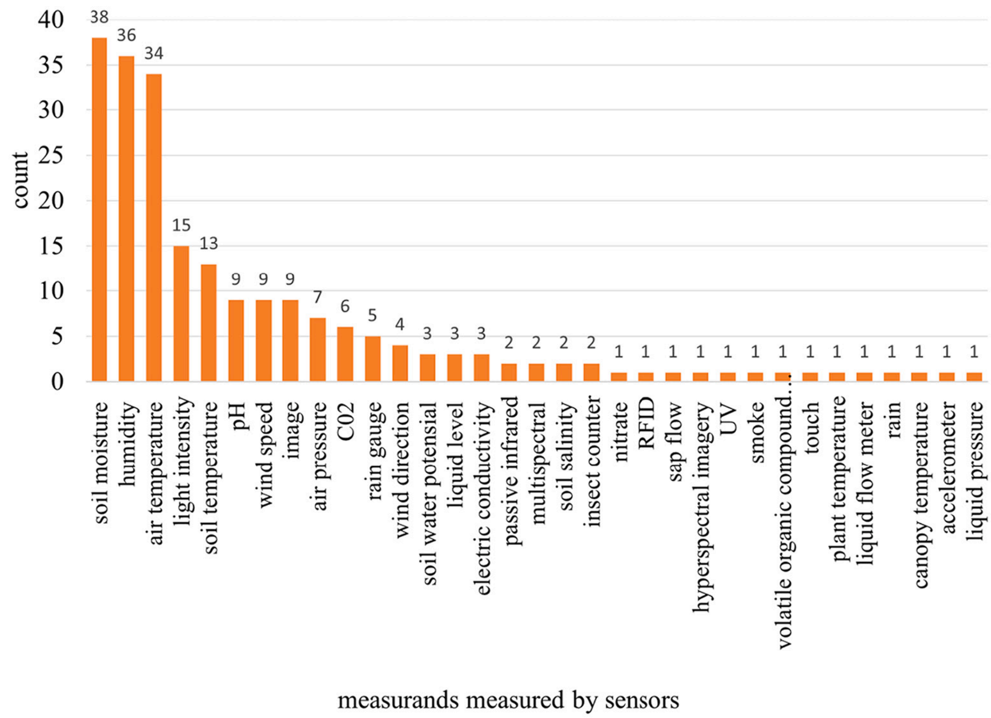

Fig. 3. Various sensors found in reviewed research papers and their frequency.

3.1.5. Mechanical sensors

Mechanical sensors convert a physical parameter of interest through a mechanical system to an electrical signal. Parameters such as flow rate, acceleration, velocity, direction, orientation, and pressure can be measured by mechanical sensors. Examples of IoT-enabled mechanical sensors found in the literature include rain gauges, mechanical flow meters, air and liquid pressure meters, and anemometers. Rain gauge is important to capture the precipitation accurately to determine the timing and quantity of irrigation when combined with soil water content sensors and evapotranspiration modeling (Kameoka et al., 2017). Tipping bucket rain sensor converts water volume it captures to an electrical signal through a simple mechanism. Measuring pressure is important for air, liquid, and soil pressure calculation. Air pressure is relevant to measure crop transpiration as the opening and closing of plant stomata are partially regulated by vapor pressure deficit. Soil compaction can be measured by the pressure sensors inserted into the soil, which are useful for measuring the impact of heavy agricultural machinery. Irrigation line pressure sensors are critical to monitor the irrigation process as the wetting pattern of irrigation systems highly depends on the irrigation line pressure. High pressure causes loss of irrigation energy while low pressure does not allow maximum irrigation area through sprinklers. Anemometers can be used to measure the wind speed which is required for calculating ET and detecting high-speed wind that could be hazardous to plants. Gas and liquid flow rate are significant parameters for crop, soil, and environmental monitoring. Conventionally crop and soil inputs in the liquid or gaseous form, such as water input (including rain), leaching water, liquid fertilizer, liquid or gaseous insecticides, are measured using flow sensors. Some cash crops or niche crops such as wasabi (Sultana and Savage, 1970) and lettuce (Sultana and Savage, 1970) need highly precise environmental conditions and flow monitoring sensors are important for meeting those conditions in the future if climate change imposes challenges to grow them. Overall mechanical sensors play a key role in Ag-IoT systems, but most of the mechanical sensors are replaced by non-mechanical sensors due to the fact mechanical sensors need frequent maintenance and have long response time.

3.1.6. Optical sensors

Optical measurands play a key role in modern agriculture. There should be a light source and an optical sensor to take the measurements. Ultraviolet (UV), visible, and near infrared (NIR) are the main wavelength regions where optical sensors are operated. It is important to note that optical sensors appear to have the least applications as IoT sensors according to the literature. Typical RGB images were used to derive RGB image-based vegetation indexes while multispectral sensors were used to derive vegetation indexes such as NDVI and NDRE (red-edge NDVI). Most of the optical sensors that generate spectral signatures or images of the target produce larger volumes of data and consume a higher amount of power compared to other sensors in Fig. 3. This appears to be a significant discouraging factor to incorporate these sensors into IoT. Naturally, signals in the visible region were used as indicators for many crops and environmental parameters such as maturation time, crop quality (Long and McCallum, 2015), crop nutrient requirement, pest pressure, as well as water and nutrient level in the soil. Historically people used their eyes (only responsive to the visible lights) to evaluate the color intensities somewhat qualitatively (e.g., comparing those to standard color cards). The introduction of these sensors has significantly improved optical measurements of crop and environmental parameters by (Akyildiz et al., 2009) enabling quantitative assessments and (Alderfasi and Nielsen, 2001) extending the spectral regions from visible only to UV and NIR. Fruit spectral signature was used to identify defects in the fruit that could not be revealed via visible light. NDVI and NDRE were used to quantitatively determine crop density as well as the nitrogen and water requirements (Scotford and Miller, 2004). We would like to highlight that more research is needed to demonstrate the optical measurand use in Ag-IoT as they can be used in a wide range of applications in agriculture.

3.1.7. Thermal sensors

Thermal measurands have a wide range of applications in Ag-IoT, and most of them are measured indirectly with optical and electrical means; for instance, measuring crop canopy temperature with infrared radiometers. In the literature, the frequent use of air and soil temperature sensors highlighted their importance in crop ET modeling and disease forecasting (Symeonaki et al., 2020). These sensors are cheap and readily available as off-the-shelf items and support a wide variety of IoT platforms (Mohanraj et al., 2016).

Thermal parameters have the potential to indirectly measure biological measurands. One such example is the sap flow sensor, which was described in one study as a transpiration measuring sensor compatible with the IoT system (Villalba et al., 2017). The sensor consisted of a flexible tree stem heater and a temperature sensor while the IoT platform calculated sap flow based on the applied heat and temperature. This sap flow measurement is proportional to transpiration (sap movement in the xylem) and therefore useful in crop ET modeling (Villalba et al., 2017). Sap flow monitoring is essential in some crops to understand the physiological behavior of plants. Rubber, maple, coconut, and palmyra palm sap are the output of the harvest, and in these cases, sap flow monitoring is useful to estimate yield, optimize production, and develop high-yielding crop varieties.

Indirectly measured canopy temperature through infrared radiometers estimates the transpiration rate and crop water stress index, which is important for water stress detection and irrigation scheduling (Alderfasi and Nielsen, 2001). Identification of pests such as wild boar through thermal measurement is an interesting application in agriculture. Furthermore, the temperature is found to affect the quality of grapefruits (sugar content) and flowering time of several crops (Pérez-Expósito et al., 2017). Temperature sensors can also record the temperature variation in plant leaves and flowering buds and give a warning about frosting time (Barker et al., 2017). This listing of thermal measurand applications concluded that thermal sensors are very important in Ag-IoT and have been demonstrated in the past literature.

3.2. Sensing platforms and main control board

Section 3.2 summarizes the statistics of the Ag-IoT sensing platforms and control boards in the literature. The answer for Question 3 in Table 1 was derived from Fig. 4.

3.2.1. Sensing platforms

Sensing platforms consist of sensor node including sensors, power supply, energy storage, actuators, main control board or the data processing unit, and structural components. Structural components determine the sensor node establishment in the field. There are two main types of IoT platforms available for crop monitoring. Stationery IoT platforms can collect continuous crop data or telemetry data targeting a single plant or a group (plot) of plants. The main advantage of stationery IoT is the high temporal resolution of the data. Mobile IoT platforms can collect data over some areal coverage and with high spatial resolution, but with limited temporal resolution.

Kumar et al. (2016) presented the development and testing of a crop monitoring mobile robot. It is capable of automatically planning the path to find crops, recognizing plants using neural networks, applying fertilizer timely, and applying water based on the feedback from soil moisture sensors, temperature sensors, and humidity sensors.

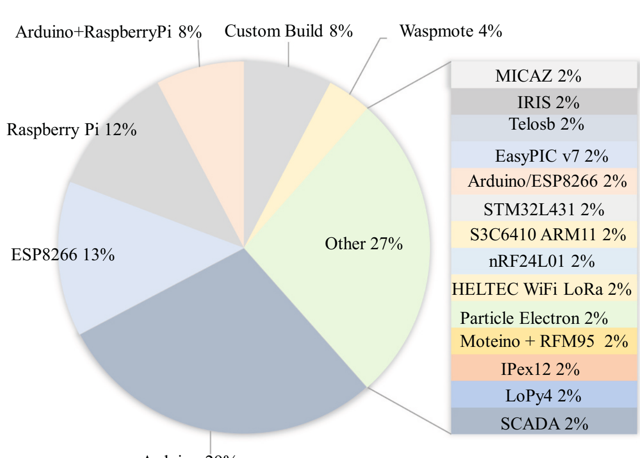

Fig. 4. Main control boards of the Ag-IoT systems present in the reviewed papers.

3.2.2. Main control boards

The communication and data processing hardware for IoT systems reported in the reviewed papers could be broadly categorized into three kinds: commercial platforms, custom build, and DIY (do-it-yourself) development boards. The commercial platforms are reliable but have limited support for integrating different or additional sensors. IPex12 (Odin Solutions SL, Peru), Particle Electron (Particle Industries, Inc., USA), MICAZ (MICAS AG, Germany), IRIS (IRIS IoT Solutions, UK), and Telosb (Advantic Sistemas y Servicios S.L., Spain) are commercial IoT systems. In the last decade, commercial IoT platforms were still at their development stage, explaining their lower use in the reviewed papers. Custom build hardware is designed by researchers based on their own requirements. Researchers have the flexibility to decide on the number and types of sensors, interfacing connections, microprocessor clock speed, IoT node memory capacity, input voltage, and the communication technology used in the node. Furthermore, the technical complexities present in developing customized sensor interfacing may also discourage researchers from using commercial systems. The custom build hardware platforms have high levels of customization but require extensive knowledge of embedded system development to design them. DIY platforms are IoT nodes designed based on commercially available development platforms, including Arduino, EasyPIC v7, ESP32, Raspberry Pi, and Wapmote. DIY development board based IoT systems are popular among researchers because of their low cost, high availability, compatibility, and easy programmability. The percentage of different hardware platforms used in the reviewed articles is given in Fig. 4. There were 52 identifiable hardware designs in the list of 115 research. Out of them, 29% of the platforms had Arduino only, 8% had Arduino and Raspberry Pi hardware jointly, and 2% used Arduino and Arducam hardware together. Ag-IoT research was dominated by Arduino-based development systems. Availability, reliability, easy programmability, and the option of supporting multiple communication protocols made Arduino-based systems popular among Ag-IoT researchers. Raspberry Pi systems were demonstrated in 12% of the IoT systems, likely due to their capability of capturing images and high computing power compared to Arduino.

Selection of the IoT platform and the main control board is an important activity in IoT system design. The mainboard must support the communication protocols and the power requirement (e.g., voltage) of the sensors and actuators. Often voltage and communications protocol converters are needed to interface sensors with the main control board. Mainboards support three types of digital memories. Volatile memory holds the instructions and data of the currently running program until the power is on. Volatile memory influences the system's performance. A larger volatile memory is needed for IoT nodes with a large amount of data generated via sensors like RGB cameras or spectral sensors. Nonvolatile memory stores data and the program when the IoT node power is turned off. The operating system, device identification data, and system settings are common data types stored in the nonvolatile memory. External nonvolatile memory (e.g., SD cards) can be used to store data or system settings, greatly expanding the data storage capability of the Ag-IoT system.

3.3. Communication technologies and IoT protocols

Section 3.3 produces the answers to research questions 4 and 5 in Table 1 while discussing findings on the literature related to wireless communication technology and IoT protocols.

3.3.1. Wireless communication technology

Wireless data transmission is a key function of an IoT system. To design a successful Ag-IoT system, it is essential to understand the radio frequency (RF) contributing factors that impact signal strength, interference, system model, bandwidth, and transmission range. Also, understanding of pros and cons of wireless communication technologies is essential for a better Ag-IoT device selection. Received power (P_r) of wireless data transmission in an unobstructed line of sight in a radio signal-free area depends on the transmitter power (P_t), transmitter and receiver antenna gains (G_{TX}, G_{RX}), the distance between the transmitter and the receiver (R), and the wavelength (λ) of the radio. This relationship is expressed in **Eq. 1**. Therefore, long wavelength radio signals such as LoRa in 900 MHz are suitable for long-distance data transmission compared to short wavelength signals such as Wi-Fi operated in 2.4–3.2 GHz without changing other variables. For long-distance communication, the plane earth loss formula is used to account for the curvature of Earth for signal strength (Nadir et al., 2008).

$$P_r = P_t G_{TX} G_{RX} \frac{\lambda^2}{(4\pi R)^2}$$

Equation 1 Friis transmission equation (Shaw, 2013).

Furthermore, radio signals are subject to reflection, diffraction, and scattering. These phenomena are illustrated in Fig. 5. In open flat agricultural fields, reflection, scattering, and diffraction may not occur unless there are large agricultural structures. In hilly areas and forests, the effects of wireless signal propagation properties may need special attention when placing IoT devices. The Fresnel Zone is the area around the visual line-of-sight that radio waves propagate out once they leave the antenna. Blockage of Fresnel Zone >40% causes severe signal losses (Tate et al., 2008). Therefore, factors such as the height and density of the crop canopies nearby, the presence of agricultural structures (e.g., irrigation pivots and storage silos), the locations to place IoT nodes, and the antenna height and position are important to account for in ensuring the signal transmission quality. In fact, the research on wireless communications in rural and agricultural landscapes has raised a lot of interest recently (Vuran et al., 2022). The signal quality is also affected by channel noise, interference, multipath fading, and attenuation. The success of data transmission is measured by a parameter called bit rate error (BRE). Based on the above discussion we would like to suggest that it is important to use wireless signal strength mapping tools during IoT system installations. Such tools will help to select the optimum IoT communication technology (for example, Wi-Fi, LoRa, Mobile Communication) suitable for each case, accounting for data transmission rates and signal losses. This practice would help farmers to reduce the capital and operational costs involved with IoT systems.

In the literature, we found that a wide variety of wireless communication technologies were used by the researchers. Out of the 35 studies where communication technology was clearly mentioned, 34% used Wi-Fi, 17% were conducted using LoRa, and 14% used Zigbee. Also 11% of the studies used ethernet or the wired internet connection. Less attention was received for mobile communication technologies such as 4G (3%), NB-IoT (3%), and GSM (3%). In some cases, researchers used two or more technologies to connect different areas in the fields such as LoRa / Wi-Fi, LoRa / TV white space (TVWS), and GSM / Zigbee. According to the findings, Wi-Fi and ethernet were common in greenhouses while others were favored in outdoor farming practices. Fig. 6 summarized the statistics of communication technology used in the literature.

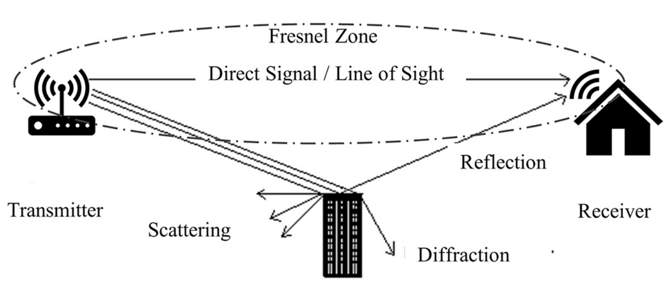

Fig. 5. Wireless signal behavior when it meets with an obstacle.

3.3.2. IoT protocols

IoT protocols are data transmission standards that allow communication between the endpoint and services with the internet being the common network. IoT protocols are broadly classified into two major groups: IoT data protocols and IoT network protocols. The data protocols correspond to the application layer whereas network protocols correspond to the perception and network layer in the standard IoT architecture (Fig. 1). IoT network protocols create networks of device connections. Wi-Fi, LoRaWAN, Zigbee, and Bluetooth are such network protocols, and the same term is used to represent wireless communication technology. Some common IoT protocols are listed in Table 3 with specifications such as frequency, data rate, and range (Triantafyllou et al., 2018; Farooq et al., 2019).

Each IoT network protocol/wireless communication technology has its advantages (Table 3). Bluetooth is a popular short-range wireless communication technology standard convenient to create personal area networks. It is possible to use Bluetooth in indoor applications such as mobile phone-connected soil water sensors and sensor networking in small greenhouses. ZigBee is useful in large indoor growing spaces and LoRa is suitable for field crop monitoring senor networks. Cellular technology is useful for indoor or outdoor spaces where the network coverage is available. Wi-Fi is suitable for both small or large indoor spaces as well as outdoor applications where there is infrastructure support available to setup Wi-Fi gateways. Cellular and Wi-Fi allow transmitting images, videos, and other larger data files such as 3D point cloud data. Bluetooth shares the same advantage but is limited to a short distance. Compared to LoRa, Zigbee, and cellular technology, Wi-Fi has high reliability in data transmission, but power consumption is high too. All these protocols were tested in real crop growing environments (Ferrández-Pastor et al., 2016; Codeluppi et al., 2020).

3.4. Cloud platforms and service models

3.4.1. Cloud platforms

Cloud is an essential part of any IoT system. IoT devices are not useful without cloud connectivity. Data gathered via individual IoT sensors become useful when connected with other relevant sensors. According to the National Institute of Standards and Technology, “Cloud computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction” (Mell and Grance, 2011). Essential

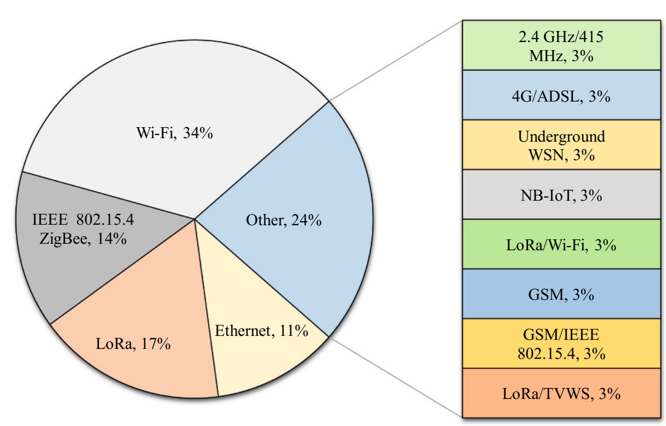

Fig. 6. Communication technologies in Ag-IoT applications.

Table 3
Common IoT Network Protocols/wireless communication technologies and their advantages.

	Frequency	Bandwidth	Range	Advantages
Bluetooth	**2.4 GHz**	Bluetooth 4.0+ **(25 Mbps)** Bluetooth 5 **(50 Mbps)** Bluetooth Low Energy (BLE) **(10 kbps)**	Bluetooth 4.0+ **(50 m)** Bluetooth 5 **(250 m)** Bluetooth Low Energy (BLE) **(50 m)**	Low latency, better responsiveness, scalability, reliability, and robustness
ZigBee	Global **2.4GHz** US **915 MHz** EU **868 MHz**	2.4 GHz **(250 kbps)** 915 MHz **(40 kbps)** 868 MHz **(20 kbps)**	**10-100 m**	Better scalability, randomization, long battery life
LoRa	**150 MHz-1GHz** Depending on the country	**0.3–50 kbps**	urban area **(2-5 km)** suburban area **(15 km)**	Long-range, bi-directional communication with high security, seamless go-to-market
Cellular	**900 MHz** **1800 MHz** **1900 MHz** **2100 MHz**	GPRS **(35-170 kps)** EDGE **(120-384 kbps)** UMTS **(384 kbps-2 Mbps)** HSPA **(600 kbps-10 Mbps)** LTE **(3-10 Mbps)**	GSM **(35 km)** HSPA **(200 km)**	Best-in-class battery life, wider deployment, reliability
Wi-Fi	**2.4 GHz or 5 GHz**	**1 Mbps-2.4 Gbps**	**100 m**	Data security and privacy protection, easy to install and connect, faster data transfers

expected characteristics of a cloud system are on-demand self-service, broad network access, resource pooling, rapid elasticity, and measured service.

Out of the 115 papers we reviewed, only 25 papers discussed cloud platforms in detail. Among them, 28% of the researchers used the ThingSpeak cloud platform developed by MATLAB as the service provider, 12% used Microsoft Azure, and 12% used Ubidots platform. Furthermore, 12% of the researchers built themselves a local data server with the required functionality. Google-based Firebase had 8% usage. Other cloud platform service providers including Amazon Web Services, cloud sense, generic cloud, sensorDB, SEnviro, and Huawei Cloud had 4% use each. The percentage distribution of these cloud platforms is given in Fig. 7.

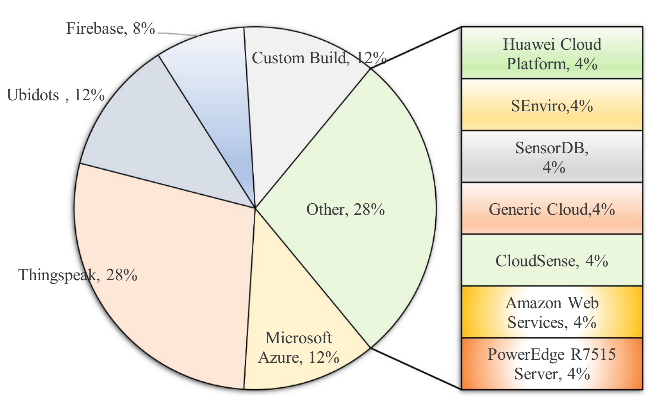

Fig. 7. Statistics of cloud service provider selection.

3.4.2. *Public, private, and hybrid cloud*

In terms of privacy policies, cloud platforms can be divided into three major models:

3.4.2.1. Public cloud. Services are offered over the public internet and available to anyone who needs to purchase them. Third-party cloud service providers own and operate the cloud resources such as servers and storage in the public cloud model. Users do not need to spend any capital expenditures to scale up; applications can be quickly provisioned and terminated; and users pay only for what they use. These are the advantages of the public cloud. Amazon Web Services and Microsoft Azure are examples of public cloud services.

3.4.2.2. Private cloud. A private cloud comprises computing resources used exclusively by users from one business or organization therefore hardware must be purchased for start-up and maintenance is required. In the private cloud model, infrastructure is not shared with users outside the organization. A private cloud can be physically placed at a data center owned by the user organization, or it can be hosted by a third-party service provider. But the organization has complete control over resources and security.

3.4.2.3. Hybrid cloud. A hybrid cloud is a computing environment that combines a public and a private cloud by allowing data and applications to be shared between them. The organizations determine where to run their applications while they control security, compliance, or legal requirements. Some organizations use a hybrid cloud model to keep sensitive data in the private cloud whereas frontal services and web portals are serviced in the public cloud for scalability. Furthermore, the public cloud can act as a supporting system if the data and usage exceeds the capacity of the private cloud.

3.4.3. *Cloud service model*

Cloud-based services provided to the users can be categorized into three major classes based on the hierarchy of the service offered. Typical cloud architecture has nine layers. They are from bottom to top in order: network, storage, server, virtualization, operating system, middleware, runtime, data, and applications. The next section will explain cloud service models in detail with hardware and software layers they belong.

3.4.3.1. Infrastructure-as-a-Service (IaaS). IaaS was the original cloud services model. For IaaS, the cloud service provider will provide the hardware and keep it up to date, but operating system maintenance and network configuration are up to the client. For example, Azure virtual machines are fully operational in Microsoft datacenters. The main advantage of the IaaS model is the rapid deployment of new computing devices. DigitalOcean, Linode, Rackspace, Amazon Web Services (AWS), Cisco Metapod, Google Compute Engine (GCE), and Microsoft Azure are some examples of IaaS.

3.4.3.2. Platform-as-a-Service (PaaS). In this cloud service model, the cloud provider manages the virtual machines and networking resources, and the cloud tenant deploys their applications into the managed hosting environment. For example, Azure App Services provides a managed hosting environment where developers can upload their web applications, without having to worry about the physical hardware and software requirements.

3.4.3.3. Software-as-a-Service (SaaS). In the case of SaaS, the cloud provider manages all aspects of the application environment, such as virtual machines, networking resources, data storage, and applications. The cloud tenant only needs to provide their data to the application managed by the cloud provider. For example, Microsoft Office 365 provides a fully working version of Microsoft Office that runs in the cloud.

3.4.3.4. Network-as-a-Service (NaaS). Software-defined networking and software-defined perimeters are services that belonged to NaaS. NaaS is a cloud model that enables organizations to easily operate the network and achieve the outcomes they expect without owning, building, or maintaining their infrastructure through the cloud. NaaS can replace hardware-centric VPNs, load balancers, firewall appliances, and Multiprotocol Label Switching (MPLS) connections. Users can scale up and scale down as demand changes, rapidly deploy services, and eliminate hardware costs.

3.4.4. Fog and edge computing

Edge computing is the moving of data processing close to where the data is generated. Wireless communication-enabled sensors with microcontrollers can be considered edge computing devices. The introduction of the edge computing paradigm was due to issues related to centralized cloud computing architecture. Data and control signal transmission latency and delays in centralized system data analytics are some disadvantages of cloud computing. Therefore, network designers proposed architectures where the computing power is distributed more evenly around the network. Fog and edge computing push the processing capability out to the edge of the network, closer to the source of the data. Such techniques are called fog computing and edge computing.

Fog computing is a computing layer between the cloud and the edge where edge devices send large amounts of data to the cloud. The fog computing layer can get the data from the edge layer before it reaches the cloud and filter what is relevant and what is not. The filtered data gets stored in the cloud, while the unrelated data can be deleted, or analyzed at the fog layer for remote access or to use in localized learning models.

Precision herbicide applications become popular with field crops. There, a moving platform that has a camera, carries and applies the herbicide at the exact location of the emerging weed. The image processing hardware and software in the moving platform do the image processing instantaneously to reduce the delay of cloud-based image processing in larger fields (Coleman et al., 2022). The centralized cloud-only needs the weed density from the moving IoT platform to forecast the future herbicide need to maintain the required quantity in the stocks. Therefore, edge computing is all about placing computing power on the very edge of the network, on the actual sensors of the device. Low power consumption and low processing power microchips or micro-controllers embedded in the devices provide the power for edge computing. For that reason, their processing capacity is much more limited but sometimes can be adequate to process images (Chamara et al., 2021).

3.4.5. Data analytics in IoT

Data analytics is one of the most important activities in any IoT system, as the decision-making of an IoT system depends on hundreds of sensors and events, which is difficult to analyze manually. Data generated by IoT devices fall under three categories. They are structured data (such as SQL storage), unstructured data (e.g., images and videos), and semi-structured data (like social media feeds). Ag-IoT systems can generate both structured and unstructured data (Lea, 2020). Stream processing and batch processing are the two main types of data processing techniques. Stream processing is useful for mobile Ag-IoT platforms since it allows real-time data processing. Batch processing can be applied in irrigation, chemigation, and fertigation applications as data are processed as a batch to make the decision.

Common data analytics activities for IoT platforms are listed in Table 4. Below are some examples how they are used in Ag-IoT for crop, soil, and microclimate monitoring. Alerting allows growers to receive an alert message when soil water use exceeds the maximum allowable depletion (Gamon et al., 2015). Sensors in the field environment are susceptible to problems like physical damage, pest attack, misalignment, and breakdown, which cause errors in data streams. These problems can be effectively alleviated by error finding. Using time-series Normalized Differential Vegetation Index (NDVI) or Crop Water Stress Index (CWSI) to determine the next irrigation or fertigation time belongs to trend analysis. Triggering sprinklers in a field based on SWC sensor values is an example of signaling. More complex decisions can be formed by combining several analytical activities. For example, in automated crop disease detection, an average daily temperature above 20 to 25 °C followed by 1–2 in. of rain, together with sugar beet leaf color change indicated a sugar beet pathogen outbreak (Wolf and Verreet, 2002). This analysis was enabled by data joining, tracking, and trend analysis.

Table 4
Data analysis activities commonly found in Ag-IoT applications.

Data analysis activity	Function
Preprocessing	Filter out data with little interest to reduce data complexity and duplication
Alerting	Raise an alert if data exceed certain boundary condition
Windowing	Apply rules on data in a predefined time window
Joining	Combine multiple data streams into a new single data stream
Error finding	Find missing values and anomalies in data streams
Tracking	Identify when or where an event has occurred
Trend analysis	Quantify change or trend of data as a function of time
Signaling	Send control signal when a decision is made

3.5. Power and energy management

Power and energy storage are the two major driving forces for IoT systems, especially for Ag-IoT located in remote fields. In the literature, we found 3 main categories of power management systems. Direct main power connected nodes is the first type and most common with indoor applications. A rechargeable battery with a recharging option such as solar, hydro, or wind is the second option. The third one has a rechargeable battery or a non-rechargeable battery but is designed to consume very low power by sending a very low amount of data intermittently. Among the 115 pieces of research we have reviewed, only 27 of them discussed the IoT system power and energy storage features. Out of these 27, 11 platforms used solar power as the main power supply while Lithium Polymer (LiPo) rechargeable batteries were used as the energy storage solution. Out of 11 indoor farming applications which explained the power management options, 9 used the main grid power supply. Research that focused on IoT system setup under high dense canopies used high power density and high-capacity battery-only solutions such as 12 V lead-acid batteries. Two studies mentioned they used battery with solar but did not disclose details about the specifications. It revealed that there are very limited power supplies available for in-field IoT implementation and the findings are highlighted in Fig. 8.

Unlike edge-computing devices, typical IoT end nodes are designed to be less power-hungry. This power consumption goes high due to certain reasons such as connected high throughput sensors, significant data processing, and massive data transmission. However, these power

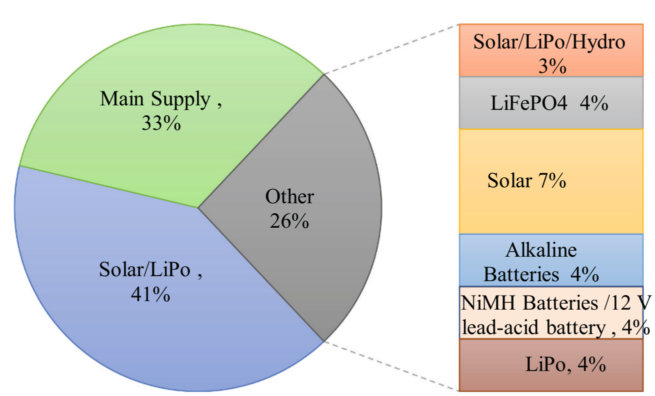

Fig. 8. Power supply and energy storage selection of the Ag-IoT systems in the reviewed studies.

consumptions can be minimized by exploiting different techniques such as the semi-active phase and sleep phase (Zhang and Li, 2019). The edge computing-enabled devices need more power. It is essential to standardize the IoT power management based on the crop and geographical location of the devices. For example, solar power is not a very promising solution for locations with large trees such as rubber, pepper, and spices that have a dense crop canopy 5–10 m above the ground (Villalba et al., 2017).

3.6. Actuators

Monitoring and controlling are two agricultural operations closely related to each other. Monitoring by itself is an open-loop operation; whereas monitoring, controlling, and again monitoring the effects of controlling make a system closed loop and can improve the efficiency of the system. Efficient controlling of the actuators based on the monitoring is a key feature in the agricultural domain for optimizing inputs, maximizing crop yield and quality, and reducing the negative environmental impacts. Fig. 9 depicts the number of actuators controlled via IoT systems that were reported in our reviewed papers. Out of the 115 studies, 54 mentioned IoT-enabled actuation. Some studies used more than one actuator, whereas most of the in-field IoT sensor monitoring systems did not mention the use of actuators.

Since water is the largest input by volume applied to farms, actuators related to water have been mostly discussed in the research work. Such controllers are pumps and solenoid valves. Controlling these two actuators were demonstrated in 22 and 8 instances, respectively. After irrigation, controlling lighting was the most occurred application in indoor farming followed by ventilation, fertigation, alert, and air conditioning. Ventilation allows outdoor air to come inside the greenhouse while air conditioning includes heating or cooling of the air. Alert meant the system sent an email or message to the farmer or the operator of the farm when a parameter exceeded a threshold value. An IoT-controlled insect repellent actuator was demonstrated twice among the 115 case studies evaluated. Automation of soil bed preparation was achieved by utilizing stepper motors in one instance of IoT-based indoor farming. According to Figure 9, water pumps and valves were the most frequently used actuators, and all these systems were closed loop control systems with soil moisture sensors and ET modeling. From the study of the above actuator-related research, it can be said that there is enormous potential to automate the controlling of the indoor crop's required environment and soil preparation. (See Fig. 9.)

3.7. Ag-IoT for crop monitoring

Out of the 115 publications reviewed, 71 systems were demonstrated in a real environment. Among them, 65% were implemented in the fields, 24% were demonstrated in indoor environments, and 11% were simulations. This is an interesting finding that reveals the huge potential of implementing outdoor or in-field IoT applications. Typically, it is easy to set up indoor IoT sensor networks due to fewer technological barriers, such as extreme environmental conditions and sensor connectivity issues. Since real applications were available only in 65% (71 out of 115) instances, further real implementations can be done to demonstrate the capability of Ag-IoT applications.

Considering the 71 systems that demonstrated the real applications, 49 were practically demonstrated with certain types of crops and 22 did not mention the specific crop they used. 15% of these systems were demonstrated with grapes while cereal crops accounted for 26%. One research was based on both grapes and oranges. In total 50% of the IoT studies focused on perennial specialty crops of higher value including grape, moringa, orange, citrus, sugarcane, silver maple, apricot, cashew, and olive (Fig. 10). This result indicates that IoT can be implemented with diverse crop types to achieve various purposes. Ag-IoT systems are easy to set up on perennial croplands as there is less soil preparation for the IoT system installation. It is important to develop techniques that allow easy IoT implementation to the annual crops as they contribute more to global food security. It is also worth to note only one research demonstrated the economic viability of IoT implementation (Chen et al., 2019). Therefore, future research to assess and understand the economic viability of IoT applications in various situations is needed.

4. Challenges of Ag-IoT systems and potential solutions

Ag-IoT faces challenges that are unique compared with IoT applications in other industries. In this section, we briefly discuss those challenges that are of utmost importance for Ag-IoT system researchers and developers. Ag-IoT challenges can be mainly classified into three sections: technical challenges, sectoral challenges, and business challenges (Elijah et al., 2018).

4.1. Technical challenges

Limitations of the advancement of technology are the reasons for technical challenges. They would likely be effectively addressed as tools and technologies advance with time. The Ag-IoT technical challenges are discussed under the three layers of the IoT architecture (Fig. 1), namely, perception layer issues, network layer issues, and application layer issues.

4.1.1. Perception layer issues

Ag-IoT systems' perception layer faces unique challenges, because of the requirements it needs to meet during crop and environmental monitoring in harsh environments (Villa-Henriksen et al., 2020). Agricultural lands have limited electricity and communication infrastructure. It is not practical or cost-effective to use wired power and communication media to connect IoT nodes in the field. Therefore, power management, device longevity, and ergonomic design are major challenges related to the Ag-IoT perception layer. Power management includes Ag-IoT node-level power generation, strategies to reduce power consumption, and energy storage. Section 3.5 Power and Energy Management revealed that most of the researchers were interested in solar

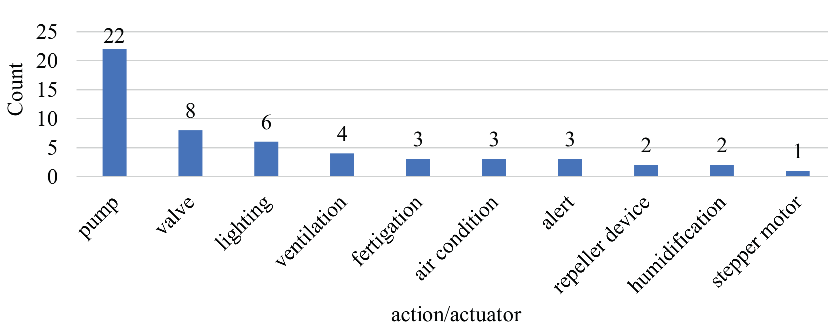

Fig. 9. Count of actuators controlled via IoT systems found in the reviewed papers.

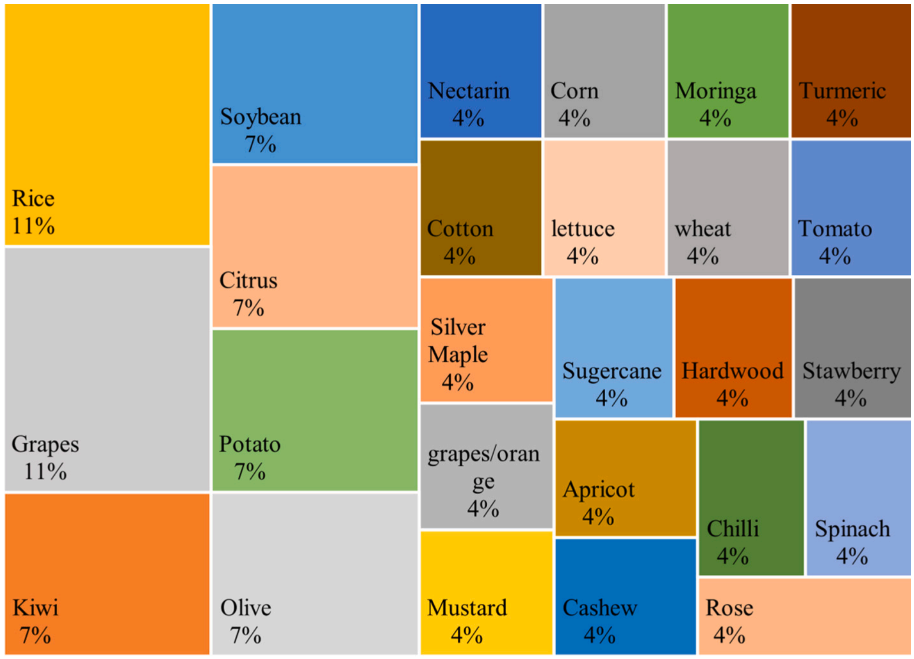

Fig. 10. Ag-IoT system implementation with different crop types.

with rechargeable batteries as the power source in agriculture. However, there is a challenge to introduce suitable power sources for the Ag-IoT systems under the tall and dense crop canopy. Micro wind turbines have the potential as an Ag-IoT power source but receive less attention in the literature (Jawad et al., 2017). Continuous improvements have been made to rechargeable batteries due to the demand for high energy to weight ratio batteries. There are several approaches available to reduce power consumption. One approach is to select sensors, actuators, and wireless protocols with low energy consumption. Selection of a node duty cycle that turns the sensor or actuator on when it reads, sends, or receives signals is another viable approach (Estrada-Lopez et al., 2018).

Harsh environmental conditions such as wind and rainfall, continuous high solar radiation, sub-zero temperatures in winter, chemicals commonly used in agriculture, and animal attacks make it difficult to keep Ag-IoT nodes in the field in operable conditions for a long time (Villa-Henriksen et al., 2020). Sensors, cables, and enclosures should be designed to withstand such conditions. Standards are available to follow in most cases, but the cost becomes high when required standards need to be escalated.

Analog signals (Analogue voltage or current), Inter-Integrated Circuits (I2C), Serial Data Interface at 1200 baud rate (SDI-12), and Universal Asynchronous Receiver/Transmitter (UART) are the common sensor to microcontroller data transmission techniques. The microcontroller development boards and commercial IoT platforms are designed to work with different voltage levels, such as 3.3 V, 5 V, 7 V, and 12 V. These different communication protocols and operation voltages have created barriers to the interoperability of the devices in Ag-IoT implementation. Research and development to standardize data communication and power supply in Ag-IoT systems would substantially increase the scalability, upgradability, and interoperability in the perception layer.

Improving ergonomic design and reducing the labor intensiveness for deploying Ag-IoT systems in the field are urgently needed. IoT-based soil water content monitoring is a good example to show this issue. Often soil sensors are buried underground for continuous measurements during a season. These sensor nodes also have an aboveground section to allow wireless communication, which could interfere with farm operations such as tillage, fertilizer application, and chemical spraying, and should be closely monitored. For annual crops, the need to remove the sensors when crops are harvested and reinstall them in the next season represents a significant logistic issue for using them effectively. Research on underground wireless communication technology (Akyildiz et al., 2009) and Internet of Underground Things (Vuran et al., 2018) is ongoing, bearing the promise to alleviate this challenge associated with Ag-IoT node installation and maintenance. No standards are currently available on Ag-IoT installation as agricultural fields and practices are highly heterogeneous. Novel solutions are necessary to encourage Ag-IoT users.

4.1.2. Network layer issues

The most common Ag-IoT network layer issues are internet coverage, standard interception, interference, propagation losses, communication range, wireless link quality, network expansion, network management, communication protocols, latency, and throughput.

As most farms are in rural areas, remote locations, or mountain regions, it is a huge challenge to get internet connectivity to them since these underpopulated areas have limited internet infrastructure. One solution could be creating a local network, a concept similar to a hybrid cloud. This type of system does not connect to the internet but still allows local servers to perform the basic IoT functionality (Akyildiz et al., 2009). Due to the recent advancement in low earth orbit (LEO) satellites, it would soon be possible to have internet connectivity via satellite as illustrated in Fig. 11 on a commercial scale (Ivanova et al., 2016). Therefore, we anticipate that, in the future, many agricultural fields will rely on satellite-based connectivity to connect their gateways to the internet. This system consists of a very small aperture terminal (VSAT) type ground antenna which is connected to the nodes through multiple gateways. Gateways can follow different communication protocols such as Wi-Fi, LoRa, NB-IoT, or Zigbee. One disadvantage of satellite-based internet connectivity is that it needs a clear sky to make a successful connection. Therefore, it is logical to have a local server for data storage and decision-making when the connection is interrupted.

Standard interception refers to difficulties in using the full potential of a communication technology due to standards imposed by regulatory authorities to limit the use. Recent advancements on long-range low throughput communication technologies such as LoRa become widely known communication protocols in Ag-IoT. To promote fair use of LoRa bandwidth, governments can regulate the use of wireless frequencies.

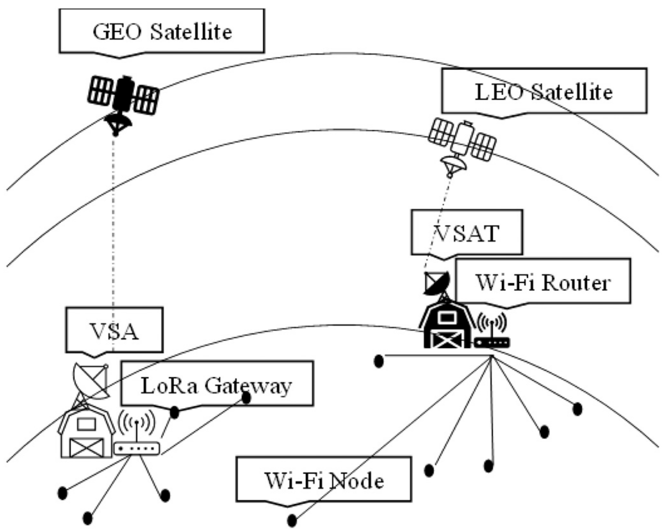

Fig. 11. Future Ag-IoT system with satellite connected internet.

For example, in Europe, the duty cycle or the transmitter uptime of the LoRa node is between 0.1% to 10%. This is a challenge in most Ag-IoT applications as there are higher volumes of data to transmit and many sensors and actuators to connect. When many IoT nodes are deployed, the interference may occur because the data transmission could use the same frequency, especially in unlicensed spectrums, such as ZigBee, Sigfox, LoRa, and Wi-Fi. Signal interference causes data loss and reduces the reliability of the systems (Elijah et al., 2018). Wireless signal propagation strength, communication range, and wireless link quality depend on the humidity, temperature, crop growth status, and crop morphological characteristics in agriculture fields (Tzounis et al., 2017; Cama-Pinto et al., 2019; Vuran et al., 2022). Thus, wireless signal propagation strength simulation and visualization software are essential in the future for the mass installation of Ag-IoT sensor nodes. Such software will reduce the complexity of node placement issues.

4.1.3. Application layer issues

Data security, data privacy, and data analysis are application layer issues. Ag-IoT data is important for a country's food security as well as for the Ag business model security. In the modern competitive world, data breaching could lead to a competitive disadvantage on Ag-business model over a competitor as well as risk the food security of a country. Therefore, more focus should be put into improving the security and privacy of data generated via Ag-IoT systems.

4.2. Sectoral challenges

4.2.1. Regulatory issues

Data ownership creates another business challenge. Companies that provide Ag-IoT services can use the data for improvements in their systems, but farmers do not receive compensation for that. There is a challenge to implement such a system to prevent data monopoly (Misra et al., 2020). Therefore, regulation and legal frameworks about the control and rights of data between farmers and IoT companies need to be established (Elijah et al., 2018).

4.2.2. Interoperability issue

According to Elijah et al. (2018), interoperability involves the ability to have technical, synthetic, semantic, and organization interoperability. Technical interoperability involves the effortless communication among IoT devices using protocols. Data interchanging between systems is semantic interoperability. Synthetic interoperability deals with IoT system-generated digital data exchange with humans, while organization interoperability involves information sharing among different regions, infrastructures, and cultures (Elijah et al., 2018).

Here we would like to introduce a challenge associated with Ag-IoT system interoperability. As most of the farmers have crop rotations and multi-cropping systems, it is essential to have Ag-IoT systems with context awareness that allows them to work with different cropping systems. The heterogeneity of agricultural systems imposes the system interoperability challenge.

4.2.3. Business issues

The cost and non-availability of skilled personnel in Ag-IoT is a business issue. Cost is a challenge for Ag-IoT implementation. There are three types of costs involved with Ag-IoT systems: the setup cost or the capital expenditure, running cost or operational cost, and upgrading cost. Due to the nature of IoT business models and being a relatively new technology, analysis on return on investment of Ag-IoT systems is not yet discussed considerably in the literature. Chen et al. (2019) highlighted that application of IoT systems on irrigation controlling in turmeric turned out to be profitable. Several factors increase capital expenditure. Remote and harsh environmental conditions that Ag-IoT systems must bear increase the production cost of Ag-IoT systems. Ag-IoT end nodes require materials that do not wear and tear due to sun, rain, and chemicals applied during crop cultivation. Communication cost is usually a standard rate, but the initial investment is required to set up the internet connection, and this cost depends on the infrastructure availability where the farms are located.

Theoretical knowledge and practical experience about the sensing/actuating system and parameters of interest are essential to set up a successful Ag-IoT system. Sensor data interpreters need an overall understanding of the agroecological principles to reach a decision (Duff et al., 2022). Reluctance to use new technology and unskilled manpower are apparent obstacles to implementing Ag-IoT in commercial production crop monitoring systems. More extension programs are needed to solve this issue while standards are necessary for Ag-IoT system development to improve the common Ag-IoT platforms that have interoperable qualities.

5. Supporting technologies

5.1. Augmented reality and IoT applications

Data visualization and real-time decision-making are important to IoT. Based on past literature this sector is the least explored area. Wearable augmentation devices improve crop monitoring and control. Smart glasses have the real-time data visualization capability to indicate the status of crops, soil, or environment (Hurst et al., 2021). An irrigation activity can be controlled manually by a farmer if he can visualize the real-time soil water content change in the field. The conditions within a greenhouse can be controlled in real-time and actuators can be controlled via voice command through a smart glass. Harvesting can be more enjoyable and more efficient (lower loss) based on image processing capable smart glasses. Vegetable or fruit pickers can be assisted through a smart glass by viewing what it detects in the fruit to decide whether to pick it or not. Untrained labor usage-related losses can be reduced by augmented reality related training.

5.2. Big data

Big data generated by Ag-IoT are mostly of heterogeneous types. The most common IoT agricultural big data are machine-generated data (Wolfert et al., 2017). These data are generated from a massive number of sensors and smart machines used to measure and record farming processes; which are in turn boosted by the IoT. Machine-generated data range from simple sensor records to complex computer logs. Big data in agriculture are generated mostly when we introduce smart sensing and monitoring with the help of IoT. The main sources of big data in Ag-IoT are: sensors, robotics, open data, data captured by airborne sensors

(Faulkner and Cebul, 2014; Cole et al., 2012), weather/climate data, yield data, soil types, agricultural census data (Chen et al., 2014) and so on. Typically, telemetry data is generated by sensors such as temperature, rotary, or linear encoder. These data are well-structured in contrast to imagery data which need post-processing. Such unstructured data have issues in terms of availability, quality, and formats (Liu et al., 2015) and can be a concern. As the number of sensors is increasing and data volumes are growing rapidly, it is becoming a matter of utmost importance to store and process big data. Some approaches to handle big data are data shrinking, scale up, scale out, and high-performance computing. Data shrinking is the process of throwing away some less important data and still being able to reconstruct the original data. Scale-up (vertical scalability) is adding additional storage and RAM to store and process the big data in the processing node. But this technique has its capacity limit. Scale out (horizontal scalability) is the concept of using parallel computers to store and process that big data. High-Performance Computing is one of the state-of-the-art techniques to handle big data, where computers with multiple cores are grouped to create an efficient network to deal with the big data. These techniques are essential for successful data handling in Ag-IoT.

5.3. Artificial intelligence in Ag-IoT

Techniques that enable machines to mimic human behavior are artificial intelligence (AI), while a subset of AI that gives machines the ability of learning without being explicitly programmed is machine learning. Deep learning techniques are a subset of machine learning techniques with multilayer neural network feasibility. The data generated from the Ag-IoTs are often used to train machine learning models for specific agricultural use cases such as yield forecast, crop stress detection, and pest spreading prediction. To be more specific, for the agricultural IoT applications, raw sensing information such as field and weather conditions and crop status can be collected and used for model training locally or in the remote end that has more computational resources. These trained models can later be used to control actuators for variable rate irrigation and site-specific pesticide/ herbicide applications. Deep learning techniques are heavily used with image processing applications in agriculture. Trained deep learning models are available for crop type detection (de Filho et al., 2020), plant phenotyping (Pound et al., 2017), fruit (Patel et al., 2011), flower (Dias et al., 2018), and leaf detection (Chamara et al., 2021), and weed detection for herbicide applications (Coleman et al., 2022). AI becomes an integral part of IoT due to its capability of using it as a data analytics tool.

6. Ag-IoT for farming systems analyses and management

In this section, we briefly discuss and envision how Ag-IoT would benefit and potentially transform farming systems analyses and management, enabled by its unprecedented data, analytics, and connected sensors and actuators.

Perhaps the most obvious advantages of Ag-IoT come from the high spatiotemporal resolution of farm-level data it generates concerning crops, soil, and microclimate (Kagan et al., 2022). The high spatial resolution data would quantify the the spatial variability of crop parameters (such as yield and leaf area index) and soil parameters (such as pH, organic matter, and water holding capacitity), and elucidate the relationships between them to identify yield-limiting factors at different parts of the field (Alfred et al., 2021). This is the underlying principle of site-specific crop management, which will be greatly enhanced through Ag-IoT. Modern Ag-IoTs take measurements at hourly and sub-hourly intervals. This high temporal resolution data allow us to observe the crop responses to environmental cues at finer time steps, and enhance our understanding on how basic plant physiological processes such as transpiration and photosynthesis vary due to short-term environmental fluctuations. Process-based crop and soil models, which are widely used to evaluate the economic and environmental consequences of farming practices, usually suffer from the lack of site-specific data to parameterize and calibrate them, especially the in-season crop data and soil data. These data are exactly what Ag-IoT sensors are good at generating, and therefore would improve the accuracy of these models for farm-level management assessment.

Networked sensors and actuators of Ag-IoT, along with the real-time data processing, transmission, and modeling, would greatly improve the decision-making cycle of farm-level management practices (Chaterji et al., 2021). The traditional crop management decision-making has several limitations. First, the decision is usually based on a single set of data, because other datasets are unavailable or expensive to obtain. Second, there is usually long latency between data generation and decision-making (e.g., several days or weeks). This long latency is in contrast to the fact that many stresses in the field (such as pest outbreak) occur and develop quickly and need real-time intervention to prevent substantial loss. Thirdly, the present management practice only addresses one factor at a time whereas in reality crops can undergo multiple stresses simultaneously. Altogether, these limitations reflect our inability to capture the complexity of the farming system. Ag-IoT has the potential to transform farm-level decision-making by enabling multi-inputs, multi-outputs decision strategies, powered by real-time data processing and relevant models run in the cloud to shorten the latency. For example, crop, soil, and microclimate sensors can simultaneously measure the crop water and nitrogen status, soil moisture content and nitrate content, and weather variables. These multi-source inputs can be fed into the models to output two variables: a nitrogen sufficiency index and a water sufficiency index. These two variables can further be converted to a nitrogen and water application rate for site-specific fertigation. This paradigm has several advantages. First, it is a multi-inputs, multi-outputs decision strategy that accounts for the interaction between the water and nitrogen stresses. Second, it reduces the cost of implementation and shortens the management cycle because two actions are combined into one (one pass of field equipment instead of two). In a similar fashion, decisions such as pesticide applications and other chemicals (fungicides, growth regulators) could potentially be further stacked to make crop production more efficient.

Traditionally, farm system analyses and management happen at the individual farm level (Köksal and Tekinerdogan, 2019). In other words, data are usually not shared or co-analyzed across the farm boundary. In the era of Ag-IoT where farm data are shared and stored in the cloud, there represents an opportunity where the analysis and modeling of Ag-IoT data can cover a group of farms or at a regional scale. These regional analyses would answer other important questions such as regional yield forecasting, pest tracking, or agricultural resource prioritization. These questions are not necessarily important for individual growers, but are at the heart of other stakeholders such as policy makers and input suppliers. Data ownership and privacy, covered in Section 4, are two big issues that should be resolved before this type of analysis may occur.

7. Conclusions and future directions

7.1. Conclusions

Ag-IoT is a promising technology that would increase resource use efficiency in agricultural systems, and is an essential tool for digital agriculture transformation. In this paper, we have overviewed impactful research related to Ag-IoT in the past decade. The data collected from these papers were categorized and analyzed under six main Ag-IoT system design parameters namely sensors, sensing platforms and main control board, communication technology and IoT protocols, cloud platforms, power and energy management, and actuators. According to the analyzed data, it is revealed that there is an increased global attention towards the Ag-IoT system-related research in the recent years. However, there are certain research gaps found in the literature. One of them is that the implementations of the sensors and the actuators seem to be limited to soil and environmental parameter monitoring and irrigation controlling. Furthermore, crop macro and micronutrient demand analyses are still at the infant stage due to the non-availability of sensors that can measure nutrients in real-time. Therefore, it is essential to improve the sensor and actuator applications in crop monitoring and controlling. In addition, heterogeneity of the system parameters (such as data, platforms, required power) is a major challenge to the Ag-IoT systems implementation, to which the improvement of the context-awareness could be a solution. Power harness options for Ag-IoT nodes need more exploration as there are limited options available and it would be a big advantage for the perennial crop monitoring. The perception and the network layers of Ag-IoT systems require more improvements to meet the sensor implementation ergonomics and long-range high-throughput data transmission, respectively. Edge computing can be a replacement of the high throughput long-range communication, but to the best of our knowledge, only a limited number of practical applications have been developed based on edge computing to date. Mobile Ag-IoT platforms such as unmanned aerial and ground vehicles have a huge potential to increase the spatiotemporal resolution in Ag-IoT-based monitoring and controlling.

7.2. Future directions

From the finding of this review, authors would like to highlight some important future requirements for Ag-IoT. The entire Ag-IoT research community needs to propose a complete system design for Ag-IoT that will be viable, open, and interpretable. The objective is to enable the interconnectivity of heterogeneous systems and sharing resources to obtain more detailed and specific agricultural data. Furthermore, in the future research work, there is a need to develop complete information perception standards and design multi-protocol compatible gateways. With some significant efforts in the above-mentioned future research directions, the entire research community will be able to solve the problems of inconsistent device interfaces and protocols, making the system faster, robust, and more convenient. Making full use of long-range low throughput communication technology, virtual reality/augmented reality, and big data/AI for Ag-IoT is yet to be thoroughly explored.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A

Number	Year	Country	Type	Title
1	2020	Greece	original	A Context-Aware Middleware Cloud Approach for Integrating Precision Farming Facilities into the IoT toward Agriculture 4.0
2	2020	China/USA	original	A Framework for Agricultural Pest and Disease Monitoring Based on Internet-of-Things and Unmanned Aerial Vehicles
3	2021	India/Saudi Arabia	original	Security Enhancement for IoT Enabled Agriculture
4	2020	Pakistan/Korea	Review	Role of IoT Technology in Agriculture: A Systematic Literature Review
5	2021	Japan	original	iPOTs: Internet of Things-based pot system controlling optional treatment of soil water condition for plant phenotyping under drought stress
6	2012	Sri Lanka	original	Development of a Sensor Based Self Powered Smart Control System for Agricultural Irrigation Systems
7	2020	United Kingdom	original	Low-Cost Automated Vectors and Modular Environmental Sensors for Plant Phenotyping
8	2019	India	original	An IoT-Based Smart Plant Monitoring System
9	2020	India	original	An Effective Approach for Plant Monitoring, Classification and Prediction Using IoT and Machine Learning
10	2021	USA	original	Development of an Internet of Things (IoT) Enabled Novel Wireless Multi Sensor Network for Infield Crop Monitoring
11	2020	UAE	original	IOT Based Growth Monitoring on Moringa Oleifera through Capacitive Soil Moisture Sensor
12	2021	China	original	Plant Growth Monitoring Cloud Platform Based on Internet of Things
13	2021	Sri Lanka	original	Implementation IoT (Internet of Things) Based Smart Agriculture Fertilizer System
14	2020	Canada/Morocco	original	A Framework of Optimizing the Deployment of IoT for Precision Agriculture Industry
15	2021	Canada/Morocco	original	IoT in Smart Farming Analytics, Big Data Based Architecture
16	2017	China	original	Monitoring Citrus Soil Moisture and Nutrients Using an IoT Based System
17	2017	Netherlands/Greece	original	IoT in Agriculture: Designing a Europe-Wide Large-Scale Pilot
18	2019	Taiwan	original	AgriTalk: IoT for Precision Soil Farming of Turmeric Cultivation
19	2016	Sweden/UAE	original	From the Internet of Things to the web of things — enabling by sensing as-a service
20	2018	United Kingdom	original	Rentable Internet of Things Infrastructure for Sensing as a Service (S2aaS)
21	2020	Portugal	review	A Systematic Review of IoT Solutions for Smart Farming
22	2019	Denmark/Finland	review	Internet of Things in arable farming: Implementation, applications, challenges and potential
23	2019	Germany/Netherlands/Italy	original	Architecture framework of IoT-based food and farm systems: A multiple case study
24	2018	France/Saudi Arabia	original	UAV-Assisted Dynamic Clustering of Wireless Sensor Networks for Crop Health Monitoring
25	2016	China	original	Node Deployment with k-Connectivity in Sensor Networks for Crop Information Full Coverage Monitoring
26	2017	India	original	An IoT based smart solution for leaf disease detection
27	2019	Spain	original	Environment Control with Low-Cost Microcontrollers and Microprocessors: Application for Green Walls
28	2017	Tunisia	original	Monitoring system using web of things in precision agriculture
29	2016	Australia	original	Internet of Things Platform for Smart Farming: Experiences and Lessons Learnt
30	2019	Spain	original	Thinger.io: An Open Source Platform for Deploying Data Fusion Applications in IoT Environments
31	2019	Spain	original	Proposal for the Design of Monitoring and Operating Irrigation Networks Based on IoT, Cloud Computing and Free Hardware Technologies
32	2019	France	review	A comparative study of LPWAN technologies for large-scale IoT deployment
33	2016	Spain	review	State of the Art in LP-WAN Solutions for Industrial IoT Services

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Number	Year	Country	Type	Title
34	2018	Spain	original	A Comprehensive IoT Node Proposal Using Open Hardware. A Smart Farming Use Case to Monitor Vineyards
35	2018	India	review	A survey on Internet of Things architectures
36	2019	China	review	State-of-the-Art Internet of Things in Protected Agriculture
37	2019	Nigeria/Turkey/Lithuania	original	Smart irrigation system for environmental sustainability in Africa: An Internet of Everything (IoE) approach
38	2017	China	original	Monitoring Citrus Soil Moisture and Nutrients Using an IoT Based System
39	2018	USA	original	Open-Source Wireless Cloud-Connected Agricultural Sensor Network
40	2019	Uzbekistan	original	Wireless sensor network-based monitoring system for precision agriculture in Uzbekistan
41	2019	Spain	original	Remote Image Capture System to Improve Aerial Supervision for Precision Irrigation in Agriculture
42	2018	India	original	A prototype model for continuous agriculture field monitoring and assessment
43	2020	Pakistan/Saudi Arabia	original	An Energy Efficient and Secure IoT-Based WSN Framework: An Application to Smart Agriculture
44	2020	India	original	Smart Irrigation and Intrusions Detection in Agricultural Fields Using I.o.T.
45	2020	Italy	original	AgriLogger: A New Wireless Sensor for Monitoring Agrometeorological Data in Areas Lacking Communication Networks
46	2020	Turkey	original	A Long-range Context-aware Platform Design For Rural Monitoring With IoT In Precision Agriculture
47	2011	China	original	A Crop Monitoring System Based on Wireless Sensor Network
48	2011	China	original	Research on WSN Channel Fading Model and Experimental Analysis in Orchard Environment
49	2015	France	original	A Scalable Context-Aware Objective Function (SCAOF) of Routing Protocol for Agricultural Low-Power and Lossy Networks (RPAL)
50	2019	China/Pakistan	original	Multi-Task Cascaded Convolutional Networks Based Intelligent Fruit Detection for Designing Automated Robot
51	2012	China	original	Design of Wireless Sensor Network Middleware for Agricultural Applications
52	2020	China	original	Design of smart agriculture based on big data and Internet of things
53	2013	China	original	Power Balance AODV Algorithm of WSN in Agriculture Monitoring
54	2019	USA	original	Energy Consumption Analysis of a Duty Cycle Wireless Sensor Network Model
55	2018	United Kingdom	book	Long-Range Communication Systems and Protocols (WAN). In Internet of Things for Architects: Learn to Design, Implement and secure your IoT infrastructure
56	2018	Indonesia	original	The Precision Agriculture Based on Wireless Sensor Network with MQTT Protocol
57	2018	India	original	Web Architecture for Monitoring Field Using Representational State Transfer Methods
58	2016	India	original	Smart Autonomous Gardening Rover with Plant Recognition Using Neural Networks
59	2019	Spain/Colombia	original	Path Loss Determination Using Linear and Cubic Regression Inside a Classic Tomato Greenhouse
60	2020	China/USA	original	An Effective Edge-Assisted Data Collection Approach for Critical Events in the SDWSN-Based Agricultural Internet of Things
61	2020	Italy	original	LoRaFarM: A LoRaWAN-Based Smart Farming Modular IoT Architecture
62	2020	China/India/USA	original	A Smart, Sensible Agriculture System Using the Exponential Moving Average Model
63	2016	India	original	Effective Architecture for Greenhouse Controlling and Monitoring using Wi-Fi Peer to Peer Direct Protocol
64	2016	Spain	original	Developing Ubiquitous Sensor Network Platform Using Internet of Things: Application in Precision Agriculture
65	2017	Portugal/Ecuador	original	A System for the Monitoring and Predicting of Data in Precision Agriculture in a Rose Greenhouse Based on Wireless Sensor Networks
66	2017	Thailand	original	Optimal Plant Growth in Smart Farm Hydroponics System using the Integration of Wireless Sensor Networks into Internet of Things
67	2017	Colombia	original	Low-Cost Fuzzy Logic Control for Greenhouse Environments with Web Monitoring
68	2018	Chins/Bulgaria/Greece	original	Sustainable energy management of solar greenhouses using open weather data on MACQU platform
69	2019	Ukraine	original	Improved Computer-oriented Method for Processing of Measurement Information on Greenhouse Microclimate
70	2017	USA	original	A Networked Sensor System for the Analysis of Plot-Scale Hydrology
71	2017	Japan	original	A Wireless Sensor Network for Growth Environment Measurement and Multi-Band Optical Sensing to Diagnose Tree Vigor
72	2018	China	original	Hyperspectral Identification and Classification of Oilseed Rape Waterlogging Stress Levels Using Parallel Computing
73	2019	China/Australia	original	Assessment of canopy vigor information from kiwifruit plants based on a digital surface model from unmanned aerial vehicle imagery
74	2015	China/USA	original	The Construction of a Precise Agricultural Information System Based on Internet of Things
75	2019	India	original	Sustainable and Portable Low Cost IOT Based Terrace Model to Grow True Organic Greens
76	2017	India	original	Precision Sugarcane Monitoring Using SVM Classifier
77	2017	Spain	original	VineSens: An Eco-Smart Decision-Support Viticulture System
78	2018	Tunisia	original	Using Cloud IOT for disease prevention in precision agriculture
79	2019	India	original	Web enabled paddy disease detection using Compressed Sensing
80	2018	Greece	original	DIRT: The Dacus Image Recognition Toolkit
81	2019	Australia	original	Low-Power and High-Speed Deep FPGA Inference Engines for Weed Classification at the Edge
82	2019	Greece	original	In-Vivo Vibroacoustic Surveillance of Trees in the Context of the IoT
83	2018	Korea	original	IoT-Based Strawberry Disease Prediction System for Smart Farming
84	2017	Greece	original	Automated Remote Insect Surveillance at a Global Scale and the Internet of Things
85	2016	India	original	Field Monitoring and Automation Using IOT in Agriculture Domain
86	2018	Spain/Portugal/Japan/ Malaysia	original	A Framework for Knowledge Discovery from Wireless Sensor Networks in Rural Environments: A Crop Irrigation Systems Case Study
87	2019	Brazil/Spain/Italy/ Finland	original	Smart Water Management Platform: IoT-Based Precision Irrigation for Agriculture
88	2019	India	original	Real-Time Irrigation Scheduling Through IoT in Paddy Fields
89	2020	Spain	original	Digital Transformation of Agriculture through the Use of an Interoperable Platform
90	2020	Brazil	original	Smart & Green: An Internet-of-Things Framework for Smart Irrigation
91	2018	Greece	original	Composting as a Service: A Real-World IoT Implementation
92	2018	Indonesia	original	Implementation of Automation System for Humidity Monitoring and Irrigation System
93	2018	Indonesia	original	Enhanced Fertigation Control System towards Higher Water Saving Irrigation
94	2020	Greece	original	An IoT Architecture for Water Resource Management in Agroindustrial Environments: A Case Study in Almería (Spain)
95	2019	Malaysia	original	An Urban Based Smart IOT Farming System
96	2019	Saudi Arabia/ India/ China	original	Sensors Driven AI-Based Agriculture Recommendation Model for Assessing Land Suitability
97	2018	Brazil	original	Calibration of Passive UHF RFID Tags Using Neural Networks to Measure Soil Moisture
98	2018	USA	original	Smart Gardening IoT Soil Sheets for Real-Time Nutrient Analysis

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Number	Year	Country	Type	Title
99	2018	Philippines	original	Wireless soil moisture detection with time drift compensation
100	2017	Chile	original	Root System Water Consumption Pattern Identification on Time Series Data
101	2020	Greece	original	Wireless Sensor Network Synchronization for Precision Agriculture Applications
102	2016	India	original	Measurement and Monitoring of Soil Moisture Using Cloud IoT and Android System
103	2018	India	original	An Improved Energy Efficient Duty Cycling Algorithm for IoT based Precision Agriculture
104	2018	Malaysia/Iraq	original	Power Reduction with Sleep/Wake on Redundant Data (SWORD) in a Wireless Sensor Network for Energy-Efficient Precision Agriculture
105	2018	Malaysia/ Iraq	original	Investigation of Empirical Wave Propagation Models in Precision Agriculture
106	2020	Spain	original	CitrusYield: A Dashboard for Mapping Yield and Fruit Quality of Citrus in Precision Agriculture
107	2018	Spain	original	An Agent-Based Simulator of Smart Communication Protocols in Wireless Sensor Networks for Debugging in Precision Agriculture
108	2020	Colombia/Belgium	original	System Assessment of WUSN Using NB-IoT UAV-Aided Networks in Potato Crops
109	2019	Iraq/Belgium	original	A smart monitoring and controlling for agricultural pumps using LoRa IOT technology
110	2019	USA	original	Energy Consumption Analysis of a Duty Cycle Wireless Sensor Network Model
111	2016	Germany	original	On the potential of Wireless Sensor Networks for the in-situ assessment of crop leaf area index
112	2021	India/Ethiopia/ Afghanistan	original	Iot-Enabled Water Management for Improving the Crop Health in Smart Agriculture Farming
113	2017	United Kingdom/ Australia	original	A practical method using a network of fixed infrared sensors for estimating crop canopy conductance and evaporation rate
114	2011	USA	original	Evaluation of a wireless infrared thermometer with a narrow field of view
115	2018	India/France	original	Design and Development of an IoT Based Smart Irrigation and Fertilization System for Chilli Farming

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