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Review

# Applying IoT Sensors and Big Data to Improve Precision Crop Production: A Review

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**Abstract:** The potential benefits of applying information and communication technology (ICT) in precision agriculture to enhance sustainable agricultural growth were discussed in this review article. The current technologies, such as the Internet of Things (IoT) and artificial intelligence (AI), as well as their applications, must be integrated into the agricultural sector to ensure long-term agricultural productivity. These technologies have the potential to improve global food security by reducing crop output gaps, decreasing food waste, and minimizing resource use inefficiencies. The importance of collecting and analyzing big data from multiple sources, particularly in situ and on-the-go sensors, is also highlighted as an important component of achieving predictive decision making capabilities in precision agriculture and forecasting yields using advanced yield prediction models developed through machine learning. Finally, we cover the replacement of wired-based, complicated systems in infield monitoring with wireless sensor networks (WSN), particularly in the agricultural sector, and emphasize the necessity of knowing the radio frequency (RF) contributing aspects that influence signal intensity, interference, system model, bandwidth, and transmission range when creating a successful Agricultural Internet of Thing Ag-IoT system. The relevance of communication protocols and interfaces for presenting agricultural data acquired from sensors in various formats is also emphasized in the paper, as is the function of 4G, 3G, and 5G technologies in IoT-based smart farming. Overall, these research sheds light on the significance of wireless sensor networks and big data in the future of precision crop production

**Keywords:** precision crop production; ICT; IoT; sensors; big data; AI

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## 1. Introduction

The world population is undergoing continuous growth and is anticipated to reach 10 billion within the next 35 years. It is imperative to make significant advancements in agricultural production and disaster management to ensure adequate sustenance for the world's population [1]. As the quantity of arable land remains static, the quality of the soil is not improving, and groundwater levels are dropping, there is an urgent need to responsibly enhance agricultural productivity [2].

Precision agriculture has transformed agricultural practices since its inception in the 1980s by utilizing technologies like remote sensing, the geographic information system (GIS), and the global positioning system (GPS). This integration has transformed crop production methods, resulting in a significant shift in agricultural mechanization thinking [3]. The combination of Internet of Things (IoT) sensors and artificial intelligence (AI) enables precision crop production. This cutting-edge technology employs sensors and artificial intelligence to optimize crop growth and yield, allowing farmers to collect detailed data about their fields and use it to make informed decisions about irrigation, fertilization, and pest control. Moreover, the greatest output benefit of precision agriculture is decreased temporal yield changes, which has increased yield stability and climate change tolerance [4].

The agricultural industry faces several significant challenges related to effectively utilizing new technologies, including discovering knowledge and correlations from historical records, processing large volumes of unstructured data in an appropriate format, managing extensive amounts of image and video data, monitoring crops using multiple sensors, and effectively communicating and integrating these data. Additionally, the adoption and accessibility of emerging technologies can be cost-prohibitive for individual farmers, while a lack of low-technology expertise requires extra training and better information and communication technology (ICT) management equipment. Ensuring the security of these systems is also a critical concern within the agricultural community [5,6].

Precision agriculture has undergone a transformation over the past three decades, advancing from strategic monitoring using satellite imaging for regional decision making to tactical monitoring and control allowed by low-altitude remotely sensed data for site-specific field-scale applications. The incorporation of data science and big data technology into precision agriculture strategies has led to a rapid analysis of data, facilitating timely decision making [7,8]. Farming could move to a more effective, productive, and sustainable paradigm through the integration of technologies such ground IoT sensing and remote sensing, using both satellite and Unmanned Aerial Vehicles (UAVs), as well as utilizing data fusion and data analytics [9]. Wireless connection methods, such as Wi-Fi, Bluetooth, and cellular networks, are utilized to transmit sensor data to a central hub, allowing farmers to monitor their farms in real time and make informed crop production decisions.

The improvement of agricultural goods and services while reducing investment costs represents a critical objective for future farming. Big data can effectively support diverse precision agriculture functions and assist in the extraction of information and insights from data in order to process important farming decisions and difficulties. In the agricultural sector, ICT plays an important role in developing breakthrough data creation, transformation, and management technologies [10].

Site-specific data collection, characterized by the acquisition of comprehensive information regarding events occurring during the vegetation period, offers a practical solution to this issue. This methodology enables the identification of underlying processes and their causes, leading to precise intervention that reduces adverse environmental effects. It creates a monitored and controlled environment in both spatial and temporal domains and sets the stage for a more advanced decision support system than is currently available. Previous studies have advocated for this approach [11,12].

This review offers an informed summary of the most recent approaches used in precision agricultural production. It meticulously investigates and highlights the cutting-edge technology and approaches that are currently transforming the agricultural practice scene. The study focuses on the application of the Internet of Things (IoT) and big data in the agricultural industry and research. The review provides light on these technologies' beneficial effects in enhancing crop yields, resource usage, and overall farm management by explaining their practical applications. Moreover, it addressed the challenges that come with integrating IoT and big data in agriculture. It discusses the challenges that have been encountered, such as data security concerns, technical difficulties, and the necessity for a strong infrastructure which are among many other limitations faces the integration of IoT in agricultural practices around the world.

## 2. Overview of Precision Agriculture Technology

### *2.1. ICT, IoT, Big Data, Cloud Computing, and Data Fusion*

Sustainable agricultural development presents a crucial solution to address rapid population growth, facilitated using ICT in precision agriculture. This approach has yielded innovative techniques that enhance agricultural productivity, efficiency, and regulation while concurrently preserving the environment [2]. To ensure long-term agricultural production, modern technologies must be used in the agricultural field, like blockchain [13,14], the IoT [15], and (AI) [16]. The most promising strategy for solving these problems is

data-driven agriculture using these technologies. (IoT) assists in data collection at all stages of agricultural production and supply chain management [17].

The internet now plays a crucial role across many industries. Within the agricultural domain, a suggested approach that involves monitoring agricultural fields utilizing the IoT is utilized. This approach employs sensors that analyze diverse parameters within the agricultural domain, leveraging wireless sensor network technology [18]. "IoT" refers to the connection of devices and tools, such as sensors, to the internet, allowing them to transfer data. The IoT is a huge network with an enormous number of objects connected to a global information infrastructure. The number of connected devices has increased many folds, giving rise to the scalability issue in the IoT. For proper communication to take place, a unique sender and receiver must be recognized, along with the identification of an appropriate path or channel [19]. In agriculture, the use of IoT technology has the potential to revolutionize the way farms operate and increase the efficiency and productivity of the industry. Another application of IoT in agriculture is the use of precision farming techniques, which involve using sensors and other technologies to gather data and make precise and timely adjustments to various aspects of farming operations. For example, GPS-guided machinery can be used to precisely apply fertilizers and pesticides, reducing the number of resources used and minimizing waste. Even though, due to the necessity for skills in interacting with sensors, the internet cloud, and end-user apps, farmers face difficulties adopting smart farming and IoT technology [20].

The Internet of Things has numerous applications in the Digital Agriculture field, including detection of plant physiological status, nutrient replenishment recommendations, water requirements, and so on [18,21]. The (IoT) offers significant benefits for agriculture and sustainable crop production, including the ability to anticipate and prepare for potential disturbances that may originate from remote locations, such as insect pest invasions and monitoring soil nutrients, water dynamics, and pest management. The other advantages of using IoT technology in farming systems are that the ability of using in yield prediction, energy and cost savings, and the establishment of indoor vertical farming systems by utilizing the information from the established IoT station there [20]. Regarding ecological aspirations, the Internet of Everything (IoE) is receiving an increasing amount of attention [22]. This increases the effectiveness of protection and hence lowers costs. Big data can be utilized for different spatiotemporal applications, such as connecting remote IoT equipment to cloud-based computing capabilities [23,24]. The use of IoT with big data analysis techniques is the basis for new decision making tools.

In agriculture, "big data" refers to the massive amount of data generated by agricultural activity and measurement. Processing and managing large amounts of data is a difficult undertaking when using standard approaches and systems [7]. Big data have a big chance in agriculture for solving various farming difficulties and, as a result, increasing agricultural production quality and quantity. Big data analytics can be used to anticipate agricultural harvesting time, soil quality, crop protection, and irrigation requirements. Furthermore, big data empowers agricultural practitioners and related industries to gain information about different factors that impede agricultural production and make efficient decisions in daily farming [2]. While it is unclear whether agriculture practitioners' information will be replaced by algorithms, big data applications are likely to revolutionize how agriculture farms are managed and operated [25,26].

The collection of data from multiple sources is a critical component of achieving predictive decision making capabilities in precision agriculture. Weather conditions play a pivotal role in determining the productivity and management of agricultural systems, emphasizing the importance of accurate area-based weather forecasting for the future of precision crop production and with further data collection from various sources would allow to monitor and optimize crop growth conditions [27]. Precision agriculture datasets typically comprise a diverse range of data related to crops, soil, and nutrients, atmospheric data, technological data such as GIS data, GPS data, and data from trucks and the Variable Rate Fertilizer (VRT) system [7,28–30].

Big data analysis is a methodical strategy that applies cutting-edge analytic tools to big data sets. This entails the integration of two technical components, namely extensive data sets and an array of analytics tool categories such as data mining, statistics, AI, predictive analytics, and natural language processing (NLP), among others. The analysis of such data is accomplished through the utilization of big data mining techniques. In the realm of smart agriculture, the feasibility study is significantly improved by the application of IoT and big data analytics in the cloud [2,18]. In Figure 1, we can see the relationship between IoT and data analytics. Because of the volume, velocity, and variety of data generated by IoTs, they are classified as "big data systems". These data are mined and processed in order to show the relationships between inputs and outputs [31].

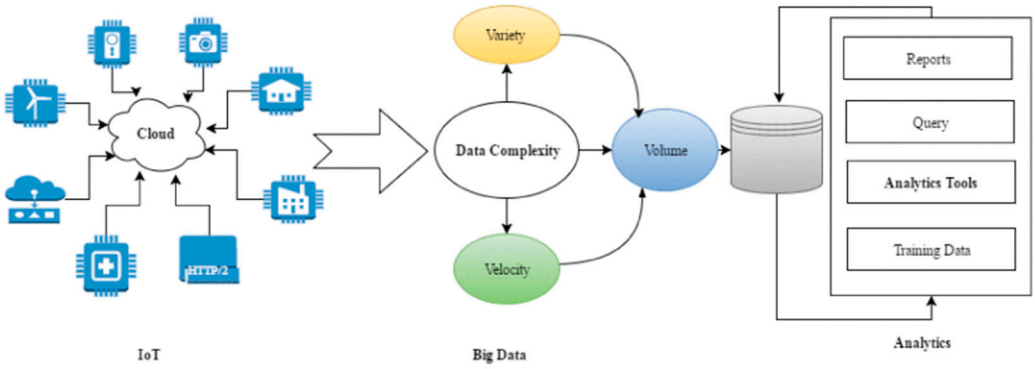


**Figure 1.** The relationship between the Internet of Things and data analytics [32].

Cloud computing is a method that allows for the sharing of resources at a low cost. Cloud computing service providers make these services available at an economical cost. The storage of agricultural data has been facilitated through the utilization of cloud computing. In the agriculture sector, cloud computing is employed in conjunction with IoT technology [33]. According to Neményi et al., 2022 [34], the combination of artificial intelligence and cloud computing constitutes a comprehensive support system for the IoT. It requires combining data from intelligent wireless sensors, such as unmanned aerial vehicles (UAVs) [35] and satellites, data acquisition systems on agricultural machinery and crop production equipment, and robots such as unmanned ground vehicles (UGVs), with precise positioning systems (such as navigation systems, real-time kinematics (RTK), and Lidar). The Wireless Sensor Network (WSN) is a wireless network made up of geographically distributed sensor stations.

Sensors → MCU → Nodes → Gateways → Clouds (server) [34].

Multisensor data fusion is a technology that facilitates the integration of data from multiple sources to create a comprehensive representation. Data fusion systems have found broad use in many different domains, including but not limited to sensor networks, robotics, video and image processing, and intelligent system design. The process of data fusion is described as a complex, multifaceted operation that involves automated detection, association, correlation, estimation, and gathering of data from multiple sources at various levels [36,37]. The practice of data fusion offers numerous benefits, primarily through improving the authenticity and availability of data. The utilization of data fusion strategies has been extensively applied in various sectors, including the food and chemical industries, with the aim of augmenting the analytical platforms' overall performance and robustness [38–40].

Munnaf et al., 2021 [41] recommend employing Site-Specific Seeding (SSS) for potato production using the proposed multi-sensor data-fusion technique to manage in-field soil and crop variabilities and improve productivity and profitability in their study. (SSS) was examined for potato production utilizing Management Zone (MZ) maps based on several soil and crop variables. Despite using more seeds, SSS increased tuber yields, and gross margins compared to Uniform Rate Seeding (URS). SSS profitability ranged from 2.34% to 27.21%, with the highest profitability in low-productivity fields. The study suggests using

SSS for potato production, along with the proposed multi-sensor data-fusion approach, to manage in-field soil and crop variabilities and improve productivity and profitability. These studies have concentrated on how cloud computing, IoT, and multisensor data fusion are integrated in precision agriculture, while Neményi et al. (2022) [34] highlighted the complementary advantages of AI, cloud computing, and IoT for comprehensive data use, cloud computing offers cost-effective data storage. Fusion of data from multiple sensors is essential to enhance data availability and validity across sectors. Munnaf et al. [41] recommends Site-Specific Seeding (SSS) with multisensor data fusion in potato production because it outperforms Uniform Rate Seeding (URS) in terms of tuber yields and profitability, especially in low-productivity fields. These results highlight the need for data-driven approaches for enhanced crop productivity and optimized resource management.

### 2.2. AI, Real-Time Monitoring, and Big Data (Mining and Analyzing)

In contemporary times, traditional yield modeling aimed at meeting the demands of sustainability and identifying yield drivers and factors restricting yield is increasingly being executed using AI. An expanding number of researchers are employing AI to model an extensive array of agricultural tasks. The technical literature sources reveal the application of diverse techniques for supporting precision agriculture decision making. AI presents a promising prospect for improving the world's food security, including closing crop yield gaps, minimizing food waste, and mitigating resource utilization inefficiencies [42,43].

Counter propagation artificial neural network (CP-ANN), SKN, and XY-F models were used along with high-resolution soil and crop data such as spatial-temporal soil types and crop production effectiveness to predict classes of wheat yield productivity. The SKN network predicts the low category of yield output the best, with a proper classification percentage of 91.3% for both cross- and independent validation. Temperature and other climate effects have also been analyzed by AI [44–46]. These researches emphasize the importance of conventional yield modeling to be integrated with AI-driven methods in precision agriculture. Applications for (AI) like CP-ANN, SKN, and XY-F models show highly promising results, especially SKN with a 91.3% classification accuracy for low yield.

Precision agriculture involves the collection of real-time and historically generated data, which is structured or unstructured in nature. With the increasing adoption of precision agriculture practices, the amount of unstructured data generated has grown significantly. Consequently, current research efforts have focused on extracting meaningful insights and knowledge from these unstructured datasets [30]. High-spatiotemporal-resolution automated monitoring of the soil, plants, and atmosphere is an important factor in converting labor-intensive, experience-based decision making in agricultural production to an autonomous, data-driven way. Real-time field data might help growers make better management decisions, and researchers could use this information to find answers to important scientific problems [47].

The implementation of fully automated decision making systems (ADMS) is essential in precision agriculture. These systems are designed to monitor multiple chemical or physical parameters of soil and plants while simultaneously regulating them to maintain optimal conditions for each specific plant or soil type. Despite the feasibility of developing such systems using existing technologies, the implementation of ADMS encounters significant challenges. ADMS generally consists of four main sections: the sensing technique, sensor interfaces, the information transmission platform, and the data processing and control unit; the crucial role of precision agriculture in utilizing both historical and real-time data for well-informed decision making is highlighted by both studies. Despite its feasibility, both studies agree that deploying ADMS is challenging. They develop a comprehensive view of the changing precision agricultural scene, combining data-driven insights with the complexities of implementing automated systems technologies. Figure 2 shows the general structure of automated decision-making systems [48].

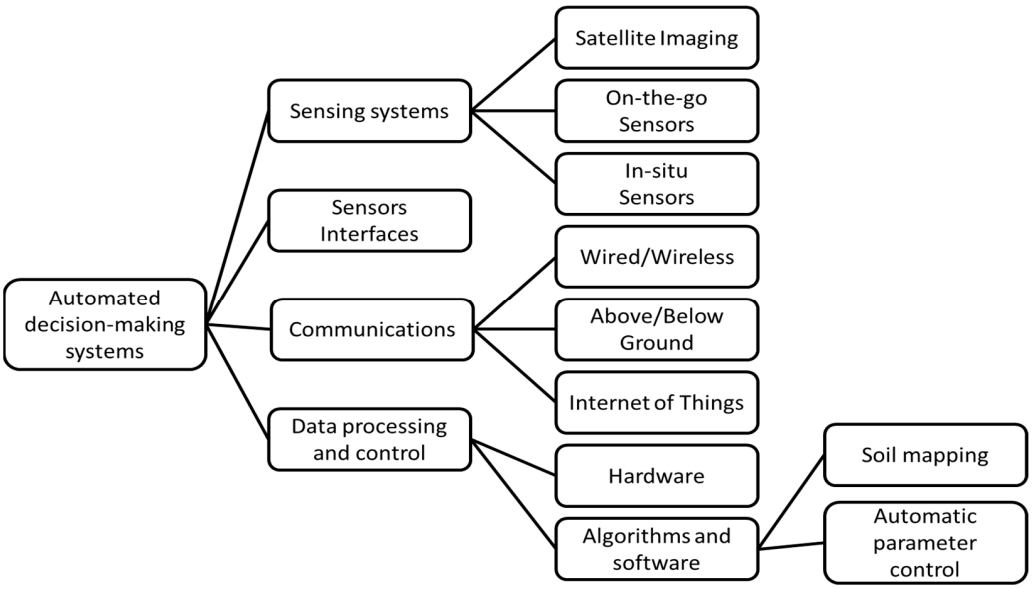


**Figure 2.** The general structure of automated decision making systems ADMS [48].

There are now three fundamental approaches accessible for soil and plant sensing systems: satellite imaging, on-the-go sensors, and in situ soil and plant sensors. Satellite imaging is a way of monitoring soil and plant quality and fertility by acquiring and analyzing multi-spectral satellite images of the field of interest [49]. This technology is very costly and limited to particular countries.

The second, more financially practical way is to attach sensors to agricultural machinery, other agricultural equipment, or even drones, known as on-the-go sensors. The last approach entails the placement of soil and plant sensors across the area, which can share data in real time [50,51]. This is the only approach capable of providing continuous, real-time data without the need for human intervention. These sensors do, however, have some drawbacks, such as the need for protection from wild animals and the need to occasionally remove them from the field during crop cultivation and harvest to prevent damage from agricultural machinery. Depending on the period of removal, this may result in gaps and data loss for several hours or days.

Real-time soil nutrient sensing has a lot of potential for the future of agriculture because nitrogen leakage and groundwater pollution have developed into significant problems for society. Nitrate sensors can be used for a variety of purposes, such as monitoring nitrate concentrations in groundwater by mounting them to groundwater pumps or estimating nitrate leaching more precisely by installing them in leaching water collectors in fields [52]. The real-time measurement of soil nutrient content, particularly nitrogen, phosphorus, and potassium, is critical for fertilization. These detectors are still in the experimental stage [53].

Utilizing in situ and on-the-go sensing systems that could record significant data and soil parameters in a short period of time is one of the needs of precision farming and crop production. This representative data collection results in average cost-effectiveness, but by analyzing the data and taking additional measurements, it could also improve our current knowledge. Vis-NIR spectroscopy can be used to measure the soil's pH, organic matter concentration, and moisture content [54]. In general, the more complicated the problem to be solved, the more data are required [55]. The analysis of big data sets is a way to identify relationships, patterns, and trends in the data [7]. Incorporating observations from farms and in situ sensing systems with current databases presents an opportunity not only to predict yields using traditional statistical techniques or DSS Decision Support Systems but also to explore the potential of machine learning (ML). This provides an avenue for more advanced and sophisticated yield prediction models to be developed [43]. For both in situ and on-the-go sensing systems the diverse and unstructured nature of the data produced by these sensors presents a significant challenge and requires the use

of advanced tools for analysis, and because of the enormous volume of data, traditional storage and processing systems must be scalable. When dealing with data from different sensor types and manufacturers, interoperability concerns may occur, making integration more difficult. Furthermore, protecting data privacy and security is essential considering the sensitivity of agricultural information. To enable efficient and secure big data use in precision agriculture, it is necessary to create strong data management strategies, implement standardized protocols, and give security measures top priority.

The integration of microchips and broadband networks with farm equipment, crops, animals, machines, and products through an IoT platform is a technological advancement that offers real-time connectivity between devices [56]. The application of IoT is particularly relevant in sustainable agriculture, given the diversity of factors involved in the agricultural ecosystem, including biodiversity, stochastic weather patterns, and the interdependence of living and non-living systems. As a result, a comprehensive approach is necessary to address these complexities. In addition, IoT and AI can help reduce the effects of climate change and greenhouse gas emissions, further emphasizing the significance of these technologies in modern agriculture [57–60]. The research studies' comparisons illustrate multiple approaches for soil and plant sensing systems in precision agriculture, each with unique benefits and limitations. Using multi-spectral images from satellite imaging to monitor soil and plant quality is highly expensive and limited to certain countries. Real-time data can be obtained through on-the-go sensors that are installed on machinery or drones, but these sensors must be protected from wildlife and occasionally removed during cultivation. Real-time soil nutrient sensing is currently in the experimental stage but is crucial for solving environmental challenges. With their diverse and unstructured data, in situ and on-the-go sensing systems provide a challenge that requires scalable storage and advanced analytical tools. For effective big data use in precision agriculture, both studies emphasize the value of robust data management, standardized protocols, and security measures.

### *2.3. Sensor Development and Sensor Platforms*

Sensors are utilized at various stages of the farming process, from planting through the packaging of the final product. The farming process can be broadly classified into distinct categories, including planting, soil management, nutrient and water management, pest and disease management, yield harvesting, and post-harvest processing, all of which can benefit from the integration of advanced sensing technologies. Figure 3 shows sensing technologies and their applications in agriculture [61,62].

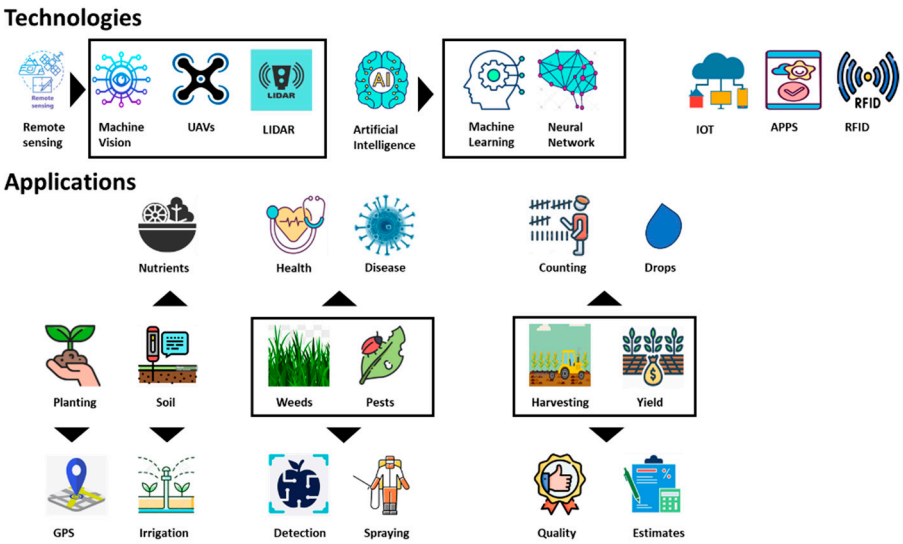


**Figure 3.** Sensing technologies and their applications in agriculture [62].

Sensors serve a vital function in enabling the conversion of real-world signals into their digital representations within Ag-IoT systems. The integration of sensors in machine components has become increasingly prevalent, providing producers with insights into the systems' dynamic loading and repetitive biotic and abiotic stresses. By collecting and comparing data from sensors positioned in the soil, crops, and animals, it is possible to identify technical improvements that prioritize criteria of ecological and economic sustainability, ultimately enhancing the soil-, plant-, and animal-friendly nature of precision agriculture [63].

The appropriate choice of sensors for an application is crucial for both inventors and users of IoT systems to ensure optimal sensor utilization. Technological advancements in sensors have significantly influenced the proliferation of the IoT. Key factors that must be considered when selecting sensors for IoT system development include low power consumption, information transfer compatibility between the computers and the sensor, precision, sensibility, repeatability, and durability [47]. Table 1 gives sensor categories and sensor measurements, and examples from the literature are provided.

**Table 1.** Sensor categories and measurements [47].

| Category of Physical Parameters | Measurement via Sensor | Sensors for Measuring the Measurand | Applications for Soil, Crop, and Microclimate Monitoring Are Found in the Literature |
|---|---|---|---|
| Sonic | Wave capacity, stage, polarization, spectrum, and wave velocity | Microphone, ultrasound distance sensor | Hardwood borer identification [64], estimation of crop canopy height [65,66] and wind velocity [67]. |
| Biological | Biomass, species kind, number, density, and level of chlorophyll | RGB camera, multispectral sensors, and load cell | The wet weight of the plant and estimated above-ground biomass [68]. Plant weight is measured continuously [69] |
| Chemical | Air quality, gas type, electrical conductivity, pH | Volatile organic compounds | Air quality [70], soil pH [71], pH of water (for irrigation), soil conductivity, irrigation water conductivity, soil gas flux, plant house $CO_2$, $O_2$ concentration [71]. |
| Electric | Charge, current, potential difference, electric field, resistance, conductivity, permittivity, (amplitude, phase, polarization, spectrum), and electric field | soil moisture sensor, humidity sensor (of the capacitive or resistive variety) | Moisture in the soil [47], air humidity [70], estimating soil nutrients, measuring stomata conductance, measuring sap flow, estimating evapotranspiration, and measuring soil electrical conductivity [71] |
| Magnetic | Magnetic field, magnetic flux, and permeability, as well as (amplitude, phase, polarization, and spectrum). | Wind speed parameter | Measurement of wind direction and speed (indirect) [71] |
| Mechanical | Position, acceleration, force, stress, strain, density, momentum, rate of mass transfer, speed of flow, shape, roughness, orientation, stiffness, compliance, viscosity, crystallinity, and structural integrity | Pressure sensors, pressure gauges, and load cells | Measurement of air pressure [70], measurement of fruit growth, wind speed, stem growth, and continuous plant weight measurement [69] |
| Optical | Wave velocity, intensity, energy, wave amplitude, phase, and polarization | Sensors for imaging, a thermal imaging camera, and an illumination sensor. | Changing light levels over the crop canopy [72], object detection (e.g., leaves, fruit, flowers) [68], extraction of plant dimensions, estimation of chlorophyll type and concentration, estimation of plant water stress, detection of leaf disease [73], canopy temperature [70] |
| Radiation | Type, intensity, and power | Neutron probe | Estimation of soil water content [74] |
| Thermal | Flux, specific heat, temperature, and thermal conductivity | Temperature sensor | Forecasting production based on leaf temperature, evapotranspiration, irrigation, and variety breeding [75]; sap flow rate estimation [76] |

When deployed on UAVs (drones, airplanes), UGVs (tiny, intelligent robots), and satellites, cameras with the Normalized Difference Vegetation Index (NDVI) can be utilized to estimate yield and using hyperspectral cameras and NDRE (normalized difference red edge) cameras can improve the estimates' accuracy. Principal Component Analysis (PCA) and an Artificial Neural Network (ANN) can be used to perform color-based crop (fruit) maturity checks. Gloves with various sensors integrated, including touch pressure sensors, imaging, inertia measurement, location, and RFID (Radio Frequency Identification), are used to classify fruits and have been applied in fungal disease classification [77–82]. Sensors that move both vertically and horizontally within the soil or remain stationary in the ground have the potential to collect critical data. With the emergence of nanotechnology, the use of increasingly smaller sensors is becoming commonplace [83]. The implementation of such sensors, coupled with the resulting data collection, can significantly reduce losses during agricultural operations and increase their effectiveness. Furthermore, the data collected facilitates the establishment of clear classification conditions based on the inherent quality of the crop, thereby mitigating the risk of incorrect classification and associated losses [34].

The authors of [84] have provided comprehensive information on techniques for disease identification in plants, emphasizing the significance of remote sensing methods. In a similar vein, ref. [85] have described an automated system for detecting facial expressions of pain in sheep with the aim of identifying diseases. Many different parameters can be measured with chemical sensors, including soil pH, soil salinity, soil nutrients, oxygen ($O_2$), carbon dioxide ($CO_2$), methane ($CH_4$), the pH and conductivity of irrigation water, and photosynthesis. The pH of soil and water is a critical parameter to determine, as it affects the solubility of nutrients, which in turn has a significant impact on plant growth and nutrient uptake. The two main categories of chemical sensors are photochemical and electrochemical. Electrochemical sensors evaluate the electrical properties of chemical reactions or the presence of substances, whereas photochemical sensors monitor the spectral signature of chemicals or chemical [86]. Some researchers attempt to continuously determine grain quality characteristics (protein content, mass density, and moisture content) because these affect the market value of the harvested crop. Grain quality factors can additionally assist in clarifying grain yield variation [87].

Another type of sensors recently under study are soil-degradable sensors that have emerged as a specialized sensing technology designed for monitoring soil parameters, including moisture content, temperature, pH levels, and nutrient concentrations. These sensors possess the unique ability to naturally degrade over time within the soil environment. Soil-degradable sensors offer several potential advantages, such as eliminating the need for sensor retrieval, minimizing soil pollution risks, and providing insights into soil dynamics without disrupting the ecosystem [88]. Inexpensive and low-maintenance biodegradable soil moisture sensors could improve existing knowledge on the spatial and temporal variability of available soil water at the field scale [89].

In their study, Sui et al., 2021 [88] developed and evaluated a biodegradable soil moisture sensor using stencil-printing. The sensor was made of environmentally friendly materials and consisted of slowly degrading encapsulants and rapidly degrading electrodes and substrates. The chosen materials allowed the sensor to function reliably in the presence of soil microbes and then quickly failed after the encapsulant degraded. The sensor eventually decomposed completely, eliminating the need for retrieval. The sensor's material selection did not hinder crop growth, as confirmed via ecotoxicity testing. Different thicknesses of encapsulants were used, and the sensor's sensitivity to volumetric water content (VWC) was measured. Accelerated degradation tests under elevated temperature conditions assessed the sensor's long-term stability. The breakdown of the sensor was characterized by showing stable performance during its functional lifetime and rapid degradation afterward. The encapsulation with a slowly degrading wax blend provided protection, reduced drift, and controlled degradation time. A linear capacitance response was observed for VWC, ranging from 0 to 72% in soil samples. Overall, these biodegradable sensors have the potential to enable maintenance-free, cost-effective, and real-time soil

moisture measurement at high spatial density for precision irrigation control in agriculture. Figure 4 presents an illustration of the mechanism for moisture sensor degradation. Wax covers the sensor while it is functional, but after the encapsulation fails, it quickly degrades. The sensor's encapsulant and other functional parts degrade in the soil.

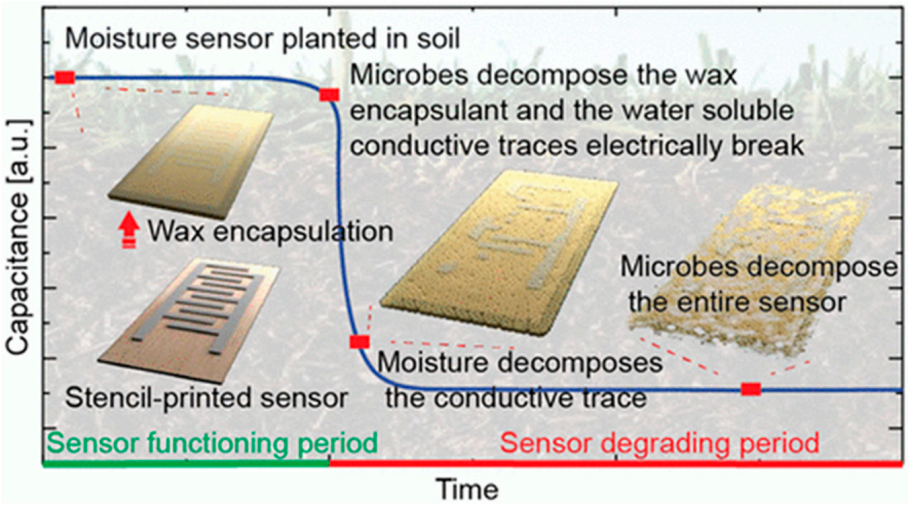


**Figure 4.** Illustration of the moisture sensor degradation mechanism [88].

These printed sensors have shown reliable performance in laboratory settings, but they still have some drawbacks, such as (1) the potential for fouling in soil over time, which could affect performance and signal drift; (2) the need for maintenance or the eventual removal of the sensors to prevent accumulation in the field; and (3) the potential toxicity of the conductive components to soil microbes and crops [90,91]. Previous papers have highlighted the changing landscape of sensor applications in precision agriculture, including yield estimation, disease diagnosis, animal health monitoring, and innovative soil parameter monitoring using biodegradable sensors. The incorporation of advanced technologies has the potential to revolutionize the collection of data in order to improve agricultural practices, which will enhance crop productivity. It has also identified challenges such as successfully integrating diverse technologies, processing huge amounts of data, ensuring standardization for connectivity, addressing high implementation costs, securing data privacy, evaluating environmental impacts, educating farmers for technology adoption, navigating regulatory constraints, ensuring sensor reliability in harsh conditions, and scaling solutions for widespread agricultural application.

### *2.4. Data Transmission Technologies*

One of the most significant advancements in infield monitoring over the past 10 years has been the replacement of wired-based complex systems with wireless sensor networks (WSN), complemented by effective power management techniques [92]. Sensor networks are used in precision agriculture to monitor field environmental conditions and other parameters. These sensors connect with one another, producing a network that collects environmental data collaboratively. WSNs are naturally specialized and have a simpler infrastructure, allowing them to transfer data easily and efficiently from the field to a remote user [93]. For the real-time monitoring of critical parameters like soil moisture and crop health, wireless sensor networks (WSN) have become essential in agriculture. They enable the effective use of water, fertilizer, and pesticides through optimizing resource management. WSNs improve data accuracy by efficiently distributing frequencies to reduce interference. Precise monitoring over large agricultural landscapes is made possible by considering signal intensity, bandwidth usage, and adaptation to changing transmission ranges. Energy efficiency is a top priority for WSNs for long-term deployment. They are essential for implementing precision agriculture and promoting sustainable farming

practices due to their scalability and strong system models that adapt to various farm sizes and changing conditions.

Data transmission via wireless constitutes a crucial component of an IoT system, particularly in the agricultural domain. Designing an effective Ag-IoT system requires comprehending the contributing elements pertaining to radio frequency (RF) that impact signal strength, interference, system model, bandwidth, and transmission range. Moreover, a thorough understanding of the advantages and disadvantages of different wireless communication technologies is important for optimal device selection. Wireless IoT sensors can track environmental factors such as humidity, temperature, luminosity, and soil moisture in real time [94–99]. Agricultural data collected with sensors will be delivered in a variety of forms based on the required level of precision and resolution, necessitating the use of appropriate interfaces to ensure compatibility. In the realm of IoT-based intelligent farming, communication protocols are essential for covering both short-range and long-range distances on the land [100].

ZigBee, Bluetooth, NB-IoT (Narrowband LPWAN technology which can coexist in LTE or GSM under licensed frequency bands) [101], and Wi-Fi are used for short ranges, while LoRaWAN, Sigfox, LTE m (Long-Term Evolution for Machines) [102] and LPWAN protocols in mobile communication networks are utilized for long ranges. The LoRaWAN (Long Range Wide Area Network) is designed to function with low power consumption and is capable of transmitting sensor signals to a central server from up to 30–40 km away on level terrain [103]. In terms of communication technologies employed for node and gateway/base station interactions, half of the reviewed literature utilized LoRa/LoRaWAN. The selection of an appropriate communication technology depends on the unique characteristics of the project, such as the required range and data rate, and thus a variety of options are available for consideration [104]. A WSN-based application was presented by [105,106], who discussed some of the scheme's advantages, Fuzzy-based Clustering Scheme, for example, attempts to reduce the deployment cost, propagation delay, and energy consumption while enhancing the reliability of the network. It is particularly well suited for large-scale monitoring applications of WSNs with higher node density. Will, real-world performance evaluation, addressing hardware and software requirements, comparing comparison with existing schemes, responding to network dynamics, and ensuring scalability in large-scale WSNs are all potential challenges should be discussed. Wi-Fi, Bluetooth, GPRS/3G/4G, ZigBee, LoRa, and SigFox were among the wireless technologies and protocol suites compared by the authors. Because of their suitable communication range and low power consumption, they demonstrated that LoRa and ZigBee wireless technologies are highly efficient for precision agriculture. It is mentioned that numerous strategies and algorithms linked to the energy efficiency of wireless sensor networks are classified. They also discussed the approaches that can be applied in PA. In the agricultural industry, 4G/3G wireless network technology is used to connect IoT-based smart devices for data sharing, precise assessment, accurate calculation, and so on. While the 3G/4G connectivity paradigm has shown great promise, there are some limitations that prevent the technology from reaching its full potential in the agricultural sector. One of the most significant limits is the operational area [107–110]. The comparison of various protocols is shown in Table 2.

**Table 2.** Communication technologies and their advantages [111].

| | Frequency | Data Rate | Range | Advantages | Reference |
|---|---|---|---|---|---|
| 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, improved responsiveness, scalability, reliability, and robustness | [111] |
| ZigBee | Global 2.4 GHz 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, and long battery life | [104] |
| LoRa | 150 MHz–GHz Depending on the country | 0.3–50 kbps | Urban area (2–5 km) Suburban area (15 km) | Long range, bidirectional, high-security, and seamless go-to-market communication | [104] |
| 2G–3G–4G | 900 MHz 1800 MHz 1900 MHz 2100 MHz | GPRS (35–170 kbps) EDGE (120–384 kbps) UMTS (384 kbps–2 Mbps) HSPA (600 kbps–10 Mbps) LTE (3–10 Mbps) | GSM (35 km) HSPA (200 km) | Superior battery life, wider deployment, and dependability | [107,110] |
| LTE-M | | 100 bps–1 Mbps | 10 k | Supports machine-type communications (mMTC) for the Internet of Things, supports a large number of devices | [102] |
| Wi-Fi | 2.4 GHz or 5 GHz | 1 Mbps–2.4 Gbps | 100 m | Faster data transfers, simple installation and connection, data security and privacy protection | [111] |
| Sigfox | 868 MHz 915 MHz 433 MHz | 100 bps | 10 km urban 40 km rural | Good battery life, long-range | [101] |
| NB-IoT | Licensed LTE frequency band | 200 kbps | 1 km urban 10 km rural | High scalability, allows connectivity of more than 100 K devices per base station, maximum payload length, guaranteed quality of service | [101] |

Despite the high speed and good connectivity provided by the 4G network, it is not feasible to interconnect all the smart farming devices in remote locations at a low installation and maintenance cost. To conduct demanding computational operations and run loaded services, a growing number of devices and a vast amount of research on IoT devices for smart farming are required. These devices also require increased intelligence, speed, scalability, secure communication capabilities, and processing power. Ultra-low latency and high connectivity are required for IoT devices to achieve quick performance and low costs. The utilization of 4G and 3G communication technologies has proven inadequate for real-time precision practices, primarily due to issues such as bandwidth limitations, connectivity issues, and slow data transfer speeds. In contrast, the integration of 5G technology within the agricultural sector has had a significant impact on various aspects, including real-time monitoring, unmanned aerial vehicles, virtual consultation, predictive maintenance, artificially intelligent robotics, data analytics, and cloud repositories. Consequently, the incorporation of 5G structures has facilitated improved speed, connectivity, scalability, and processing power, thereby enabling the resolution of existing limitations [100,112–114]. The

important areas in the agriculture sector where the development of a 5G mobile network could be beneficial are highlighted in Figure 5.


**Figure 5.** Areas of 5G in the agricultural sector [100].

While 3G may have coverage limitation, the adoption of 4G in IoT-based smart farming ensures reliable connectivity. The anticipated release of 5G revolutionized data transport with its ultra-fast, low-latency communication. However, extensive infrastructure development is needed for 5G implementation. The decision between various technologies requires balancing elements like coverage, speed, and the infrastructure's preparedness, reflecting the shifting connectivity environment in precision agriculture.

5G technology allows the increasing usage of IoT applications in digital agriculture and the advancement of precision farming technologies, allowing spot spraying and real-time image collecting without latency. As a result, overall agricultural efficiency, resource optimization, and sustainability improve. The use of 5G in agriculture represents a paradigm change, providing farmers with advanced technologies to handle the problems of modern farming while also contributing to global food security [100,114].

6G provides better connectivity and faster, more reliable communication. It provides higher data rates for real-time transmission, lower latency for near-instantaneous responses, and supports massive IoT connectivity, which allows to increase the productivity of Agricultural applications. 6G also seeks to increase energy efficiency, optimize resource consumption, and extend device battery life [115].

The constraints and challenges of implementing 5G in precision crop production include low coverage in rural regions, reliability and latency-related issues, energy consumption challenges, and implementation costs that have not been highlighted. 6G, which is still in its early stages, may face hurdles in infrastructure deployment, moving from 5G, unclear adaptation to environmental conditions, and resolving data security and privacy concerns. The precise constraints in the expanding field of precision agriculture are dependent on ongoing improvements and the specifics of different implementations.

The comparison of 3G, 4G, 5G, and 6G in precision agriculture discussed in the previous works reveals a changing landscape. While 4G promises a reliable connection in IoT-based smart farming, 5G transforms real-time data transit with ultra-fast, low-latency communication, although at the expense of significant infrastructure construction. The widespread implementation of 5G in agriculture has a beneficial impact on sustainability, resource optimization, and efficiency. In order to increase productivity in agriculture, the expected 6G technology intends to provide better connectivity, faster and more dependable communication, higher data rates, lower latency, and extensive IoT support. Both 5G and the potential 6G network have challenges, such as coverage limitations, problems with reliability, latency concerns, energy consumption issues, infrastructure deployment difficulties, and data security and privacy issues in precision crop production.

For agricultural sensor data to be presented in a variety of ways, communication protocols and interfaces are essential. Wu et al., 2023 and Chen et al., 2015 [116,117] presented a cyber–physical infrastructure that enables the seamless integration of diverse

sensors and transparently handles their physical differences throughout the World Wide Web (WWW). The infrastructure makes it possible to utilize sensor web accessibility and web processing services, which allow applications to access sensor data without knowing its physical details. IoT communication protocols (such as, MQTT, TLS, DTLS, and AES) are crucial for enabling secure communication between resource-constrained devices and services on fog, edge, and cloud nodes, as well as HTTP/HTTPS and WebSockets, make it possible to transmit data over the web [118]. A lot of Dashboards and standardized models improve the visualization of data. The selection depends on sensor types, network architecture, and the most appropriate data presentation style chosen to support decision making in precision agriculture.

## 3. Discussion

### *3.1. Amount of Needed Data for Precision Crop Production*

Precision crop production involves the use of advanced technologies to optimize crop yield and reduce waste. Among the key components of precision crop production is the collection of data from multiple sources (sensors, satellites, etc.). The amount of data needed from sensors in precision crop production is related to many aspects. On the one hand, collecting large amounts of data is essential for achieving the best possible results in precision crop production. Sensors should be used to collect data on a wide range of variables, including soil moisture, temperature, and nutrient levels, as well as plant health indicators such as leaf color, height, and growth rate [43]. One important principle is that the amount of data needed will depend on the specific crops being grown as well as the environmental conditions in which they are being grown. It also depends on the goals of the farmer. For example, crops that are more sensitive to changes in temperature or moisture levels may require more frequent data collection than crops that are more resilient. If the goal is to increase yield, then collecting a large amount of data may be necessary to identify the factors that are most important for achieving this goal. The authors of [119] examine in their article the use of affordable air pollution sensors for air quality monitoring and how machine learning techniques can increase the accuracy of the sensor data. The study shows data from two low-cost, self-built air pollution nodes that were installed at a Barcelona official reference station for four months and collected high-resolution data from five electrochemical sensors as well as temperature and humidity measurements. During the four months of testing, they gathered about 5.5 million samples of row data from each sensor. The Field Monitoring Laboratory in Mosonmagyaróvár has been operating in two experimental fields since April 2020. The primary goal is to build an IoT data collection technology based on site-specific precision crop production demand. The laboratory produces more than 100 sensed data points; the data are collected with the LoraWan communication protocol in 10–15 min intervals, depending on sensor type. A system structure was designed that can integrate the database from different sensors (from different producers). The server development is implemented in the .NET language. MS SQL databases are used to store sensor data. There were more than 2 million raw data collected in the maize vegetation season, and more than 3 million raw data were collected over the last three years [43].

The high-resolution data enables an analysis of signal processing, sensor sampling approaches, filtering, and calibration of low-cost sensors. In the same context, it would be clear how crucial it is to analyze and clarify the data acquired to determine how factors like atmospheric, soil, and plant characteristics affect the development of precision crop production. The development of big data and IoT has led to an explosion in the number of connected devices and sensors, generating vast amounts of data that can be analyzed for insights. While these technologies have numerous advantages, they also present some significant disadvantages that need to be addressed.

### *3.2. Advantages and Disadvantages of IoT Sensors and Big Data in Precision Crop Production*

The implementation of IoT and big data analytics in agriculture has yielded notable benefits. IoT sensors and stations facilitate the real-time tracking and monitoring of various processes, leading to improved operational efficiency and enhanced crop yield optimization. Decision makers can utilize big data analytics to make informed and data-driven decisions. Moreover, big data analytics can enhance accuracy by providing accurate predictions, trends, and insights. Cost savings are also achieved using IoT sensors, which minimize waste, improve asset utilization, and reduce energy consumption. These sensors generate data that can be utilized to adjust irrigation and fertilization schedules, ensuring that crops receive appropriate amounts of water and nutrients at the optimal time. It also has some notable drawbacks; one of the primary limitations is the high cost associated with implementing these technologies. Additionally, managing the vast amounts of data generated by these sensors can also be complex and challenging, requiring the necessary infrastructure and expertise to manage and analyze the data effectively. Moreover, the reliability of IoT sensors and stations is not always guaranteed, and they are prone to errors and failures, which can lead to incorrect data and flawed decision making. Another disadvantage is the potential for data overload, whereby the sheer volume of data collected can be overwhelming and challenging to process, resulting in difficulty filtering out irrelevant data and identifying critical data points. This can cause delays in decision making, leading to missed opportunities or increased costs this is consistent with [120–122].

Challenges with IoT integration in precision agriculture include knowledge gaps among farmers, a decrease in agricultural area, and the effects of climate change. Data privacy issues highlight the necessity for efficient approaches. Future prospects include developments in machine learning, AI, and sensing technologies aimed at enhanced proactive decision making. It is crucial to fill the knowledge gap and provide scalability for various farming needs. The agriculture industry, technology developers, and authorities may work together to promote an environment that encourages greater adoption. Opportunities will be opened for a sustainable and technologically advanced future in precision agricultural production by overcoming challenges and continued research.

## 4. Conclusions

The collection of data on various crop-related variables provides farmers with a comprehensive understanding, allowing them to make informed decisions for optimized yields. However, caution is required, as a large amount of data can lead to information overload, requiring a focus on relevant information. The vast amount of raw data provides an excellent platform for in-depth research of crops such as maize vegetation seasons, providing significant insights into growth, development, and long-term performance. This dataset can be used for trend analysis, pattern recognition, and potential predictions to enhance maize cultivation practices. The amount of data needed for a field plot is determined by the research objectives, precision requirements, and available resources. While more data points improve the representativeness and accuracy, practical factors like plot size and study complexity also play a role. It is important for researchers to carefully plan their data collection strategy, taking into consideration the specific research goals and the trade-off between data quantity and quality. This ensures that an adequate amount of data are collected to provide meaningful insights and draw reliable conclusions while also considering practical constraints. Furthermore, the real-time monitoring of IoT sensors improves agricultural operating efficiency by giving valuable data for informed decisions. Despite the benefits, big data and IoT sensor adoption requires careful consideration due to associated challenges such as security, complexity, privacy concerns, and reliability issues, necessitating a thorough review of their benefits and drawbacks before implementation.

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