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Review

The Implementation of "Smart" Technologies in the Agricultural Sector: A Review

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Abstract: The growing global population demands an increase in agricultural production and the promotion of sustainable practices. Smart agriculture, driven by advanced technologies, is crucial to achieving these goals. These technologies provide real-time information for crop monitoring, yield prediction, and essential farming functions. However, adopting intelligent farming systems poses challenges, including learning new systems and dealing with installation costs. Robust support is crucial for integrating smart farming into practices. Understanding the current state of agriculture, technology trends, and the challenges in technology acceptance is essential for a smooth transition to Agriculture 4.0. This work reports on the pivotal synergy of IoT technology with other research trends, such as weather forecasting and robotics. It also presents the applications of smart agriculture worldwide, with an emphasis on government initiatives to support farmers and promote global adoption. The aim of this work is to provide a comprehensive review of smart technologies for precision agriculture and especially of their adoption level and results on the global scale; to this end, this review examines three important areas of smart agriculture, namely field, greenhouse, and livestock monitoring.

Keywords: IoT; precision agriculture; smart farming; Agriculture 4.0

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1. Introduction

The development of agriculture in the forthcoming decades needs to pursue ambitious goals, including ensuring food safety, improving product quality, and the adoption of sustainable agriculture methods and practices [1–3]. In this context, smart farming (also termed "smart agriculture") can prove to be an invaluable tool for achieving these goals [4–7]. Digital technologies are part of the new strategic solutions for the development of agriculture and they have the ability to increase the scale, efficiency, and effectiveness of farm production [8]. The Food and Agriculture Organization (FAO) of the United Nations calls this role the "Digital Agricultural Revolution", while other sources characterize it as "Agriculture 4.0" [9–14]. In the context of "Agriculture 4.0", precision agriculture focuses on utilizing data from multiple and diverse sources to improve crop yields and on ensuring that the strategies used for crop management are applied in a cost-effective fashion. This spans across multiple resource utilization domains, including the application of fertilizers and plant protection substances, as well as irrigation [4,15,16]. Precision agriculture focuses on the exploitation of technologies such as GPS, sensors, and data analytics; in a wider context, smart farming aims at harnessing the power of information and communication technologies (ICTs) to optimize complex farming systems, utilizing human labor more effectively and enhancing crop quality and quantity [17–19] while also including the aspect of collaboration [20]. In this paper, our main focus is on precision agriculture; however, important developments from the area of smart farming, such as the use of AI, are also taken into account.

Further, considering the current state of the agricultural sector and the imperative to address climate neutrality concerns, the widespread adoption of Agricultural Green Production Technologies (AGPTs) is widely acknowledged as a fundamental approach. AGPTs offer innovative solutions and practices that promote sustainable agriculture and contribute to the overall goal of achieving climate neutrality in the agricultural industry [21–23].

The objective of this study is to conduct a comprehensive review of issues and aspects related to the implementation and deployment of intelligent technologies in the agricultural sector. This paper discusses the challenges faced by the agricultural industry in meeting the increasing demands caused by population growth, which necessitates higher agricultural outputs and improved product quality while, in parallel, ensuring sustainability. Furthermore, this review examines the technologies and methods available to address these challenges, as well as the difficulties encountered by farmers when adopting new technologies and integrating them into their farming practices. It covers various systems related to smart agriculture, including those employed in open fields and greenhouses, smart water supply systems, and the broader application of IoT systems in the agricultural sector, as well as the implementation of IoT systems for livestock tracking in pastures. A search was conducted to track the evolution and acceptance of technology based on the chronological publication of pertinent scientific articles and publications at large. Additionally, this paper highlights examples of applications that have been successfully implemented in different countries worldwide and discusses governmental programs designed to support the agricultural sector.

Topics concerning precision agriculture have been studied in a number of literature surveys that have been published in the past few years. Surveys [8,24,25] undertake a global view of the application of ICTs in precision agriculture. References [26–28] focus on the use of artificial intelligence and machine learning-based techniques in the domain of precision agriculture, while references [29–31] examine the use of UAVs for performing precision agriculture tasks. Since the Internet of Things (IoT) has proved to be a key enabler for precision agriculture and plays a pivotal role in the design and implementation of precision agriculture systems, several surveys have focused on aspects of the application of IoT in precision agriculture, including architectures, technologies, practices, and applications [32–37]. Finally, the factors that influence the acceptance and take-up of precision agriculture are studied in a number of surveys (e.g., [38–40]), while a number of scientific papers explore the development of precision agriculture in specific countries, also considering governmental projects for the uptake of precision agriculture [41–44].

This paper, besides considering more recent developments than those already published in the literature, undertakes a more global perspective, considering multiple aspects affecting the implementation and uptake of precision agriculture, and more specifically (a) challenges and concerns, (b) technological developments, (c) the state and evolution of the IoT and its use in precision agriculture, (d) application areas of precision agriculture, and (e) implementation projects and success stories that have been carried out in different countries. The different aspects are interrelated, since, for instance, IoT acts as an enabler for applications, while success stories may be a positive factor regarding the acceptance and uptake of precision agriculture methods. Figure 1 illustrates the relationships between the precision agriculture aspects surveyed in this paper.

The rest of the paper is structured as follows. Section 2 presents the data collection method and process. Section 3 presents the challenges and concerns faced by farmers and ranchers when implementing smart farming programs and adopting IoT systems and wireless sensor networks. Section 4 presents the evolution of technology as shaped by the writing of scholarly articles. Section 5 briefly presents IoT technology and how it is applied to smart agriculture. Section 6 presents a brief description of the three main applications in precision agriculture. Section 7 presents implementation projects and success stories that have been carried out in different countries. Finally, Section 8 presents the conclusions.

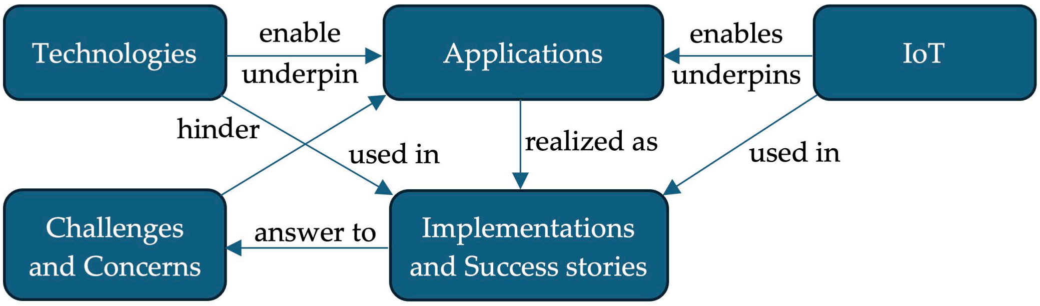

Figure 1. Relationships between the precision agriculture aspects surveyed in this paper.

2. Data and Methods

The purpose of this paper is to give an overview of the current situation in the agricultural sector regarding the adoption and implementation of the smart agriculture model. Through this approach, data are also provided on government support for the adoption, support, and development of relevant projects.

The methodology used in this review was based on the PRISMA approach (Figure 2), which is a systematic and rigorous method for reviewing and synthesizing studies available in the literature [45].

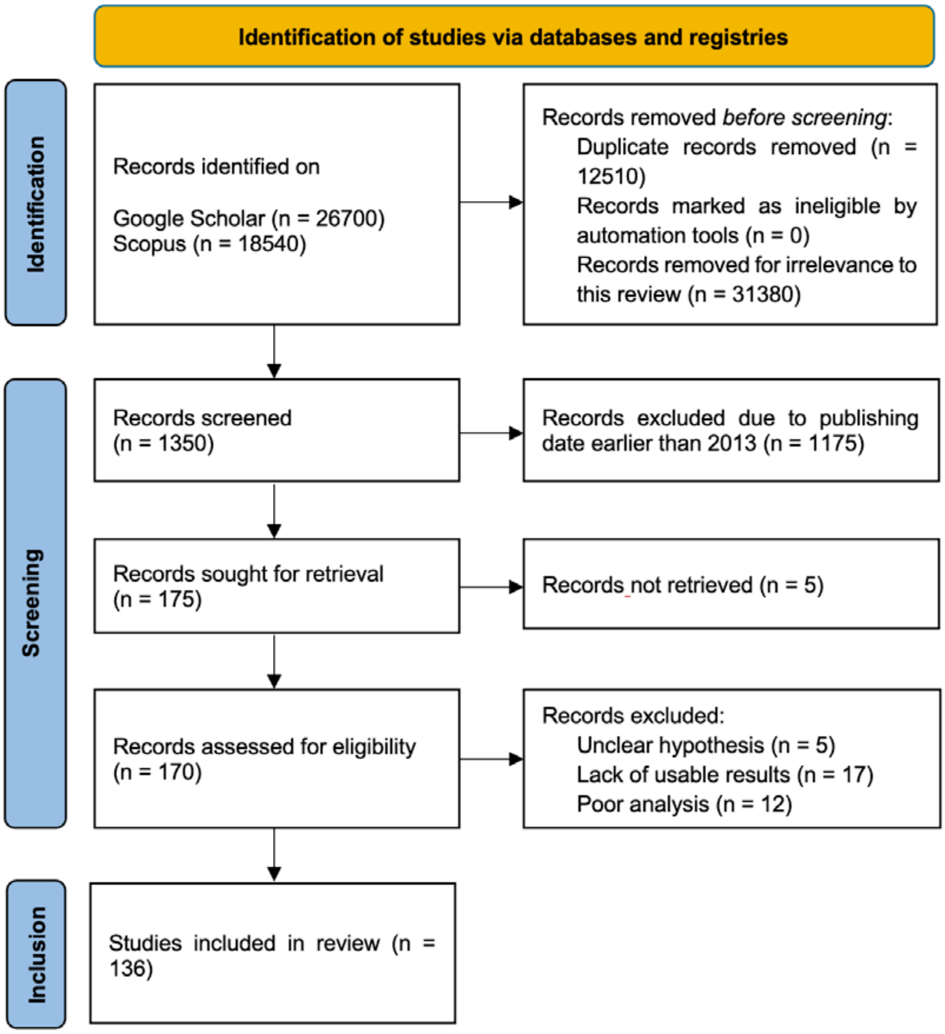

Figure 2. PRISMA flowchart for the set of keywords on precision agriculture.

For the collection of data, relevant publications from scientific conferences, in international scientific journals, and the internet were identified and studied. Some seminal papers were used both for the extraction of relevant information and for identifying additional sources (through their citation lists and by examining which works cite the seminal papers). Searches were also conducted in scientific publication databases and on the internet. The Scopus platform was chosen for this work. When compared to the Web of Science platform, Scopus boasts a higher number of records [46–48]. While it falls slightly behind Google Scholar in terms of records [49,50], Scopus excels in the quality of the metadata it provides. Moreover, it offers greater ease of data extraction when compared to Google Scholar [49,51–55]. Table 1 lists the basic sources used for data retrieval and for the identification of additional sources.

Table 1. Basic sources for data retrieval and for identification of additional sources.

Source Type	Description	Year of Publication	Use
Scientific publication	A Survey on the Role of IoT in Agriculture for the Implementation of Smart Farming	2019	Extracting data and identifying new scientific publications.
Scientific publication	Understanding technology acceptance in smart agriculture: A systematic review of empirical research in crop production	2023	Extracting data and identifying new scientific publications.
Scientific publication	What Drives the Adoption of Agricultural Green Production Technologies? An Extension of TAM in Agriculture	2022	Extracting data and identifying new scientific publications.
Scientific publication	A Life Cycle Framework of Green IoT-Based Agriculture and Its Finance, Operation, and Management Issues	2019	Extracting data and identifying new scientific publications.
Scientific publication	A Review of the Applications of the Internet of Things (IoT) for Agricultural Automation	2020	Extracting data and identifying new scientific publications.
Database	Scopus		Extracting data using queries.
Internet			Searching for programs and directions.

Relevant scientific publications were collected from the Scopus [56] academic database by applying appropriate search filters. To extract the desired results, we employed the queries presented in the following table. Please note that in the second query, the placeholder text *keywords for the specific technology* were duly substituted by appropriate keywords that described the technology in question, e.g., “smart irrigation”, “Agricultural Robots”, or “Livestock Monitoring” (Table 2).

Table 2. Search queries used to locate scientific publications in Scopus.

Description	Query
Query for the number of precision agriculture articles in the period 1981–2023.	TITLE-ABS-KEY (precision AND agriculture) AND PUBYEAR > 1980 AND PUBYEAR < 2024
Query for the number of articles related to precision agriculture and to each new technology, along with the year of their first publication.	(TITLE-ABS-KEY (precision AND agriculture) AND TITLE-ABS-KEY (*keywords for the specific technology*)) AND PUBYEAR > 1980 AND PUBYEAR < 2024
Query for the number of articles related to precision agriculture per year.	TITLE-ABS-KEY (precision AND agriculture) AND PUBYEAR = year

3. Challenges and Concerns

As stated above, advanced technologies are taken up in farming to meet the growing demands for product quantity and quality and also promote sustainability. One important driver of the adoption of precision agriculture is the Internet of Things (IoT) [57], which is anticipated to support numerous smart farming activities and tasks. Nevertheless, the widespread implementation of IoT systems in agriculture encounters obstacles, such as the substantial investments required for agricultural IoT systems and the limited technological proficiency of farmers. In order to better study and identify these challenges, we have categorized the applications of IoT techniques in agriculture into three groups, namely (a) controlled environment planting, (b) open-field planting, and (c) livestock breeding, following the classification introduced in [58].

3.1. Precision Agriculture Adoption Models and Related Variables

The widespread adoption of IoT systems in open-field agriculture, which is crucial for addressing global food challenges, has not yet been achieved. The implementation of IoT systems in agriculture entails not only technical considerations but also significant challenges related to finance, operation, and management (FOM). The high cost of investment stands as the primary concern to be addressed. Both large-scale farmers and smallholders are hesitant to undertake these costs without clear and enticing benefits and increased convenience [58].

The factors that influence the individual acceptance of information technology (IT) entail several external variables. These variables include situational involvement and intrinsic involvement [59], age, computer training and management support, level of education, and prior experience [60]. Additionally, the compatibility and characteristics of the technology task also play a significant role in determining acceptance [61].

Facilitating conditions (FCs) encompass the technical and organizational infrastructures that provide support for IT systems. This construct is commonly used in research to gauge users' perceptions of the assistance available for implementing IT. Teo [62] conducted a study and discovered that both technical and organizational support had substantial impacts on the behavioral intention to use technology.

To enhance technology receptivity within the agricultural sector, conclusions from the use of technology acceptance models, such as the Technology Acceptance Model (TAM) [63] and the unified theory of acceptance and use of technology [64], can be considered. These models incorporate various factors such as computer self-efficacy (confidence in using computers), computer stress (perceived stress associated with using computers), and the variable of age, and these factors appear to be widely applicable to all domains and forms of technology [65–67]. By considering factors like computer self-efficacy, computer stress, and age, these models offer insights into how to promote technology adoption among agricultural professionals.

Computer self-efficacy refers to an individual's perception of their own ability or competence in using computers and other forms of information technology (IT). On the other hand, computer anxiety represents a feeling of fear, discomfort, or apprehension when it comes to using IT. Although these two concepts differ, they are often related, as individuals with high self-efficacy tend to have lower levels of anxiety towards IT usage. In other words, individuals who feel confident in their abilities to use computers are generally less anxious when it comes to utilizing IT systems.

In research on IT acceptance, the age variable has been included as an extension due to the observation that older individuals, sometimes referred to as "digital immigrants" because they were born or raised before the widespread use of digital technology, often exhibit higher levels of computer anxiety. Several researchers have incorporated age and even gender variables into their studies on IT acceptance [65,66]. Talantis, Shin, and Severt [67], in their study on participant acceptance of conference mobile applications (apps), found that the perceived usefulness of the app was the strongest predictor of users' attitudes toward the app. However, they observed that ease of use was the only significant variable that differed among age groups. They also acknowledged that the attendees' age group influenced their technology preferences.

The skill level and efficiency of a country's workforce are widely recognized as crucial factors in its industrial development. These capabilities are heavily influenced by the quality of education and training within the nation. Information technology plays a significant role in transforming the landscape of education and training, contributing to the development of necessary skills and enhancing workforce efficiency. The integration of information technology in education and training initiatives can have a profound impact on the skill level and capabilities of individuals, ultimately driving industrial development in a country. Additionally, the availability of skilled personnel enhances the confidence of users that efficient support will be available when required, reducing thus computer anxiety.

3.2. Agricultural Green Production Technologies and Factors Affecting Their Adoption

Considering the benefits from the application of Agricultural Green Production Technologies (AGPTs) and the considerable margins to increase their adoption, there has been a substantial increase in studies examining the factors influencing farmers' adoption of AGPTs. Several research papers [68–70] have explored this topic and have identified various determinants that contribute to farmers' adoption behavior.

AGPTs are considered essential in addressing the significant environmental challenges associated with agriculture, such as reducing greenhouse gas emissions. By embracing them, the agricultural sector can strengthen its capacity to adapt to climate change and mitigate environmental damage.

By employing sustainable practices, farmers can optimize their production methods and yield higher-quality crops while minimizing negative environmental impacts. This dual approach enables farmers to increase their income without compromising the ecosystem.

Moreover, AGPTs hold significant value for developing countries. By adopting AGPTs, developing countries can mitigate the adverse effects of traditional farming practices, such as excessive use of chemicals and unsustainable land management. This not only protects the environment but also promotes long-term agricultural development that can support the livelihoods of farmers and contribute to overall economic growth.

One set of determinants is related to farmers' characteristics. Factors such as education level, household labor force, part-time farming level, and land management scale have been found to have a significant influence on the adoption of AGPTs. Farmers with higher education levels may be more receptive to new technologies and possess the necessary knowledge and skills to adopt AGPTs effectively. The availability of labor within the household and the extent of part-time farming involvement can also impact the adoption decision, as these factors affect the resources and time available for implementing AGPTs. Additionally, the scale of land management, including the size of the farming operation, can influence farmers' ability and willingness to adopt AGPTs.

By understanding these characteristics and their influence on farmers' adoption behavior, researchers and policymakers can develop targeted strategies to promote the adoption of AGPTs. Tailoring interventions and support programs based on farmers' specific characteristics can help overcome barriers and facilitate the widespread adoption of sustainable agricultural practices.

The potential of precision agriculture has been highlighted through recent scientific reviews. Monteiro at al. focused on the precision livestock farming aspects of monitoring animal health and safety though standard monitoring technologies but not IoT [71]. Nowak provided a short review (17 papers) on the use of satellite-based technologies for precision agriculture and reports on the adoption differences between North America and Europe [72]. Memon et al. focused on the use of mobile applications and machine learning algorithms for drones in precision agriculture in [73], providing a thorough examination of the specific advantages and limitations of those technologies in a specific region. Another work focused on the review of strategies and KPIs, measuring environmental variables for agroforestry and precision livestock farming [74]. Very recent works provided an in-depth analysis of

IoT technologies for precision agriculture in cotton production [75]. A recent short review by Maruya at el. provided a shortlist of technologies for precision agriculture in general [76]. Finally, another recent review examined the technologies and sensors that record data for precision agriculture, mainly farming [77].

All the above works either focus on specific aspects of precision agriculture or on specific technologies (traditional and IoT-related) relevant to certain regions. Our work undertakes a more global perspective, considering multiple aspects affecting the implementation and uptake of precision agriculture, including challenges and concerns, technological developments, the maturity and evolution of precision agriculture, and success stories. Moreover, our work considers the interplay between these different aspects, while it also offers a more expanded approach that includes findings from the global region (all continents). Finally, this paper considers the recent technological developments in IoT-related technologies used for precision agriculture and examines their use in three important application areas, namely field, greenhouse, and livestock monitoring.

4. Evolution of Technology

The development of technology in precision agriculture can be observed through the process of publishing scientific papers. By using specific queries in the Scopus [56] scientific database, relevant results were obtained.

The results presented in this section provide insights regarding the year of appearance of new technologies in agriculture and the number of scientific publications until today (Table 3).

In the first row, we can observe the year of publication along with the number of scientific papers focusing on precision agriculture for the period 1981–2023. In subsequent rows, the years of publication are accompanied by the corresponding number of scientific papers on the application of each emerging technology in the domain of precision agriculture until today.

The number of publications per year reflects the interest of the scientific community and companies in the progress and application of precision agriculture and intelligent agriculture systems. This is depicted in Figure 3, and we can observe that there is an increasing number of publications per year, demonstrating the rising interest in precision agriculture and related fields and technologies. Note that for the year 2023, only the papers published in the first six months, i.e., up to the point when the queries were run against the academic databases, are accounted for.

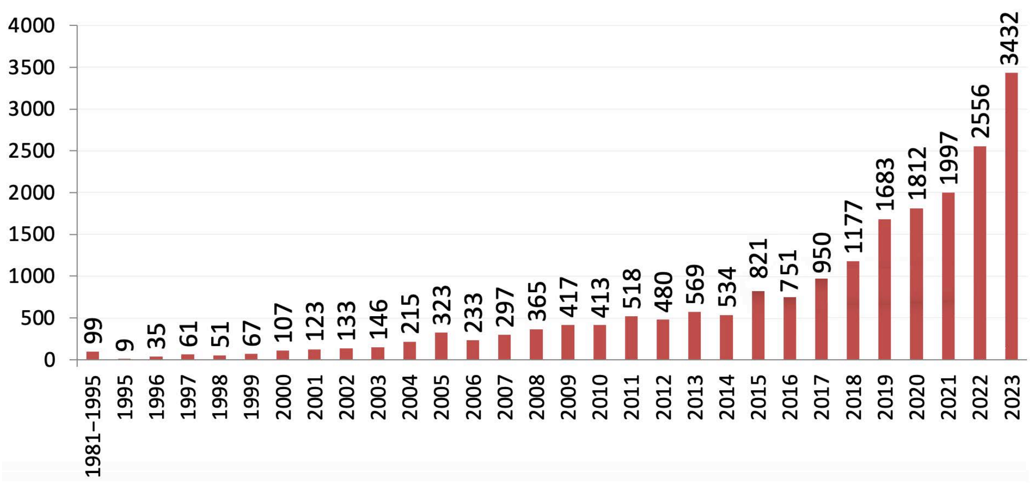

Figure 3. Number of scientific publications on precision agriculture and related technologies per year.

Table 3. The evolution of technology in agriculture as reflected through the publication of scientific papers.

Technology	Year of First Scientific Publication	Number of Scientific Papers Published until Today
Precision Agriculture	1981	18,540
Field Monitoring	1993	1806
Precision Farming	1995	4037
Satellite Imagery	1996	589
Precision Irrigation	1997	1927
Decision Support Systems	1997	875
Remote Sensing	1997	3008
Geographic Information Systems	1997	499
Variable-Rate Technology	1997	488
Agricultural Robots	1998	2123
Livestock Monitoring	2000	375
Smart Irrigation	2001	392
Greenhouse Monitoring	2001	201
Sensor Nodes	2001	633
Autonomous Agricultural Machinery	2002	100
Unmanned Aerial Vehicles (UAVs)	2002	1753
Artificial Intelligence	2003	1011
WSN in Precision Agriculture	2003	492
Climate and Weather Prediction Models	2005	33
Global Positioning System	2005	767
Light Detection and Ranging	2006	73
Drones	2008	664
IoT in Precision Agriculture	2011	1358
Smartphone Apps and Mobile Technology	2018	10
Blockchain and Supply Chain Management	2020	12

5. IoT Technology in Precision Agriculture

IoT technology has found diverse applications in the field of agriculture, revolutionizing various agricultural processes. It has been successfully employed in farm management [78], farm monitoring [42], livestock monitoring, irrigation control [79], greenhouse environmental control, autonomous agricultural machinery, and drones [58,80–86], thereby contributing to agricultural automation.

For instance, farmers can leverage wireless sensors and mobile networks integrated with IoT technology to monitor farming conditions in real-time and efficiently manage their farms. This allows for immediate responses to changes in environmental factors, optimizing resource utilization and improving productivity. Furthermore, IoT-enabled systems enable farmers to collect and analyze valuable data, which can be used to generate yield maps. These maps facilitate precision agriculture techniques, enabling farmers to produce high-quality crops while minimizing costs [87].

By leveraging IoT technology, farmers can enhance their decision-making processes, streamline operations, and achieve greater efficiency and sustainability in agricultural practices. The ability to monitor and control agricultural processes in real time, coupled with data-driven insights, empowers farmers to optimize resource allocation, reduce waste, and increase overall productivity in a cost-effective manner.

Over the past few decades, IoT technologies have been widely applied to specific agricultural processes, utilizing various sensors and network technologies. The advancements in sensor and network technology have led to the availability of different types of networks for users to choose from. Each sensor and network system comes with its own advantages and disadvantages, allowing farmers to select the most suitable sensors and networks based on their specific farm conditions and working environments. This enables farmers to implement highly efficient and cost-effective IoT-based agricultural practices.

However, it is important to note that the current use of IoT in agriculture has mostly focused on individual solutions, rather than on a comprehensive management of the entire agricultural process. For instance, IoT has predominantly been employed for monitoring and controlling greenhouse environments. While these applications have proven beneficial, there is still untapped potential in utilizing IoT for managing crops and agricultural machinery across the entire agricultural system [81].

In summary, farmers can leverage IoT technologies by carefully selecting sensors and network systems tailored to their farm conditions. Although IoT has primarily been implemented as isolated solutions, there is scope for expanding its use to encompass comprehensive agricultural management, covering aspects such as crop management and machinery control.

5.1. IoT-Supported Application Categories in Agriculture

Recent advancements in wireless sensor networks have significantly facilitated the measurement of various types of data [88]. These breakthroughs have opened up opportunities for IoT to tackle diverse agricultural challenges and enable sustainable and efficient farming practices [89]. In the field of agriculture, IoT finds application in a wide range of activities, which can be broadly categorized into four main areas, i.e., management systems, monitoring systems, control systems, and unmanned machinery [90], as illustrated in Figure 4.

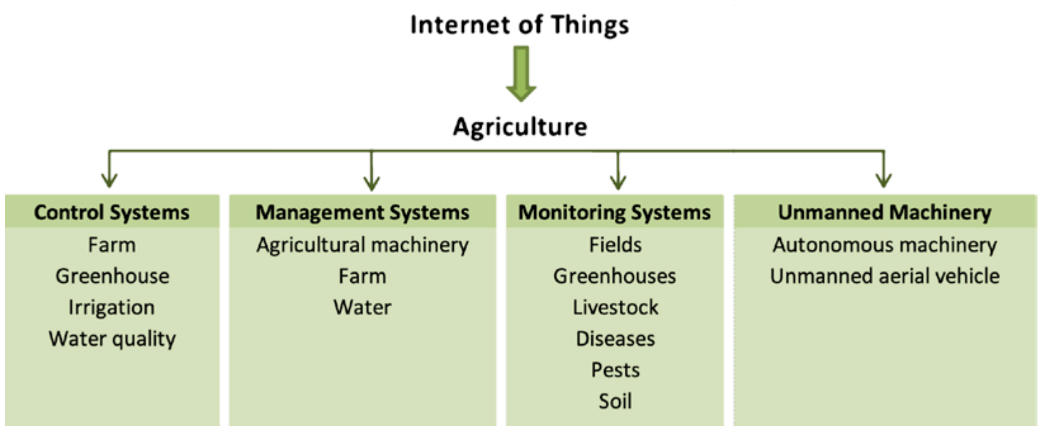

Figure 4. The four primary application areas of IoT in precision agriculture [42] and their subcategories.

Management systems encompass IoT applications that assist farmers in overall farm management, including tasks such as resource planning, logistics, and decision-making processes. Monitoring systems utilize IoT to collect real-time data from sensors placed in the agricultural environment, allowing farmers to monitor factors such as temperature, humidity, soil moisture, and crop growth. Control systems leverage IoT to enable the remote control and automation of various agricultural processes, such as irrigation, nutrient delivery, and pest management. Unmanned machinery refers to the use of IoT-enabled devices such as drones or robots for tasks like crop monitoring, spraying, and harvesting.

By leveraging IoT technology within these four categories, agriculture can benefit from enhanced management capabilities, improved monitoring and data-driven decision-making, precise control over agricultural processes, and increased automation to optimize efficiency and productivity. These advancements contribute to the goal of sustainable and efficient farming practices [91,92].

Indeed, IoT represents the integration of multiple devices that communicate, sense, and interact with their internal and external environments through embedded technology [93]. It has emerged as a prominent megatrend in next-generation technologies, capable of impacting various industries and business sectors. The extended benefits of IoT include advanced connectivity of end devices, systems, and services, leading to transformative opportunities.

IoT offers suitable solutions for a wide range of applications, including but not limited to smart healthcare, smart cities, security, retail, traffic congestion management, industrial control, and agriculture [94]. In each of these domains, IoT enables the integration of devices and systems, resulting in enhanced capabilities, efficiency, and improved decision-making processes.

In agriculture, IoT offers significant benefits by enabling smart farming practices. It allows for the real-time monitoring of environmental conditions, automated irrigation systems, precise application of fertilizers and pesticides, and data-driven decision-making, leading to improved crop yields, resource efficiency, and sustainable agriculture [95].

Overall, IoT has become a transformative technology that has the potential to revolutionize various industries by providing advanced connectivity, intelligent systems, and a wide range of applications with extended benefits [96].

5.2. IoT as an Enabler for Precision Agriculture

A considerable amount of research has been conducted to explore the application of IoT technology in agriculture, leading to the development of smart farming solutions [97]. The introduction of IoT has revolutionized the agricultural landscape by addressing various complexities and challenges faced by farmers [98].

The advancement of technology has created the expectation that IoT can offer solutions to problems such as water scarcity, cost management, and productivity issues, which farmers commonly encounter [99]. Cutting-edge IoT technologies have been effective in identifying and resolving these issues, allowing for increased productivity and reduced costs. The implementation of wireless sensor networks has played a crucial role in collecting data from sensor devices and transmitting them to central servers [100].

The data collected through sensors provide valuable insights into environmental conditions, enabling effective monitoring of the entire agricultural system. However, monitoring environmental conditions and crop productivity alone does not encompass the full evaluation of crops. Several other factors significantly impact crop productivity, including field management, soil and crop monitoring, prevention of unwanted objects, protection against wild animal attacks, and prevention of theft [101].

By leveraging IoT technology, farmers and technologists can address these challenges by collecting and analyzing data from various sources, enabling them to make informed decisions and optimize agricultural processes. IoT-based solutions contribute to improved crop management, enhanced productivity, and more efficient resource utilization, thereby supporting sustainable and profitable agriculture.

5.3. Architectural Patterns for IoT-Based Systems

IoT technology facilitates the efficient scheduling of limited resources, optimizing productivity in agriculture. Figure 5 illustrates a schematic diagram representing the emerging agricultural trends, showcasing seamless and cost-effective interactions through secure connectivity across individual components like greenhouses, livestock, farmers, and field monitoring. IoT-based agricultural networks, enabled by wireless devices, enable the real-time monitoring of crops and animals.

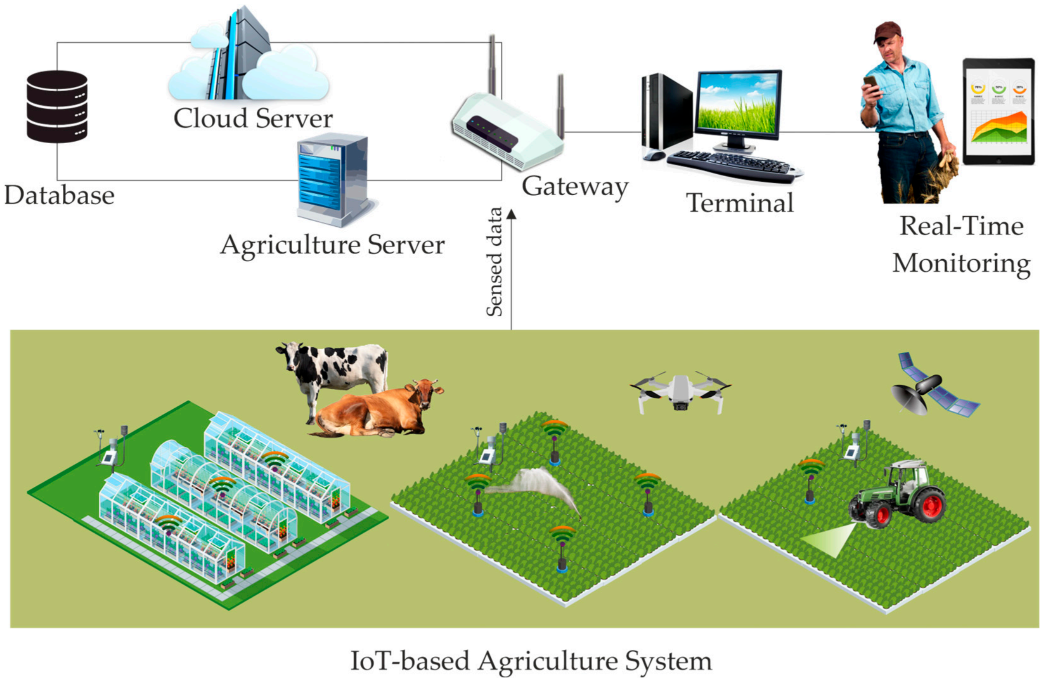

Figure 5. A schematic diagram representing the emerging agricultural trends, showcasing seamless and cost-effective interactions through secure connectivity across individual components like greenhouses, livestock, farmers, and field monitoring.

The role of agricultural information systems, which encompass servers, gateways, and agriculture databases, is essential in storing agricultural records and providing on-demand agricultural services to authorized users [82].

Through IoT-based systems, farmers can monitor and manage their agricultural operations more effectively, ensuring optimal utilization of resources. Real-time data collection and analysis enable timely decision-making, precise resource allocation, and proactive intervention in case of any anomalies. This integrated approach enhances productivity, minimizes waste, and supports sustainable farming practices [101].

Furthermore, the secure connectivity and data storage provided by IoT networks offer reliable access to agricultural records and enable authorized users to access essential information and services when needed. This promotes efficient decision-making, facilitates collaborative efforts, and supports the development of agricultural strategies tailored to specific needs.

Overall, IoT technology in agriculture offers a comprehensive and connected approach, integrating data from various sensors and devices to optimized resource management, enhance productivity, and foster sustainable agricultural practices [81].

6. Applications of Precision Agriculture

In the realm of smart agriculture, monitoring plays a critical role, encompassing three main applications: field monitoring, greenhouse monitoring, and livestock monitoring.

6.1. Field Monitoring

Field monitoring applications focus on reporting various conditions and parameters related to the agricultural field. This includes monitoring soil quality, temperature, humidity, gas levels, and pressure (both air pressure and water pressure), as well as monitoring crop diseases. IoT-based sensors provide real-time data on these aspects, enabling farmers to assess the health of their crops, identify potential issues, and make informed decisions regarding irrigation, fertilization, and disease management [102].

Figure 6 illustrates a scenario in which multiple crop parameters are monitored by deploying agricultural devices and sensors in all over the field [82]. Sensors can also be used for automations installed on the field, e.g., to monitor automatic irrigation systems.

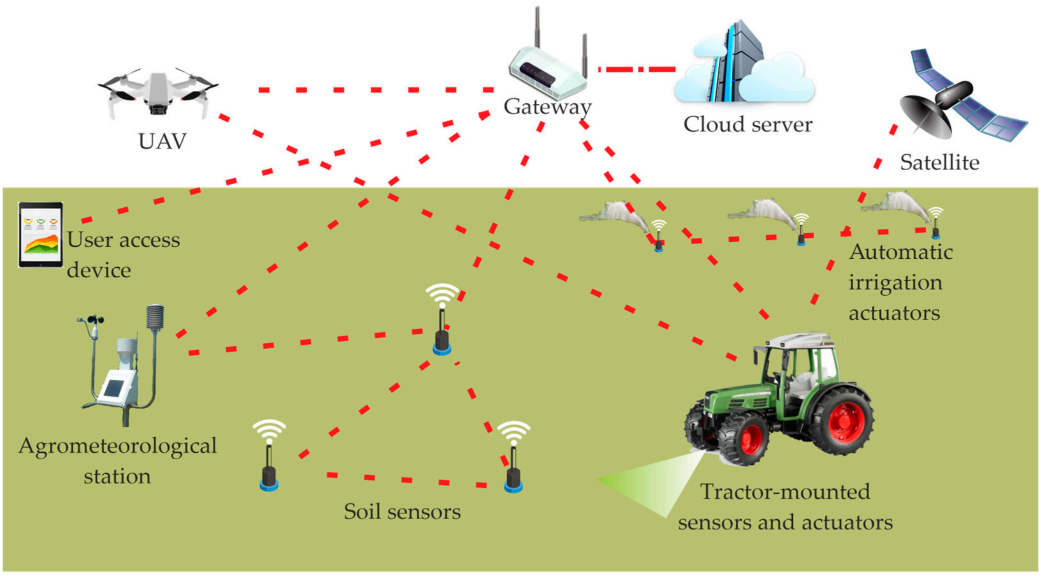

Figure 6. A scenario for remote monitoring in precision agriculture, involving the comprehensive monitoring of multiple crop parameters.

The information system depicted in Figure 6 comprises the following components:

- Sensor nodes: These are small devices equipped with various sensors that measure environmental parameters, such as temperature, humidity, soil moisture, light intensity, CO_2 levels, etc. These sensor nodes are distributed strategically throughout the farm or greenhouse. Sensor nodes may be hosted on larger assemblies, such as agrometeorological stations, while they can also be mounted on farm vehicles, such as tractors.
- Communication protocols: WSNs and IoT systems use wireless communication protocols, such as Zigbee, LoRaWAN, Wi-Fi, or Bluetooth, to enable seamless data transmission between the sensor nodes and the central gateway.
- Central gateway: The central gateway acts as a data aggregator and communication hub. It receives data from all the sensor nodes within its range and transmits these data to the cloud or a local server for further processing.
- Connectivity: The central gateway is typically connected to the internet, enabling remote access to the data collected by the sensor nodes. Farmers can access these data through computers, smartphones, or other devices.
- Satellite or unmanned aerial vehicle analysis: The analysis of data obtained from satellite or drone imagery in conjunction with node data also provides useful information for farming and guidance for autonomous machinery.
- Cloud or server: Data collected by the central gateway are sent to a cloud-based platform or a local server for storage, analysis, and visualization.

The field monitoring information system [42,103,104] collects, analyses, and correlates diverse types of data, which can vary depending on the specific parameters being monitored and the requirements of the farmers. Some common types of data include the following:

- Environmental parameters: Data related to temperature, humidity, soil moisture, light intensity, CO_2 levels, and other environmental conditions. These data help farmers to optimize irrigation, ventilation, and other climate control systems.
- Crop and plant health: Data on the growth and health of crops, including information about nutrient levels, disease presence, and pest infestations. These data allow farmers to take timely action to protect and enhance crop health.

- Water and resource management: Data on water consumption, water quality, and resource usage to optimize water and resource management practices.
- Weather data: Some remote monitoring systems may also integrate weather data from external sources to make more informed decisions based on weather forecasts.
- Alerts and notifications: In case of any abnormal conditions or critical events, the system may send alerts and notifications to the farmers, allowing them to respond promptly.

6.2. Greenhouse Monitoring

Smart greenhouse [105–108] designs leverage IoT devices and sensors to create a controlled environment that minimizes the need for manual intervention. These intelligent systems continuously measure and monitor different climate parameters such as temperature, humidity, light intensity, and CO_2 levels. By collecting data and analyzing the specific requirements of the plants, IoT devices can automatically adjust and optimize the greenhouse environment to create the ideal conditions for plant growth and productivity [106].

Figure 7 illustrates a wireless sensor network (WSN) that monitors the greenhouse environment. The network is divided into multiple parts, which process the data and provides feedback [82].

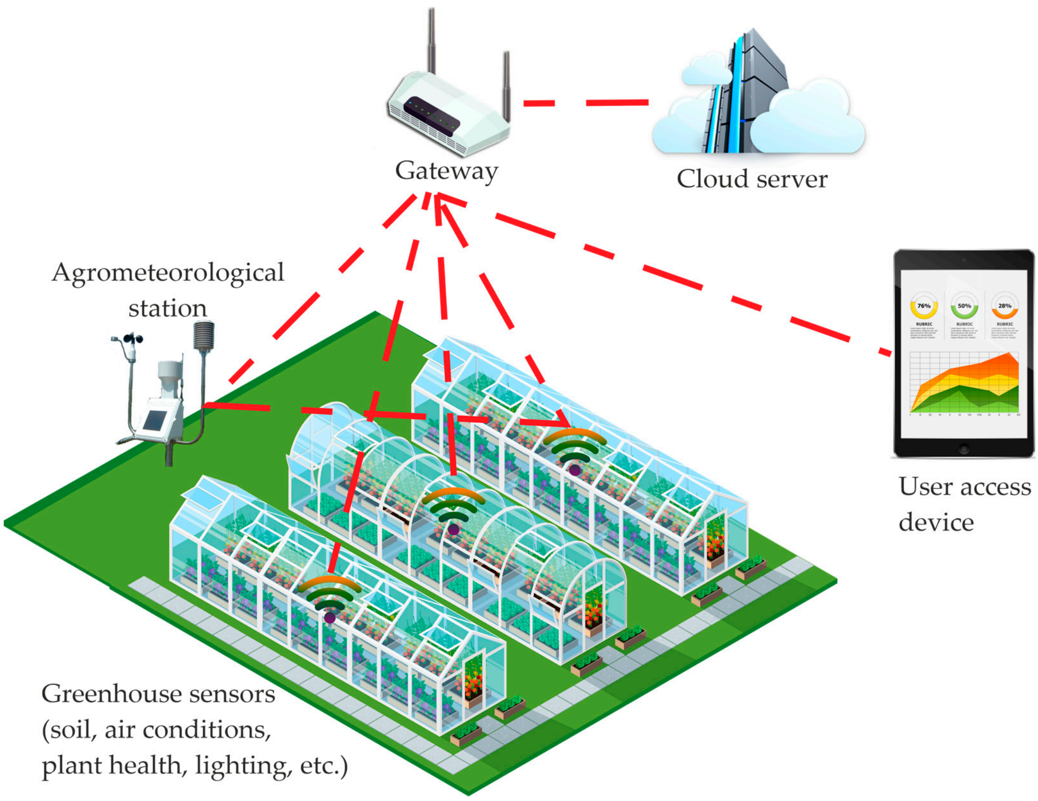

Figure 7. A visualization scenario for the remote monitoring of a greenhouse environment with the establishment of a wireless sensor network to facilitate data collection and analysis.

The WSN depicted in Figure 7 includes sensor nodes, communication protocols, and a central gateway component, with a functionality similar to that of the corresponding components of the field monitoring information system [104]. Furthermore, it includes the following elements:

- Network infrastructure: WSNs may utilize mesh network topologies, where each sensor node can communicate with neighboring nodes, creating a self-organizing and resilient network.

- Data routing: Data are routed through the network from the sensor nodes to the central gateway using multi-hop communication. This allows the data to be relayed through intermediate nodes to reach the gateway even if direct communication is not possible.

The greenhouse environment-monitoring WSN collects, analyses, and correlates diverse types of data, which can vary depending on the specific parameters being monitored and the requirements of the farmers [109,110]. These data may include:

- Environmental parameters: Data on temperature, humidity, light intensity, CO_2 levels, and soil moisture are continuously collected from the sensor nodes. These data provide valuable insights into the greenhouse's climate conditions.
- Plant health: Some sensor nodes may be equipped with sensors to monitor specific plant health parameters, like leaf temperature, chlorophyll content, or nutrient levels. These data help assess the health and growth status of the plants.
- Irrigation management: Soil moisture data assist in optimizing irrigation practices. The sensor nodes transmit soil moisture levels, allowing farmers to regulate watering and prevent under- or overwatering.
- Climate control: Data from temperature and humidity sensors aid in managing climate control systems like heating, ventilation, and cooling to create an optimal growth environment for plants.
- Lighting management: Light intensity data help in adjusting artificial lighting systems within the greenhouse to supplement natural light and optimize photosynthesis.
- Data analytics: The collected data are sent to a central system or cloud platform for storage, analysis, and visualization. Advanced data analytics can provide insights into trends, patterns, and anomalies, aiding in better decision-making.

6.3. Livestock Monitoring

An IoT-based livestock scenario involves using IoT devices like smart collars and sensors to monitor the health, behavior, and location of livestock. Farmers can track vital signs and manage feeding, water consumption, and grazing patterns, all while receiving real-time data on their smartphones or computers. This data-driven approach enhances animal welfare, breeding programs, and overall farm productivity.

An IoT-based livestock scenario is shown in Figure 8 [43,82].

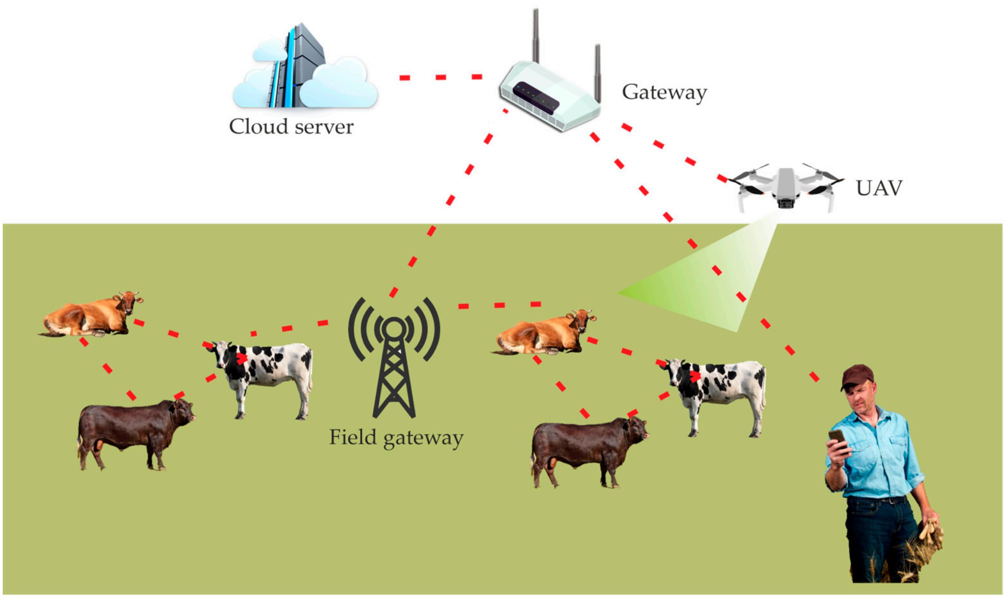

Figure 8. An IoT-based livestock scenario to monitor the health, behavior, and location of livestock.

An IoT-based livestock system comprises the following components:

- IoT devices: Livestock monitoring systems involve the use of IoT devices such as smart collars, ear tags, or implants that are attached to individual animals. These devices are equipped with various sensors to collect data about the animals' health, behavior, and location.
- Communication protocols: IoT devices in livestock monitoring systems typically use wireless communication protocols like LoRaWAN, NB-IoT, or cellular networks to transmit data to the central data management system.
- Central data management system: A central data management system serves as the data aggregator and processing hub. It receives data from all the IoT devices attached to the livestock and stores the data for further analysis.
- Data storage and analysis: Data collected from the IoT devices are stored in databases or cloud-based platforms. Advanced data analytics tools are used to process the data and derive valuable insights about the livestock's health and behavior.
- Connectivity: The central data management system is connected to the internet, enabling farmers or livestock managers to remotely access and monitor the data collected from the IoT devices. Data management and analysis systems are connected to the internet through a gateway, while a field gateway typically arranges for the transferring of the sensed data to data management and analysis systems.

In livestock monitoring systems [111–113] based on IoT technologies, various types of data are collected and transmitted:

- Vital signs: Data related to the animals' vital signs, including body temperature, heart rate, respiratory rate, and activity levels.
- Behavioral data: Information about the animals' behavior, such as eating patterns, rest times, and movement, which helps in assessing their well-being and detecting any signs of distress or abnormal behavior.
- Location tracking: IoT devices with GPS capabilities provide real-time location data of the livestock, enabling farmers to monitor their movement and grazing patterns.
- Health parameters: Some IoT devices may collect specific health parameters like rumination activity, which can indicate the overall health and well-being of the animals.
- Reproductive data: For breeding purposes, IoT devices can track the estrus cycles and fertility levels of individual animals, helping farmers optimize breeding programs.
- Alerts and notifications: The system can send alerts and notifications to farmers or livestock managers in real time if any abnormal conditions or critical events are detected, allowing for prompt action.

Overall, IoT technology empowers farmers to monitor livestock health, field conditions, and greenhouse environments using specialized sensors and intelligent devices. This real-time monitoring enables farmers to proactively manage their agricultural operations, make data-driven decisions, and ensure optimal conditions for livestock, crops, and greenhouse plants [93,102,107,114].

7. Implementation Projects and Success Stories

In the following paragraphs, examples of successful pilot projects in precision agriculture, greenhouses, and animal husbandry implemented in various countries are presented. It is acknowledged that not all countries with programs in this domain can be covered. Therefore, in Table 4, we list examples of countries based on criteria such as geographical location and their ranking in terms of development levels, as outlined in the relevant report from the International Monetary Fund in relation to lifetime income [115].

Table 4. Classification table of countries according to their geographical location and level of development according to the International Monetary Fund in relation to lifetime income.

Continent	Level of Development		
	Higher-Development Countries	Middle-Development Countries	Lower-Development Countries
Africa	Seychelles	South Africa	Ethiopia Kenya Uganda
Asia	Israel Japan	Malaysia Thailand	India China Pakistan
America	United States Canada	Mexico Colombia	As of the writing of this review, no reports were found of the development of government smart agriculture programs in countries of these categories.
Europe	Denmark Netherlands Sweden	As of the writing of this review, no reports were found of the development of government smart agriculture programs in countries of these categories. The search included countries such as Moldova, Ukraine, Albania, Bosnia and Herzegovina, North Macedonia, and Kosovo.	
Oceania	Australia New Zealand	As of the writing of this review, no reports were found of the development of government smart agriculture programs in countries of these categories in Oceania. The search included countries such as Fiji, Samoa, Tonga, Papua New Guinea, Solomon Islands, and Vanuatu.	

7.1. Precision Farming

Precision agriculture techniques, such as yield monitoring, variable-rate application of fertilizers and pesticides, and GPS-guided machinery have been adopted, resulting in improved crop productivity, resource optimization, and cost savings. Projects focusing on data-driven decision-making, sensor technologies, and autonomous systems have significantly enhanced crop yields and resource efficiency. Precision farming techniques, including soil mapping, yield monitoring, and variable-rate application of inputs, have demonstrated improved crop productivity and optimized resource utilization.

Wireless sensor networks have been developed to create water control systems that monitor water consumption in fields. These systems have been successfully implemented and tested in various agricultural settings. The implementation results have provided valuable insights into optimal environmental conditions for crop growth. For instance, a humidity level of 70–80% is suitable for the growth of lemons, while the ideal temperature range for achieving high productivity in both vegetables and lemons is between 29 °C and 32 °C [42]. By utilizing wireless sensor networks and water control systems, farmers can effectively monitor and manage water usage in their fields. This technology enables them to optimize irrigation practices, conserve water resources, and create favorable growing conditions for different crops. The application of such water management systems contributes to sustainable agriculture practices and efficient resource utilization.

Low-cost platforms like the Agri-Talk IoT platform have been developed specifically for precision farming, with a focus on monitoring soil conditions [116]. The implementation of the Agri-Talk IoT platform has yielded significant positive outcomes. It has resulted in a 40–60% increase in chlorophyll levels in turmeric plants, surpassing traditional cultivation methods. Moreover, the platform has enabled a remarkable 70% saving in water during the cultivation process. Notably, the adoption of the Agri-Talk IoT platform has proven to be financially rewarding. By investing USD 14,000 in the platform, farmers have generated a revenue of USD 140,000. This achievement highlights the economic viability and effectiveness of the Agri-Talk IoT platform compared to conventional cultivation methods.

IoT-based agriculture production systems have been developed to monitor temperature, humidity, water consumption, and moisture content, among other crop parameters, with the aim of increasing crop productivity [44]. These systems allow for a comparison of water consumption before and after the implementation of IoT technology, revealing a significant decrease of approximately 30% in water usage. For greenhouse farming, remote sensing and control systems have been developed to monitor temperature, soil moisture, CO_2 levels, and light [105]. Systems implemented for bell pepper plants have demonstrated the effectiveness of these technologies in increasing yield and enabling remote monitoring of farms. By providing real-time monitoring and control of environmental variables, the system optimizes growing conditions for crops in greenhouses. Leveraging IoT for monitoring and control, farmers can improve resource efficiency, reduce water consumption, increase crop production, and remotely manage their farms.

The adoption of smart irrigation technologies addresses water scarcity challenges, particularly in arid regions, optimizing water usage and improving crop yields. The application of data analytics has become integral to agriculture, offering farmers insights into crop management, pest control, and soil health. Government initiatives complement these efforts, ranging from subsidies for agricultural inputs to credit accessibility and training programs focused on modern farming practices. Commitment to climate-smart agriculture aims to fortify farmers against the impacts of climate change, encouraging adaptive practices. Furthermore, youth involvement in agriculture is facilitated through technology-driven initiatives, training programs, and financial support for agribusiness start-ups.

Precision agriculture involves utilizing cutting-edge technologies such as GPS-guided tractors, precision irrigation systems, and data analytics tools. These technologies enable farmers to optimize resource use and tailor farming practices to the specific needs of different areas within a field. Variable-Rate Technology (VRT) is a prominent feature, allowing farmers to precisely apply inputs such as fertilizers and pesticides based on real-time data and localized conditions. This approach not only maximizes yields but also contributes to sustainable and resource-efficient farming. Remote sensing technologies and satellite imaging play crucial roles in monitoring crop health and assessing soil conditions. Digital farming platforms have gained popularity, offering real-time data, weather forecasts, and decision support tools. These platforms empower farmers to enhance their decision-making processes, contributing to more effective and responsive farming practices. Subsidies and incentives encourage farmers to embrace these advanced technologies, aligning with broader goals of enhancing agricultural sustainability and resilience [117–119].

Challenges include infrastructure and training. Ongoing exploration signifies a proactive approach to leveraging technology for agricultural advancement [120–123].

7.2. Greenhouses

Advanced greenhouse technologies, such as climate control systems, automated irrigation, and fertilization, have been implemented, resulting in higher crop yields and improved environmental sustainability. High-tech greenhouses equipped with automated systems for temperature, humidity, and lighting control have successfully produced high-quality and high-yielding crops. IoT-based greenhouse environment monitoring systems have been proposed, utilizing low-cost and low-power wireless technology [108]. The practical implementation of these systems has demonstrated their reliability and effectiveness. By enabling remote and timely instructions, the system reduces the need for manual labor, thereby lowering labor costs. This technology has the potential to significantly reduce operational expenses in greenhouse farming [41].

A comparison between traditional farming methods and the IoT-enabled approach revealed significant reductions in fertilization rates (about 60%) and pesticide usage (up to 80%). Additionally, the implementation of IoT technology significantly reduced labor costs by 60%. Tasks that previously required 60 laborers can now be managed by just 6 individuals, thanks to the efficient utilization of IoT technology. These examples highlight the transformative potential of IoT technologies in the agricultural sector. By implementing IoT systems for environment monitoring, remote control, and precision management, farmers can optimize resource usage, reduce costs, and improve productivity.

Greenhouse programs [124,125] stand as robust and dynamic initiatives within countries' agricultural landscapes. Employing modern technologies and precision agriculture practices, these greenhouses facilitate year-round production, ensuring a steady supply of fresh fruits and vegetables for both domestic consumption and international markets. At the forefront of innovation, these greenhouses integrate automated climate control, irrigation systems, and advanced monitoring, contributing to efficient resource use. The adoption of greenhouse technologies by smallholder farmers underscores an inclusive approach, fostering economic development within local communities.

Research and development initiatives, often carried out through collaborations between research institutions, government bodies, and private enterprises, fuel continuous advancements in greenhouse practices. Greenhouse programs, rooted in the principles of sustainability, emphasize responsible environmental practices, including efficient water use and integrated pest management [126].

At the heart of these initiatives is the empowerment of smallholder farmers, achieved through targeted training programs that impart knowledge on greenhouse management and sustainable farming practices. The floriculture industry, buoyed by modern greenhouse technologies, notably contributes to flower exports while concurrently fostering the export of vegetables to regional markets. Research and development activities, facilitated by innovation centers and collaborations with institutions and international organizations, underscore a commitment to continuous improvement in greenhouse farming.

Beyond economic development, greenhouse programs play a pivotal role in climate-smart agriculture. By providing a controlled environment, they mitigate the impacts of unpredictable weather patterns, contributing to overall resilience in the face of climate change. The diversity of crops cultivated, including specialty vegetables and floriculture products, underscores the versatility of the greenhouse sector.

Sustainability is a cornerstone, with a commitment to environmentally conscious practices such as water conservation and integrated pest management. Continuous innovation is propelled by robust research and development initiatives, fostering collaboration between research institutions, industry bodies, and growers. Education and training programs empower greenhouse operators, disseminating knowledge on best practices and technological advancements. The dual presence of small-scale operators in peri-urban areas and large-scale commercial enterprises ensures a varied and resilient greenhouse landscape. Community engagement initiatives, including educational programs and farm tours, promote awareness and support for sustainable agricultural practices [110,127–129].

7.3. Animal Husbandry

In several countries, precision livestock farming techniques are being implemented to enhance animal welfare and productivity. These techniques include automated feeding systems, remote monitoring of animal health, and behavior analysis. By utilizing precision technologies such as robotic milking systems and sensor-based monitoring of grazing patterns, farmers can optimize milk production and herd management.

Advanced platforms have been developed to monitor the location, behavior, and pasture grazing of animals. These platforms use wearable collars to track the movement of animals within the farm. This technology enables the monitoring of essential parameters such as grazing patterns, activity levels, and overall well-being. The data collected by these systems provides valuable insights into the animals' living conditions, helping farmers make informed decisions about their management and welfare. These animal monitoring and tracking platforms demonstrate the potential of IoT technologies to significantly enhance livestock management practices [43].

Disease control remains a top priority, with comprehensive vaccination programs and accessible veterinary services ensuring the health and well-being of livestock populations. Research and development initiatives, often in collaboration with international organizations, drive advancements in breeding, nutrition, and disease management. These efforts are crucial in developing more resilient livestock breeds and improving overall animal health.

Economically, animal husbandry is a substantial contributor to many countries' GDP. It provides significant employment and income opportunities, particularly in rural areas. As livestock development programs evolve, they continue to be vital components of agricultural resilience and rural livelihoods. These programs adapt to emerging challenges and contribute significantly to national food security by ensuring a stable supply of high-quality animal products [130–132].

The integration of precision livestock farming techniques and IoT technologies represents a significant step forward in the modernization of agriculture. By improving the efficiency and effectiveness of livestock management, these innovations help create a more sustainable and productive agricultural sector. The combination of advanced technology, government support, and international collaboration paves the way for continued progress in livestock farming, ensuring the sector's growth and sustainability.

7.4. Food Traceability

In the horticulture, agriculture, and dairy industries, traceability measures are increasingly being incorporated to monitor the production, processing, and distribution of products. This integrated approach enhances quality control and ensures adherence to regulatory standards. National traceability standards not only address domestic needs but also align with international requirements, facilitating the export of food products to global markets. Government regulatory oversight ensures the effective implementation of traceability systems by industry stakeholders.

Leveraging IoT technologies, platforms such as Mi-Trace and MTSB enable comprehensive tracking and tracing of agricultural products throughout the supply chain [133]. These systems ensure transparency, quality control, and regulatory compliance. Traceability solutions provide valuable information about the origin, handling, and distribution of products, allowing sellers and exporters to verify the authenticity and quality of their goods. These IoT-based solutions improve fruit traceability and bolster the agricultural export market. By implementing traceability systems, sellers and exporters can build consumer trust, ensure food safety, and maintain product integrity throughout the supply chain. This technology-driven approach not only benefits the fruit industry but also enhances the country's reputation as a reliable source of high-quality agricultural products in the global market.

In pursuing technological advancements, countries like Sweden are exploring innovative solutions, including blockchain and digital tools, to enhance the efficiency and transparency of traceability systems. These technologies align with broader efforts to meet consumer demands for transparency and reliable information about the origin of food products. Collaboration between authorities and food producers is crucial for implementing and maintaining effective traceability systems. This partnership ensures compliance with traceability requirements and enables a rapid response to any food safety-related issues [134–138].

Food traceability programs [112,139,140] reflect a growing commitment to ensuring the safety, quality, and regulatory compliance of agri-food products. Various countries have implemented traceability systems across different sectors, underscoring their commitment to maintaining high standards in the food supply chain. Traceability regulations monitor and control the production, processing, and distribution of food products, particularly in sectors where accurate traceability is vital to consumer safety and international trade [134,141–144].

8. Conclusions

In this study, we have presented a comprehensive review of issues and aspects related to the implementation and deployment of intelligent technologies in the agricultural sector. We discussed the challenges faced by the agricultural industry in achieving increased agricultural outputs and high product quality, while catering for sustainability. Subsequently, this study reviewed the technologies and methods that can be employed to respond to these challenges, as well as the impediments faced by farmers concerning the uptake of new technologies and their integration into their farming practices. It covered various systems related to smart agriculture, including those employed in open fields and greenhouses, smart water supply systems, and the broader application of IoT systems in the agricultural sector, as well as the implementation of IoT systems for livestock tracking in pastures. The evolution and use of technologies in the context of precision agriculture were tracked and recorded based on the chronological publication of pertinent scientific articles and publications at large. Important applications, as well as implementations and success stories in various countries, were also identified through relevant publications and presented.

Advances in technology, especially in the field of IoT, have made available a multitude of devices that can be used for the purposes of precision agriculture. These devices are also becoming more efficient and affordable, facilitating the installation and use of precision agriculture systems. In parallel, the developments in artificial intelligence pave the way for exploiting the data sourced from field sensors to unlock new potential in field, greenhouse, and livestock management; to this end, sensor data may be fused with data from other sources, including advances in agronomy or data from markets.

Precision agriculture is receiving increased attention and, besides it being taken up by individual farmers, countries are launching and implementing pilot and full-scale programs to support farmers in using and exploiting precision agriculture practices. In this context, higher-development countries have made better progress than middle- and low-development countries. It is expected that all countries will follow this route, especially in the light of the effects of climate change, where extreme conditions are more frequent, and early warnings and intervention are becoming more and more important to avoid damage in crops, demotion of harvest or loss of animal capital. Precision agriculture is also an important driver of the adoption of sustainable practices in agriculture, an aspect that further underscores its importance.

The present review will serve as a guide for further research, facilitating the exploration of practical applications and of the relevant literature. This literature survey underscores a notable global trend towards embracing new technologies in agriculture, evident in ongoing technological advancements and a growing body of scientific publications addressing intelligent agriculture. While acknowledging this positive momentum, this paper emphasizes challenges associated with the adoption of new technologies in agriculture, specifically related to the age, knowledge, and education level of farmers. It underscores the importance of targeted actions for maximizing the benefits of technological developments, including improved resource management, enhanced product quality, increased crop production, and heightened profitability. To create an environment enabling successful applications of intelligent agricultural systems, climate change mitigation, and comprehensive support for the agricultural sector, this paper recommends a combination of advanced technologies, financial assistance, and tailored training programs for farmers.

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