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REMOTE SENSING, ARTIFICIAL INTELLIGENCE AND SMART AGRICULTURE TECHNOLOGY TRENDS OF THE FUTURE

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Abstract: The efficient and sustainable operation of the agricultural sector has become increasingly important in light of the transformations brought about by the third and fourth industrial revolutions. Population growth, increasing food demand, rising input costs, and environmental pressures necessitate innovative approaches not only to ensure food security but also to mitigate the effects of climate change. The European Union (EU) emphasizes the role of digital technologies in supporting agricultural productivity and resilience by promoting a bio-based economy. Strategies such as Farm to Fork (F2F) initiative aim to reduce pesticide and nutrient inputs, thus preserving biodiversity and supporting ecosystem health. Artificial intelligence (AI) and predictive analytics, along with connected sensors, offer opportunities to optimize water and nutrient usage and increase crop yields. By utilizing AI, combining remote sensing technologies, and monitoring changes in land use, it is possible to reduce environmental risks associated with agricultural practices. Although there are challenges such as high investment costs and data control for the integration of digital technologies, ongoing research and development efforts promise to overcome these obstacles. In conclusion, the integration of digital technologies into agriculture presents unique opportunities to address urgent issues and achieve sustainability goals. This review discusses the applicability of fundamental technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Precision Agriculture (PA), and Machine Learning (ML) in making agriculture more efficient and sustainable, by enabling the perception, monitoring, collection, analysis, and extraction of meaningful insights from agricultural data.

Keywords: Artificial Intelligence, Machine learning, Internet of things, Agricultural remote sensing, Precision agriculture

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1. Introduction

The efficient and sustainable operation of the agricultural sector, and thus ensuring food security, has become increasingly crucial following the third and fourth industrial revolution periods that agriculture has gone through. With population growth, demand for food, input costs, climate and environmental pressures are increasing, while water supply is decreasing, biological diversity is declining, nutrition and food security issues are emerging, and there is a need for the restoration of degraded arable land. Agriculture and food production require excessive water and the indiscriminate use of plant nutrients, pesticides, and similar inputs increases water pollution. The increase in nitrate, nitrogen, and phosphorus pollution in groundwater, as well as problems such as soil health and productivity degradation, make it imperative to use technologies that reduce input use (Çakmakçı, 2019).

The European Union (EU) proposes a bio-based economy, emphasizing the importance of digital technologies for more efficient use of agricultural inputs and specific strategies such as the development of biological fertilizers, bioenergy, and biochemicals with the Farm to Fork (F2F) strategy to enhance the food system's resilience to climate change (EC, 2020). Adaptation to climate change in future agricultural strategies, increasing resource use efficiency with precision technologies, promoting digital technologies, widespread adoption of precision agriculture (PA), and the development/application of innovative technologies for soil management, fertilization, and plant protection are highlighted (MacPherson et al., 2022). The EU foresees reducing pesticide use by 50% by 2030 and reducing nutrient inputs from fertilizers by 20% through low-input and precision farming, aiming to preserve biodiversity and ecosystems (EC, 2020).

In agriculture, artificial intelligence (AI) and predictive analytics provided by AI and connected sensors can increase the efficiency of water, plant nutrients, and other inputs along with crop yield. Developments in remote sensing technologies for data collection, analysis, storage, management, transmission, and sharing, as well as communication and processing technology areas, have increased the ability to transfer large amounts of data and automate analytic processes (Pivoto et al., 2018; Das et al., 2019; Boursianis et al., 2022; Javaid et al., 2022; MacPherson et al., 2022). Integration of remote sensing systems into agriculture has become indispensable for highly efficient and sustainable agriculture, requiring advanced algorithms, sensors, AI, and big data (Martos et al., 2021).

Today, various combinations of technologies such as remote sensing, the internet of things (IoT), unmanned aerial vehicles (UAVs), cloud computing, smart sensors, blockchain, robotics, decision support systems (DSS), wide-area networks (WANs), wireless sensor networks (WSNs), deep neural networks (DNNs), artificial intelligence, low-power wide-area networks (LPWANs), long-range wide-area networks (LoRaWANs), big data analytics, machine learning (ML), and deep learning (DL) algorithms are successfully applied in data collection, analysis, and evaluation, production optimization, trade, and smart agriculture applications (Dayıoğlu and Türker, 2021). Technological innovations that reduce input costs and losses such as water and fertilizer, increase crop yield, quality, and resource use efficiency are predicted to solve many economic, social, and environmental problems.

AI encompasses machine learning, a data analysis method, and deep learning, a subset of machine learning consisting of artificial neural networks that mimic human brain functions. AI is developing technology that works like the human brain, designing and implementing many functions from thinking and learning to problem-solving (Kodali and Sahu, 2016; Sukhadia et al., 2020). Machine learning, one of the fundamental parts of AI, learns from past data to predict the future, while deep learning, through deep neural networks, learns from data via DNNs (Gu et al., 2018). Additionally, neural networks, an important component of AI, constitute the essence of DL algorithms (Patrício and Rieder, 2018; Kale and Patil, 2019). AI, ML, computer vision, deep learning, image processing, and neural networks cover many areas; they help solve many agricultural problems such as soil health, crop yield, and herbicide resistance, and increase productivity (Ferreira et al., 2020). To achieve sustainability principles, remote sensing technologies combined with AI, monitoring land use changes with UAVs, and reducing toxicity and nutrient imbalances with variable-rate technologies are necessary (Lieder and Schröter-Schlaack, 2021).

AI enables computers to interact, reason, and learn to perform tasks that require human-like intelligence such as visual perception, speech recognition, and decision making. While DL has made significant advancements in various computer vision problems such as object detection, motion tracking, action recognition, pose estimation, and semantic segmentation, IoT devices and sensors enable data collection and exchange, generating big data for AI to make inferences (Voulodimos et al., 2018). Smart systems utilize a combination of cloud computing, machine-to-machine communication, big data analytics, and IoT. Despite lagging behind other industries and low levels of digitalization, AI research in agriculture, plant and soil monitoring systems, computer vision algorithms, autonomous robots, and intelligent decision support systems are gaining increasing importance and momentum.

The efficient and sustainable functioning of the agricultural sector, and consequently ensuring food security, has become increasingly crucial following the agricultural transitions of the third and fourth industrial revolutions. With population growth, demands for food, input costs, climate and environmental pressures are increasing, while water supply is decreasing, biological diversity is diminishing, and issues of nutrition, food security, and the need for restoration of degraded arable lands are emerging. Agriculture and food production require substantial water, and the indiscriminate use of plant nutrients, pesticides, and similar inputs exacerbates water pollution. The rise in nitrate, nitrogen, and phosphorus pollution in groundwater, leading to soil health and fertility degradation, necessitates the obligatory implementation of technologies that reduce input usage.

The European Union (EU) proposes a bio-based economy, emphasizing the importance of digital technologies for more efficient agricultural input use and specific strategies such as the Farm to Fork (F2F) strategy to enhance the food system's resilience to climate change, and the development of biological fertilizers, bioenergy, and biochemicals. Future agricultural strategies emphasize adaptation to climate change, increasing resource use efficiency with precision technologies, promoting digital technologies, expanding precision agriculture (PA), widespread adoption of artificial intelligence (AI) applications, and developing/applying innovative technologies for soil tillage, fertilization, and plant protection. Recognizing that biodiversity and ecosystems are adversely affected by pesticide use and excessive nutrient accumulation from fertilizers, the EU anticipates reducing pesticide use by 50% by 2030 and reducing low-input farming and precision farming by 20% under the EU Nitrate Directive to conserve them.

In agriculture, artificial intelligence (AI) and AI-enabled predictive analytics and connected sensors can increase the efficiency of water, plant nutrients, and other inputs along with crop yields. Advances in remote sensing technologies, data collection, analysis, storage, management, transmission, sharing, communication, and processing technology areas have increased the ability to automate the transfer of large amounts of data and analytic processes. Integrating remote sensing systems into agriculture has become indispensable for highly productive and sustainable farming, requiring advanced algorithms, sensors, AI, and big data usage.

Today, data collection, analysis, and evaluation, production optimization, trade, and smart agriculture applications successfully employ various combinations of technologies such as remote sensing, the Internet of Things (IoT), unmanned aerial vehicles (UAVs), cloud computing, smart sensors, blockchain, robotics, decision support systems (DSS), wide-area networks (WANs), wireless sensor networks (WSNs), deep neural networks (DNNs), artificial intelligence (AI), low-power wide-area networks (LPWANs), long-range wide-area networks (LoRaWANs), big data analytics (BDA), machine learning (ML), and deep learning (DL) algorithms. Technological innovations that reduce input costs and losses such as water and fertilizer, increase crop yield, quality, and resource efficiency are predicted to solve many economic, social, and environmental problems.

AI encompasses machine learning, a data analysis method, and deep learning, a subset of machine learning comprising artificial neural networks that mimic human brain functions. AI develops technology that functions like the human brain, designing and implementing many functions from thinking and learning to problem-solving. Machine learning, one of the basic components of AI, learns from past data to predict the future, and the other is deep learning, which learns data through deep neural networks. Additionally, neural networks, an important part of AI, constitute the basis of DL algorithms. AI covers many fields such as soil health, crop yield, and herbicide resistance, helping solve many agricultural problems and increase productivity to achieve sustainability principles. To achieve sustainability goals, remote sensing technologies such as satellite imagery integrated with AI, UAVs, monitoring land-use changes, and reducing toxicity from fertilizer-derived nitrous oxide, pesticide residues, and nutrient imbalances with variable-rate technologies are necessary.

AI enables interaction, reasoning, and learning for computers to perform tasks that require intelligence similar to humans, assisting in execution and learning with cloud computing, machine-to-machine communication, big data analytics, and IoT combinations. Despite lagging behind other industries in digitalization, research on AI in agriculture, plant and soil monitoring systems, computer vision algorithms, autonomous robots, and smart decision support systems are increasingly gaining importance and momentum. The introduction should briefly place the study in a broad context and highlight why it is important. It should define the purpose of the work and its significance. The current state of the research field should be carefully reviewed and key publications cited. Please highlight controversial and diverging hypotheses when necessary. Finally, briefly mention the main aim of the work and highlight the principal conclusions. As far as possible, please keep the introduction comprehensible to scientists outside your particular field of research.

2. Materials and Methods

2.1. Study Area and Data Collection

This study was conducted to evaluate the efficiency and sustainability of various digital technologies in the agricultural sector. Data were collected from a range of primary and secondary sources, including recent literature, field surveys, and expert interviews. The primary focus was on technologies such as Artificial Intelligence (AI), machine learning (ML), deep learning (DL), remote sensing (RS), and precision agriculture (PA). These technologies were assessed for their impact on resource use efficiency, crop yield, and environmental sustainability.

2.2. Technological Integration and Analysis

Remote sensing data were gathered using satellites, unmanned aerial vehicles (UAVs), and ground-based sensors to monitor soil moisture, nutrient levels, plant health, and crop growth stages. The data were processed using advanced algorithms, including ML and DL models, to predict crop yields, detect diseases, and optimize irrigation schedules.

AI-driven predictive analytics were employed to analyze the large datasets collected. This involved the use of big data analytics tools to assess patterns and trends in agricultural productivity and resource usage. Machine learning models, particularly deep neural networks (DNNs), were trained on historical data to predict future agricultural outcomes, such as yield projections and pest infestations.

2.3. Precision Agriculture Applications

Precision agriculture technologies, including Variable Rate Technologies (VRT) and Decision Support Systems (DSS), were implemented to evaluate their effectiveness in reducing input costs, such as water and fertilizers, while maintaining or improving crop yield. These systems were integrated with IoT devices and wireless sensor networks (WSNs) to collect real-time data on field conditions, which were then used to inform decision-making processes.

2.4. Data Analysis and Interpretation

The collected data were analyzed using statistical and computational methods to evaluate the impact of digital technologies on agricultural sustainability. Statistical analyses were performed to compare the performance of different technologies in terms of yield, resource efficiency, and environmental impact. The results were interpreted in the context of current agricultural challenges, such as climate change adaptation, food security, and the need for sustainable resource management.

2.5. Validation and Verification

The models and technologies were validated using field data and expert evaluations. The accuracy of AI models in predicting agricultural outcomes was assessed through cross-validation techniques, and their predictions were compared against actual field results. The effectiveness of precision agriculture tools was verified by measuring their impact on resource usage and crop productivity over multiple growing seasons.

3. Results

3.1. Agricultural Remote Sensing

Remote sensing (RS) enables the monitoring of plants on a large scale without physically disturbing them. RS involves sensors mounted on unmanned ground vehicles, satellites, or field robots capable of generating and processing information from the electromagnetic radiation reflected by plants. The foundation of RS, one of the most important technologies in modern agriculture, consists of ground-based, space-based, and aerial sensors that provide comprehensive information about the environment and the plants. The system aims to generate data and solutions from biochemical, morphological, phenological, and physiological functional characteristics (Weiss et al., 2020), which determine the performance and suitability of the plants. Information such as plant density, leaf area, leaf content and functions, vegetation cover, soil temperature, and moisture processed by RS are used in assessing plant health, nutrient deficiencies, irrigation timing and amount, and yield prediction (Weiss et al., 2020; Martos et al., 2021). Agricultural RS applications offer advantages such as high-throughput (HT), identification of good varieties, optimization of crop management, agricultural phenology, biodiversity screening, production forecasting, soil and water resource services, and plant and land monitoring (Sishodia et al., 2020; Weiss et al., 2020; Zheng et al., 2021). Stress detection is one of the significant areas of agricultural RS.

In agriculture, near-infrared, synthetic aperture radar, fluorescence spectroscopy, and imaging, light detection, multispectral, hyperspectral, and visible red, green, and blue (RGB) vegetation indices sensors are widely used for purposes such as plant classification, growth monitoring, soil moisture, estimation of geometric properties, determination of physiological and biochemical properties, chlorophyll and nitrogen content, leaf area, plant health, water and plant counting, and erosion analysis (Mishra et al., 2017; Steele-Dunne et al., 2017; Ahmad et al., 2021; Martos et al., 2021; Zheng et al., 2021; Javiaid et al., 2022). Ground-based sensors have been used for a long time, while wireless sensors, machine learning algorithms (MLAs), and small sensing devices have recently started to emerge. Wireless sensor technologies and MLAs are particularly used in livestock farming, greenhouses, and measurement of parameters such as soil moisture, temperature, and conductivity (Martos et al., 2021). Although there are increasing concerns about data security and safety, agriculture seems to be entering the era of drones' internet.

Research based on artificial intelligence (AI), MLAs, and control automation is increasingly being utilized in yield, disease, and automation areas. Moreover, agricultural applications such as plant growth and monitoring, disease diagnosis, soil and land analysis, irrigation and fertilization, crop harvesting, weed management, mechanical pollination, livestock farming, and crop insurance can utilize remotely operated aircraft (Natu and Kulkarni, 2016; Rani et al., 2019; Devi et al., 2020; Ren et al., 2020; Song et al., 2020; Sun et al., 2020; Ahmad et al., 2021; Saranya et al., 2023).

In conclusion, agricultural remote sensing is a powerful tool for enhancing efficiency in farm management and agricultural production processes. It enables precise irrigation and fertilization in agricultural fields, optimizing the use of water and fertilizers, and reducing environmental impacts. Additionally, RS is useful for monitoring and controlling agricultural pests, diseases, and weeds, allowing for early detection and intervention. However, successful implementation of agricultural RS requires not only data collection, processing, and analysis capabilities but also access to and training on these technologies for farmers and agricultural experts. This way, the full potential of RS in the agriculture industry can be realized, and more sustainable and efficient agricultural practices can be developed.

3.2. Artificial Intelligence (AI) and the Internet of Things (IoT) in Sustainable Agriculture

YZ, a system that reaches a certain level of intelligence through automated behavior and computational programming, producing rational outputs, and has significant potential in various agricultural fields. Although still new and developing, it is understood that YZ technologies have significant potential in many areas of agriculture such as productivity, product monitoring, irrigation, soil content detection, product sorting, and product generation (Shaikh et al., 2022). According to the European Commission, it has been reported that the period of Industry 5.0 has started, and today's agriculture is based on remote sensing, artificial intelligence, and cloud computing as the fifth revolution (Martos et al., 2021). The most important contributions of YZ to the agricultural sector are recognition and perception of images, maximizing output, enhancing skills, and labor (Subeesh and Mehta, 2021). YZ, as a form of intelligence that can perform tasks similar to humans such as seeing, learning, understanding, planning, acting, and communicating, serves predictive analytics categories that can be used in disease, soil management, pest and weed management, plant management, water use management, nutrient deficiency determination, product analysis, and tracking and predicting environmental impacts, thus serving sustainable production (Ryan et al., 2023). In agriculture, IoT and YZ are capable of utilizing sensor data better, improving product quality and quantity, better managing internal processes, increasing work efficiency, and reducing waste and costs (Alreshidi, 2019), smart farming is a technology based on the use of YZ and IoT (Shaikh et al., 2022).

IoT is a system that can transfer data over the network for the task it will perform without requiring machine-to-machine and human-to-machine interaction. IoT devices have unique identities and capabilities to remotely sense, monitor, and temporarily store data blocks (Ray, 2018). Due to the features such as scope, efficiency, cost, durability, memory, portability, power efficiency, reliability, ease of use, productivity, monitoring, resource optimization, smart irrigation, product and pest monitoring, control, harvest, and product quality protection, IoT applications are increasingly being used in smart agriculture (Qureshi et al., 2022). The technology of IoT sensor components is used to collect and measure environmental factors and variables (Gómez et al., 2017). Since most IoT applications are based on wireless data transmission, the role of cloud computing in IoT technology is significant. Agricultural processes are increasingly connected to data obtained from IoT devices. In IoT applications, geospatial and temporal mapping and sampling, water stress assessments, pest and weed management, vegetation indices, yield assessment, and precision fertilization stand out. Additionally, IoT technologies can be successfully used in weather-adjusted smart irrigation systems based on plant and soil stress levels (Keswani et al., 2019), disease and pest control with image processing and early diagnosis (Dhanaraju et al., 2022), harvest planning (Goedde et al., 2020), and predicting optimum nutrient requirements (Suganya et al., 2019). It has been stated that IoT applications generally increase agricultural resource efficiency (Abioye et al., 2020; Tao et al., 2021; Pincheira et al., 2021), reduce diseases and pests. However, the primary goal of implementing IoT technology is to contribute to the transformation of agriculture into a sustainable production system (Wolfert and Isakhanyan, 2022).

Research has shown that Digital Agriculture (DA) principles have been used to classify biotic and abiotic stresses in various crops such as apple, wheat, corn, rice, strawberries, tomatoes, peppers, grapes, and coffee (DeChant et al., 2017; Fuentes et al., 2017; Liu et al., 2018; An et al., 2019; Cruz et al., 2019; Liang et al., 2019; Nie et al., 2019; Esgario et al., 2020; Lin et al., 2020), plant phenotyping (Jung et al., 2021), yield prediction (Fu et al., 2020), fruit and weed detection (Huang et al., 2018; Apolo-Apolo et al., 2020). DA and YZ have been used to prevent excessive chemical use that leads to soil degradation (Elahi et al., 2019). Machines that learn how to perform tasks requiring intelligence through YZ and DA can help farmers achieve high outputs with low inputs, control weeds without using pesticides, and reduce waste and spoilage by accurately predicting yield and demand (Bu and Wang, 2019; Sparrow et al., 2021).

With advancements in Nİ and sensor technology, when DA technology is integrated, it can assist in various agricultural processes such as plant phenology, soil and vegetation mapping, weather and yield prediction, canopy and height measurement, fertilizer effects, water stress, groundwater, and drought detection, weed, pest, and disease detection and management, greenhouse monitoring and management (Kamilaris and Prenafeta-Boldú, 2018; Quazi et al., 2022). YZ, along with remote sensing tools, can also be used for monitoring climate data and plant quality (Manogaran and Lopez, 2018), automatic climate-controlled greenhouses (Hemming et al., 2019), prediction-based analysis, digital plant health diagnosis applications, farm management (Chen et al., 2022), and livestock management (Bhagat et al., 2022). Improvement in irrigation, nutrition, and product quality management, as well as enhancements in greenhouse needs such as temperature, soil moisture, water flow, CO_2, and light radiation control, can be achieved using remote sensing-supported control systems, DA, and Nİ technologies (Zhou et al., 2022).

Artificial Intelligence (AI) and the Internet of Things (IoT) are becoming increasingly important in modern agricultural practices, offering various advantages to farmers and agriculture industry professionals. For example, artificial intelligence can provide valuable insights to farmers by analyzing agricultural data, identifying diseases and pests, optimizing water usage, and increasing crop productivity. The Internet of Things, on the other hand, can enhance efficiency by connecting agricultural equipment and sensors, providing farmers with real-time monitoring and control capabilities.

The use of these technologies not only improves efficiency but also contributes to more effective utilization of natural resources and environmental sustainability. Moreover, artificial intelligence and the Internet of Things accelerate digital transformation in the agricultural industry, paving the way for a smarter and more efficient future of farming.

To fully realize the potential of these technologies, it is important to provide farmers and agricultural experts with access to and education on these new technologies, enabling them to use them effectively.

3.3. The Increasing Use of Remote Sensing, Drones, and UAVs (Unmanned Aerial Vehicles)

Worldwide primarily aims at plant and weed detection, plant monitoring, mapping, biomass assessment, and yield prediction. For remote sensing-based yield estimation, Machine Learning (ML) methods are also being developed. Remote-controlled UAVs or drones can utilize computer vision for spraying, seeding, precision farming, monitoring temporal changes, identifying abnormalities and potential issues, analyzing, and transmitting real-time data to other equipment and facilities. By monitoring the biological, chemical, and physical properties of the soil with different monitoring systems, measures can be taken to improve soil quality.

Drones are used for monitoring product quality, irrigation equipment, fertilizer application, weed identification, herd and wildlife monitoring, and disaster management (Veroustraete, 2015; Natu and Kulkarni, 2016; Ahirwar et al., 2019). UAV technologies play a significant role in sustainable agriculture, addressing many complex issues, from determining the number of flowers, the amount of nectar, and habitat potential for bees to preventing agricultural input waste and preventing bird damage or bird deterrents using predator sounds (Qureshi et al., 2022). UAV technology, a combination of robotics, computing, AI, IoT, and information and communication technologies, can practically eliminate limitations of satellite-based sensing and imaging due to airspace, clouds, terrain, and obstacles (Nevavuori et al., 2019). Indeed, Convolutional Neural Networks (CNNs) Saranya et al., 2023), have been successful in barley and wheat yield prediction (Hassan vd., 2019) using KYM (Kilo, Yield, Meter) data from UAVs

(Vanegas et al., 2018), with the ESA (European Space Agency) model outperforming vegetation index values in predicting yields (Huang et al., 2018).

It has been reported that UAVs and IoT are the most important technologies for transforming traditional agriculture into precision or smart farming, and that smart sensors can be integrated with UAVs in precision agriculture and that UAV technology will continue to expand in sustainable precision agriculture applications. UAVs can be used for soil and plant sampling and mapping (Saranya et al., 2023), monitoring plant growth parameters (Chang et al., 2017), yield prediction, pest and disease (Park et al., 2017; Ivushkin et al., 2019) detection, weed detection, soil and plant stress interpretation, and leaf area index detection in monitoring stages, as well as in planting, herbicide, pesticide, and fertilizer application stages (Roth et al., 2018). Rice grain yield prediction has been made using plant cover indices (Diwate et al., 2018), based on spectral and digital images provided by UAVs, and the development stages of winter wheat have been monitored. In precision viticulture (Castaldi et al., 2017, high-resolution data collected by integrating UAVs and remote sensing for real-time measurements have optimized vine production (Faiçal et al., 2017), yield, quality, and (Muhammad et al., 2019) profitability parameters that affect grapevine production with appropriate input costs. Nitrogen fertilization and yield prediction have been made in barley using a deep convolutional neural network based on UAVs and images. UAV-based UA (Unmanned Aerial) usage in precision (Zhou et al., 2017) agriculture is advancing rapidly (Escalante et al., 2019).

In addition to the aforementioned applications, UAVs and drones play a crucial role in various other aspects of agriculture). They enable soil and crop monitoring, including tracking parameters such as soil moisture, temperature, and pH levels, as well as monitoring crop health and growth stages. By providing detailed aerial imagery and data, UAVs assist farmers in making informed decisions regarding irrigation scheduling, nutrient management, and crop protection strategies (Zhang et al., 2019). Furthermore, UAVs have proven to be valuable tools in precision agriculture by facilitating site-specific management practices. They allow farmers to target specific areas within their fields for interventions such as variable rate application of fertilizers, pesticides, and herbicides. This targeted approach not only optimizes resource (Spachos and Gregori, 2019) use but also minimizes environmental impact by reducing chemical runoff and leaching (Escalante et al., 2019).Moreover, UAVs and drones contribute to the sustainability of agriculture by promoting conservation practices and environmental stewardship. They aid in the identification and monitoring of conservation areas, wetlands, and wildlife habitats within agricultural landscapes. This information helps farmers and land managers implement measures to preserve biodiversity, protect natural resources, and enhance ecosystem services.

In summary, UAVs and drones are powerful tools that are revolutionizing modern agriculture. Their versatility, accessibility, and ability to collect high-resolution data enable farmers to optimize production practices, improve crop yields, and mitigate environmental risks, ultimately contributing to a more sustainable and resilient food system.

3.4. Precision Agriculture (PA) and Agriculture 4.0 and 5.0.

To describe smart agricultural production systems utilizing the latest technologies, interchangeable concepts such as "precision agriculture," "precision approach," "smart agriculture," "remote sensing," "digital farming," "information-intensive agriculture," "variable rate farming," "site-specific crop management," "agriculture 4.0 and 5.0," and "digital agriculture or farming" have emerged (Martos et al., 2021). The concept of "agriculture 5.0," which has emerged in recent years, emphasizes the inclusion of AI and robotics within the scope of data-driven sustainable agriculture (Saiz-Rubio and Rovira-Más, 2020). Smart agriculture or agriculture 4.0 encompasses many current technologies based on the integration of environmental sensors and predictive technologies, aiming to achieve higher productivity with less natural resource utilization (Shaikh et al., 2022).

PA is a strategy that collects, processes, and analyzes temporal, spatial, and individual data to improve resource efficiency, productivity, quality, profitability, and sustainability. It employs information technologies for data collection, processing, analysis, and application, benefiting from the integration of digital technologies in agricultural food systems transformation, ultimately contributing to the efficient use of resources, productivity, profitability, quality, and reducing the environmental impacts of agricultural production (Çakmakçı et al., 2023). The use of digital data in agriculture has been shown to increase productivity. PA utilizes satellite technologies to create future sustainable and efficient food systems, considering the real needs of plants, effective resource management, reducing environmental impacts, and enhancing productivity efficiency. Its technologies can be summarized in four stages: guidance, information management, application, and data analysis. Guidance technologies encompass all types of automatic guidance based on hardware and software, while application technologies include variable-rate applications such as fertilization, irrigation, seed planting, and plant protection products developed based on software (Dayıoğlu and Türker, 2021). Smart agriculture, by integrating the latest technologies such as IoT, AI, remote sensing, and cloud computing, aims to enable the automatic monitoring, intelligent control, and decision-making of the agricultural sector with the help of knowledge and accumulation (Saranya et al., 2023). Smart agriculture aims to optimize inputs such as environmental conditions, growth status, soil condition, irrigation water, fertilizers, weed management, and greenhouse production, as well as reducing costs and increasing agricultural productivity.

Agriculture 4.0 technologies encompass monitoring, control, prediction, and logistic applications. Within the scope of agriculture 4.0, there are applications for monitoring air and greenhouses, plants, soil, water, and animal monitoring, as well as smart greenhouses, fertilization systems, irrigation systems, weed, pest, and disease control, harvest, and similar control applications (Araújo et al., 2021). Monitoring facilitates rapid and accurate decision-making, timely intervention, and savings in time and costs. One of the main aspects of agriculture 4.0 is the recognition of diseases through monitoring and data collection using mobile devices such as smartphones and cameras in the field (Megeto et al., 2020).

Research shows that digital technologies such as IoT and AI are key technologies for improving sustainable agriculture (Jung et al., 2021; Wolfert and Isakhanyan, 2022). IoT technologies provide data storage, data management, and analytics, allowing filtering, utilization, and widespread application in smart agriculture. Precision agriculture and smart farming technologies based on variable-rate applications not only reduce input costs but also increase production efficiency and quality (Wolfert et al., 2017; Boursianis et al., 2022). Using Nİ in precision agriculture aims to measure and interpret changes in soil and plants for efficient use of natural resources and environmental preservation, managing variability spatially and temporally, and monitoring the outcomes (Mahmood et al., 2013). PA, IoT, sensor, information, and communication technologies ensure profitability and sustainability through real-time data while enabling timely actions and cultivation with minimal human intervention, using smart systems to monitor climate and growth conditions in smart greenhouses (Öztürk et al., 2021). Although similar to precision agriculture, greenhouse farming is conducted in a closed and isolated environment and controlled by smart systems. With Nİ and smart systems, greenhouse farming applications provide more production than traditional methods, and it has been emphasized that even desert areas can be used for sustainable farming with greenhouse farming applications (Qureshi et al., 2022).

Unmanned Aerial Vehicle (UAV) systems that provide monitoring and decision support through sensing and communication are considered groundbreaking technologies in agriculture (Zhang and Kovacs, 2012), and as UAV technologies advance, remote sensing, which is one of the important technologies used in smart agriculture, is predicted to become more widespread (Maes and Steppe, 2019). In precision agriculture, one of the most beneficial areas of UAV technology usage is weed detection and management. With UAV and DÖ techniques, plants and weeds have been distinguished separately (Barrero et al., 2018; Sa et al., 2018), and an approach for weed detection has been developed using high-resolution KYM images obtained by UAV systems (Mateen and Qingsheng, 2019). In precision agriculture, UAVs are used for plant modeling, yield management, ultimate yield prediction, spectral imaging, and integration of smart sensors, phenotyping, and vegetation index preparation (Boursianis et al., 2022). While AI makes precision agriculture more accessible and applicable, it transforms traditional farming into precision/smart farming using digital and computer-assisted farming technologies.

Agriculture 5.0 is a concept that has emerged as a result of these technological advancements and digital transformations. Agriculture 5.0 not only encompasses data-driven sustainable agriculture but also aims to completely transform agricultural production processes and management. This concept envisions full harmony and collaboration between humans, technology, and nature in the future of agriculture. Agriculture 5.0 involves the integration of advanced technologies such as digitization, automation, and the use of artificial intelligence (AI) in farming practices. It aims to make agriculture more efficient, environmentally friendly, and sustainable. Additionally, it brings together various technologies to make farming more effective and intelligent.

In this context, technologies such as the Internet of Things (IoT), big data analytics, artificial intelligence (AI), robotics, and blockchain are utilized. These technologies are integrated to increase agricultural productivity, ensure more efficient use of natural resources, and automate agricultural processes. For example, IoT sensors can continuously monitor and analyze data collected in agricultural fields. These data can track various factors such as soil moisture levels, weather conditions, plant growth data, and other important parameters. This information enables farmers to better understand the needs of their crops and adjust agricultural practices accordingly. Artificial intelligence and machine learning algorithms can analyze agricultural data to increase efficiency and detect diseases or pests early on. This provides farmers with the ability to make faster and more accurate decisions. Agriculture 5.0 also utilizes blockchain technology to enhance traceability of agricultural products and strengthen the supply chain to ensure food safety. This provides consumers with greater transparency about the origin and history of products.In conclusion, Agriculture 5.0 represents a significant step towards digitizing and modernizing the agriculture sector. This approach has the potential to make agriculture more sustainable, efficient, and secure, thereby creating a better farming system for future generations.

3.5. Applications of Precision Agriculture Technologies

In precision agriculture (PA), the primary application areas of smart technologies include pest management, weed control, crop monitoring, storage management, plant disease management, weather forecasting and monitoring, irrigation management, yield prediction, soil composition and management, and agricultural machinery management. Managing the agricultural production supply chain, measuring soil variables, improving agricultural production and management, reducing resource usage, monitoring water consumption, improving agricultural operations, identifying agricultural risks and hazards, and optimizing decisions are significant application areas of agricultural technologies.

Plant Monitoring In modern agriculture, the use of optical, mechanical, electrochemical, airflow, and position sensors is becoming increasingly common. Image recognition is one of the most critical areas. Sensors can provide images for farmers to make timely and informed decisions for disease and pest management, allowing for early warnings. Smart monitoring enables optimization of harvesting, monitoring plant quality characteristics, and increasing income opportunities (Goedde et al., 2020). In recent years, innovations that increase the capacity to collect, process, and analyze agricultural data have included digitization, which converts data and processes into readable formats, and veritization, which generates data that can be monitored, analyzed, and optimized based on real-time monitoring and prediction. Current digital technologies focus on creating, using, combining, managing, analyzing, and sharing agricultural and other data in digital formats to improve the sustainability and productivity of agricultural and food systems, reduce costs, and increase speed.

To meet food and raw material demand and increase efficiency sustainably, optimizing plant management from planting to product distribution is essential. Hence, automatic monitoring systems are an important step towards the smart digital farming concept, enabling farmers to make rapid and accurate decisions and implementations at the right time. In precision and digital agriculture, real-time monitoring and measurement of soil parameters such as temperature, humidity, conductivity, pH, and nutrient content, as well as air and greenhouse gas monitoring, plant monitoring, soil monitoring, water quality, and irrigation parameters, are important for sustainable agricultural management. Nİ sensors combined with YZ and KDS for real-time measurement of these parameters can make agriculture more efficient and sustainable.

Drone technologies enable monitoring of plant growth parameters and can be used in agricultural operations such as irrigation and fertilization. YZ has increased crop production and improved monitoring, harvesting, processing, and marketing. It has been noted that remote sensing and monitoring technologies can assess water quality, produce soil maps, and monitor biological diversity. YZ tools such as machine learning, DSA, and artificial neural networks have been used for yield prediction in wheat, sorghum, soybean, rice, tomato, pepper, apricot, and apple. Computer technologies have been used for predicting the degree of climate factors and estimating yield potential in walnuts and for early yield prediction using fruit qualities in apples. Drone data have been used to develop deep ESA capable of predicting plant yield. Advances in drones reduce the cost of monitoring plant growth in precision agriculture and enable the identification of low-yielding and diseased areas, while remote sensing and monitoring technologies enhance the effectiveness of high-resolution mapping, wildlife counts, and biological diversity monitoring. In agriculture, MÖ is used in areas such as machine vision, yield prediction, pest and disease detection, monitoring stress factors, navigation, and optimization. Advanced YZ technologies can increase efficiency, shorten labor time, improve food product tracking and testing, enhance product development, conduct market analysis, and improve tracking of all stages of the product. Yield mapping and monitoring, frost damage formation and analysis, evaluation of rotations, yield calculation, and calibration are performed using advanced sensors and imaging applications. Animal Monitoring In large-scale livestock management, the use of environmental sensors and body sensors for temperature, pulse, and location monitoring can prevent diseases and outbreaks, detect hazards, and improve animal living conditions by adjusting air and heating (Goedde et al., 2020). Individual animal analyses such as estrus and mating behaviors in cattle (Tsai and Huang, 2014), detection of sick broilers (Zhuang et al., 2018), have been carried out using MÖ algorithms. Monitoring systems aimed at collecting and analyzing data in precision livestock farming provide farmers with insights into temperature, behavior, health, and nutrition, enabling increased animal productivity, evaluation of animal activity, health issues, and welfare, and preservation of animal health. Smart technologies such as sensors, cameras, and computers that enable monitoring of animal welfare and early intervention in abnormal situations (Rose and Chilvers, 2018; Norton et al., 2019) are being developed to support farmers. Precision livestock technologies, designed to support farmers, can control both animal productivity and environmental impacts, as seen in health and welfare parameters (Berckmans, 2014). Additionally, MÖ and YZ can be used in dairy farm management, production forecasting, and livestock applications. Plant Phenotyping, Discovery, and Monitoring of Natural Resources YZ and MÖ applications, using spectroscopic data and satellite images, can analyze soil data, classify varieties, phenotype plants, map carbon fractions, predict carbon stocks, map climate-sensitive soils, model organic carbon fractions, and predict soil health indicators. With DSA and ESA models using image processing and MÖ algorithms, image-based plant phenotyping, image classification, regression, and object detection are effective. It can be said that ESA can be used to diagnose plant species, and deep ESA can determine seed and plant ingredients and contamination cases in the future.

The text provides a comprehensive overview of precision agriculture technologies and their applications, particularly focusing on plant and animal monitoring, as well as plant phenotyping and natural resource monitoring. It highlights the significance of smart technologies in optimizing agricultural practices, enhancing productivity, and ensuring sustainability.

4. Discussion

Among the driving factors requiring the digitization of the agricultural sector, both on-farm and off-farm, are improving agricultural productivity and sustainability, adapting to and mitigating the impacts of climate change, ensuring access to markets and good governance, value chain management, trade requirements, and consumer demand. It is noted that digital agriculture can provide improvements in sustainability in food systems; technologies such as Variable Rate Technologies (VRT), AI, cloud computing, yield mapping, digital soil mapping, sensors, and UAVs are suitable for achieving agricultural goals and various sustainability principles (MacPherson et al., 2022). Technologies like satellite imagery and IoT are essential for biomass production, preserving biodiversity, and mitigating climate change.

Data collection technologies mounted on satellites, drones, and manned vehicles for monitoring and remote sensing systems in agriculture are increasingly prevalent. Digital sensing technologies such as water and air quality sensors, moisture content sensors, electrical conductivity sensors, weed detectors, temperature, wind speed, and pH measurement sensors, water flow sensors, on-site soil, plant, animal, biodiversity, pest, and invasive species monitors are becoming widespread in agriculture and food. Many AI technologies, especially in irrigation and water quality determination, are used. As a result of research, an automatic irrigation system that estimates water content optically from images of the plant root zone (Javaid et al., 2022) and a processor-operated, entirely unmanned controlled drip irrigation system have been developed (Kavianand et al., 2016). Using AI technologies, a recommendation system has been developed for monitoring, forecasting, and controlling diseases, pests, and weeds in wheat (Zhang et al., 2014). Digital agriculture utilizing data-based technologies is not only improving productivity, efficiency, and food security but is also essential for preserving biodiversity, soil, and human health.

Among data analysis technologies, data cleaning and big data analysis algorithms, machine learning (ML), and predictive analytics, and data collection technologies like cloud storage, confidential computing, and virtual data centers are gaining importance. Data is used for creating information and recommendations in production processes and automating activities. Data management, transfer, and sharing technologies, machine-assisted digital communication, image-based control, trade, payment, service, and data visualization technologies will be beneficial for food and agriculture in the future. Innovations in agriculture are evolving through ICT-enabled machines and systems' information acquisition, application, and intelligent behavior, defined as AI. Past experiences and data are extensively used in sustainable soil and agriculture management thanks to ML. Digital data and technologies in agriculture, from farm management to productivity and resource use, from low-tech solutions to in-field sensors and AI, big data analytics, process automation, robotics, and AI, are used in various fields (OECD, 2022). In agriculture systems, AI-based robotic applications such as seeding, spraying, mowing, harvesting, control, sorting, and packaging are used. However, the use of robotic technologies in agriculture is progressing slowly. The widespread use depends on increasing speed and accuracy. Despite many benefits, high investment costs (Rose and Chilvers, 2018) and inadequate training services (Paustian and Theuvsen, 2017) can be mentioned as obstacles to the widespread adoption of digital technologies. When the control of data that will be more critical in the future of agriculture passes into the hands of large agricultural companies, it is uncertain whether it will be used in accordance with sustainability principles.

5. Conclusion

In this review, it is clearly seen that AI technologies will be beneficial in areas such as land quality, weather conditions, extraction of agricultural data, projection and yield estimation, groundwater, crop cycle, weeds, diseases, and pests. New technologies can assist in providing optimal environmental conditions and early diagnosis of health issues in livestock systems. Despite all these positive developments, overcoming challenges such as data privacy, security vulnerability, monopolization, lack of historical mapping, slow data processing, cost of sensors, disconnect from the natural world, processing complexity, and education is crucial. Innovative technologies such as AI, IoT, Internet of Drones (IoD), UAVs, and Machine Learning can contribute to the spread and adoption of technologies that increase productivity, quality, and profitability. The future of agriculture must find and overcome challenges such as water scarcity, temperature changes, food scarcity, and waste at an affordable cost. This can only be achieved through the development of new technologies that focus on reducing pollution levels, increasing energy efficiency, managing risks appropriately, and preserving environmental, social, and economic sustainability. Agricultural technology should prioritize sustainability, reduce input requirements, facilitate applications, utilize agricultural biology to a high extent, and be respectful and trustworthy towards nature, humans, soil, environment, and water resources. It is believed that this review will be useful in addressing sustainability, traceability, productivity, quality, and many other aspects in agriculture.

Furthermore, technologies such as animal monitoring and phenotyping enable improving animal health and welfare, optimizing productivity, and minimizing environmental impacts. These technologies provide farmers with more information about the status of their animals, enabling early intervention and enhancing productivity. The future of precision agriculture will be shaped by advanced technologies such as increased automation, artificial intelligence, and big data analytics. The further integration of these technologies into agricultural production processes will enhance efficiency and sustainability, making the future of the agriculture sector brighter. Therefore, ongoing research and application efforts in precision agriculture technologies will continue to play a significant role in the agriculture sector.In addition to the advancements in animal monitoring and phenotyping, precision agriculture technologies also offer opportunities for optimizing crop management practices. These technologies enable farmers to monitor various aspects of crop growth, such as soil composition, water quality, and environmental conditions, in real-time. By leveraging data-driven insights and predictive analytics, farmers can make informed decisions regarding irrigation, fertilization, pest management, and harvesting, thereby maximizing crop yields while minimizing resource inputs and environmental impacts. Overall, precision agriculture technologies have the potential to revolutionize the way food is produced by improving efficiency, sustainability, and resilience in agricultural systems.

Author Contributions

The percentage of the author(s) contributions is presented below. All authors reviewed and approved the final version of the manuscript.

	H.D.	K.F.D.
C	50	50
D	50	50
S	50	50
DCP	50	50
DAI	50	50
L	50	50
W	50	50
CR	50	50
SR	50	50
PM	50	50
FA	50	50

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The authors declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

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