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Review

AI and Related Technologies in the Fields of Smart Agriculture: A Review

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Abstract: The integration of cutting-edge technologies—such as the Internet of Things (IoT), artificial intelligence (AI), machine learning (ML), and various emerging technologies—is revolutionizing agricultural practices, enhancing productivity, sustainability, and efficiency. The objective of this study is to review the literature regarding the development and evolution of AI as well as other emerging technologies in the various fields of Agriculture as they are developed and transformed by integrating the above technologies. The areas examined in this study are open field smart farming, vertical and indoor farming, zero waste agriculture, precision livestock farming, smart greenhouses, and regenerative agriculture. This paper links current research, technological innovations, and case studies to present a comprehensive review of these emerging technologies being developed in the context of smart agriculture, for the benefit of farmers and consumers in general. By exploring practical applications and future perspectives, this work aims to provide valuable insights to address global food security challenges, minimize environmental impacts, and support sustainable development goals through the application of new technologies.

Keywords: artificial intelligence (AI); IoT; precision agriculture; smart farming; vertical farming; indoor farming; zero waste agriculture; precision livestock; smart greenhouses; regenerative agriculture

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1. Introduction

The agricultural sector is undergoing a transformative evolution driven by the integration of cutting-edge technologies. As global population growth continues to escalate and climate change imposes new challenges, there is a pressing need to transform traditional farming practices—exploiting new technologies—to ensure food security, sustainability, and efficiency. This paper explores the advancements and applications of modern technologies in diverse agricultural domains: open field smart farming, vertical and indoor farming, zero waste agriculture, precision livestock, smart greenhouses, and regenerative agriculture (Figure 1).

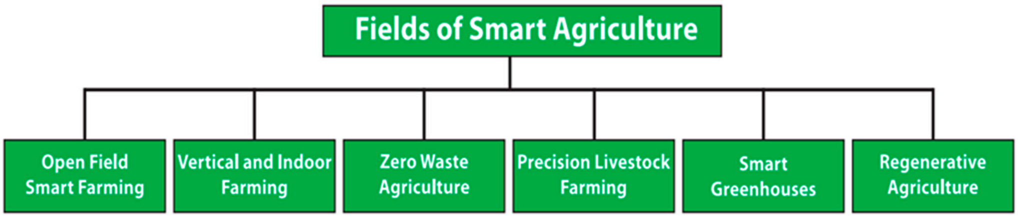

Figure 1. Fields of smart agriculture.

Open field smart farming harnesses the power of the Internet of Things (IoT), artificial intelligence (AI), and other new technologies to optimize crop production and resource management. The IoT refers to the concept of allowing an autonomous and automated exchange of information between real-world devices, exploiting network technologies such as Radio-Frequency IDentification (RFID) and Wireless Sensor Networks (WSNs). Some of these devices, termed *sensors*, gather information concerning their environment (e.g., soil moisture, air temperature and humidity, animal temperature, and heart rate), while a second group of these devices, referred to as *actuators*, arrange for performing actions that modify their environment (e.g., perform irrigation, turn air conditioning on or off, regulate lighting, or issue alerts for farmers). Finally, a third group of devices provide services for storing and managing sensed data, as well as taking data-driven decisions on the actions that should be taken by actuators [1,2]. In this context, drones and UAVs provide aerial imaging and precision spraying, while satellite imaging offers extensive data on crop health, soil conditions, and weather patterns, enabling more informed decision-making [3].

The term artificial intelligence (AI) refers to the technology and science pertaining to the creation and functioning of systems that generate outputs such as content, forecasts, recommendations, or decisions for a given set of human-defined objectives [4]. AI applications in precision agriculture span across the whole agriculture value chain, including soil management, the monitoring of plant/livestock health, logistics, price forecasts, etc. [5]. AI applications utilize a multitude of algorithm techniques, with the majority of them being based on machine learning [6]; however, new developments such as generative AI (i.e., a set of computational techniques that generate seemingly new, meaningful content such as text, images, or audio from training data [7]) and regenerative AI (AI techniques that allow for the development of intelligent systems that can adapt and evolve and repair themselves [8]). In the rest of this paper, the term AI will be used to refer to mainstream machine learning-based applications, while the trends and potential of using generative and regenerative AI in precision farming will be analyzed in the Discussion Section.

In order to promote transparency, verifiability, and immutability of data—including sensed data and decisions taken by AI—blockchain technologies can be used [9]. Blockchain is a decentralized, distributed database that stores data in chains of cryptographically secure and immutable blocks. In the domain of precision agriculture, blockchain technology can be used to store records created during all stages of the agricultural value chain, including cultivation, harvesting, processing, storage, and transport of crops (and crop-based products), as well as livestock breeding. Ensuring data transparency, verifiability, and immutability promotes trust and enables detecting and combating fraud [9–11].

Vertical and indoor farming techniques transform urban agriculture by maximizing space utilization and minimizing environmental impacts. Hydroponics and aeroponics allow for soilless cultivation [12], and LED grow lights offer energy-efficient lighting solutions tailored to plant needs [13]. The integration of advanced technologies—such as the IoT, AI, and automated climate control systems—ensure optimal growing conditions, further enhancing productivity and sustainability in controlled environments [14].

Zero waste agriculture focuses on creating circular systems where waste is minimized and repurposed. The use of biodegradable materials and anaerobic digesters transforms agricultural waste into biogas and organic fertilizers [15]. Aquaponics, a symbiotic system combining aquaculture and hydroponics, exemplifies the potential of integrated waste-free farming practices [16]. The realization of the objectives of zero waste agriculture necessitates the incorporation of cutting-edge technologies like the IoT, AI, biotechnology, and renewable energy systems.

Precision livestock management employs wearable health monitors and automated feeding systems to monitor and enhance animal health, welfare, and productivity [17]. Genomic selection utilizes genetic information to improve breeding programs, and enhances characteristics such as disease resistance and productivity [18].

Smart greenhouses integrate the IoT, AI, and automated systems to maintain optimal growing conditions, improve crop yields, and enhance resource efficiency. Automated irrigation systems and robotic harvesters reduce labor costs and water waste, while integrated pest management systems use sensors and AI to manage pest populations sustainably [19–21].

Regenerative agriculture aims to restore soil health, increase biodiversity, and amplify carbon sequestration [22], promoting long-term ecological sustainability. Technologies such as cover cropping, soil health sensors, and carbon sequestration measurement tools are required to advance these practices [23]. AI and the IoT further enhance the monitoring and implementation of regenerative techniques [24,25].

Additionally, general new technologies like 5G connectivity, biotechnology, robotics, and machine learning are revolutionizing agricultural practices. AI-driven predictive analytics and decision support systems, along with the rapid data transfer capabilities of 5G, are enhancing the efficiency and sustainability of farming operations [26]. Biotechnology, including CRISPR (Clustered Regularly Interspaced Short Palindromic Repeats) and other gene-editing tools, is developing crops with improved characteristics [27], while robotics and automation are streamlining planting, weeding, and harvesting processes [19,20,28].

The primary objective of this study is to conduct a comprehensive review of the integration of advanced technologies in the agricultural sector, including AI, the IoT, blockchain, and other emerging innovations. This research examines the impact of these technologies on the transformation of traditional farming practices in various agricultural sectors, such as open field smart farming, vertical and indoor Farming, zero waste agriculture, precision livestock farming, smart greenhouses, and regenerative agriculture. These areas cover both the transformation of more traditional farming practices (open field farming, livestock, and greenhouses), as well as more recent farming trends (vertical and indoor farming, zero waste farming, and regenerative farming).

Synthesizing the latest research, technological advances, and practical applications, this study offers a comprehensive understanding of how these innovations address some of the most pressing global challenges, such as food security, environmental sustainability, and climate change in the above sectors of farming. This paper highlights the potential of these technologies to boost productivity, reduce waste, and create more resilient agricultural systems that are able to adapt to the demands of a growing global population and a changing climate. This research also contributes to a broader understanding of how technological innovation can address global agricultural challenges and supports the continued evolution of the agricultural sector into a more sustainable and resilient industry.

Furthermore, this study serves as a comprehensive resource to guide future research and development efforts in sustainable agricultural technologies. It aims to foster collaboration between researchers, policymakers, and industry stakeholders, facilitating the creation and implementation of innovative solutions that will drive the agricultural sector toward greater sustainability and efficiency. The insights provided in this paper not only create a road map for future technological developments but also highlight the importance of integrating these technologies into real agricultural practices to achieve long-term sustainability goals.

Key scientific questions addressed in this review include the following:

- RQ1. Optimizing resource management: how can emerging technologies such as AI and the IoT optimize resource management in agriculture?
- RQ2. Advantages and challenges of vertical and indoor farming: what are the benefits and challenges of applying AI and, in general, emerging new technologies to the development of vertical and indoor farming techniques?
- RQ3. Sustainability through zero waste agriculture: how can AI, the IoT, and new technologies in general be applied to zero waste agriculture so that it can develop and contribute as a sustainable agricultural practice?
- RQ4. Precision animal farming for improved animal health: what is the role of AI and, more generally, emerging new technologies in improving animal health and productivity?
- RQ5. Advances in smart greenhouses: how do smart greenhouses incorporate advanced technologies such as AI, ML, and the IoT to enhance crop production?
- RQ6. Enhancing regenerative agriculture with modern technologies: how can regenerative agriculture practices be improved by AI, ML, and more generally new technologies?

By addressing these critical scientific questions, this review synthesizes current research and technological advancements, offering practical insights and future prospects for sustainable agricultural development. The findings provide a valuable foundation for further research, guiding interdisciplinary collaboration and innovation aimed at addressing global challenges such as food security, environmental sustainability, and climate change.

The remainder of this paper is structured as follows. Section 2 elaborates on the methods and procedures used for data collection, providing a comprehensive overview of the techniques used to gather relevant information for this study. Sections 3–8 explore various sectors of agriculture, detailing the technologies that have been or are being developed and applied to these sectors. It also discusses the specific challenges and concerns faced in implementing these new technologies, including issues related to integration, scalability, and farmer adoption. Section 9 summarizes the data presented in the research, listing answers to the RQs. Finally, Section 10 summarizes the findings and ideas from the previous sections, presenting the overall conclusions of this study. It also offers answers to the critical RQs raised above and outlines future research directions and possible strategies to overcome the identified challenges, to further advance the field of smart agriculture.

2. Data and Methods

The objective of this study is to conduct a comprehensive review of the integration of advanced technologies in the agricultural sector, including AI, the IoT, blockchain, and other emerging innovations. This study will reveal application areas of technologies in different fields of smart agriculture, and provide insights on the current situation in the agricultural sector concerning the uptake and implementation of the smart agriculture model.

This review adopts a research methodology based on the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) guidelines and recommendations. PRISMA offers a systematic and rigorous methodology for reviewing and synthesizing the available literature [29]. Figure 2 illustrates the application of the PRISMA methodology in the context of the presented research.

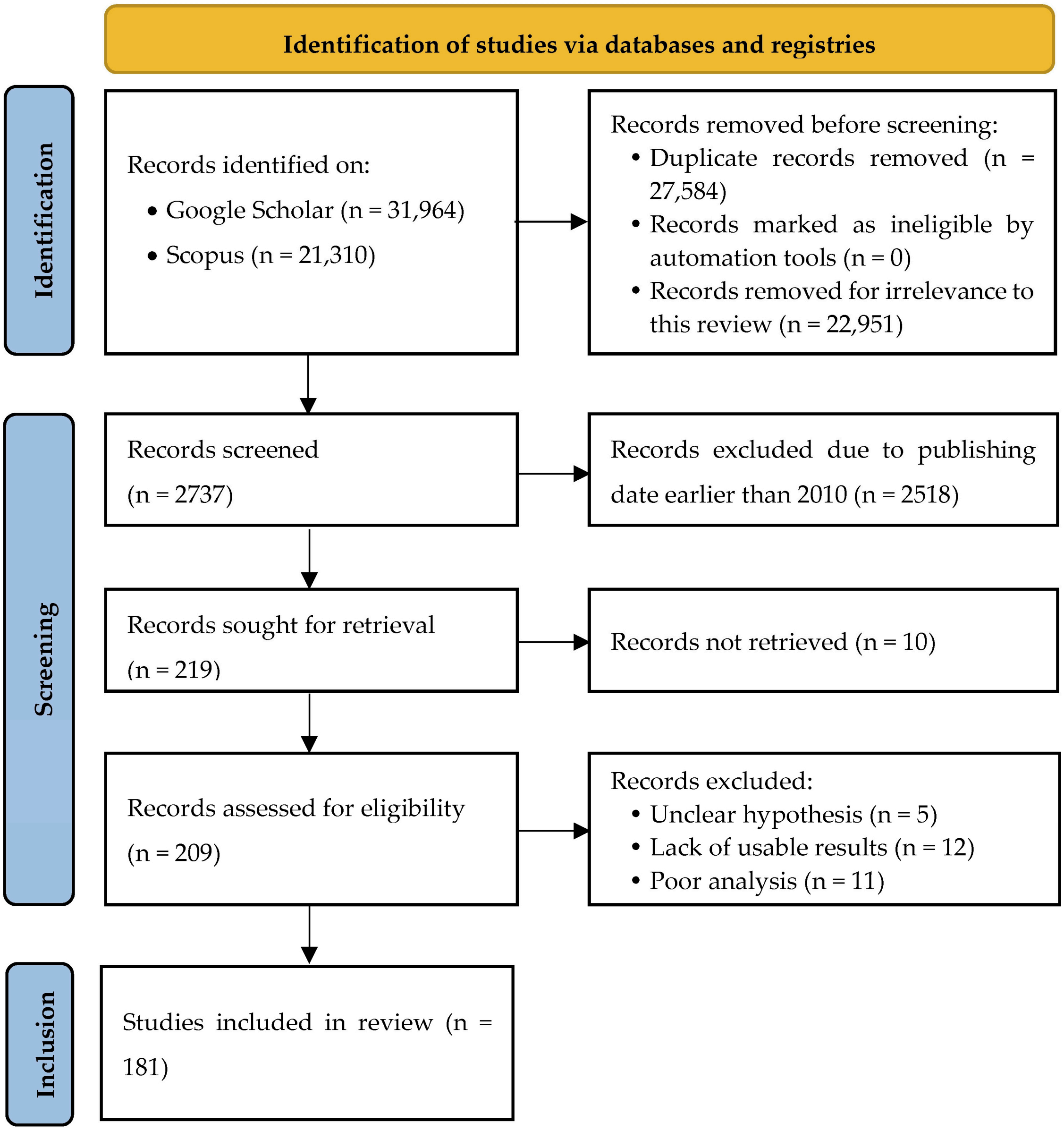

Figure 2. PRISMA flowchart for the precision agriculture sectors' set of keywords.

In order to collect the data, relevant publications at scientific conferences, in international scientific journals, as well as on the internet were identified and studied. Some important papers (cf. Table 1) were used both as information sources and for identification of the additional literature: firstly, the citation lists of these papers were examined; secondly, searches for additional documents citing these papers were performed. Scientific publication databases were also used to identify relevant papers by issuing queries and examining the query results. Table 2 lists the databases used and the associated querying modes.

Table 1. Important scientific publications used both as information sources and for identification of the additional literature.

Description	Year of Publication
A Wireless Sensor Network Deployment for Soil Moisture Monitoring in Precision Agriculture.	2021
Unmanned Aerial Vehicles (UAV) in Precision Agriculture: Applications and Challenges.	2021

Table 1. *Cont.*

Description	Year of Publication
Robotics, IoT, and AI in the Automation of Agricultural Industry: A Review.	2020
Satellite Imagery in Precision Agriculture.	2024
Machine Learning in Agriculture: A Comprehensive Updated Review.	2021
Seeing the Lights for Leafy Greens in Indoor Vertical Farming.	2020
Latest Advancements on Livestock Waste Management and Biogas Production: Bangladesh's Perspective.	2020
Livestock Management with Unmanned Aerial Vehicles: A Review.	2022
A Review of Traditional and Machine Learning Methods Applied to Animal Breeding.	2024
Energy-Saving Design and Control Strategy towards Modern Sustainable Greenhouse: A Review.	2022
Is Blockchain a Silver Bullet for Supply Chain Management? Technical Challenges and Research Opportunities.	2020
Enhancing Water Management in Smart Agriculture: A Cloud and IoT-Based Smart Irrigation System.	2024
Plant Demand Adapted Fertilization in Organic and Precision Farming.	2021
Renewable Energy and Sustainable Agriculture: Review of Indicators.	2023

Table 2. Scientific publication databases used for retrieving additional research works and associated querying modes.

Database	Use
Scopus	Extract data using queries
Google Scholar	Search for articles by keyword, author, and article title

Searches were also conducted in scientific publication databases and on the internet. The Scopus and Google Scholar platforms were chosen for this work, that is to exploit the increased rigor of Scopus and the wider comprehensiveness of Google Scholar. Relevant scientific publications were collected from the Scopus academic database by applying appropriate search filters. To extract the desired results, we employed the queries presented in Table 3. For the last query, the following variations were made:

1. The placeholder text *keywords for domain selection* was replaced by keywords describing smart/precision agriculture in general, or describing a specific sector of smart agriculture surveyed in this paper. More specifically, the following keyword combinations were used as replacements: (a) "precision AND agriculture", (b) "smart AND agriculture", (c) "smart AND farming", (d) "regenerative AND agriculture", (e) "smart AND greenhouses", (f) precision AND livestock, (g) "zero AND waste AND agriculture" and (h) "vertical AND indoor AND farming";
2. The placeholder text *keywords for the specific technology* was substituted by appropriate keywords that described the technology in question, e.g., "Internet of Things", "agricultural robots", "satellite imaging", "blockchain", "hydroponics and aeroponics" or "artificial intelligence" (cf. Table 2).

Substitutions (1) and (2) listed above were applied in combination, i.e., when the placeholder text *keywords for domain selection* was replaced by "precision AND agriculture", the placeholder text *keywords for the specific technology* was iteratively replaced by appropriate keywords describing the pertinent technologies ("Internet of Things", "agricultural robots"). This procedure was repeated for each of the replacement texts used for "keywords for domain selection".

Table 3. Search queries used to locate scientific publications in Scopus.

Description	Query
Query for precision agriculture articles	TITLE-ABS-KEY (precision AND agriculture)
Query for smart agriculture articles	TITLE-ABS-KEY (smart AND agriculture)
Query for smart farming articles	TITLE-ABS-KEY (smart AND farming)
Query for regenerative agriculture articles	TITLE-ABS-KEY (regenerative AND agriculture)
Query for smart greenhouses articles	TITLE-ABS-KEY (smart AND greenhouses)
Query for smart livestock articles	TITLE-ABS-KEY (precision AND livestock)
Query for zero waste agriculture articles	TITLE-ABS-KEY (zero AND waste AND agriculture)
Query for vertical indoor farming articles	TITLE-ABS-KEY (vertical AND indoor AND farming)
Query for the number of articles related to precision agriculture, as well as each new technology, along with the year of their first publication.	(TITLE-ABS-KEY (*keywords for domain selection*) AND TITLE-ABS-KEY (*keywords for the specific technology*)) AND (PUBYEAR > 1980 AND PUBYEAR $\leq$ 2024)

The development of technology in precision agriculture can be observed through the publication of scientific papers. Table 4 illustrates insights regarding the year of appearance of each of the new technologies in agriculture, and the number of scientific publications concerning each specific technology until today.

Table 4. 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
Sensors/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

Table 4. *Cont.*

Technology	Year of First Scientific Publication	Number of Scientific Papers Published Until Today
IoT in precision agriculture	2011	1358
Smartphone apps and mobile technology	2018	10
Blockchain and supply chain management	2020	12

In the first row, Table 4 lists the year of publication along with the number of scientific papers focusing on precision agriculture for the period 1981–2025. Each of the subsequent rows concerns the use of a specific technology in the context of precision agriculture and lists the year of the first relevant scientific publication and the total number of scientific papers concerning the application of the specific technology in the domain of precision agriculture until today.

3. Open Field Smart Farming

Open Field Smart Farming represents a paradigm shift in agricultural practices, leveraging advanced technologies such as the IoT, AI, and data analytics to optimize crop production, resource management, and sustainability. The integration of these technologies addresses the critical challenges of environmental sustainability, including minimizing waste and reducing the impact on the environment. Additionally, open field smart farming reduces the need for agricultural inputs like water, fertilizers, and pesticides, thus tackling resource-scarcity issues, and improves farming efficiency and productivity, leading to increased yields [30,31]. Consequently, precision farming can contribute to the mitigation of food scarcity and insecurity issues provided that appropriate action is taken to alleviate the effects of additional factors related to food scarcity and insecurity, which include conflict and insecurity, economic shocks, weather extremes, loss of biodiversity [32–34], and lack of fairness [35].

In the following subsections, we discuss the most important emerging technologies that, in combination with AI, contribute to the transformation of the open field smart farming sector; these technologies are illustrated in Figure 3.

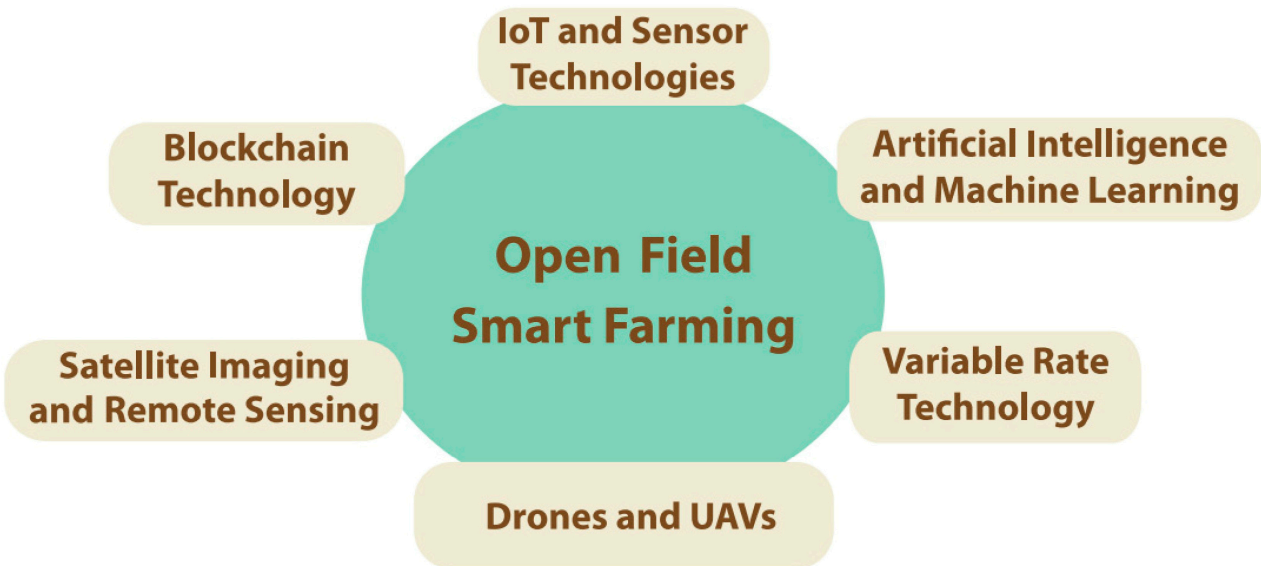

Figure 3. Technologies of open field smart farming.

3.1. IoT and Sensor Technology

The IoT plays a crucial role in open field smart farming by enabling real-time monitoring and data collection from various sensors deployed across the farm. These sensors measure parameters such as soil moisture, temperature, humidity, nutrient levels, and crop health. For instance, soil moisture sensors supply continuous data that can be fed into precise irrigation systems that deliver optimal quantities of water to plants, ensuring water conservation and fostering optimal crop growth [36–38]. Furthermore, the risk of over-irrigation is reduced, thus limiting the probability of nutrient leaching.

3.2. Drones and UAVs

Drones and Unmanned Aerial Vehicles (UAVs) are extensively used in modern agriculture. Drones employ advanced imagery sensors, such as high-resolution cameras, multispectral, and hyperspectral sensors, capturing detailed aerial imagery of fields. This imagery is subsequently analyzed to provide insights concerning crop health, pest infestations, nutrient deficiencies, fruit ripeness, soil composition, etc.; this enables the early detection of issues and application of targeted measures, including the precision spaying of pesticides or fertilizers, achieving a reduction in the use of chemicals, and enhanced crop yields [39,40].

3.3. Satellite Imaging and Remote Sensing

Satellite imaging and remote-sensing technologies enhance the monitoring capabilities of farmers, offering information on the condition of crops, soil wealth, and weather conditions. Through satellite imagery—which is analyzed using remote-sensing algorithms—cultivators may identify water stress areas, obtain insights on crop vigor, and estimate harvest times, thus becoming empowered to manage their farms more efficiently [3,41–43].

3.4. Artificial Intelligence and Machine Learning

AI and ML are key enablers for the transformation of farming processes, revolutionizing the usage and analysis of agricultural data. AI and ML techniques are used for processing big data streams obtained from a multitude of sources, including IoT devices, drones, and satellites, producing predictive models and actionable insights. For instance, AI-based techniques can analyze historical data and current weather conditions to make predictions on pest outbreaks, enabling farmers to apply proactive pest management [44,45]. Additionally, tools based on ML can be used for the planning of land usage, including the selection of crop types and varieties, for the tuning of planting schedules, for producing forecasts on crop yields and prices, and others. Farmers may exploit these outcomes not only to enhance farm productivity but also to drive other processes of the agricultural cycle more efficiently, for example, ensuring the availability of storage areas and optimizing farm-worker hiring, to name a few.

3.5. Blockchain Technology

Blockchain technology is emerging as a powerful tool that may be exploited in the farming process to underpin transparency and traceability in agricultural supply chains. In particular, blockchain technology can be used to store records created during the cultivation, harvesting, processing, storage, and transport of crops (and crop-based products) in a transparent and verifiable fashion. These records can offer data on the origin, cultivation process, pesticides and fertilizers used, crop quality, processing methods, storage and transportation conditions, etc., of agricultural products. Through these records, a reliable traceability framework can be established, contributing to the promotion of consumer information and trust, fraud detection and prevention, while food safety can be ensured [9–11].

In order to utilize blockchain technologies, appropriate infrastructure must be installed and made operational. To this end, either private or public blockchain architectures can be employed. Richard et al. [46] analyze the cost of the two options, concluding that the use of private blockchain infrastructures entails significantly reduced costs; however, this approach requires increased technical knowledge for the setup, monitoring, and right-sizing of the blockchain system. Notably, the number and power of the machines/data centers required to support blockchain technology varies depending on the type of blockchain and the scale of the application. Public blockchains (e.g., Ethereum) are based on nodes distributed globally, while private blockchains may have nodes hosted in local or regional data centers, tailored to specific use cases. The scale of the blockchain may vary, depending on the operator's size and intended use; for instance, a single farm using blockchain to store information for its own products only will require a small-scale infrastructure, while organic product certifiers using blockchain to store records for all products they certify will require infrastructure of a larger scale.

It is worth noting that while blockchain provides mechanisms to support the immutable and verifiable storage of traceability and quality-related information, it does not automatically solve the challenges associated with points of mixing or the re-entry of mixed products. Effective traceability requires the integration of real-time monitoring systems, such as IoT devices, to capture and record data as events occur. In addition, well-defined management protocols must describe how data for each mixing or separation event is recorded and stored, ensuring that even complex supply chain scenarios can be transparently monitored. By implementing such measures, blockchain technology can help promote consumer trust, detect and prevent fraud, and improve food safety.

3.6. Precision Agriculture Tools

Precision agriculture tools facilitate site-specific farming practices through the integration of state-of-the-art technologies. Variable Rate Technology (VRT) assesses the potential and needs of different field zones, and these computations are subsequently used as input to farming processes, such as fertilization, seeding, and pesticide application [47,48]. The benefits of this focused approach include the minimization of wastage, reduction in environmental impact, maximization of crop performance, and improvement in yield quality [49].

3.7. Challenges and Future Prospects

Despite the promising advancements, the adoption of open field smart farming technologies faces several challenges, including high initial costs, technical complexity, and the need for robust data infrastructure. However, ongoing research and innovation are providing solutions with reduced costs and enabling their use by users with more limited technological expertise. As the IoT, AI, and blockchain continue to evolve, their integration into open field farming is expected to become more seamless and widespread, paving the way for a more sustainable and efficient agricultural future.

4. Vertical and Indoor Farming: Harnessing New Technologies for Sustainable Agriculture

It is estimated that, by 2050, the Earth's population will reach 9.7 billion [50–52]. As a result, an increase in food production by 50% is necessary [53] in order to (a) cover the needs of the additional population, and (b) address the issues of hunger and undernourishment, which currently affect 29.3% percent of the global population (2.3 billion people) that are facing moderate or severe food insecurity [54]. However, arable land per capita is forecast to be less than 0.2 hectares by 2050, sustaining a reduction of 66% compared to the corresponding amount in the year 1970 [55]. Therefore, it is imperative to substantially raise farming productivity. These issues are further aggravated due to the reduction in soil nutrients in arable land, climate diversity, and climate change repercussions [56].

Vertical and indoor farming are innovative agricultural practices designed to maximize space utilization and minimize environmental impact by growing crops in controlled, often urban, environments [57]. Crops of this type can also be grown reliably all year round as they are not dependent on local weather conditions [58]; this aspect also makes them immune to climate change effects. These agricultural systems are particularly important because they contribute to addressing the food security challenges posed by urbanization, climate change, and the reduction in arable land. The minimization of pesticides and fertilizers required in these crops leads directly to a reduction in greenhouse gas emissions, such as nitrogen monoxide [59]. The integration of advanced technologies, such as the IoT, AI, LED lighting [60], and automation systems is pivotal in enhancing the efficiency and productivity of these farming systems.

Figure 4 illustrates the most important technologies applied in the field of vertical and indoor agriculture.

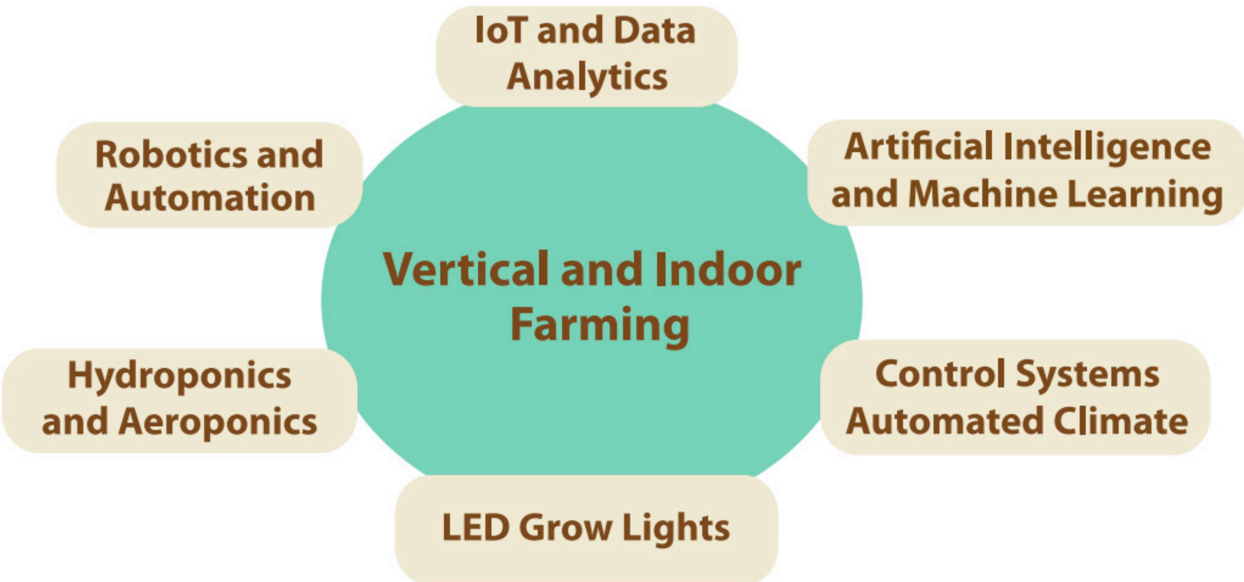

Figure 4. Technologies of vertical and indoor farming.

4.1. *Artificial Intelligence and Machine Learning*

The difficulties that must be faced in vertical and indoor agriculture crops are also presented in the simultaneous monitoring of multiple indicators, the development of advice on the optimal use of actions for the correct growth of plants, as well as their holistic monitoring.

To address these issues, technologies such as AI and ML are used, and although they are investigated infrequently [61], their adoption in such systems has the potential to improve product quality and production in the long term [55], resulting in these systems becoming more sustainable and productive over time.

Vertical hydroponics have been shown to achieve improved harvest and efficiency [62] compared to traditional soil cultivation. This result is attributed to (a) reduced water evaporation and (b) the potential to exercise precise control on the supply of nutrients to plants. The integration of AI and ML in vertical hydroponics can further enhance the farming process efficiency, supporting (i) disease detection and diagnosis, (ii) the analysis of plant traits, (iii) plant growth monitoring and pertinent alert provision, (iv) stress detection, and (v) yield quantity estimation. These functionalities empower farmers to take proactive measures in order to protect their crops and maximize yield. The use of AI and ML can additionally underpin the successful and efficient cultivation of specific plant categories, such as exotic and medicinal plants, in a sustainable fashion. Overall, through this process, food security can be enhanced while additionally, health and well-being can be promoted [63].

4.2. Hydroponics and Aeroponics

Hydroponics and aeroponics are soilless farming techniques where plants grow in nutrient-rich solutions or mist environments. More specifically, in hydroponics, plants grow in water-based nutrient solutions, enabling precise control over nutrient provision and eliminating issues related to soil, such as poor drainage, incorrect soil pH, or erosion [16]. In aeroponics, on the other hand, plants are suspended in the air and their roots are misted with nutrient solutions; this ensures increased oxygen availability, which in turn—in conjunction with the precise provision of nutrients—supports faster plant growth and higher yields [64,65].

4.3. LED Grow Lights

Light-emitting diode (LED) technology is increasingly utilized in indoor farming installations due to its capability to support optimal plant growth by providing energy-efficient and spectrum-tuned lighting. LED lighting allows customizations of the emitted light wavelengths, and this feature is exploited to provide each cultivation with the lighting conditions that are most suitable for their photosynthesis process. Blue light plays an important role in photomorphogenesis, affecting photosynthesis, chlorophyll synthesis, and shoot elongation (1), especially when combined with red light. Red light is efficient for photosynthesis (2) but its exclusive use can cause abnormal growth (3), making the addition of blue light necessary. Green light improves photosynthesis in the lower layers and facilitates the assessment of plant condition. The combination of red and blue light proves to be the most efficient, enhancing growth and yields, while the incorporation of green light in such combinations offers even better results. Infrared light can promote flowering and shoot elongation but without blue light, growth may be abnormal [66–68]. This leads to a number of benefits, including enhanced plant growth, acceleration of flowering, and an improvement in crop yields while additionally, energy consumption is substantially reduced [13]. LED lighting also enables multi-layered vertical farming, where crops are cultivated in vertical layers, thus increasing space utilization efficiency [60,69,70].

4.4. Automated Climate Control Systems

The success of vertical and indoor farming is highly dependent on the provision of optimal growing conditions for plants. To this end, farmers utilize automated climate control systems that regulate key parameters, including humidity, temperature, light wavelength and intensity, as well as CO_2 levels. In this context, IoT sensors monitor the environment and stream their measurements as input to AI-based algorithms, which determine the adjustments that need to be made to ensure optimal conditions. Finally, these adjustments are realized through suitable actuators [14].

4.5. Robotics and Automation

Numerous tasks in vertical and indoor farming are transformed through the use of robotics and automation. The range of affected tasks spans across the whole agricultural cycle, including planting, pruning, harvesting, and packaging. The adoption of these technologies leads to reduced labor costs, elevated operational efficiency, and underpins multiple precision agriculture practices. For example, computer vision systems can accurately identify produce that is ready for harvesting, and direct robotic arms can collect them with high precision, significantly reducing potential damage to crops [28,71]. Automated solutions may also be applied to irrigation and fertilizer delivery systems, allowing for precise control over the nutrient and water supply, optimizing resource usage, promoting sustainability, and ensuring plant health and yield quality.

4.6. IoT and Data Analytics

Data analytics are pivotal to vertical and indoor farming. Data analytics, fueled by measurements sourced from IoT sensors, provide real-time insights into plant health and environmental conditions. Sensors collect a wide range of data concerning important parameters, such as soil moisture, levels of nutrients, leaf wetness, air quality, and lighting conditions. These data are transmitted to cloud-based platforms where they are analyzed to inform decision-making processes [72]. Advanced data analytics and AI can identify patterns and trends, enabling predictive maintenance, optimizing resource allocation, and improving overall farm management.

4.7. Vertical Farming Structures and Design

Vertical farming employs special structures and designs, such as modular and stackable systems, to improve space utilization and promote scalability. To this end, movable racks and automated conveyor systems are installed, through which plants are transported through different growth stages, ensuring that each plant receives optimal light exposure and nutrient delivery. These systems are more widely used in urban environments, overcoming space limitations and reducing the distance between production locations and consumer markets [73].

4.8. Economic and Environmental Benefits

Vertical and indoor farming reap significant benefits from technological advancements in vertical and indoor farming. These advancements allow for the deployment of systems that require less land area, water consumption, and chemicals compared to traditional farming. Many crops are grown in indoor farms with controlled environments and, therefore, are protected more effectively from pests and diseases, increasing food security and limiting crop losses [74]. Food resilience and the continuous supply of farming products are also promoted through the ability to grow crops across all seasons at vertical farms. Finally, by allowing the placement of production farms close to consumption points, transportation costs and the related environmental impacts are reduced.

4.9. Challenges and Future Prospects

Despite the numerous advantages, vertical and indoor farming methods face challenges, including (a) significant costs for the initial setup, (b) increased energy consumption—and the consequent energy costs—for lighting and climate conditioning, and (c) the need for skilled workers who can operate the technologically advanced systems. However, ongoing research and technological innovations are addressing these issues by developing more energy-efficient systems, reducing costs, and improving the scalability of vertical farms. As urban populations continue to grow and the demand for sustainable food production increases, vertical and indoor farming approaches are poised to play a critical role in the future of agriculture.

5. Zero Waste Agriculture: Integrating Advanced Technologies for Sustainable Farming

Zero waste agriculture is an innovative approach focused on creating circular agricultural systems where waste is minimized, repurposed, and reintegrated into the farming cycle. This paradigm shift from conventional farming aims to enhance sustainability, improve resource efficiency, and reduce the environmental impact of agricultural activities. The integration of advanced technologies, such as the IoT, AI, biotechnology, and renewable energy systems is pivotal in achieving the goals of zero waste agriculture. Figure 5 depicts the most important technologies applied in the field of zero waste agriculture.

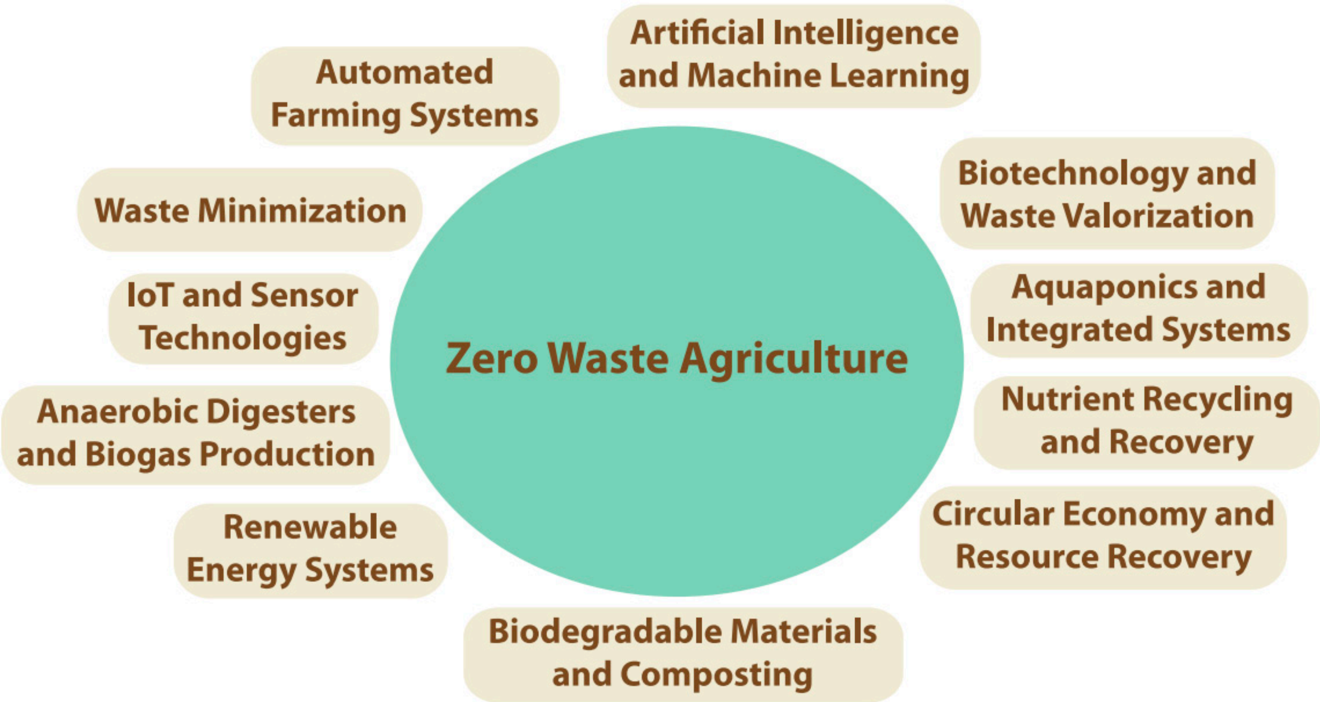

Figure 5. Technologies and sectors of zero waste agriculture.

5.1. Artificial Intelligence and Machine Learning

Interestingly, almost all agricultural activities produce waste. Recent studies reveal that agricultural activities generate approximately five billion tons of waste each year worldwide. Improper disposal of these wastes can lead to serious environmental contamination, posing significant threats to human health, while considerable economic losses are also incurred. It is therefore imperative that (a) waste production is minimized and (b) any wastes generated are properly disposed of, recycled, or used to create value for the environment and agriculture. We find that ”reducing”, ”reusing”, and ”recycling” field waste can significantly reduce the environmental footprint of agricultural practices, potentially reducing greenhouse gas emissions by up to 25% and saving water resources by 15% [75]. The application of AI and ML can ensure automation and precision application, thus reducing waste compared to human or traditional manufacturing processes [76].

5.2. Biodegradable Materials and Composting

One of the fundamental principles of zero waste agriculture is the use of biodegradable materials and composting to manage organic waste. Organic waste from crops and livestock can be composted to produce nutrient-rich compost, which is then used to improve soil health and fertility. Advanced composting technologies, including aerobic and anaerobic digesters, accelerate the decomposition process and enhance the quality of the compost produced, enabling the simultaneous production of biogas as a renewable energy source [77–80]. This closed-loop system reduces the need for chemical fertilizers and promotes a sustainable nutrient cycle.

It is worth noting that while composting is not a zero-emission process, having emissions that contain CO_2 (as a result of organic material decomposition), methane (CH_4), ammonia (NH_3), and nitrous oxide (N_2O) can contribute to constraining the growth of greenhouse gas emissions [81]. The key to this procedure is the controlling of emissions through the addition of organic and inorganic materials [82,83], through inoculating microorganisms [84], or by employing physical methods [85,86]. A survey on methods for constraining greenhouse gas emissions during composting or exploiting these emissions is given in [87].

5.3. Anaerobic Digesters and Biogas Production

Anaerobic digestion is a technology that converts organic waste into biogas and digestate through microbial processes in the absence of oxygen. Biogas, after complete treatment to remove the carbon dioxide it contains as raw biogas [88], is primarily composed of methane and can be used as a renewable energy source for heating, electricity, and vehicle fuel. When methane is burned, carbon dioxide is produced, which returns to the atmosphere; however, this carbon dioxide production is considered carbon-neutral as it comes from biomass and not fossil fuels [79]. The digestate, a by-product of anaerobic digestion, is a nutrient-rich material that can be applied to fields as an organic fertilizer [15]. This process not only manages waste efficiently but also reduces greenhouse gas emissions by capturing methane that would otherwise be released into the atmosphere.

An extensive study on the potential of anaerobic digestion for limiting greenhouse gas emissions is presented in [89]. The study highlights the importance of a number of parameters, including soil carbon storage efficiency in the baseline, heat recovery rate in the biogas production process, and digestate handling, in order to achieve environmental benefits from anaerobic digestion. These parameters should be carefully considered in all anaerobic digestion installations.

5.4. Aquaponics and Integrated Systems

Aquaponics combines aquaculture (fish farming) with hydroponics (soilless plant cultivation) to create a symbiotic system where waste produced by fish is used as a nutrient source for plants. In turn, the plants filter and purify the water, which is recirculated back to the fish tanks. This integrated system minimizes waste, conserves water, and maximizes resource use efficiency [16]. Integrated systems are used in aquaponics to improve water quality, adjust nutrient levels, and set environmental conditions to optimal values. Consequently, integrated systems contribute to the enhancement of aquaponic systems' productivity and sustainability.

5.5. Waste Minimization

Smart farming technologies contribute to the goal of minimizing waste in farming. These technologies enable farmers to apply inputs such as fertilizers, pesticides, and water precisely where and when they are needed, reducing over-application and runoff. For instance, VRT allows for the site-specific management of inputs based on soil and crop variability, ensuring the optimal use of resources and minimizing environmental impact [90]. Remote-sensing technologies, including drones and satellite imagery, provide detailed, real-time insights into crop health and soil conditions. These insights enable targeted interventions that reduce input waste and improve crop yields [91].

5.6. Biotechnology and Waste Valorization

Biotechnology is a key driver of the valorization of waste produced in various phases of the agricultural production cycle into products of high value, thus playing a crucial role in zero waste agriculture. Biofuels, bio-based chemicals, and biodegradable plastics are produced from agricultural remains using biotechnological techniques such as enzymatic hydrolysis and fermentation. For instance, microbial fermentation processes are applied to lignocellulosic biomass from crop residues to produce bioethanol [92]. Waste valorization achieves a three-fold goal to (a) reduce waste, (b) create useful (by-)products, and (c) create additional income for agrarians.

5.7. IoT and Sensor Technologies

IoT and sensors enable the monitoring and control of agricultural processes in real time, improving their efficiency and minimizing waste production. For example, precision irrigation systems source data from soil moisture sensors and compute the exact amount of water to be delivered, reducing the waste of water and preventing soil degradation [36]. Similarly, sensors are used to monitor environmental conditions that affect plants, including humidity, temperature, and air quality. These data are then used for decision-making in agricultural processes, such as irrigation or temperature and air conditioning, ensuring optimal growing conditions and minimizing resource use. IoT sensors are also used in inventory tracking and merchandise condition monitoring, supporting farmers in managing inputs more effectively, reducing waste and losses [93,94].

5.8. Nutrient Recycling and Recovery

Waste produced during various processes contains considerable amounts of nutrients. Nutrient recycling and recovery technologies allow for capturing these nutrients and further exploiting them in plant cultivation activities, such as fertilization, closing the nutrient loop, minimizing waste production, and reducing the need for use of synthetic fertilizers. Current developments allow for the production of fertilizers that are environmentally safe and rich in nutrients by capturing nutrients from human and animal waste [95]. Nutrient recycling and recovery technologies are an important means of achieving sustainable nutrient management since they considerably reduce the environmental impact related to the essential goals of soil fertility enhancement and crop production support.

5.9. Automated Farming Systems

Robotics and AI systems are increasingly integrated into automated farming systems, increasing the efficiency of plant cultivation operations and reducing labor costs. Automated farming systems currently support a number of farming tasks, including planting, weeding, irrigation, and harvesting, delivering elevated precision and efficiency and, in parallel, minimizing waste and plant damage [96]. Automated farming systems obtain data from a wide and diverse range of sources, including imagery, hyperspectral sensors, climate-related sensing devices, etc., to drive and optimize farming practices, minimize the use of resources, and increase crop yield quantity and quality. For instance, plant disease management systems exploit imagery and weather data to detect or forecast disease outbreaks, and appropriately recommend plant protection applications in a timely and efficient fashion, enhancing productivity and reducing both waste and environmental impact [97].

5.10. Renewable Energy Systems

Farmers are increasingly installing and using renewable energy systems such as wind power converters and solar cells. The energy harvested from these systems is then used in agricultural processes, leading to reduced costs, a decreased use of fossil fuels, smaller carbon footprints, and increased sustainability [98]. However, to fully realize the benefits, these systems need to be connected to the grid or energy storage, which significantly increases costs and can increase the carbon footprint due to the materials required. Nevertheless, these systems remain critical for the transition to sustainable agriculture, especially when combined with practices that optimize their use. For instance, solar power-driven irrigation systems achieve improved efficiency and sustainability for water management in agriculture [99–101]. Furthermore, [102] reports on the use of biomass to provide power for dryers, while [103] provides a survey on the use of renewable energy in agriculture.

5.11. Circular Economy and Resource Recovery

The circular economy is an indispensable part of zero waste agriculture, underpinning the recovery of waste materials and their use as inputs in other processes, either within the agricultural production cycle (e.g., using waste as fertilizers [104]) or outside the agricultural sector (e.g., using biomass from waste to produce biofuel [105]).

5.12. Challenges and Future Prospects

Implementing new technologies in zero waste agriculture presents several challenges, including high initial investment costs, technological complexity, and the need for farmer education and training. However, ongoing research and development are making these technologies more affordable, user-friendly, and accessible. As the awareness of sustainability issues grows and supportive policies are adopted, the uptake of advanced technologies in zero waste agriculture is expected to increase, contributing to a more resilient and environmentally friendly food system.

Future directions for zero waste agriculture involve the continued integration of emerging technologies, such as blockchain for supply chain transparency, advanced genetic engineering for waste reduction, and enhanced data analytics for better decision-making. Blockchain technology can enhance transparency and traceability in agricultural supply chains by securely recording every transaction and the movement of goods in an immutable ledger. However, the benefits of blockchain depend on reliable data entry and system integration. For example, IoT sensors need to record data at every stage, such as harvest, transport, and storage, to ensure accurate records. In addition, management protocols are needed to address challenges such as product mix-ups or segregation. Collaborative efforts between researchers, policymakers, and farmers will be crucial in overcoming challenges and driving the widespread adoption of zero waste practices.

6. Precision Livestock Farming: Harnessing Advanced Technologies for Sustainable Animal Husbandry

Precision livestock farming (PLF) is an innovative approach that leverages advanced technologies to enhance the management, welfare, and productivity of livestock. By integrating IoT devices, AI, and other emerging technologies, PLF aims to optimize resource use, improve animal health, and reduce the environmental impact of livestock farming. This analysis elaborates on the key technologies and their applications in precision livestock farming, highlighting their benefits and challenges (Figure 6).

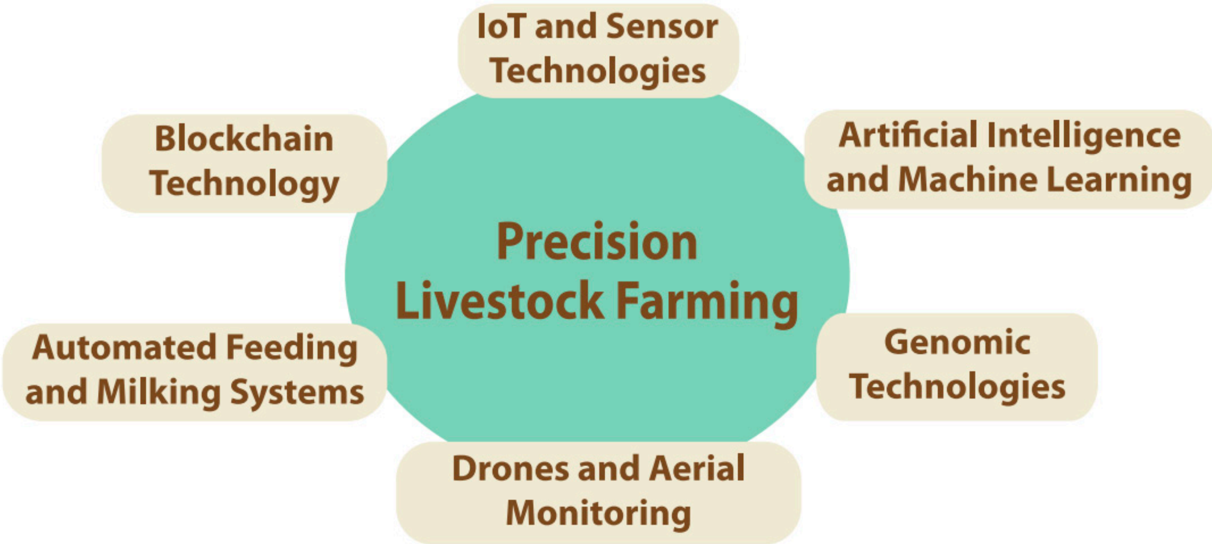

Figure 6. Technologies of precision livestock farming.

6.1. IoT and Sensor Technologies

IoT and sensor technologies are important drivers for the realization of PLF, supporting the real-time monitoring and collection of data regarding a multitude of aspects of (a) animal health and (b) environmental conditions. Sensors are either placed in the animals' environment or attached to animals and continuously monitor a wide range of parameters including body temperature, feed intake, movement, and heart rate. Environmental sensors are typically placed in the animals' environment and provide measurements on parameters such as temperature, humidity, air pollutants, and air quality in barns. The data are then analyzed and the necessary actions for achieving optimal living conditions are determined. The execution of these actions ensures optimal living conditions, which in turn reduces the risk of disease outbreaks [106]. Wearable sensors allow for monitoring the animals' location as well as their physiological measurements, enabling the detection of illness or stress indications, which are then used to determine and execute suitable and timely interventions [107].

6.2. Artificial Intelligence and Machine Learning

IoT and sensor technologies generate vast amounts of data, which can then be processed by AI and ML algorithms. These technologies can identify patterns, trends, and anomalies in their input data, which can be correlated to the animals' health (e.g., early signs of diseases), needs (e.g., feeding times), behavior (e.g., monitoring poultry movement to provide the optimal time of ranging [108]), therefore enabling farmers to take appropriate actions in a timely fashion. Additionally, AI algorithms can supply farmers with predictive analytics. AI-powered systems can also be used in resource-usage optimization, in conjunction with the abovementioned goals, allowing the formulation of optimal feeding strategies through the analysis of feed intake and growth rate data, ensuring both the minimization of food waste and the intake of the appropriate amount of nutrients [109]. Animal reproduction is an additional area for the application of AI and ML algorithms, where these technologies can predict reproductive events and enable the detailed monitoring of pregnancy status, improving breeding efficiency, minimizing the overall risk in the reproduction process and leading to improved results [110].

AI and ML algorithms can also be exploited to promote environmental comfort and animal welfare. Morgan-Davies et al. [111] identify more than 80 separate livestock welfare concerns that are reported by farmers, classifying them under four broad categories (nutrition, health, environment, and behavioral interactions), linking each concern to measurable indicators—which can be obtained via technological means—and assessing the suitability of different technologies to obtain measurements. Once adequate volumes of labeled measurements have been obtained, ML models can be built; these models can then be exploited to classify new measurements into positive or negative welfare classes and provide farmers with timely and accurate information regarding the welfare of animals—recommending actions for restoring welfare, where appropriate.

Nevertheless, the application of AI and ML algorithms for improving production, optimizing resource utilization, or ensuring animal welfare entails several challenges. Firstly, a number of studies have asserted a high diversity in species, animal husbandry environments, and individual behavioral traits for animals, including feeding and drinking behavior [107,112]. Under this setting, devices that are suitable for some specific species or breeds may be inappropriate for others, leading to suboptimal performance or physical discomfort or harm [112,113]. Researchers have also expressed concerns that the use of technology needed to obtain the data that drive AI algorithms may lead to arrangements that demote animal welfare, e.g., prolonging hours under lighting to facilitate image/video capture by cameras [113,114]. In this context, legislation needs to be modernized to take into account recent technological developments, assisting farmers to take all necessary measures to comply with ethical standards. The European Commission has announced the modernization of animal welfare legislation, which dates back to 1998 (Council Directive 98/58/EC); however, so far only partial improvements have been made, such as the COM/2023/770 final proposal for a regulation on the protection of animals during transport and related operations [115].

At the technological level, species and breed diversity pose the need for specialized models to best fit the characteristics of each particular breed, while individualized behavioral traits entail the risk of failing to correctly classify measurements obtained from specific animals since these may not fit the patterns recorded in the models. To address these challenges, transfer learning [116] can be employed to allow the use of models created for particular breeds/contexts for other breeds/contexts, while techniques for tackling overfitting [117] can be employed to improve the performance concerning the correct classification of new data.

6.3. Automated Feeding and Milking Systems

Automated feeding systems are used to provide livestock with precise quantities of food, taking into account the individual needs of animals. Rations delivered to animals are adjusted dynamically, both in terms of nutrient mixture and quantity, achieving optimal nutrition delivery and minimizing food waste [118,119]. Automated milking systems are used to automate the milking process, improving the quality of the milk and the efficiency of the production procedure. In addition to these benefits, automated milking systems can analyze milk composition and flow patterns to detect early symptoms of mastitis, a disease commonly occurring in dairy cows [120].

6.4. Drones and Aerial Monitoring

Drones are increasingly used in livestock management to provide information about the location of livestock, monitor their movement, and assess the quality of grassland. Additionally, exceptional conditions such as injury of animals can be detected. This is accomplished by obtaining visual or thermal imagery from cameras mounted on the drones, and then processing the images using AI algorithms [121]. Drones provide an aerial, bird's-eye view of the fields, aiding farmers to manage their herds in a more efficient manner; this is especially important for large herds and/or extensive grazing lands [122]. Thermal imaging may also be used to detect heat stress in animals to warrant timely interventions to ensure animal welfare [123].

6.5. Blockchain Technology

Blockchain technology, due to the distributed and secure nature of data management it provides, can enhance transparency and traceability in the livestock supply chain. By recording every transaction and movement of livestock on a decentralized ledger, blockchain ensures the authenticity of information related to animal origins, health records, and treatment histories. However, the benefits of blockchain depend on the accuracy of the data entered into the system, which requires reliable data collection methods—such as IoT sensors or other monitoring technologies—at every stage of the supply chain; this also extends to the cooperation of third parties involved in the livestock management, such as veterinarians and certification agencies. Ensuring data transparency, verifiability, and immutability through the use of blockchain promotes trust and enables fraud detection and combating [9–11], while it additionally facilitates compliance with regulatory standards [124]. Moreover, blockchain can underpin the certification processes for organic and animal welfare standards, reducing administrative burdens on farmers [125].

6.6. Genomic Technologies

Advancements in genomic technologies allow for the genetic screening and selection of livestock with desirable characteristics, such as resistance to specific diseases, increased growth rates in relation to the particular conditions in a specific location, and enhanced reproductive performance. By integrating genomic data with PLF systems, farmers can make informed decisions regarding the breeding of livestock, enhancing herd health and productivity. Techniques like Clustered Regularly Interspaced Short Palindromic Repeats (CRISPR) gene editing offer great potential for developing livestock with improved traits, although ethical, biodiversity, and regulatory considerations are raised and require addressing [126]. Genomic information also supports precision medicine approaches, where treatments and interventions are tailored to the genetic profile of individual animals [127].

6.7. Environmental Monitoring and Management

PLF technologies contribute to environmental sustainability by optimizing resource use and minimizing waste. IoT sensors and AI systems can manage manure disposal, reducing the environmental impact of livestock farming. Manure management systems can monitor waste production and nutrient content, enabling the efficient use of manure as fertilizer, thus promoting the circular economy and reducing the risk of water pollution [128]. Animal waste can also be utilized for the production of energy [129], contributing to the reduction in environmental pollution from waste disposal and limiting dependency on fossil fuels.

6.8. Challenges and Future Directions

While PLF offers numerous benefits, it also presents challenges including (a) high initial investment costs, (b) data management complexities, and (c) the need for farmer education and training. Ensuring data security and privacy is another critical concern, given the sensitive nature of health and operational data collected from farms [17,130]. However, ongoing advancements in technology, increased computer literacy, and decreasing costs are making PLF more accessible to farmers of all scales.

Future directions for PLF include the integration of advanced robotics, enhanced data analytics, and the development of more sophisticated AI models. These AI models could be used to predict diseases, detect abnormalities in animal behavior, optimize nutrition tailored to the specific needs of each animal, and automate complex decision-making processes such as resource management and production planning [131]. For instance, sophisticated AI models could simulate the entire livestock breeding ecosystem, helping predict the cascading effects of environmental changes or conservation interventions. Collaborative efforts between researchers, technology developers, and farmers will be essential to address challenges and drive innovation in this field. By embracing these technologies, the livestock industry can achieve higher levels of sustainability, animal welfare, and productivity.

7. Smart Greenhouses: Integrating Advanced Technologies for Sustainable Crop Production

Smart greenhouses are a significant advancement in agricultural technology, leveraging the IoT, AI, and various other emerging technologies to create optimal growing conditions for crops. These high-tech environments enhance resource use efficiency, improve crop yields, and contribute to sustainable agricultural practices. This section explores the key technologies involved in smart greenhouses, their applications, and the benefits they offer (Figure 7).

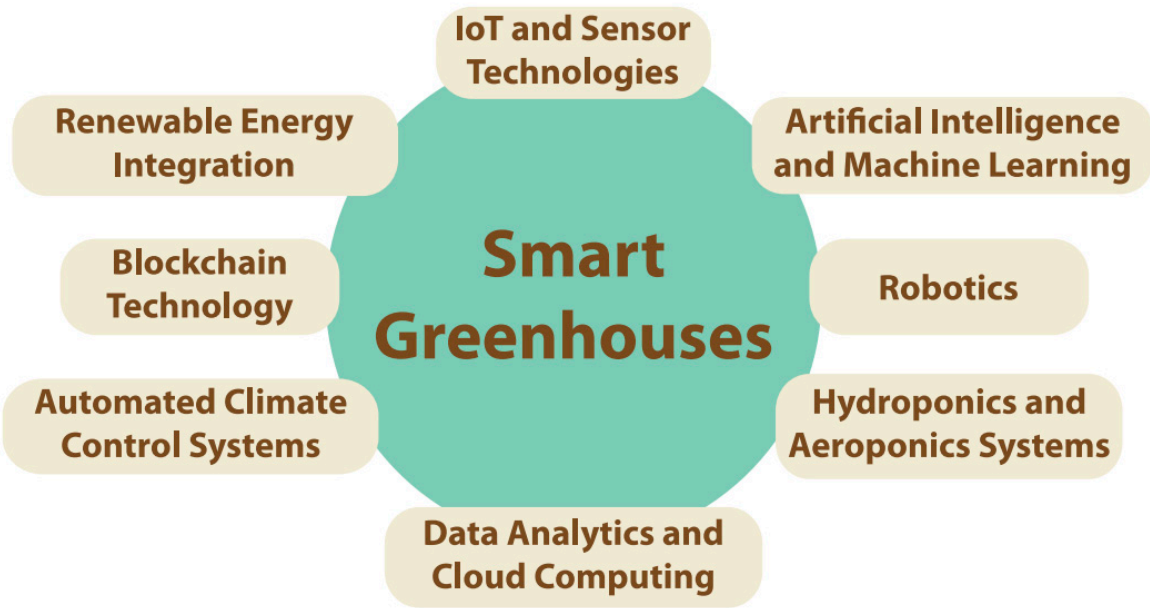

Figure 7. Technologies and sectors of smart greenhouses.

7.1. IoT and Sensor Technologies

IoT and sensor technologies form the backbone of smart greenhouses, providing continuous monitoring and control of environmental conditions, thus contributing to the key goal of greenhouses. Sensors measure the parameters such as temperature, humidity, soil moisture, light intensity, and CO_2 levels. The data are transmitted in real time to a central system that arranges for adjusting the greenhouse environment accordingly. For example, soil moisture sensors can trigger automated irrigation systems to maintain optimal soil moisture levels, reduce water usage, and prevent over-irrigation [96,132].

7.2. Artificial Intelligence and Machine Learning

AI and ML algorithms analyze the data collected by IoT sensors to optimize greenhouse management. Optimization spans across multiple areas of greenhouse management, including the prediction of crop growth patterns, early disease detection, and recommendations on adjustments to environmental conditions. ML models can process historical data to identify the optimal growing conditions for specific plant types, contributing to the enhancement of productivity and elevating resource usage efficiency [44,45]. AI-based systems can also be used for the formulation of optimal lighting schedules in greenhouses with LED grow light installations, delivering the required amount of light to the plants at the right times [133].

7.3. Automated Climate Control Systems

Maintenance of optimal growing conditions is a key goal for greenhouses. Automated climate control systems are a critical enabler toward the attainment of this goal. Automated climate control systems exploit the data sourced from IoT sensors to determine deviations from optimal temperature, air quality, lighting, and other environmental parameters, and make the necessary adjustments in real time. For instance, if data provided from lighting sensors indicate over-exposure to direct sunlight, automated shading systems can be triggered to block sunlight inflow [134–136].

7.4. Hydroponics and Aeroponics Systems

Smart greenhouses often use hydroponics and aeroponics systems, which are soilless farming techniques where plants grow in nutrient-rich solutions or mist environments. These systems enable the delivery of nutrients to plants with elevated precision and control. In hydroponics, IoT sensors can be used to monitor the pH of the solution and its nutrient content in real time, allowing for timely and accurate interventions to ensure that plants grow under optimal conditions and are fed with the correct mix and amount of nutrients [137]. Similarly in aeroponic systems, the fine mist composition can be monitored and precisely controlled to provide optimal growing conditions, improve nutrient uptake efficiency, and minimize resource usage [64,138].

7.5. Renewable Energy Integration

Smart greenhouses need considerable amounts of energy to drive environmental condition-regulation systems, including lighting, heating, and cooling systems. The energy needed for these systems can be harvested from renewable energy sources, such as solar panels and wind turbines, leading to a reduction in reliance on fossil fuels [139] and the lowering of operational costs and carbon footprint. The energy harvested from these systems during peak production hours (plentiful sunlight or strong wind) can be saved in energy storage systems, such as batteries, to cater for energy provision in periods where energy inflow from renewable sources is not adequate [140,141]. The use of renewable energy promotes the goals of sustainability and environmental friendliness of smart greenhouses.

7.6. Robotics

Robotics are an important enabler concerning the automation and efficiency of tasks in smart greenhouses. Robotics systems are used in the final link of the "sense–decide–act" chain [142], executing actions that are taken after collecting data from sensors and processing them using AI systems to make informed decisions on different smart greenhouse tasks, including irrigation, fertilization, plant protection, and pest control. Robotics can also be used to automate repetitive and labor-prone tasks, such as planting, pruning, and harvesting, leading to labor cost reduction and increased precision. For instance, robotic systems driven by AI algorithms can identify and harvest ripe products with high accuracy [143,144].

7.7. Data Analytics and Cloud Computing

Data analytics include algorithms that process the data concerning the smart greenhouse operation, identifying trends and patterns in crop growth, the usage of resources, as well as environmental conditions and their effect on plants to produce meaningful insights, enabling data-driven decision-making. Cloud computing offers the necessary infrastructure for the storage, management, and processing of these data, providing a centralized interface through which farmers may monitor and manage the smart greenhouse operation without time or location restrictions [145,146]. Cloud infrastructure eases the financial, technical, and administrative burden for farmers since it has proven to be less costly than privately owned infrastructure; additionally, the infrastructure management, maintenance, and support tasks are offloaded to the cloud provider [147].

7.8. Blockchain Technology

Blockchain technology provides an infrastructure for storing information in a secure way, enhancing transparency, trust, and traceability in smart greenhouse operations. Data and information are organized in transactions that are stored on a decentralized ledger. Blockchain ensures that all information related to crop production, such as seed origin, growth conditions, and harvest dates, is securely documented. This transparency strengthens consumer trust and underpins compliance with regulations and standards on food safety and quality. It is worth noting that blockchain technologies can be utilized across all stages of the smart greenhouse value cycle, including cultivation, harvesting, post-harvesting processing, and logistics, providing a tamper-proof record of the entire process from the field to the end-consumer [148,149].

7.9. Environmental and Economic Benefits

The adoption and use of AI and related technologies in smart greenhouses offers significant environmental and economic benefits. By optimizing resource use, smart greenhouses can reduce water and energy consumption, minimize the use of chemical fertilizers and pesticides, and lower greenhouse gas emissions. These gains not only contribute to environmental sustainability but also reduce operational costs, increasing the viability of greenhouse farming. Furthermore, the integration of these technologies in smart greenhouses increases the ability to produce larger quantities and higher-quality crops in controlled environments throughout the year, enhancing food security and reducing dependence on seasonal and imported produce [14,150].

7.10. Challenges and Future Directions

Despite the numerous benefits, the implementation of smart greenhouse technologies presents challenges such as high initial investment costs, technical complexity, and the need for specialized knowledge and training. Ensuring data security and privacy is also a critical concern, given the extensive use of IoT devices and cloud computing. However, advancements in technology and decreasing costs are making smart greenhouses more accessible to farmers. Moreover, government and institutional initiatives—such as the National e-Governance Plan in Agriculture (NeGPA) in India [151] as well as the World Bank Group's Climate Change Action Plan (2021–2025) [152]—can assist in overcoming financial barriers for the adoption of advanced technologies in precision agriculture.

8. Regenerative Agriculture: Leveraging Advanced Technologies for Sustainable Soil Health and Ecosystem Restoration

Regenerative agriculture is a holistic approach to farming that aims to restore soil health, enhance biodiversity, minimize carbon footprint, and improve ecosystem resilience. By integrating advanced technologies, such as the IoT, AI, drones, and blockchain, regenerative agriculture can be more effectively implemented, monitored, and managed. This section explores the use of these technologies in regenerative agricultural practices, highlighting their benefits, applications, and future prospects (Figure 8).

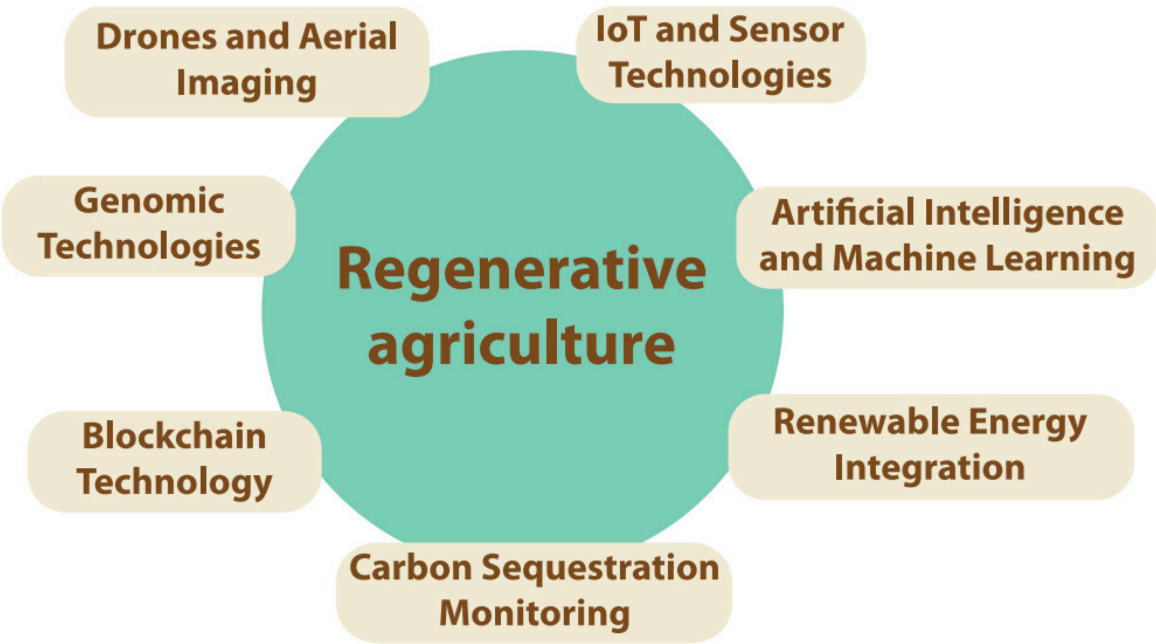

Figure 8. Technologies and sectors of regenerative agriculture.

8.1. IoT and Sensor Technologies

IoT and sensor technologies are pivotal in monitoring soil health and environmental conditions in real time. Sensors placed in the soil can measure parameters such as moisture levels, nutrient content, pH, and temperature. These parameters can be exploited to monitor and manage soil health, ensuring optimal conditions for plant growth. For example, measuring soil moisture through sensors can provide the necessary information for automated irrigation systems to supply the appropriate amount of water, saving resources and avoiding over-irrigation [153]. Equally, hyperspectral nutrient sensors can provide measurements concerning the amount of nutrients in the soil, which can be used to guide the fertilization process, ensuring the sufficiency of nutrients and preventing over-application [154].

8.2. Artificial Intelligence and Machine Learning

AI and ML are key enablers for the transformation of farming processes, playing a crucial role in the usage and analysis of agricultural data. AI and ML techniques process data streams acquired from different sources such as IoT sensors, satellites, and drones and output predictions, recommendations, and actionable insights. Examples include the recommendation of crop rotations to maximize the benefits of regenerative agriculture, or the application of cover cropping to prevent soil erosion and reduce tillage [155]. ML models process both repositories of historical and streams of real-time data to recommend the best-suited regenerative agriculture practices for specific fields and cultivations, improving overall farm management [156]. AI-driven decision support systems can also aid farmers to reduce labor costs and minimize resources needed for their farms through recommending appropriate regenerative practices to be used and/or providing consultation to farmers on how specific practices should be applied [157,158].

8.3. Drones and Aerial Imaging

Drones equipped with high-resolution cameras can provide detailed visual aerial imagery of fields. Similarly, other drone-mounted equipment, such as multispectral cameras, can be used to obtain aerial imagery of fields outside the visual spectrum, which conveys information about multiple aspects of the cultivation including nutrient levels, fruit ripeness, etc. Aerial imaging is important since it can reveal patterns that are not visible from the ground level, facilitating the detection of pest infestations, soil erosion, or nutrient deficiencies. When the analysis of drone-sourced data manifests the presence of a condition, farmers can plan and implement appropriate interventions, including the application of cover cropping to erosion-prone areas, or the application of organic amendments to areas with low soil fertility [159]. Aerial imagery can also be used to assess the effectiveness of regenerative practices in longitudinal studies, documenting visual evidence of the improvements in soil health and the resilience of crops [160].

8.4. Blockchain Technology

Blockchain technology enhances transparency and traceability in regenerative agriculture. By recording every step of the farming process on a decentralized ledger, blockchain ensures that all information related to soil management, crop production, and carbon sequestration is documented and stored securely in a tamper-proof fashion. This transparency builds consumer trust and facilitates compliance with organic and regenerative certifications [160,161]. It is worth noting that blockchain technologies can be utilized across all stages of the regenerative agriculture value cycle, including planning, cultivation, harvesting, post-harvesting processing, and logistics, providing a tamper-proof record of the entire process from the field to the end-consumer [148,149].

8.5. Renewable Energy Integration

Integrating renewable energy sources into regenerative agriculture operations reduces the environmental footprint and enhances sustainability. Solar panels, wind turbines, and biogas systems can power farm equipment, irrigation systems, and processing facilities, reducing reliance on fossil fuels [139]. Renewable energy systems can be monitored and managed using the IoT and AI technologies, ensuring optimal performance and efficiency. By combining renewable energy with regenerative practices, farms can achieve a higher level of sustainability and resilience [162].

8.6. Genomic Technologies

Genomic technologies enable the selection and breeding of crops that are well-suited to regenerative practices and local conditions. These technologies are used to analyze the genetic profiles of crop varieties, assisting farmers in identifying those varieties that have traits that contribute to soil health and ecosystem resilience [163]. These traits include, among others, deep root systems, drought resistance, and nutrient efficiency. Genomic technologies are also used in the process of developing new crop varieties through plant breeding or through advanced techniques such as CRISPR and other gene-editing tools, enhancing the effectiveness of regenerative agriculture [164].

8.7. Carbon Sequestration Monitoring

Carbon sequestration is a key goal of regenerative agriculture. To this end, carbon levels in soil are monitored and verified using advanced technologies. More specifically, IoT sensors and remote-sensing technologies are used to quantify the carbon content. These measurements are stored to allow for the tracking of level changes along the time axis. These data, combined with tags concerning the regenerative practices used in specific areas, are fed to AI algorithms to estimate the amount of carbon sequestration achieved by different regenerative practices, providing important insights that can be exploited in climate mitigation efforts [165]. Both the data gathered throughout the monitoring process and the insights computed can be stored using blockchain technologies, providing guarantees for the integrity of data, and supporting transparency and verifiability of records associated with carbon-sequestration activities [166].

8.8. Environmental and Economic Benefits

The integration of advanced technologies in regenerative agriculture offers significant environmental and economic benefits. By restoring soil health and enhancing biodiversity, regenerative practices improve ecosystem services, such as water filtration, pest control, and pollination. These improvements contribute to greater resilience against climate change and extreme weather events [23]. Economically, regenerative agriculture can reduce input costs by minimizing the need for synthetic fertilizers and pesticides, while potentially increasing yields and market value through improved soil health and crop quality [167].

8.9. Challenges and Future Directions

Despite the numerous benefits, the implementation of regenerative agriculture technologies presents challenges such as high initial investment costs, technical complexity, and the need for farmer education and training. Ensuring data security and privacy is also a critical concern, given the extensive use of IoT devices and blockchain technology [17,168]. However, ongoing advancements in technology and decreasing costs are making regenerative agriculture more accessible to farmers.

9. Discussion

Incorporating advanced technologies into modern farming practices is proving to be vital in transforming the agricultural sector into a more productive, sustainable, and resilient one. Examining the applications and impacts of these technologies across a range of areas within the agricultural sector—including smart open field farming, vertical and indoor farming, zero waste farming, precision farming, smart greenhouses, and regenerative agriculture—it is established that innovations, such as AI, the IoT, and sensors but also data analytics, big data, drones, and blockchain are revolutionizing traditional agricultural practices. Figure 9 illustrates the linkage between areas of the agricultural sector and advanced technologies.

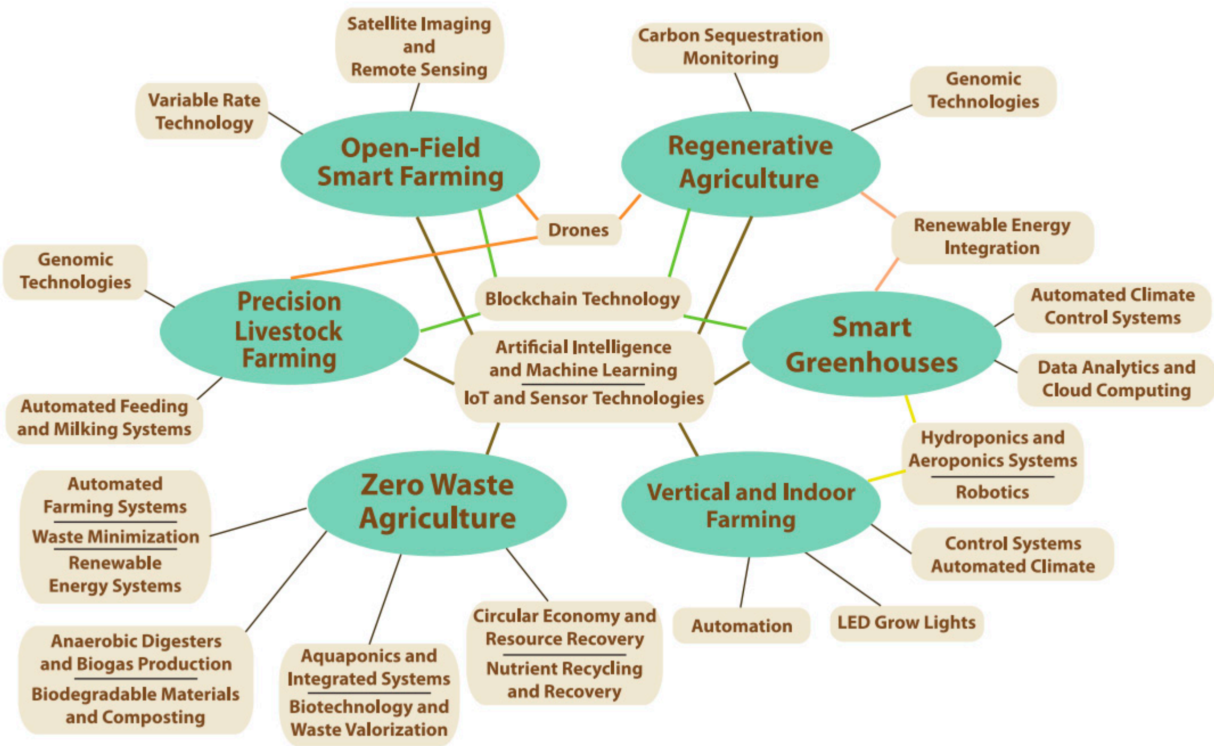

Figure 9. Use of state-of-the-art technologies in areas of precision farming.

The necessity of developing and applying these technologies and, additionally, the necessity of integrating AI and ML algorithms—as well as IoT systems—in all branches of agriculture is underlined by the answers given to the critical scientific questions posed and analyzed in this study. These highlight the significant contribution of these innovations to the agricultural sector. It is established that the incorporation of these technologies can transform the way crops are grown, monitored, and managed, leading to increased production, reduced resource usage and waste, and greater sustainability.

AI and ML algorithms can analyze large datasets to predict weather conditions, soil moisture, and other important factors that affect plant growth. These forecasts can help farmers adjust their cropping practices and avoid losses. Ground-mounted IoT sensors can collect data regarding soil conditions, including moisture, temperature, and conductivity. These data can be analyzed by AI algorithms to determine the exact amount of water and other nutrients the crop needs, thereby reducing the environmental footprint of agriculture. The analysis can be extended to include data obtained from additional sources, such as sensors, satellites, and historical data, to optimize production and maximize profits. Images from drones or sensors can be analyzed by deep learning algorithms to detect early signs of disease and pests in plants, allowing farmers to take the necessary steps to tackle the problem before it spreads. Robots and autonomous vehicles can perform a number of tasks such as sowing, fertilizing, and harvesting with greater precision and efficiency than humans.

The application of AI and new technologies, such as the IoT and robotics, can bring significant benefits to vertical and indoor farming techniques. These technologies help improve productivity as AI can control and optimize factors such as light, temperature, and humidity, enabling greater yields with reduced resource consumption. At the same time, the consumption of water and pesticides is reduced since indoor crops in a controlled environment are more efficient and protect plants from pests and diseases. Robotics and the IoT help reduce the need for human labor, while the ability to monitor crops in real time ensures more accurate decisions. Vertical cultivation, in addition to saving space and the possibility of growing food in urban areas, allows for a reduction in transport costs and the environmental footprint. However, the use of these technologies is associated with a number of challenges. The initial cost for investing in AI, the IoT, and robotics equipment is high, which can be a barrier for smaller producers. In addition, energy requirements are high, particularly for lighting and maintaining climate control. The security of the data collected through sensors is also an important issue as it is necessary to ensure that they are protected from cyber-attacks. Therefore, the balance between the benefits and challenges for the sustainable development of vertical and indoor cultivation with the help of AI and new technologies is critical.

In the development of zero waste agriculture, AI and ML, the IoT, and new technologies in general can contribute to reducing waste, promoting more sustainable agricultural practices, and reducing the environmental footprint of agriculture. Thanks to AI, the analysis of big data obtained from IoT systems and intelligent algorithms allows for the optimal use of resources, reducing the overconsumption of water, fertilizers, and energy. For example, AI can predict crop needs in real time, ensuring the accurate application of fertilizers and nutrients, which reduces losses and waste while helping to manage resources properly. Additionally, automation technologies, such as robotics, can manage crop harvesting and processing with minimal waste. Robotic solutions are able to separate products and waste more efficiently, allowing for the reuse or recycling of biological materials, e.g., for composting or energy production. The integration of the circular economy into zero waste agriculture is also enhanced by these technologies as production residues can be used in other processes or transformed into new products, reducing the ecological footprint of agriculture. Despite the significant potential of these technologies, challenges also appear, of course, such as the cost of implementation and the need for specialized personnel to manage the systems. The integration of AI and IoT systems into traditional agricultural units requires time and investments in training and infrastructure. The energy required by these technologies, particularly in areas with limited access to renewable energy sources, may also increase the environmental footprint, although renewable energy sources could mitigate this problem.

AI, ML, and new technologies can also play a decisive role in improving animal health and productivity. AI, through the analysis of real-time data obtained from the use of IoT technologies and wearable devices such as biosensors, enables the accurate monitoring of animal health, alerting farmers to potential health problems in a timely fashion, allowing for suitable interventions. Early disease detection and diagnosis reduce the need for massive antibiotic use and improve animal welfare. ML can analyze high data volumes coming from animals and their environment using advanced algorithms. This allows their diet to be predicted and optimized, ensuring that each animal receives the nutrients exactly corresponding to its individual needs. Thus, productivity increases as animals grow faster and healthier. In addition, automation technologies such as automatic feeding systems can more effectively manage animal nutrition and living conditions, reducing waste and improving production efficiency. These systems can adjust the amounts of food according to the needs of the animal, ensuring optimal results and minimizing costs. However, using these technologies in livestock farming is also associated with implementation challenges, as outlined below:

(a) The installation and maintenance costs of AI and IoT systems can be high, especially for smaller farmers;
(b) Data analysis requires specialized knowledge;
(c) Increasing the need for trained personnel and data security is a critical aspect as the collection and storage of vital personal animal information could be vulnerable to cyber-attacks.

New technologies for smart greenhouses, such as AI, ML, and the IoT, lead to enhanced crop production, optimized growing conditions, and increased efficiency. AI is used to monitor and analyze environmental conditions inside the greenhouse, such as temperature, humidity, and light. These data are collected by IoT systems. AI can be used on the data to automatically adjust heating, lighting, and irrigation systems, ensuring optimal conditions for plant growth and reducing the waste of resources, such as water and energy. ML algorithms can predict plant growth, detect problems—such as nutrient deficiencies or disease occurrence at early stages—and recommend corrective measures before problems have an impact on production. This allows producers to make more targeted decisions, reducing the risk of crop loss and improving product quality. At the same time, automated irrigation and fertilization systems, based on data from sensors, ensure that plants receive exactly the amount of water and nutrients they need, without excess. Saving resources and reducing energy consumption contribute to the sustainability of production. In addition, smart systems allow the cultivation of plants, regardless of the season, providing constant production throughout the year while reducing the dependence on climatic conditions.

Regenerative agriculture practices can be significantly improved using AI, ML, and other new technologies, enhancing processes efficiency and sustainability. AI can be used to analyze large amounts of data collected from soil, crops, and the environment, enabling the monitoring of soil health and optimal management of agricultural land. With the help of IoT sensors that monitor real-time indicators, such as moisture, organic matter content, and microbial activity, farmers can make data-driven decisions to regenerate the soil and increase its fertility. Through ML algorithms, farmers can predict soil and plant needs more accurately or when and how actions such as seeding, fertilization, or crop rotation should be conducted, ensuring that regenerative farming practices maximize organic matter restoration of the soil and reduce erosion. This helps restore soil health and absorb carbon dioxide from the atmosphere, thereby helping to reduce greenhouse gas emissions. At the same time, automation technologies can monitor and manage agricultural practices more precisely, allowing farmers to know when it is the right time for regenerative processes, such as covering the soil with plants or incorporating the right crops to enhance biodiversity. This allows for immediate adaptation to changes in environmental conditions, reducing resource wastage and ensuring that land is used in the most sustainable way. Moreover, the use of drones and satellite imagery can monitor vegetation and crop conditions on a large scale, allowing problems such as erosion or fertility loss to be detected earlier than with traditional methods.

To date, a number of publications have reported concrete results concerning the successful application of new technologies in the agricultural sector, strengthening the confidence of farmers in precision farming practices and promoting their adoption and take-up. In the following paragraphs, we briefly summarize a number of success stories; for more concrete examples, the interested reader may refer to [5,31].

- Artificial intelligence systems developed in Dutch greenhouses have been shown to reduce energy consumption by up to 15%, demonstrating the potential of artificial intelligence to contribute to more sustainable agricultural practices [169];
- Approximately 20–40% of crops are lost annually due to pests and diseases as a result of a lack of good monitoring of the condition of the crop [170]—a percentage that can be minimized by using IoT systems for real-time crop monitoring. An example of real-time disease detection in wheat fields, driven by AI, resulted in a 20% reduction in yield losses compared to traditional methods, highlighting the significant impact of AI in enhancing crop health and yield [171];
- IoT platform implementation is yielding significant positive results, such as the Agri-Talk IoT platform, which has led to a 40–60% increase in chlorophyll levels in turmeric plants, surpassing traditional cultivation methods. Furthermore, it enabled a remarkable 70% saving in water during the cultivation process. In particular, the adoption of the Agri-Talk IoT platform has proven to be economically rewarding. By investing USD 14,000 in the platform, farmers have generated USD 140,000 in revenue. This achievement highlights the economic viability and efficiency of the Agri-Talk IoT platform compared to conventional farming methods [31,172];
- The adoption of agricultural robots in the US, Europe, and many countries in Asia has expanded and improved the efficiency of agriculture as they have reduced operational costs and operating times [53]. In addition, they can reduce environmental pollution by up to 80% of pesticides. They are also practical tools to provide unconventional solutions for smart agriculture to address labor shortages, especially in the spread of diseases such as COVID-19. This result is due to the fact that many agricultural robots, such as robots for harvesting, seedlings, weed detection, irrigation and pest control, livestock applications, etc., can perform more than one function [173].

Adopting smart farming systems poses challenges, including learning new systems and dealing with setup costs. Strong support is crucial for integrating smart farming into practice. Understanding the current state of agriculture, technology trends, and challenges is essential for a smooth transition and acceptance of technology. Both large-scale and smallholder farmers are reluctant to undertake these costs without clear and comprehensive benefits and increased convenience. Also, to enhance technological receptivity within the agricultural sector, factors such as computer self-efficacy, computer anxiety (excessive anxiety related to computer use), and the age variable should be examined [31]. These factors are also underscored by the United Nations Development Programme [30], which refers to barriers due to a lack of digital infrastructure since more than 600 million people live in areas not covered by mobile networks; thus, the 2G connectivity that is essential for any precision agriculture application is not available, while a smaller percentage of farmers has no access to electricity.

Certainly, the support provided by each government to farmers, both financially and by providing appropriate education, should be intensified as we can see worldwide (Table 5) that several countries have adopted and developed smart agriculture systems but others have not taken steps in this direction.

Table 5. Classification table of countries according to geographical location, 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 on the development of governmental smart agriculture programs in countries of these categories.
Europe	Denmark Netherlands Sweden	As of the writing of this review, no reports were found on the development of governmental 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 on the development of governmental 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.	

The perception must be adopted that strengthening the agricultural sector in terms of the use of new technologies will help both in improving living conditions at an individual and broader social level as well as in the global effort to address the impacts of climate change. The following Table 4 classifies countries according to their geographical location and their level of development according to the International Monetary Fund in relation to lifetime income, which have or have not developed smart agriculture programs [31].

Considering the aspect of literacy and digital skills, the advent of generative AI can provide the tools for overcoming relevant barriers. Generative AI-based chatbots can be used to create natural language interfaces for precision agriculture systems, making them accessible to farmers with basic digital skills. For instance, Darli [174] is an AI-based chatbot aiming to provide small-scale farmers, especially in developing regions, with crop-specific guidance on farming practices, disease diagnosis, as well as market and logistics advice. Darli is available in 27 languages, facilitating communication with its users. The AI chatbot by Digital Green [175] follows a different model, addressing agricultural extension agents who are professionals providing training and information for farmers. Under this model, small-scale farmers resort to agricultural extension agents for instructions and advice, and agents employ the chatbot to formulate timely, accurate, and tailored advice to the requests they receive. This is particularly important in countries such as India, Kenya, and Ethiopia, where agents are few and the diversity of crops, conditions, and individual situations that need to be handled is significant.

Generative AI has the additional potential to deliver benefits for multiple stakeholders in the precision agriculture domain. In its 2024 report, Microsoft identified eight precision agriculture stakeholder classes (farmers; input providers/agronomists; consumers; retailers; food manufacturers/supply chain agents; bankers; policymakers; and researchers/data scientists), where each stakeholder may participate in multiple use cases [176], including decision-making for seeds, purchases, and management (farmers); purchasing decisions and sustainability (retailers); coordination with farmers on prices and food standards (food manufacturers/supply chain agents); and so forth. An example of generative AI application in the livestock management domain is the application provided by DataMars that helps farmers to better manage their animals, improving their welfare as well as their productivity while it additionally assists farm-supporting partners such as advisors and feed companies to meet sustainability targets [175]. Generative AI can also be used to support machine learning methods used in multiple precision agriculture domains, addressing the issue of data scarcity: indeed, in multiple areas of precision agriculture there is a shortage of labeled training data, inhibiting the creation of ML models. In this context, the potential of generative AI to process large amounts of unlabeled historical data together with small amounts of labeled data can be exploited, creating pipelines where generic patterns can be identified and accurate predictions can be made [177]. Moreover, generative AI can be used for the creation of synthetic training datasets, which can be used in the absence of real-world datasets [177].

Regenerative AI is a recently introduced term referring to systems that are able to generate new content, insights, or solutions autonomously [178]. In the context of precision agriculture, regenerative AI holds promise for novel applications spanning all stages of the agriculture value chain, including new research and development. The work in [178] highlights eight areas of precision farming where regenerative AI systems can play a significant role, outlined as follows: (i) precision farming and crop management; (ii) market forecasting and pricing; (iii) supply chain optimization; (iv) sustainability and regenerative agriculture; (v) risk management; (vi) smart contract generation and management; (vii) data-driven innovation; and (viii) consumer engagement and transparency. It is worth noting that while machine learning-based and generative AI-based applications already cover aspects of these areas, regenerative AI extends the potential of applications beyond the scope currently covered. For instance, in the area of crop management, regenerative AI can generate comprehensive, adaptive models for plant growth that take into account real-time data such as disease outbreaks, soil nutrient levels, and weather conditions, facilitating the formulation of optimized planting schedules. Additionally, in the sustainability area, regenerative AI can be used to promote biodiversity and ecosystem resilience through the development and simulation of scenarios that consider practices for soil health improvement, such as crop rotation and intercropping. For more information, the interested reader is referred to [178–180].

Overall, AI, ML, and new technologies can drastically improve regenerative agriculture practices, helping to restore soil health, increase productivity, and reduce environmental footprints. Despite the challenges, the use of these technologies—which are constantly evolving and their costs decreasing—enhances the sustainability and resilience of agricultural systems, supporting farmers to manage their arable land more effectively.

10. Conclusions

This study has conducted a comprehensive review of the integration of advanced technologies in the agricultural sector, including AI, the IoT, blockchain, and other emerging innovations. Toward this goal, this study has examined scientific works that were identified through a systematic search in scientific databases, considering additional seminal papers and practice reports. Through this process, this study has identified six areas of smart farming (open field smart farming, vertical and indoor farming, zero waste agriculture, precision livestock farming, smart greenhouses, and regenerative agriculture) and has surveyed within each of these the application fields of advanced technologies, as well as the benefits and challenges associated with the applications of these advanced technologies in each area. In parallel, this study has recorded data concerning the uptake and implementation of the smart agriculture model in the target areas.

In conclusion, the successful integration and increased take-up of AI, ML, and other state-of-the-art technologies is essential for the agricultural sector. Through the use of these innovations, farmers can achieve higher productivity, resilience, and sustainability while, at a more global scale, the overall security and sustainability of the food system can be enhanced.

The objective of this study is to conduct a comprehensive review of the integration of advanced technologies in the agricultural sector, including AI, the IoT, blockchain, and other emerging innovations. This study will reveal application areas of technologies in different fields of smart agriculture and provide insights into the current situation in the agricultural sector concerning the uptake and implementation of the smart agriculture model.

This paper is intended to serve as a reference for researchers and practitioners alike by synthesizing current research, technological developments, and case studies on agricultural practices across different precision farming sectors. It comprehensively overviews the benefits, challenges, and future perspectives of the broad integration of AI and ML, the IoT, drones, and blockchain in agriculture, offering insights into further research as well as practical applications. Through the identification of existing challenges and further needs, areas for future research and development in sustainable agriculture technologies are outlined, with many of them entailing interdisciplinary collaboration and innovation.

In addition, this paper examines critical global challenges, such as food security, environmental sustainability, and climate change. It highlights how advanced technologies can contribute to addressing these issues, providing a road map for researchers, policymakers, and practitioners to develop and implement effective strategies. Bridging the gap between technological innovation and practical application in agriculture, this manuscript supports the advancement of knowledge and the development of sustainable agricultural systems worldwide.

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