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Review

From field to data: A global review of precision agriculture for smart and sustainable farming systems

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Abstract: Precision agriculture (PA) utilizes advanced technological systems to enhance crop productivity and farm efficiency while minimizing negative ecological consequences. Contemporary agricultural challenges, including weeds, plant diseases, pest infestations, inefficient irrigation and soil management, and suboptimal crop practices, have resulted in significant yield losses and negative environmental impacts. These issues are compounded by the rising global demand for food, driven by population growth, and the finite availability of arable land. Addressing these complex problems requires innovative and adaptive solutions. PA offers a viable pathway forward, leveraging its core strengths of flexibility, accuracy, cost-efficiency, and enhanced operational effectiveness to transform production systems. In this article, we examined the convergence of advanced technological systems, such as artificial intelligence (AI), the Internet of Things (IoT), variable-rate application technologies, remote sensing, and Geographic Information Systems (GIS), to tackle the pressing agricultural constraints imposed by shrinking natural resources and rising global population demands. Additionally, we provided a review of the contemporary status of PA, encompassing recent technological advancements in unmanned aerial systems (drones), sensor networks, and machine learning (ML) applications. The scope for future innovation in this domain is extensive, heralding a transformative phase in agriculture characterized by heightened efficiency and sustainability, which is critical for ensuring global food security.

Keywords: precision farming; big data; artificial intelligence models; innovative and adaptive solutions; pest and disease management; weeds monitoring

1. Introduction

Precision agriculture (PA) is an agricultural management approach that integrates advanced technologies and data-driven information to monitor and manage spatial and temporal variability within farming systems [1–3]. With an estimated 9–10 billion people on the globe by 2050 [3–5], PA is gaining substantial importance in contemporary agricultural science. To meet future global demand, food output must expand by an estimated 70% before the year 2050 [1,5,6]. This is a challenging endeavor [4] because it further strains the environment and already limited resources [1–3]. PA is therefore necessary to ensure sustainability, minimize negative environmental effects, and increase output while employing less inputs of all kinds in more efficient methods [2,3]. Unpredictable variables, including fluctuating weather, heterogeneous soil properties, weeds, pest and diseases pressures, and evolving crop physiology, collectively shape the dynamic process of plant development and its eventual outcomes [7]. PA has emerged as a possible solution to the growing worldwide need for sustainable food production and the requirement for effective resource management. It was created in the middle of the 1980s with the goal of improving crop yield production and quality while lowering operating costs and minimizing environmental pollution [8]. The development of this approach originated with the integration of technologies such as yield monitors, geographic information systems (GIS), and global positioning systems (GPS) [9–11]. It later expanded to include the Internet of Things (IoT) [12,13] , big data analytics [14,15], and artificial intelligence (AI) [4,16,17]. These technologies function as data sources across the three primary stages of agricultural production [2,18,19]. By providing solutions to maximize inputs, boost output, and lessen environmental effect, these technology advancements are significantly contributing to the change of agricultural practices [20,21]. These cutting-edge technologies were incorporated into agriculture in 2017, changing PA to Agriculture 4.0, or smart farming [18,22]. The period beginning around 2011 marked the emergence of the Fourth Industrial Revolution, commonly termed Industry 4.0. This transformative phase is characterized by the convergence and integration of several foundational technologies, including the IoT, big data analytics, AI, advanced robotics, and blockchain [18,23].

IoT technology systems [24,25], cloud computing, wireless sensor networks, and the utilization of AI methods including machine learning (ML) [26,27] are some of these developments. The application of intelligent agricultural operations is facilitated by all of these developments [28]. The effectiveness of PA is increasingly dependent on the ability to define spatial variability and manage the issues that hinder crop growth due to the growing use of these cutting-edge technologies in agriculture [29,30].

Moreover, PA aims to improve resource utilization and reduce uncertainties related to tracking farm responses to temporal and spatial variations [31]. It includes a range of instruments and technology that help farmers make well-informed choices for the best possible resource management [32]. PA also aims to increase productivity and efficiency in farming methods by concentrating on the appropriate actions, in the appropriate area, at the appropriate time, and in the appropriate manner [33].

Srinivasan [34] distinguished PA from conventional farming by its foundation in precisely identifying in-field variability and linking spatial and temporal data to specific management actions. This paradigm enables farm management from a novel perspective, which can result in decreased operational costs, the optimization of yield and quality according to each site's potential, more efficient resource use, and enhanced environmental stewardship.

PA has the capacity to fundamentally reshape the agricultural sector, delivering substantial gains in economic returns, operational output, and ecological sustainability. Its positive influence further encompasses enhancements in produce standards, conservation practices, working conditions, supply chain security, and the vitality of farming communities [35,36]. Furthermore, the spatial and temporal analysis of farms, whether within contiguous regions or specific agro-ecological zones, can reveal regional trends in sustainability factors and guide the development of targeted solutions. The development of georeferenced datasets for individual fields across a region serves two primary analytical purposes: First, it facilitates a quantitative summary of the prevalence and intensity of both constraining and enabling factors affecting sustainability, within individual fields and across the broader landscape. Second, this spatial analysis enables the identification of the specific factors and system components that underpin the productive performance of each distinct cropping system [34]. Successful precision agricultural ideas and practical applications are examined throughout this review to learn more about their successes and difficulties. Our goal is to provide a thorough understanding of how PA may continuously grow to promote sustainable agricultural practices and meet global food security concerns by identifying future developments that are necessary. The future of PA and its beneficial effects on agriculture and society at large are highly promising due to the integration of scientific research and technological advancements. As depicted in Figure 1, while in Section 1 we provide an overview, in Section 2, we explain the methods and applications of PA. The Next Frontier of Sustainable Farming is covered in Section 3. The future is illustrated in Section 4. Finally, our conclusion on direction in precession agriculture is in section 5.

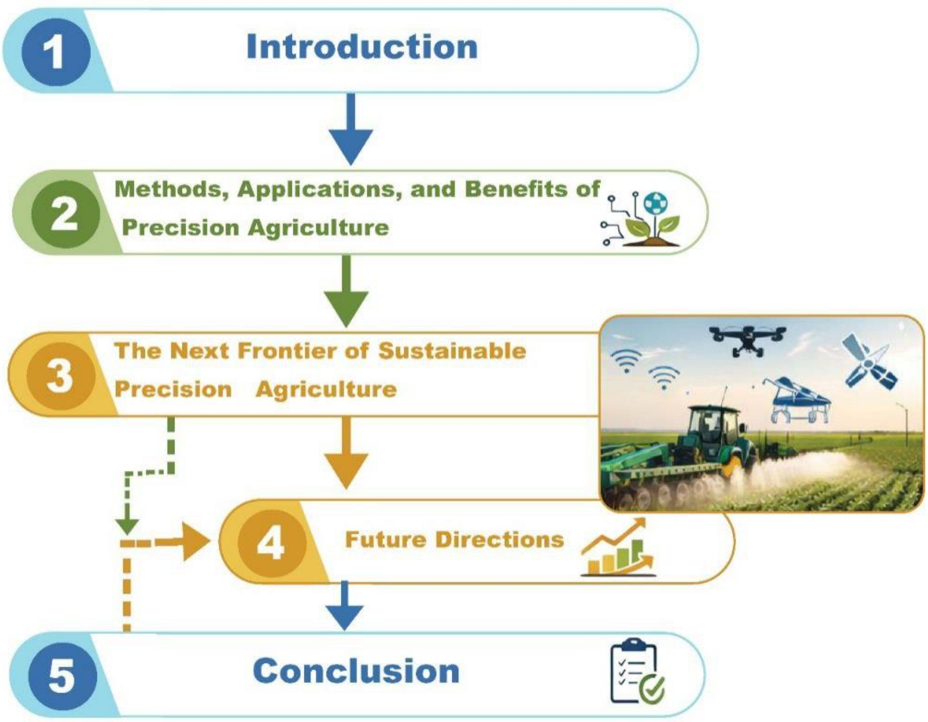

Figure 1. Outlines of the research.

1.1. Review scope and methodology

The article is structured as a narrative, integrative review and not a systematic review in the PRISMA sense, as the topic deliberately crosses several technological domains, from remote sensing, GIS, the IoT, big data, variable-rate technologies, and AI, which seldomly are covered under a single systematic protocol. However, the literature used for this review was identified and screened via a formal procedure rather than ad hoc reading. The search for candidate publications was performed in Scopus, Web of Science, Google Scholar, and the digital repositories of major publishers (MDPI, Elsevier, Springer Nature, Frontiers, and IEEE Xplore) by combining the search terms "precision agriculture", "smart farming", "Agriculture 4.0", "remote sensing", "GIS", "Internet of Things", "artificial intelligence", "machine learning", "variable rate technology", "digital twin", "edge computing" and "agricultural robotics". There was no fixed start date, since the conceptual evolution of PA was tracked through several seminal contributions from the 1980s and 1990s, but the search was biased in the direction of publications from 2018 to 2026 to keep the technological discussion up to date, with particular attention to the period 2023–2026 for recent advances in AI, IoT, and unmanned aerial systems. Eligible sources were peer-reviewed journal articles, peer-reviewed conference proceedings, and selected institutional reports (e.g., FAO) published in English and directly related to a technological, agronomic, or socio-economic aspect of PA. Non-peer-reviewed material, opinion pieces without technical content and publications outside the agricultural domain, were excluded. Moreover, where studies were associated with a closely related technology, preference was given to the most recent, most cited, or most methodologically detailed contribution. While this procedure does not remove the selection bias that is inherent to any narrative review, it provides a transparent and traceable basis for the synthesis that is presented in the following sections. In particular, Sections 3.5 and 3.6 move beyond description toward a comparative and critical reading of the literature.

Individual pieces of this landscape have been reviewed in depth, including AI applications for PA [37], the broader trajectory of smart farming [38], and, in particular, yield prediction techniques [39]. This review differs from these contributions in scope and emphasis: Rather than treating any single technology in isolation, we integrated remote sensing and GIS, the IoT, big data, variable-rate technologies, and AI within one analytical framework (Sections 2 and 3), added an explicit side-by-side comparison of the maturity, applications, and limitations of these technologies (Section 3.5), and discussed adoption barriers, i.e., cost, interoperability, and cybersecurity, together with emerging directions such as digital twins, edge AI, federated learning, and autonomous field robotics (Sections 3.6 and 4). Rather than a deeper treatment of any single sub-technology, this integrative and comparative framing is the principal added value of this work relative to the review literature.

2. Methods, applications, and benefits of PA

PA entails data-driven management choices that increase the efficiency of resource utilization, minimizing agricultural costs and the negative environmental effects of agriculture [40]. PA encompasses three fundamental operational stages: diagnosis, decision-making, and implementation [41]. These stages are directly supported by a technological framework consisting of data acquisition systems, decision-support tools, and equipment capable of executing variable-rate inputs based on data analysis [2]. Before the era of smart farming, the evolution of PA was marked by the integration of information and communication technology (ICT) into machinery to gather real-time field data. This phase involved the application of technologies such as remote sensing, automated hardware and software systems, telematics, drones, autonomous vehicles, GPS, and robotics within agricultural operations [38]. This period represents the foundational state of PA prior to the advent of more advanced, interconnected smart systems.

2.1. Acquisition and gathering of data

To identify and diagnose different aspects of agriculture, data collection and decision support technologies are crucial. PA utilizes a diverse array of sensing technologies to gather detailed, site-specific data on field and crop conditions. This includes direct measurements from ground-based sensors and soil monitors, as well as information captured through remote sensing platforms like drones, manned aircraft, and satellites [1,2,42]. Therefore, sensing functions as a vital management tool within PA [3,42]. It involves the systematic observation and data collection on key field variables, including climatic and soil conditions, fertilizer needs, water availability, as well as pressures from pests and diseases [3].

2.1.1. Remote sensing

Sensor platform and sensor type are two ways to categorize remote sensing systems used for PA and agriculture in general. Usually, satellites, airplanes, and ground-based platforms are used to install sensors [43]. The geographical, spectral, radiometric, and temporal resolution that each remote sensing sensor provides varies [44]. The spatial resolution of a sensor is defined by the ground area represented within a single pixel. Temporal resolution refers to the time interval required for a satellite to complete a full orbital cycle and revisit the same geographic location for observation. A considerable number (10s to 100s) of infectious bands with a low width (<20 nm) and small wavelength increments are present in hyperspectral images [45]. To extract valuable information on crop conditions, the dimensionality of hyperspectral data was reduced using a variety of vegetation indices and statistical and ML techniques, including random forest and deep convolutional neural network (CNN) [8,46,47]. While contemporary satellites often provide images with high spatial (under 5 meters) and temporal (daily) resolution, most publicly available satellite data remains too coarse for the detailed requirements of many PA applications [43]. These requirements vary significantly by task. For instance, estimating crop biomass and yield typically demands a higher spatial resolution of 1–3 meters, whereas variable-rate fertilizer and irrigation treatments can often utilize coarser data of 5–10 meters [48]. For more precise operations such as weed mapping and targeted herbicide application, a much finer resolution, exceeding the scale of individual weed patches (e.g., 5–50 centimeters), is essential [49].

Compared to satellites, aerial platforms such as UAVs often offer photos with a higher spatial resolution (<5 m). In general, sensors installed on satellites, aircraft, and unmanned aerial vehicles (UAVs) are passive, meaning they require a light source of their own. On the other hand, some of the satellites, like the ERS-1/2's active microwave instrument (AMI), have active sensors [43]. Active proximity sensors are found on many ground-based remote sensing devices. For instance, active proximity sensors are present in commercial variable fertilizer rate application systems like Crop Circle and Green Seeker. These advanced sensing technologies enable the collection of highly accurate and consistent vegetation indices, such as the Normalized Difference Vegetation Index (NDVI). Their reliability stems from a minimized sensitivity to variations in daylight, which ensures that measured reflectance data is primarily indicative of crop nutrient status. Moreover, agriculture is increasingly using two more sensors, thermal infrared and microwave, mounted on new satellites.

Crop water stress and irrigation needs can be estimated using thermal infrared sensors, which monitor the energy released by a target (such as crops) to determine its temperature [50]. However, the use of microwave satellite sensors in PA is limited by their coarse spatial resolution (10s of km), particularly for passive sensors. For application in PA, a variety of techniques have been devised and applied to downscale passive microwave data to a finer resolution [51–53]. The effective implementation of satellite-based PA relies on sensors with appropriate spatiotemporal characteristics. A summary of key historical and operational satellite systems, their resolutions, and their primary agricultural applications is provided in Table 1.

Table 1. Satellite sensors used in precision agriculture, showing their spatiotemporal resolutions and primary applications: Source Sishodia et al. [43].

Satellite and Operational Period	Sensor and Spatial Resolution	Revisit Time	Precision Agriculture Use Cases
Landsat 1 (1972–1978)	Multispectral (80 m)	18 days	Monitoring crop development [54]
AVHRR (1979–present)	Multispectral (1.1 km)	Daily	Regional nutrient assessment [55]
Landsat 5 TM (1984–2013)	Multispectral (30 m), Thermal (120 m)	16 days	Estimating biomass [56] forecasting yield [57], tracking crop progress [58]
SPOT 1–2 (1986–2008)	Multispectral (20 m)	2–6 days	Irrigation planning and water use efficiency [59]
IRS 1A (1988–1996)	Multispectral (72 m)	22 days	Managing water and fertilizer application [60]
Airborne LiDAR (from 1995)	Multispectral (~10 cm)	N/A (campaign-based)	Mapping terrain and supporting site-specific nutrient plans ([61]
Radarsat-1 (1995–2013)	C-band SAR (30 m)	1–6 days	Crop growth observation [62]
IKONOS (1999–2015)	Multispectral (3.2 m)	3 days	Yield prediction [63] soil characteristics [64] nutrient management [55] evapotranspiration calculation [65].
EO-1 Hyperion (2000–2017)	Hyperspectral (30 m)	16 days	Early detection of plant diseases [66, 67]
Terra/Aqua MODIS (1999,2002–present)	Multispectral (250 m – 1 km)	1–2 days	Yield modeling[68] and large-area crop condition monitoring [69],
Terra ASTER (2000–present)	Multispectral & Thermal (15–90 m)	16 days	Assessing crop water stress and scheduling irrigation [70]
QuickBird (2001–2014)	Multispectral (2.44 m)	1–3.5 days	Identifying crop diseases [71]

Continued on next page

Satellite and Operational Period	Sensor and Spatial Resolution	Revisit Time	Precision Agriculture Use Cases
Aqua AMSR-E (2002–2016)	Microwave Radiometer (5.4 km – 56 km)	1–2 days	soil moisture and water management [72]
SPOT-5 (2002–2015)	Multispectral (10 m VNIR, 20 m SWIR)	2–3 days	Crop yield estimation [73].
ResourceSat-1 (IRS-P6) (2003–2013)	Multispectral (5.6 m Pan, 23.5 m SWIR)	5 days	Nutrient management and monitoring, [74]
KOMPSAT-2 (2006–present)	Multispectral (4 m)	5.5 days	Crop yield assessment [74]
Radarsat-2	C-band SAR (1–100 m)	3 days	Leaf area index (LAI) and biomass estimation [75]
RapidEye Constellation (2008–present)	Multispectral (6.5 m)	1–5.5 days	Water management [76] yield prediction [77], crop growth and chlorophyll monitoring [78]
WorldView-2 (2009–present)	Multispectral (1.4 m)	1.1 days	High-resolution crop growth monitoring [79]

2.2. Making decisions, organizing, and executing

Actions are carried out in accordance with the decisions made using data-driven technology once decisions are made through the analysis of collected data. Most fields differ in terms of diseases, climate, and soil characteristics [80].

Three separate stages that follow a cyclical pattern comprise the PA process. These stages include the monitoring and data collection phase, the precision treatment application phase, and the data analysis and treatment plan phase [81]. The relevant data is post-processed and combined with soil and crop models in the first stage to divide the area into management zones (MZs) with uniform treatment requirements. MZs serve as intervention zones when particular treatments are administered [82,83]. To prepare the soil for planting, MZs apply the proper amounts of water, fertilizer, or agrochemicals. To plan and carry out any crop-management action (such as watering, spraying herbicides or insecticides, or eliminating weeds) locally and only when necessary, the soil and the crop are continuously monitored and mapped during the crop’s growth [81]. During the harvest phase, the mature crop is collected, and its yield is quantified and analyzed. Autonomous treatment application is not required for this phase; the only condition is that the treatments be provided in accordance with the plan from the previous phase. All information gathered in earlier stages and during any other monitoring activity is processed in the final phase to provide maps that show field conditions, including topography, soil composition, soil nutrients, crop status, and yield maps [81].

2.2.1. The role of geographic information systems (GISs) in PA

Through sophisticated spatial data analysis and mapping, Geographic Information Systems (GISs) have become essential to contemporary agriculture, transforming the way farmers run companies [84,85]. GIS technology captures, stores, analyzes, and displays spatial or geographical data by integrating hardware, software, data, and people. Drones, satellite systems, GPS receivers, and field sensors employed for data collection fall within this category [86–88]. Coordinates, elevation, and environmental characteristics are among the spatial data that these devices store. Data processing, spatial analysis, and visualization are all made possible by GIS software. ArcGIS by Esri, QGIS, and Google Earth Engine are popular GIS programs that provide mapping, modeling, and agricultural decision assistance [89]. GIS uses a variety of data types, such as imaging (satellite, aerial, drone), attribute data (descriptive information about spatial objects), and spatial data (geographical elements like points, lines, and polygons). Farmers, agronomists, and geospatial specialists employ GIS technologies to interpret data, support decision-making, and implement PA methods [89]. Functioning as a core component of climate-smart agriculture, GISs enable data-driven analysis, predictive modeling, and adaptive management strategies. By synthesizing historical weather patterns and modeling future climatic scenarios, GIS empowers farmers to build more resilient and sustainable agricultural systems. This is achieved through actionable strategies such as selecting climate-resilient crop varieties, optimizing planting schedules, and implementing targeted mitigation measures [84,90,91].

Consequently, GIS-driven methodologies enable a proactive approach to managing climate-related risks. They enhance the efficiency of resource use and strengthen the adaptive capacity of farming operations, which is essential for safeguarding food security amid a changing climate. The integration of GIS into climate-smart frameworks thus holds significant promise for bolstering agricultural resilience, minimizing environmental impacts, and supporting sustainable development in the face of ongoing climatic shifts [89].

Precision Livestock Farming (PLF) enhances animal management by integrating advanced technologies like GISs, leading to optimized pasture use, improved livestock health, and more sustainable practices [88,92,93]. A key application of GISs within PLF is the monitoring of grazing behavior. This is achieved by deploying GPS-enabled collars or tags on livestock, which generate spatial data on animal movement and grazing patterns. Through the analysis of this data, farmers can assess grazing intensity, measure pasture utilization rates, and effectively manage rotational grazing systems. Farmers utilize GIS-generated maps to refine grazing strategies, preventing overgrazing, supporting pasture recovery, and maintaining biodiversity within rangelands. GISs facilitate the creation of digital maps detailing pasture conditions, soil fertility, and vegetative coverage. Through spatial analysis, these systems identify key metrics such as soil health, nutrient dispersion, and viable grazing zones. To promote sustainable resource management and enhance livestock nutrition, GIS-integrated decision support tools recommend optimized stocking rates, rotational grazing schedules, and required rest periods for pasture regeneration [89].

3. The next frontier of sustainable farming: Precision agriculture

Agriculture is entering the dawn of a new, data-centric revolution, driven by approaches that integrate diagnostics, decision-making, and automated performance at every stage of production [2,22,94]. Human involvement has largely shifted toward maintenance and supervisory roles [41]. While earlier industrial revolutions gradually modernized farming, the ongoing fourth industrial revolution, characterized by digitization and connectivity, is fundamentally reshaping agriculture. This transformation is marked by data-driven management, tool-based automation, an emphasis on sustainability, increased professionalization, and reduced environmental impact through smart technologies [95]. Key innovations such as robotics, drones, big data, AI, computer vision, 5G, cloud computing, the IoT, and blockchain are being integrated into farming systems [4,5,18,22]. As a result, agricultural systems are becoming increasingly intelligent and autonomous [29,96].

3.1. Big data

The combination of unstructured and organized data that is expanding at an unforeseen rate is known as big data. The term "big data" describes the massive volume of digital data that is challenging to handle and analyze with traditional computing tools and technology [97]. The term "big data" is frequently used to characterize a contemporary trend in which technology and sophisticated analytics combine to produce new, practical processing methods. Big data is made up of significant volumes of information produced by cellphones, social media, and other digital communication devices [98]. The amount of data is growing significantly, making it more difficult to collect, organize, store, manage, share, analyze, and visualize using conventional database software tools [98]. It makes it possible to search, aggregate, and relate agricultural statistics to obtain the best farming results. Decisions regarding crop selection, yield forecasting, fertilizer application, pest and diseases control, market price projections, and agricultural policy can be informed by correlating remote sensing variables, such as crop health indicators, Leaf Area Index (LAI), and soil maps, with statistical data on factors like precipitation, temperature, and historical yields [99].

Applications in the farming sector are covered by Big Data studies. They perform a variety of functions, including forecasting, producing useful information from vast amounts of data, raising production rates, lowering production costs and food loss, lowering the risk of disasters, introducing sustainability in the food supply chain, making intelligent decisions, automating the farming process and minimizing human interaction, fault analysis, managing water and fertilizers, and identifying crop diseases [100–114].

Due to their intricacy, these goals are challenging to achieve by conventional techniques. Big Data technology can address these problems with greater effectiveness, quicker reaction times, and broad scalability [115]. The platforms, methodologies, and tools for implementing Big Data within agriculture are advancing rapidly. As a versatile and powerful technological resource, Big Data supports a wide spectrum of agricultural applications. It serves as a foundational technology for enhancing productivity in areas such as precision farming, food security assurance, supply chain optimization, environmental monitoring, land and agricultural zone identification, fertilization planning, disease detection and management, soil analytics, and intelligent decision-support systems [115].

3.2. Internet of Things

The IoT is a network of physical objects equipped with sensors, software, and connectivity, enabling them to gather and share data over the internet. These interconnected devices, which vary from everyday consumer items to complex industrial equipment, can communicate with users and other systems to enable automated data exchange and interaction [116] (Figure 2).

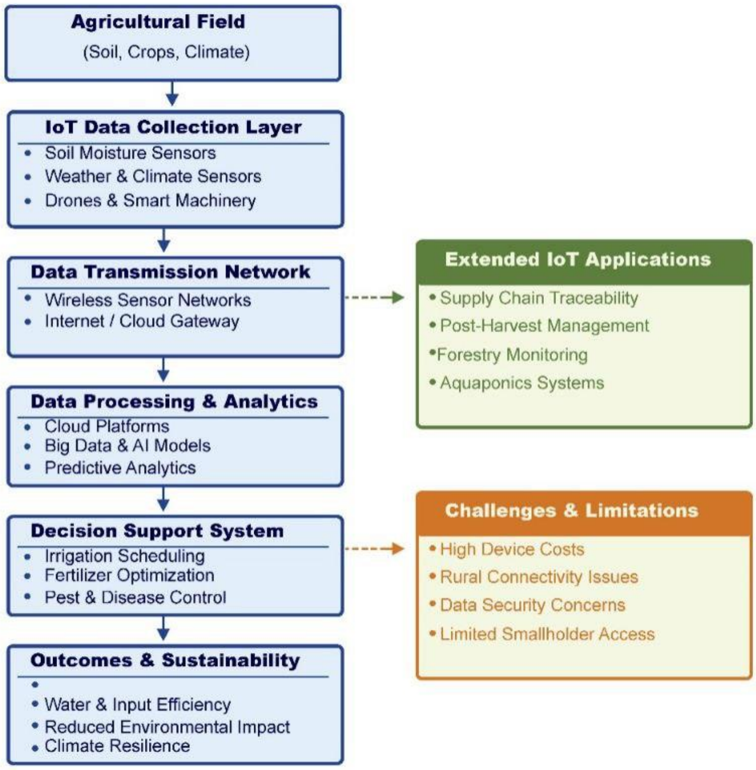

Figure 2. Uses, extended applications, and limitations of the Internet of Things.

Improved crop output, more sustainability, and a revolution in resource management are all benefits of IoT's introduction into agriculture [117]. Through sensor networks, drones, and intelligent irrigation, all these technologies offer the most up-to-date information on crop health, weather, and soil moisture. Using this knowledge, producers may make informed decisions about pest management, fertilizer, and irrigation techniques that maximize yield while cutting waste. This intelligent irrigation system automatically controls the amount of water in the soil using data from soil moisture, saving water and promoting crop growth [118]. IoT applications include supply chain management systems that guarantee traceability and lower post-harvest losses, real-time forestry monitoring to track environmental changes, and aquaponics farming systems that combine hydroponics with aquaculture [119].

In addition to monitoring field characteristics, IoT-enabled devices enable remote equipment control, automate farming activities, and provide warning signals for predictive analytics, transforming conventional farming practices into data-driven ones. Through the digital empowerment of smallholders, this technology-driven revolution directly supports the demand for climate-resilient and sustainable agriculture [120]. This kind of integration lowers labor costs, increases productivity, and lessens agricultural-related environmental damage. IoT adoption in agriculture is expected to increase; however, for widespread adoption and long-term viability, problems including device and equipment costs, rural connection, and data security issues must be resolved. These obstacles align with larger structural disparities in Indian agriculture, where smallholders frequently lack access to infrastructure and contemporary tools [120].

Farmers may increase yields and resource efficiency by making decisions about planting, fertilizing, and harvesting based on real-time data gathered in the field. In addition to the IoT, they employ big data analytics to forecast weather, pest outbreaks, and other potential threats. Globally, the IoT revolution is a crucial improvement in agriculture to satisfy sustainable needs, lessen environmental effects, and meet the ever-increasing food demands of a growing population. In view of climate change and concerns about food security, future technological developments have great potential to further transform farms through more automation, accuracy, and advances in sustainable farming [116].

3.3. Variable rate technologies

By enabling farmers to administer inputs, including fertilizers, seeds, insecticides, and irrigation water site-specifically, while accounting for the geographical variability of soil attributes and crop requirements, variable rate technologies (VRT) represent a fundamental transformation in contemporary agricultural practice. Empirical research indicates that the adoption of VRT in cotton production systems leads to a quantifiable reduction in the application rates of bulk inputs such as fertilizer, lime, and seed [121]. This measured reduction directly corresponds to significant input cost savings and enhanced resource-use efficiency at the field scale. Furthermore, studies document a strategic increase in the application of other inputs, including irrigation and sprayer-applied crop protection materials. This shift reflects a more targeted and precise input utilization, which is associated with optimized crop performance and improved yield outcomes.

3.3.1. Variable rate seeding

Variable rate seeding (VRS) is a PA technology that adjusts the volume of seeds sown according to specific field conditions, such as variations in soil properties. This site-specific approach optimizes plant populations, leading to enhanced crop productivity and improved farm economic returns [122]. Based on data accessibility and the degree of technological implementation, the economic advantage of employing VRS in corn cultivation, as opposed to Uniform Rate Seeding (URS), has been estimated between $0.15 and $12.83 per hectare [123]. Further analysis indicates that in soybean production, the use of a VRS simulation model can potentially elevate profitability by $5 to $57 per hectare over conventional fixed-rate methods [124]. These findings underscore the financial viability of integrating VRS into diverse crop production systems [26]. Although adoption of VRS remains limited, interest is expanding due to technological advancements and increasing ease of application. The integration of VRS platforms with high-resolution satellite and positioning systems enables growers to develop and deploy customized seeding maps, facilitating precise seed placement and thereby enhancing potential yields [125].

3.3.2. Variable rate nutrient application

Variable rate nutrient application (VRNA) is a PA practice in which fertilizer or manure is applied at differing rates across distinct zones of a single field, guided by a predefined application map [26]. This site-specific management strategy aims to lower overall fertilizer use while maintaining or increasing yield, improving crop quality, and enhancing environmental outcomes [126]. The primary advantages of VRNA include greater potential profitability and significant ecological benefits. For nitrogen (N), VRNA offers economic and environmental gains, though adoption among producers remains limited. In the case of phosphorus (P), VRNA can provide long-term economic returns by strategically building soil-test phosphorus levels over time. The effectiveness of variable rate nutrient management can be further improved through real-time sensor technologies, which optimize nitrogen application by dynamically responding to actual crop needs [127].

3.3.3. Variable rate irrigation

Variable rate irrigation (VRI) refers to the capability of applying water at varying depths across sections of a field in a spatially defined manner, based on specific crop requirements and field conditions [128]. The benefits and limitations of VRI technology vary depending on site-specific characteristics, leading to different outcomes from one field to another. VRI systems is influenced by multiple factors, including crop type, equipment longevity, water pricing, and energy costs associated with pumping [129]. When implemented appropriately, site-specific VRI has the potential to enhance crop water productivity, promote the conservation of water and energy, and contribute to broader environmental sustainability [130].

3.4. Artificial intelligence, machine learning, and deep learning in precision agriculture

Since computers were first adopted for farm management in the early 1980s, multiple computational strategies have been introduced to tackle agricultural problems. Early solutions included structured databases and rule-based decision support tools designed to organize information and offer prescriptive advice [131–133]. Moreover, systems built on AI have shown markedly improved performance in terms of precision, flexibility, and predictive capacity, representing a major technological advancement beyond earlier digital methods [133]. Applications of AI, ML (ML), and deep learning (DP) are illustrated in Figure 3.

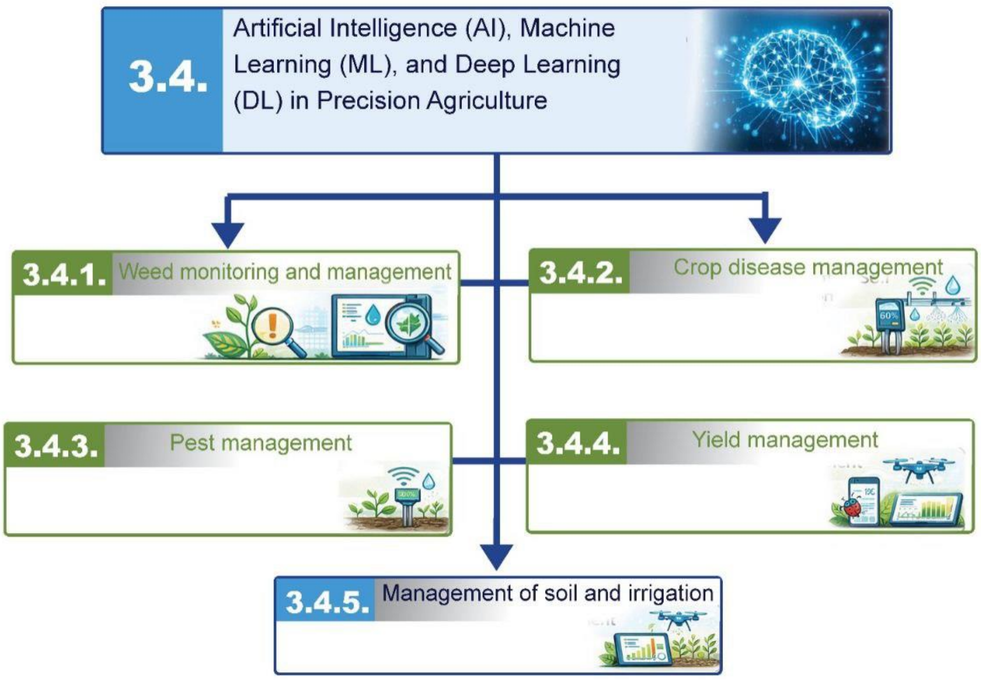

Figure 3. Application of artificial intelligence, ML, and deep learning in the agricultural sector.

3.4.1. Weed monitoring and management

Plants classified as weeds are undesirable species that compete directly with cultivated crops for essential growth resources, including space, water, and soil nutrients. They pose a serious threat to agricultural operations and can lead to substantial losses in output. Thus, controlling weeds is essential to farming and agriculture. Moreover, reducing natural supplies for undesired weeds means fewer alternate hosts for insect pests and diseases [37].

A computer vision-based system for weed management, developed by Wu et al. [134], was engineered to mitigate latency inherent in plant detection algorithms. Their solution integrated a non-overlapping multi-camera array to compensate for processing delays. To augment detection accuracy, the system's architecture implemented a naïve biased Bayesian classifier, which was enhanced through the incorporation of a biased probabilistic model. Chen et al. [135] proposed a method for detecting weeds and corn seedlings that employs multi-feature fusion combined with a Support Vector Machine (SVM) classifier. In their study, they systematically evaluated 18 distinct fusion strategies, each integrating six different image features, to identify the optimal combination. The application of Principal Component Analysis (PCA) for dimensionality reduction enhanced overall accuracy. The highest detection performance was achieved through the fusion of rotation-invariant Local Binary Pattern (LBP) features with features derived from a Gray level-Gradient Co-occurrence Matrix (GGCM).

Reedha et al. [136] used transformer neural networks to classify crops and weeds from pictures with a high resolution captured by UAVs. The ViT model outperformed other CNN-based models such as ResNet and EfficientNet when used to learn and identify images of crops and weeds in fields of spinach, parsley, and beetroot. Furthermore, real-world, real-time implementation is scarce, despite numerous researchers achieving high precision in controlled situations. Moreover, research on hardware integration and the use of AI models in dynamic, field-based scenarios is severely lacking [37].

3.4.2. Crop disease management

The occurrence of disease in crops or livestock reduces agricultural output, presenting a significant barrier to satisfying rising global food demand. Effective management of crop pathogens is therefore a critical component in maximizing potential harvest yields [37]. Genetics, soil type, rainfall, aridity, wind, and temperature are some of the variables that might lead to diseases in crops and/or cattle [137]. Crop disease management is a significant challenge, particularly in large-scale agriculture due to these characteristics and the variable nature of disease causes. Huang [138] suggested employing neural networks and image processing techniques to identify and categorize illnesses in Phalaenopsis seedlings. Fuzzy logic has been used in other studies to create AI-based crop disease control systems. Sannakki et al. [139] suggested assessing leaf illness using fuzzy logic and machine vision.

Research into the automated classification of plant diseases has evolved significantly through the application of artificial neural networks. An early approach by Muthukannan et al. [140] utilized multiple neural network architectures to analyze the morphological and textural features of leaves for disease identification. Subsequently, Mohanty et al. [141] advanced the field by implementing a deep CNN trained on a large-scale dataset comprising 54,306 publicly available images. This model demonstrated a high degree of accuracy, successfully diagnosing 26 distinct diseases across 14 crop species with a reported success rate of 99.35%.

A deep learning approach for detecting olive tree diseases was introduced by Lachgar et al. [142]. The method utilized the MobileNet CNN architecture, enhanced through a process of fine-tuning. The optimized model achieved perfect classification accuracy on its training data. When evaluated on a separate test set without the use of data augmentation techniques, it maintained a high performance level, attaining an accuracy rate of 92.59% across assessment metrics.

In general, crop disease management has been the main focus of research on AI-driven agricultural solutions, with deep learning becoming the most popular method in recent years. CNNs and other deep learning models have been used in much research to identify and categorize crop illnesses using visual data; usually pictures of diseased plants [141–151].

Advancements in diagnostic accuracy over successive recapitulations have demonstrated the significant potential of these models. Although these models have shown encouraging outcomes, their dependence solely on image-based inputs has drawbacks. Similar visual symptoms may be present in some disorders, which could result in misdiagnosis [37].

3.4.3. Pest management

One of the biggest issues in agriculture is insect infestations, which typically result in lower agricultural yields. In addition to causing disease and infestation, these insects damage crops by consuming plant parts such as leaves, stems, roots, and flowers. Over time, researchers have developed computerized systems capable of identifying agricultural pests and generating corresponding management recommendations [152]. Consultations on pest control and detection have typically served as the foundation for the use of AI in that field [153].

The intelligent diagnosis of jute pests using deep CNNs and transfer learning was proposed in [115], with an accuracy of 95.86%; the model, the VGG19 CNN pretrained network using the ImageNet database, has been incorporated into useful Android and iOS applications.

Obasekore et al. [39] suggested an extensible, robot-centered method based on deep learning. The robot uses RGB data from a camera sensor divided into peripheral and foveal line-of-sight vision to capture insect problem larvae. For peripheral and foveal vision, the VGG19 classifier (with 99% accuracy) and the faster RCNN detector with VGG16 as the basis network were employed, respectively.

3.4.4. Yield management

Predicting and managing yield is one of the most difficult challenges in agriculture. Without effective yield management, production loss will happen even in cases where crop growth is at its best. Estimating agricultural expenses and creating marketing plans are two further benefits of crop yield prediction. Prediction models can be used to investigate factors influencing such yields field [154].

Farming activities are increasingly utilizing technologies like AI, satellite imagery, ML, cloud computing, and advanced analytics. Farmers have been able to increase the quantity of food products and achieve maximum average yields as a result of more effective, sustainable, intelligent, and economical agriculture. The storing, categorization, and forecasting of yield amounts are typically the foundation of AI applications in that field [155].

In their research, Sun et al. [156] described how the random forest algorithm is used to forecast winter wheat yield in China (2014–2018) using satellite data, climatic data, and spatial information. The outcome demonstrates that the accuracy of random forests was superior to that of multiple linear regression.

Li et al. [157] employed open-source programming platforms, integrating automated hyperspectral narrowband vegetation indices with AI-driven automated ML (AutoML), to model crop yields for spring wheat, pea-oat mixtures, and spring barley with red clover. Cao et al. [158] developed a winter wheat yield prediction model for the period 2005–2014. Their approach utilized three distinct data categories: Satellite imagery, historical climate records, and subseasonal-to-seasonal (S2S) atmospheric forecast data. ML techniques, including XGBoost, Random Forest, and Support Vector Regression (SVR), alongside traditional Multiple Linear Regression, were applied. The research demonstrated that incorporating S2S dynamical predictions significantly enhanced forecast accuracy compared to using observed climate data alone, with the XGBoost algorithm delivering particularly robust performance. Effective yield estimation and management are vital, as they directly inform critical agricultural decisions, from strategic resource allocation to market planning.

As a result, it is crucial to incorporate all facets of agriculture when forecasting production and its management, in addition to making predictions based on variables like water, climate, and soil.

3.4.5. Management of soil and irrigation

Soil provides the essential foundation for crop development, supplying vital nutrients, water, and structural support. Consequently, effective soil and irrigation management are fundamental to agricultural success. To date, the implementation of AI within these domains has primarily focused on key areas such as soil type classification, nutrient level monitoring, and the prediction of rainfall and soil moisture to optimize irrigation scheduling and crop productivity.

To address data scarcity in aquaponic systems, Dhal et al. [159] applied a ML classifier with advanced error estimation techniques to dynamically regulate nutrient levels based on plant requirements. Their results indicated that a linear Support Vector Machine (SVM) classifier, paired with a semi-bolstered resubstitution error method, provided an effective solution. Wei et al. [160] focused on predicting annual irrigation water use in the Kansas High Plains. By integrating pumping records, remote sensing data, and climate variables within a Random Forest regression model, they successfully captured the spatiotemporal variability of irrigation amounts.

In a 2023 study conducted in a semiarid, arid region, Mohamed et al. [161] integrated GISs with an adaptive neuro-fuzzy inference system (ANFIS), a hybrid AI methodology, to evaluate and forecast soil pollution caused by heavy metals. Their results demonstrated that the ANFIS model provides a more accurate and effective means of estimating pollution levels compared to conventional methods. These outputs offer a practical, evidence-based foundation for policymakers to develop targeted remediation strategies aimed at mitigating heavy metal contamination in vulnerable soils.

El Behairy et al. [162] applied fuzzy inference, a widely utilized AI technique in agricultural modeling, to evaluate the adaptive capacity of wheat crops. Fuzzy systems are particularly valuable for representing and managing imprecise or qualitative agricultural data. These researchers implemented a Mamdani-type fuzzy inference system to classify land suitability for wheat cultivation based on integrated soil parameters, including chemical properties, physical structure, and fertility levels.

The accuracy of the fuzzy inference system’s output relied on two key design elements: The formulation of IF-THEN rules, derived primarily from expert agronomic knowledge, and the selection of appropriate membership functions, specifically sigmoidal, Gaussian, and zmf types, to accurately quantify how each input variable influence the suitability assessment. The combined GIS and fuzzy logic approach proved to be more precise, efficient, and faster in determining optimal wheat-growing zones compared to traditional evaluation methods.

Moreover, Gouda et al. [163] found that the GPR model and the ANN with a multilayer feed forward network provide useful frameworks for soil organic carbon (SOC) prediction. The Gaussian Process Regression (GPR) model with the Matern 5/2 kernel obtained a higher R^2 value of 0.89 than the ANN, which obtained an R^2 value of 0.84. These results validate the correctness and dependability of the models and are backed by statistical and visual analyses via cross-validation.

El Behairy et al. [164] demonstrated that combining regression analysis with artificial neural networks (ANN) using a comprehensive dataset of soil's physical, chemical, and fertility properties results in a highly accurate assessment of soil quality. By identifying important soil quality categories and restrictions, this approach improves agricultural productivity and decision-making in arid zones.

Finally, El Behairy et al. [165] proposed that, with ML and DL, soil quality prediction has the potential to be incredibly precise and effective. This sets DL and ML applications apart from other methods since they can predict the soil quality index without requiring more complex calculations. They recommend that researchers assess soil quality across larger areas and forecast it using more precise, contemporary, and quick techniques, utilizing a range of activation functions and algorithms.

Predictive models for soil and irrigation, enhanced by AI, have proven to be effective decision-support tools. These systems leverage integrated datasets, including historical trends, climatic projections, and real-time environmental sensor data, to optimize the management of these vital resources. Despite the effectiveness of these models, there is an increasing need to take into consideration environmental contaminants and uncertainties that may have an impact on their accuracy. The effectiveness of AI models and crop output can be greatly impacted by elements, including deteriorating water quality, rising soil salinity, and excessive soil acidity [166].

In addition to these natural factors, human activities, including neighboring farming practices, industrial operations, and improper environmental management, can make it more difficult to maintain soil and water cleanliness. Inadequate waste management and excessive chemical use by farms or factories can contaminate nearby water sources, causing soil deterioration and water contamination. Therefore, to provide more thorough predictions and strategies, AI models for soil and irrigation management must also take these anthropogenic factors into account [167].

3.5. Comparative synthesis and critical analysis of precision agriculture technologies

In the previous sections, we treat a wide range of technologies individually. Combining them into a comparative frame brings out the differences in maturity, cost, and type of agronomic problem for which each is best suited. Table 2 presents the major agricultural applications, advantages, and limitations of the major technological categories addressed in this review: remote sensing and GIS, the IoT, big data and cloud/edge analytics, variable rate technologies, AI and ML, and unmanned aerial systems and field robotics.

Table 2 reveals three patterns that do not emerge when each technology is discussed only in its own subsection. Technologies that rely primarily on optical or radar remote sensing (Table 1) are the most mature and least capital intensive at the farm level because much of the underlying infrastructure, satellites, public data portals, is shared across users. Their main limitation is spatial or temporal resolution rather than cost [170]. Second, technologies that require dedicated on-farm hardware such as IoT sensor networks, UAVs, variable-rate equipment, and robotics are the most spatially precise but also the most expensive initially and most sensitive to the interoperability and maintenance constraints discussed in Section 3.6 [36,169]. Third, AI and ML are less a stand-alone technology, but rather an analytical layer that determines the amount of value that can be extracted from the other technology groups. The main limitation evident across the studies reviewed here is not predictive accuracy under controlled or benchmark conditions, which is frequently reported as over 90% [39,42,141,161], but rather the comparatively small number of studies that validate these models on independent, real-world field data instead of the dataset on which they were trained [37]. This pattern suggests that future critical appraisal of PA technologies should report accuracy metrics and the geographical scope and independence of validation data used. We revisit this point in Section 5.

Table 2. Comparative summary of key precision agriculture technology groups: Representative applications, advantages, and limitations.

Technology Group	Representative Applications	Key Advantages	Key Limitations
Remote sensing and GIS	Crop monitoring, yield forecasting, soil and terrain mapping, climate-smart land-use planning	Broad spatial coverage; long historical archives; many free public data sources [43]	Trade-off between spatial and temporal resolution; cloud cover and fixed revisit intervals constrain timeliness [43]
Internet of Things (sensor networks)	Smart irrigation scheduling Soil moisture, temperature, humidity and water level monitoring in real time Remote control via cloud [168]	Continuous, site-specific real-time data; enables automated, low-latency response [116,117]	High device and maintenance cost; rural connectivity gaps; device/platform heterogeneity [42,120]
Big data and cloud/edge analytics	Multi-source data fusion, predictive analytics, large-area yield and disease forecasting	Scales across large, heterogeneous datasets; supports advanced statistical and AI analysis [98,115]	Cloud variants need reliable connectivity; edge variants need local compute capacity; data-governance complexity [169]
Nutrients application	Site-specific seeding, fertilizer/manure application, irrigation depth control	Documented input savings and yield gains under appropriate conditions [121,123,124]	Requires accurate management-zone delineation; economic benefit varies by field, crop, and data availability [124,129].
Artificial intelligence & machine learning	Weed, disease and pest detection, yield prediction, soil-quality and salinity assessment	High reported accuracy under controlled/benchmark conditions; rapidly improving architectures [39,141,161]	Comparatively few studies validate models on independent, real-world field data rather than the training dataset [37]
UAVs and field robotics	High-resolution scouting, targeted spraying, autonomous weeding and harvesting	Fine spatial precision; reduces labor and chemical inputs; enables continuous operation [81,170]	High capital cost; limited cross-platform interoperability; reduced robustness under variable field conditions [170]

3.6. Challenges and barriers to adopting precision agriculture

In addition to the technical performance reported in the studies reviewed above, there are several recurring barriers that determine whether a given PA technology is actually adopted at the farm level rather than remaining a research-scale demonstration. The first is cost. Variable-rate seeding, sensor networks, UAV platforms, and particularly autonomous field robots all entail high upfront capital costs, the returns of which are realized over several growing seasons. This puts small and medium-sized farms at a disadvantage compared to large commercial farms [170]. Retrofit kits and robot-as-a-service business models have been proposed as ways to lower this barrier, but evidence on their effectiveness in heterogeneous, smallholder-dominated agricultural systems remains limited.

The second is Interoperability. Smart-farming sensors, machinery, and software platforms are often made by different manufacturers as closed, proprietary systems, forcing farmers to deal with several disconnected dashboards and data formats instead of a single integrated decision-support environment [42,44,170]. This fragmentation increases time to decision, increases cost of ownership, and restricts scalability of PA beyond the specific combination of equipment for which a given farm was originally configured. Common communication protocols and modular, standards-based architectures are widely identified in the literature as a precondition for realizing the full benefit of the technologies discussed in Sections 2 and 3 [170].

The third hurdle is cybersecurity and data privacy. As PA increasingly depends on continuously connected IoT sensors, cloud platforms, and AI-based decision tools, the attack surface available to malicious actors expands accordingly; documented threats include sensor-data tampering, denial-of-service attacks against field-deployed devices, and unauthorized access to farm-management platforms [5,171]. However, considering the low cybersecurity awareness and the security budgets at the farm level compared to other critical infrastructure sectors, deception-based threat-intelligence techniques and lightweight farm-appropriate intrusion-detection methods have been proposed as more practical alternatives to the heavier security architectures used in industrial settings [171].

Finally, the issue of rural connectivity and digital literacy remains a constant challenge, especially in areas with patchy broadband or mobile network coverage, which not only limits the use of IoT- and cloud-dependent applications but also the training needed for farmers and technicians to operate and repair the equipment discussed in this review [120]. These four barriers, cost, interoperability, cybersecurity, and connectivity/skills, together offer a partial explanation as to why the technological capability documented in Sections 2 and 3 has yet to translate into uniform adoption and are revisited in Section 4 in relation to emerging architectures, such as edge computing and federated learning, that are explicitly designed to mitigate several factors at once.

4. Future directions

With advances in technology, AI, collaborative monitoring techniques, and real-time predictive modeling, GIS-driven agriculture has a bright future [172–174]. These developments have the potential to transform precision farming and advance sustainable farming methods globally. Drone technology, hyperspectral imagery, and new satellite constellations improve the capture of spatial data at higher resolutions. These tools enable accurate management decisions by offering comprehensive information into crop health, soil moisture levels, and pest infestations. Moreover, these developments enable real-time monitoring and adaptive management techniques for crop yield forecasts and optimal resource usage when combined with GIS [89]. The ongoing development of technology will determine the future of sustainable PA. New technologies that are more accessible, economical, and easy to use for farmers, especially small and medium-sized farms, need to be developed. PA is anticipated to become more economical and efficient with the introduction of 5G technology and the IoT [175]. It is anticipated that the usage of drones and other UAVs for mapping and agricultural monitoring would grow, giving farmers access to real-time data on crop yields and health. Additionally, the accuracy and effectiveness of PA methods can be enhanced by the advancement of ML algorithms and AI [175]. The creation of reliable hardware systems that can process real-time data for weed identification and classification in a variety of environmental situations should be the top priority for researchers. This move toward useful, in-field applications will represent a significant advancement in the development of more effective and sustainable weed control strategies [37].

The remainder of this section develops three emerging directions that extend the technologies discussed in Sections 2 and 3 and that, in several cases, directly target the adoption barriers identified in Section 3.6.

4.1. Digital twins

A digital twin is a virtual representation of a real field, crop, or farm system that is continually updated to reflect the real-time status and can be used to model management scenarios before they are applied to the ground. In agriculture, digital twins combine data streams from the sensors, satellites and UAVs mentioned in Section 2 with mechanistic or machine-learning crop models for decision support on irrigation scheduling, fertilization, and pest management under simulated "what-if" conditions rather than trial and error in the field [176]. Reviewers address applications along the crop lifecycle from soil and nutrient management to post-harvest logistics and farm-machinery optimization, but also highlight that most deployments are in the digital-shadow phase, i.e., a one-way flow of data from the field to the model, rather than the fully closed-loop, bidirectional twin envisioned in the concept [176]. The primary barriers to moving from digital shadow to full digital twin are the same limitations in data acquisition and interoperability noted in Section 3.6, along with the computational cost of executing detailed crop-process models in near real-time [176].

4.2. Edge AI and federated learning

Most of the ML applications reviewed in Section 3.4 were developed and validated on cloud hosted infrastructure, which assumes a level of connectivity that, as noted in Section 3.6, is not available on many farms. Edge AI counteracts this by implementing lightweight and optimized models directly on the field deployed hardware, i.e., sensor nodes, gateways, drones, or single board computers—such that the inference takes place locally, with less latency, bandwidth requirements and when the connectivity is interrupted [169]. An example of this approach is one in a closely related agricultural risk-management setting, where a Raspberry Pi-based platform running Random Forest and logistic-regression classifiers was used offline to detect fire risk from smoke and flame sensor readings, reporting cross-validated accuracies above 94% with no dependency on the cloud infrastructure [177]; the same edge-deployment logic applies directly to the weed, disease, and pest-detection models discussed in Section 3.4. Federated learning brings this to the farm level. Instead of sending raw field data to a central server, each farm or device trains a local model, and only model updates are shared, which are then aggregated to form an improved global model without any individual farm's raw data ever leaving their premises [169]. This leads to two consequences for the technologies discussed earlier in this review: First, it provides a partial technical solution to the data-privacy and cybersecurity problems discussed in Section 3.6, because sensitive yield, soil, or financial data associated with an individual farm do not need to be centralized [169,171]. Second, it enables training machine-learning models for tasks such as disease or pest detection on data pooled across many farms and regions, directly addressing the limited-validation-data problem identified in the comparative analysis of Section 3.5, while keeping the data local [169]. The cloud, edge, and device layers are increasingly designed to work together rather than as competing alternatives, with the cloud reserved for computationally heavy model training and historical analysis, and the edge and device layers for the real-time monitoring and control functions that are most sensitive to connectivity loss [169].

4.3. Autonomous agriculture and field robotics

The execution end of the data–decision cycle consists of autonomous tractors, robotic weeders and harvesters, and coordinated UAV–ground-robot systems. These systems take inputs from remote sensing, IoT monitoring, and AI-based decision models and directly transform them into variable-rate field operations without a human operator in the loop. Cross-country evidence shows that agricultural robotics deployed at scale can reduce herbicide use by up to 95% and pesticide use by up to 90% via targeted, plant-level application, while autonomous platforms powered by electric or hybrid can cut fuel-related emissions by up to 50% compared to conventional machinery [170]. Such gains are, however, concentrated in regions and farm types where the adoption barriers discussed in Section 3.6 have already been largely overcome: Robotics adoption to date remains highest for large, well-capitalized operations in North America, Europe, Oceania, and parts of East Asia, whereas uptake on smallholder farms is limited primarily by the upfront cost of the equipment and by the lack of standardized platforms that can be adapted to the heterogeneous field sizes, crops, and terrain typical of smallholder agriculture [170]. The question of robustness in variable field conditions (dust, uneven terrain, changing light) remains an open engineering challenge, and evidence of sustainability gains from robotics is largely derived from controlled trials or early-stage commercial deployments rather than long-term, farm-scale data, a limitation that mirrors the validation-data concern raised for AI models in Section 3.5 [170]. Hence, it is not progress in the capabilities of any one robot that will determine how fast autonomous field operations will go from demonstration projects to everyday practice, but progress in standardized, interoperable robotic platforms.

5. Conclusions

PA, as a central component of Agriculture 4.0, utilizes digital transformation to enhance farm management. The adoption of Fourth Industrial Revolution innovations has driven significant developments, including the use of UAVs (drones), global positioning systems (GPS), advanced data analytics, and AI, all of which support data-informed agricultural decision-making. This review functions as a practical guide for agricultural producers and agribusinesses pursuing the implementation of Industry 4.0 solutions. By examining the applications of IoT networks, automation platforms, analytical tools, and site-specific management methods, it cultivates a deeper awareness of the potential and complexities inherent in smart farming. Equipped with these insights, stakeholders can pursue strategic technology adoption and planning with greater confidence, thereby advancing sustainable production and encouraging cross-sector collaboration.

Besides this descriptive contribution, this review contributes three elements to the literature, which are described in Section 1.1. First, we explicitly state the narrative-review methodology, search strategy, and inclusion criteria used to assemble the evidence base, rather than leaving the literature-selection procedure implicit. Second, we bring together the technologies discussed in Sections 2 and 3 into one comparative table and ecosystem diagram (Section 3.5, Table 2) and into an explicit discussion of the cost, interoperability, cybersecurity, and connectivity barriers that govern their adoption (Section 3.6), rather than treating each technology in isolation. Third, we extend the outlook of Section 4 to digital twins, edge AI, federated learning, and autonomous field robotics, relating each emerging direction to the adoption barrier it is most suited to tackle. Future work building on this synthesis would particularly benefit from longer-term, farm-scale validation of decision tools based on AI under real, not benchmark, field conditions and comparative cost-benefit data of PA technologies across farm sizes and regions, as both gaps are consistently identified in the sections of this review.

Author contributions

Aleksandra O. Utkina: Conceptualization, investigation, writing–original draft, methodology; Dmitry E. Kucher: Supervision; Mohamed Shokr: Validation, formal analysis, writing–review and editing; Nazih Y. Rebouh: Conceptualization, writing–original draft, methodology, supervision, project administration, writing–review and editing. All authors have read and approved the final version of the manuscript for publication.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

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

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