Vijayakumar *et al. Discover Food* (2025) 5:265
https://doi.org/10.1007/s44187-025-00576-3

Discover Food

REVIEW **Open Access**

Opportunities, challenges, and interventions for agriculture 4.0 adoption

Shanmugam Vijayakumar[1,2*], Varunseelan Murugaiyan[2], S. Ilakkiya[3], Virender Kumar[2], Raman Meenakshi Sundaram[1] and Rapolu Mahender Kumar[1]

*Correspondence:
Shanmugam Vijayakumar
vijitnau@gmail.com
[1] ICAR-Indian Institute of Rice Research, Hyderabad 500030, India
[2] International Rice Research Institute (IRRI),
Los Baños, Laguna 4031, Philippines
[3] Department of Aerospace Engineering, MIT Campus, Anna University, Chennai 600 044, India

Abstract
Higher production costs, declining profitability, labor shortages, increasing wages, environmental degradation, and freshwater scarcity are major issues in agriculture. Agriculture 4.0, a data-driven transformation, addresses these issues through modern technologies like Internet of Things (IoT), artificial intelligence (AI), big data analytics, unmanned aerial vehicles (UAVs), and agricultural robots. It automates farm operations, enhances crop yield, food quality, safety, traceability, resource use efficiency, early issue detection, and minimises waste. By collecting and analyzing real-time data on soil, crop, and weather, Agriculture 4.0 enables tailored soil and crop management, reducing external inputs cost, mitigating labor constraints, protecting environment, increasing climate resilience, and promoting long-term sustainability while safeguarding natural resources. Despite its potential, the adoption of Agriculture 4.0 remains slow and uneven, particularly in developing nations and among smallholder farmers. This review examines the key barriers to adoption and proposes strategies for scaling implementation. Major obstacles include high initial investment costs, fragmented land holdings, diverse cropping systems, limited farmer awareness, lack of technical skills, inadequate digital literacy, complex AI algorithms, unreliable infrastructure, insufficient high-quality training data, poor internet connectivity, data privacy concerns, and a lack of supportive government policies. To overcome these challenges, a multi-faceted approach is necessary. This includes developing cost-effective sensors, user-friendly algorithms, and versatile machinery tailored for small-scale farms. Additionally, investments in rural infrastructure, public-private partnerships, farmer training programs, and policy interventions, such as subsidies, tax incentives, and regulatory frameworks are critical to ensuring equitable access and maximizing the benefits of Agriculture 4.0 for sustainable and inclusive agricultural growth.

Keywords Big data analytics, Drone, Robots, Digital agriculture, Smart farming

1 Introduction

1.1 Evolution of agriculture: from agriculture 1.0 to agriculture 4.0

Throughout human history, agriculture has remained a fundamental aspect of existence, evolving significantly in how food is produced. This evolution is delineated into distinct

Graphical abstract

phases known as agricultural revolutions (Fig. 1). The first agricultural revolution, or Agriculture 1.0, emerged approximately 10,000 years ago, marking the transition from nomadic hunting and gathering to settled farming [1]. It involved the domestication of plants (like wheat, barley, rice, maize) and animals (sheep, goats, cattle) for food, labor, and materials. Basic tools like grindstones and early plows were developed [2]. This pivotal shift led to the establishment of permanent settlements and the advent of early agricultural practices [3]. A more stable and reliable food supply enabled population growth and led to permanent settlements, fostering the development of villages and early urban centers. This era also saw the emergence of land ownership and the initial alteration of landscapes through practices like irrigation and slash-and-burn agriculture.

In the 18th century, the second agricultural revolution, or Agriculture 2.0, dawned with the introduction of agricultural mechanization aimed at enhancing land productivity and output [4]. This period, often overlapping with the Industrial Revolution, hence called Industrial Agriculture. This era witnessed a significant departure from traditional farming methods toward more modern, market-driven, and intensive system. Breeding crop and animals for desired traits (e.g., larger size, more meat/wool production) began. Mechanization of tasks with inventions like the seed drill, improved plows, and later, threshing machines and tractors, diminishing the reliance on manual labor [5, 6]. The development of factories and new materials like iron enabled better farm tools, shifting agriculture from subsistence to a commercial enterprise [7]. The consolidation of common lands into larger farms boosted efficiency but displaced small farmers. Increased efficiency reduced the need for farm labor, driving people to urban centers and providing a stable food supply and workforce for burgeoning industries.

The third agricultural revolution, or Agriculture 3.0, also known as the Asian Green Revolution, unfolded between the 1960s and 1990s. This period saw the introduction of high-yielding crop varieties, irrigation systems, and the widespread use of fertilizers to bolster crop productivity [8]. Agriculture 3.0 played a crucial role in sustaining a burgeoning global population and enhancing food security worldwide. However, it was not without criticism.

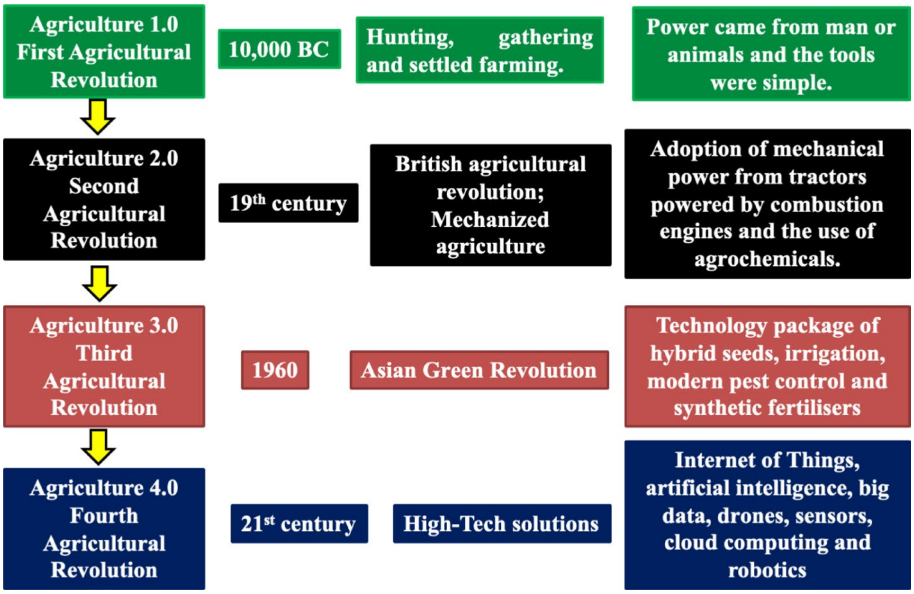

Fig. 1 A historical perspective on the agricultural revolution and its key components

1.2 Agriculture 3.0

Agriculture 3.0 led to exacerbated inequality among farmers. The introduction of high-yielding crop varieties, fertilizers, and modern irrigation provided larger farms with a significant competitive advantage over smallholder farmers, concentrating wealth and resources in the hands of a few large farms while disadvantaging smallholder farmers [9]. Fertilizers have played a crucial role in enhancing crop yields, but their imbalanced application and over-reliance have contributed to environmental issues such as eutrophication in streams and lakes, depletion of nutrients like potassium, zinc, boron, and iron, soil fertility degradation, and greenhouse gas emissions [10–12]. High-yielding varieties introduced during the Green Revolution displaced traditional crop varieties, resulting in a loss of genetic diversity [13]. Additionally, inefficient irrigation practices and excessive groundwater withdrawal for irrigation have led to a rapid decline in groundwater levels and increased soil alkalinity [14, 15].

Climate change, marked by unpredictable weather patterns and frequent extreme weather events such as floods and droughts, has caused significant crop losses and increased challenges in crop production [16, 17]. The rising prevalence of pests and diseases, coupled with their rapid resistance development to pesticides, further burdens farmers, resulting in reduced yields, increased production costs, and pesticide residues in soil and food. The migration of young people to urban areas for better wages and living conditions leads to an aging farming population and labor shortages [18, 19]. Inadequate infrastructure, including poorly maintained roads and insufficient storage facilities, complicates crop transportation and storage, leading to spoilage and waste [20]. The major sustainability issues of Agriculture 3.0 are summarized in Fig. 2.

The Food and Agriculture Organization (FAO) of the United Nations reports that approximately 500 million family farms worldwide produce nearly 85% of the world's food [21]. These small-scale farms often rely on manual crop scouting for assessing crop health and diagnosing pests and diseases, a process that is both time-consuming and inefficient. Additionally, decision-making is purely based on farmers experience,

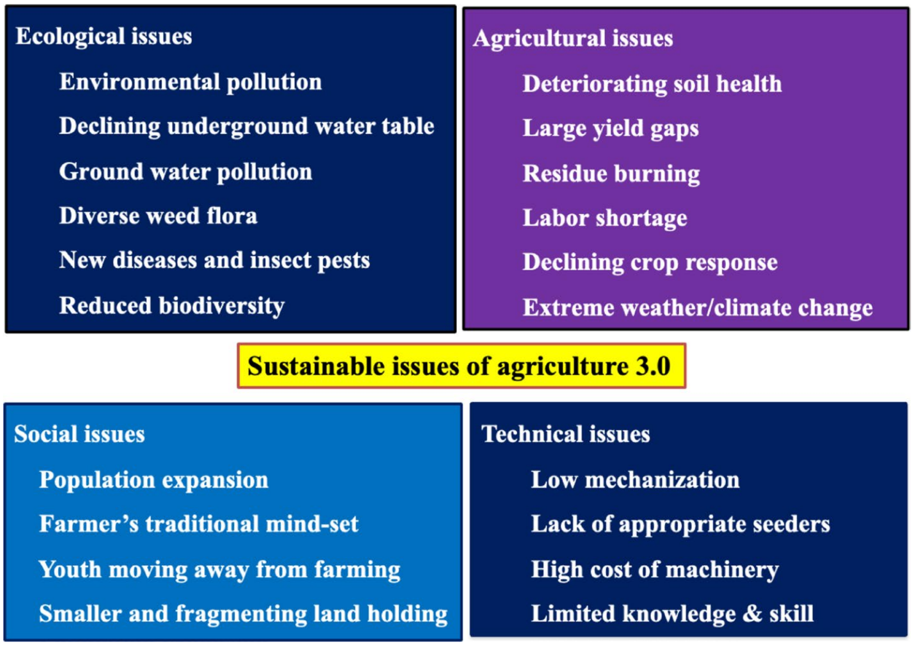

Fig. 2 Sustainable Issues of Agriculture 3.0

neglecting the considerable spatial and temporal variability within fields [22]. Small-scale farmers typically lack access to timely, accurate information on weather patterns, crop health, and the technology and equipment that could boost productivity and efficiency [23]. As a result, managing farms effectively using Agriculture 3.0 methods is becoming increasingly difficult and unsustainable. Addressing these multifaceted challenges is essential to ensure the long-term resilience and sustainability of agriculture, and Agriculture 4.0 emerged as a feasible option.

1.3 Agriculture 4.0

Today, we are on the cusp of the fourth agricultural revolution, known as Agriculture 4.0, Farming 4.0, Smart Farming, or Digital Farming. According to the FAO definition, Agriculture 4.0 is agriculture that integrates a series of innovations like precision farming, IoT and big data in order to achieve greater production efficiency [24]. Agriculture 4.0 has four key objectives: boosting productivity, optimizing resource allocation, adapting to climate change, and minimizing food waste [5]. Different authors have defined it differently. Agriculture 4.0, hereafter referred to as smart farming, is a modern farming practice that leverages cutting-edge technologies such as sensors, unmanned aerial vehicles (UAVs), global positioning systems (GPSs), robotics, artificial intelligence (AI), and big data analytics to apply inputs more efficiently, including pesticides, fertilizers, tillage, and irrigation water, and achieve higher crop yields and better quality without harming the environment [5, 25–27]. The overarching goal of smart farming is to make agriculture low-input, more efficient, sustainable, and accessible to all people [6, 28]. Smart farming leverages digital technologies to address concerns like sustainability, efficiency, profitability, resilience, and traceability and transparency [2]. The exact commencement of this revolution remains a matter of ongoing debate, with some articles suggesting that it began in approximately 2002 [29].

The escalating global demand for food, coupled with the pressing need for sustainable agricultural practices, necessitates innovative approaches to enhance productivity and resource efficiency. The adoption of smart farming has the potential to ignite a new techno-green revolution, offering a transformative pathway to achieve these goals. While the adoption of selective smart farming components is evident in several developed countries [30], the broader global adoption, especially in the Global South, remains nascent despite the immense untapped data potential, signaling a missed opportunity [31]. Even in regions with higher uptake, a comprehensive and integrated adoption of all smart farming components is often lacking. This review is thus motivated by the critical need to synthesize the existing knowledge on the benefits, opportunities, and challenges associated with the adoption of key smart farming technologies, thereby providing valuable insights for fostering a more widespread and effective techno-green revolution in agriculture. This review seeks to address the following key research questions:

(i) What are the documented benefits of agricultural robots, UAVs, and big data analytics in smart farming?
(ii) What opportunities exist for the widespread adoption of agricultural robots, UAVs, and big data analytics, drawing insights from the experiences of early adopters?
(iii) What are the primary challenges hindering the adoption of agricultural robots, UAVs, and big data analytics, and what feasible recommendations can be proposed to overcome these barriers?

2 Methodology

This review systematically synthesizes the current literature on agricultural robots, unmanned aerial vehicles (UAVs), and the application of Big Data Analysis in agriculture. The methodology adhered to the principles of systematic literature review to ensure a comprehensive, unbiased, and reproducible search and selection process.

2.1 Search strategy and information sources

An extensive and systematic literature search was conducted across multiple prominent online databases to identify relevant research and review articles. The primary databases utilized were ResearchGate, Google Scholar, IEEE Xplore, and ScienceDirect. The search strategy was developed using a combination of keywords related to the core themes of the review. Boolean operators (AND, OR) were employed to refine search queries and ensure comprehensive coverage. The keywords and their combinations were as follows:

Agricultural Robots: (“agricultural robot” OR “spraying robot” OR “mechanical weeding robot” OR “multi-purpose robot” OR “laser weeder”) AND (“challenges to adoption of agricultural robots” OR “intervention for large-scale adoption”).

Unmanned Aerial Vehicles (UAVs) in Agriculture: (“Unmanned aerial vehicles” OR “UAVs” OR “drones”) AND (“applications of UAV in agriculture” OR “weed detection and mapping” OR “livestock monitoring” OR “pesticide spraying” OR “water stress mapping” OR “advantages of UAV in agriculture”) AND (“challenges to adoption of UAVs”).

Big Data Analysis in Agriculture: (“Big Data Analysis application in agriculture” OR “big data analytics in agriculture”) AND (“tools and platforms for big data analysis and visualization” OR “various applications of big data analytics in agriculture” OR “Digital Agro-advisory” OR “Disease identification and management” OR “Automated decisions on irrigation and fertilization” OR “Price forecast” OR “Enhancing food supply chain transparency and traceability" OR "Precision weed control" OR "Detection of agricultural machinery failure" OR "Soil physio-chemical property analysis") AND ("challenges to the adoption of Big Data Analytics" OR "challenges to the adoption of smart farming").

To ensure a thorough search, variations and synonyms of these keywords were also considered during the search process (e.g., "drones" for "UAVs", "smart farming challenges" for "challenges to the adoption of smart farming"). The search was not restricted by publication date to capture the historical development and latest advancements.

2.2 Eligibility criteria

Articles were included in the review if they met the following criteria:

Language: Published in English.Relevance: Directly addressed agricultural robots, UAVs in agriculture, or Big Data Analysis applications in agriculture.Content Type: Research articles, review articles, conference papers, and book chapters.Focus: Provided insights into applications, challenges, or required interventions for large-scale adoption within the specified domains.Articles were excluded if they were not available in full text, opinion pieces, news articles, or informal reports without a clear methodological basis.

2.3 Study Selection Process

The retrieved articles from the initial database searches were systematically screened in two phases: (i) Title and Abstract Screening: All identified articles were initially screened by reading their titles and abstracts to remove irrelevant studies and duplicates. (ii) Full-Text Review: Articles deemed potentially relevant after the initial screening underwent a full-text review. During this phase, articles were critically assessed against the predefined eligibility criteria. Any discrepancies or uncertainties regarding inclusion were resolved through discussion among the review team.

3 Smart farming: innovative solutions to contemporary agricultural issues

Smart farming technologies enable farmers to manage their operations with greater precision, addressing the specific needs of crops and soil at smaller spatial and temporal scales. Through real-time data on soil moisture and nutrient levels collected from sensors and monitoring devices, smart farming allows precise tracking of crop and soil conditions [27, 32, 33]. The concept focuses on applying the right resources at the right time and place to enhance efficiency. By analyzing data on weather, soil physio-chemical properties, and crop status using advanced data analytics and machine learning (ML), smart farming detects unforeseen issues that might go unnoticed during periodic visual inspections and develops predictive models [30, 34]. This could help farmers make more informed decisions about crop management, allowing them to optimize yields, reduce waste, and increase profitability [27, 35, 36]. This site-specific application lowers production costs, conserves resource, improves food quality, mitigates greenhouse gas emissions and environmental impacts, and supports food safety [4, 33, 37].

Smart farming represents a significant shift away from traditional farming practices toward a more data-driven, technology-enabled approach to agriculture. It automates tasks such as planting, harvesting, and pest control and minimizes labor needs [4, 38]. For example, intelligent tractors use precise location data to ensure accurate seed placement and optimal fertilizer distribution. Precise weather forecasting enables farmers to adjust planting, irrigation, and harvesting schedules, reducing exposure to extreme weather events. In developing countries, traditional irrigation systems often operate at low efficiency (25–30%) due to outdated infrastructure and diesel dependence, resulting in higher greenhouse gas emissions and production costs [15, 38]. Smart farming improves irrigation efficiency by using weather forecasts and soil moisture sensors to optimize schedules, supporting reliable production in water-scarce areas [39, 40]. Additionally, it enhances market access by providing real-time information on demand and supply, helping smallholder farmers with limited resources and poor market access to compete globally and reduce postharvest losses. The major advantage of smart farming is summarized in Table 1.

4 Agricultural robots

Agricultural robots play a significant role in smart farming by providing efficient solutions to various agricultural tasks. Robots equipped with sensors, cameras, and algorithms are capable of monitoring soil moisture, temperature, and nutrient levels in real time [46–48]. They also identify and remove weeds or pests without the need for chemical sprays, thus reducing their environmental impact and increasing their efficiency [49, 50]. For example, spraying robots apply pesticides and fertilizers with the exact amount of chemicals needed, thereby avoiding the excess application of pesticides and safeguarding the environment [51, 52]. They automate several agricultural operations, such as planting, weeding, irrigation, and harvesting (Table 2). Planting robots ensure precise seed placement at the right depth and distance from each other [53, 54], while harvesting robots collect crops, reducing the need for manual labor and improving efficiency [47]. Overall, agricultural robots could help farmers reduce labor demand, minimize production costs, increase efficiency, and improve crop yields.

Robotic spot spraying for sugarcane leveraging computer vision and deep learning demonstrated 97% as effective as broadcast spraying while reducing herbicide usage by an average of 35% (up to 65% in low-weed areas). Crucially, it also led to a 39% reduction in herbicide concentration and a 54% reduction in load in irrigation runoff, highlighting its potential to cut herbicide use and improve water quality without compromising weed control [55]. An AI-powered robotic system for precise weed control in rice fields, developed at SOA University in Bhubaneswar, India, uses a YOLOv5 machine learning framework. This robot showed exceptional accuracy in tests, varying by only 2% from the true weed count and achieving an impressive 95% weed control rate. It surpasses manual methods in both precision and speed, highlighting the vital need to deploy such AI innovations widely in modern agriculture [56].

Multipurpose robots are versatile machines capable of performing various agricultural tasks such as ploughing, sowing, weed control, irrigation, harvesting, and transportation (Fig. 3). These robots eliminate the need for multiple specialized machines, handling labor-intensive and repetitive tasks year-round. Their flexibility drives cost reduction and promotes automation adoption in agriculture. High-value conventional and organic horticultural crops stand out as prime candidates for agricultural robots, primarily because of their heavy reliance on manual labor, high production cost, and higher pesticide residue risk associated with the cultivation of these crops. Table 2 presents a comprehensive list of commercialized agricultural robots, their designated uses, and their corresponding capacities.

Table 1 Smart farming technology: targets, interventions, outputs, and potential areas of application

Target	Problem	Intervention	Output	Potential area	References
Increasing crop yields	Low yield, higher yield gap	Improved decision-making processes	Precise establishment of tillage, sowing, irrigation, application of fertilizers and pesticides, harvesting, etc.	Rainfed, salt-affected, waterlogged, and low-fertility soil	[25, 41]
Efficient irrigation water use	Declining ground water table and lower crop productivity in rainfed conditions compared to irrigated conditions.	IoT-based automated irrigation schedule using real-time data of soil moisture levels, weather forecasts, and crop water requirements.	Precise and weather forecasting. Automated irrigation and water saving.	Arid, semi-arid, and rainfed areas where water is scarce. Greenhouse farming, orchards and urban agriculture where water is expensive.	[42, 43]
Addressing the agriculture labor crisis	Shortage of agricultural work force and increasing labor wages	Autonomous tractors, harvesters, robots, with AI and computer vision features and UAVs to perform various agricultural tasks	Reduced need for manual labor. Lower production cost.	Areas facing an acute scarcity of agricultural labors and rising labor wages.	[43]
Efficient fertilizer & pesticide use	Imbalanced fertilization, multi-nutrient deficiency, lower nutrient use efficiency and environmental pollution	Precision fertilizer and pesticide application in response to the varying conditions within the field.	Reduced environmental pollution. Resource saving. Lower production costs. Maximizes crop yield and profits. Prevents soil degradation.	Regions practicing intensive agriculture. Areas with problem soil and indiscriminate use of pesticides.	[28, 44, 45]
Enhanced crop quality	Pesticide residue in food produce. Inferior food quality.	Identify potential issues and take corrective actions early to prevent the indiscriminate application of pesticides. Avoid use of toxic chemicals.	Production of high-quality and traceable products that meet the demands of consumers and export markets. Reduced pesticide load in the food.	Health-conscious markets, export-oriented agriculture, and regions emphasizing organic and sustainable farming.	[40]
Climate resilience	Extreme weather events such as flood, drought, cyclone, heat waves, and cold waves damage the crop and cause yield loss.	Early warning through accurate prediction of extreme weather events using advanced weather monitoring systems, including satellites, and sensors.	Helps farmers to effectively adapt to extreme weather patterns. Allows farmers to take precautionary measures and make accurate decisions to minimize crop damage.	Regions that are more vulnerable to extreme weather events and areas experiencing extreme weather events more frequently.	[40]
Better market access	Higher middleman commission, price volatility, lack of transparency, limited access to markets, and unstable market demand.	Access to digital markets, including e-commerce platforms, facilitates direct connections between farmers and consumers, eliminating the need for intermediaries.	Connects farmers directly with consumers, eliminating intermediaries. Helps farmers to select high-return crops, stay informed about market trends.	Remote and underserved rural areas, developing countries, regions with difficult terrain, island nations, and arid regions	[28]

Fig. 3 Oz multi-purpose robot. **a** furrowing, **b** hoeing, **c** sowing, **d** transporting

4.1 Challenges to the adoption of agricultural robots

Robots often exhibit low detection/recognition rates, especially on weeds, insect pests and disease. For example, RobHortic, a field robot designed to detect pests and diseases in horticultural crops using RGB, multispectral, and hyperspectral sensors, achieved a detection rate of only 66.4% for images obtained in the laboratory and 59.8% for those obtained in the field [58]. Most agricultural robots are battery-powered, resulting in limited operating time due to constrained battery capacity [50, 57]. Agricultural robots slow operation speed and navigation complexity limit their area coverage per unit of time. Consequently, multiple robots may be needed to cover large areas, which increases the initial investment cost. Concerns over job displacement and the potential impact of the use of agricultural robots on rural communities need to be adequately addressed [59].

Robots require regular maintenance to ensure optimal performance. Any system breakdown can lead to delays in agricultural operations and potential yield loss [60]. Farmers often need to hire specialized technicians, which is challenging in many regions due to the absence of service providers. Additionally, farmers generally lack the technical skills to address these issues themselves, as this technology is new to them [61]. Agricultural robots also raise safety concerns, such as potential damage to crops in the event of a malfunction. Additionally, accidental exposure to laser robots could harm crops and pose health risks (eye injuries or burns) to operators and bystanders. Agricultural robots generate vast amounts of data; however, the lack of adequate infrastructure for data storage and analysis hinders their adoption and limits their potential to deliver valuable insights to farmers.

4.2 Intervention to overcome the challenges of agricultural robots

Agri-robots need to be energy efficient to operate for extended periods without frequent recharging or refueling [60]. The development of solar power robots could address

Table 2 Commercial agricultural robots and their use in agriculture

Robot	Developer	Country	Purpose	Special features	Power	Suitable crop	References
Herbicide spraying robot							
Ecorobotix	Ecorobotix AG	Switzerland	Autonomously detect and spray herbicides to control weeds with high accuracy.	Cover up to 3 hectares per day.	Solar-powered	Cereals, vegetables, and orchards	[49]
See & Spray system	Blue River Technology	United States	Uses cameras and AI to identify individual plants and determine the required treatment.	Precisely apply fertilizer and herbicides to individual plants. Save herbicide up to 70%.	Tractor powered	Cotton, soybeans, and corn	[52]
Mechanical weeding robot							
Tertill	Franklin Robotics	United States	Equipped with a spinning string trimmer to cut weeds at its base and a watering system to water the plants.	Affordable, eco-friendly, saves water, and avoids the use of chemical herbicides.	Solar-powered	Home & vegetable garden	[51]
Vitirover	Vitirover	France	The machine autonomously cuts grass, weeds, and other vegetation using a range of cutting blades that can be adjusted to different heights.	Uses soil moisture and temperature sensors to make decisions about irrigation and other management practices.	Solar-powered	Vineyards	[46]
Ted	Naio Technologies	France	Mechanical weeding (4.5 km/h), traction (upto 20% slope)	8 h per day autonomy, work output 5 ha/day	100% electrical	Vineyards	[50]
Aigro UP	Dutch ag-tech startup		Autonomous weeding and mowing	Up to 10 h of operational time	Dual Li-Ion battery	Narrow rows of crops, under the canopy of orchards	
Multipurpose robot							

Table 2 (continued)

Robot	Developer	Country	Purpose	Special features	Power	Suitable crop	References
Thorvald	Saga Robotics	Norway	Perform planting, weeding, and harvesting. UV-C treatment for powdery mildew control. Predatory mites dispensing and runner cutting.	Provides flower and fruit counts for yield prediction.	Battery powered	Strawberry, grapevine, and orchards	[57]
Oz	Naio Technologies	France	Close-to-crop and crop row weeding mechanically, furrow making, hoeing, and seeding	Oz can carry up to 80 kg and tow as much as 200 kg on a flat land.	Lithium batteries	For vegetables.	[50]
Dino	Naio Technologies	France	Autonomous weeding and sowing. It's larger, heavier (900 kg), and works faster.		Lithium batteries	Larger row crops (onion)	
Orio	Naio Technologies	France	Seeding, cultivating, weeding, collecting data and more	5.5 km/h Speed	Iron-Phosphate Lithium batteries	Lettuce, onions, carrots, parsnips, cabbage, leeks, cauliflower, garlic, cilantro, mint, etc.	
SwarmBot robot	SwarmFarm Robotics	Australia	Perform planting, weeding, and harvesting. Offers services like soil testing and mapping, yield mapping, and data analytics.	Multiple robots operate together to cover large areas quickly and efficiently. Reduce soil compaction.	Fuel powered	Row crops, turf grass, and orchards	[47]

Table 2 (continued)

Robot	Developer	Country	Purpose	Special features	Power	Suitable crop	References
FarmDroid F20			Seeding and weeding with 8 mm precision. Payback period as low as 2 years	Row spacing 22.5–90 cm.	Solar powered	Multiple crop	

battery-related issues and ensure energy efficiency. Using renewable energy sources would also reduce operational costs by lowering electricity expenses [62]. A survey of 174 farmers in Bavaria, Germany, by Spykman et al. [63] revealed a strong inclination towards non-purchase options like contractor services and machinery sharing through agricultural cooperatives or rental service providers. This approach not only mitigates the challenges of high initial costs and maintenance but also ensures the effective utilization of expensive robotic equipment.

There is a need to develop multipurpose robots capable of efficiently performing various tasks, such as plowing, sowing, weeding, irrigation, and harvesting. This approach would alleviate the financial burden on farmers, as they would not need to invest in separate robots for each operation. Instead, a single robot can efficiently perform multiple tasks [54]. Nevertheless, the cost of technology is expected to decrease over time, making agricultural robots a viable option for boosting production in the future. Sophisticated path planning and obstacle avoidance capabilities are crucial for overcoming the significant technical hurdle of navigating uneven terrain and avoiding obstacles like rocks and irrigation equipment. Agri-robots must adapt to diverse agricultural environments, necessitating the development of intelligent algorithms and sensors capable of recognizing and responding to changes [64]. Efforts should focus on developing robust infrastructure for storing and analyzing the large datasets collected by agricultural robots [65].

5 Unmanned aerial vehicles

Unmanned aerial vehicles (UAVs), commonly known as drones, are aircraft without human pilots on board. They enable farmers a bird's-eye view of their field, offering valuable insights into issues like moisture stress, soil fertility variations, and pest or disease infestations [66, 67]. Farmers can regularly inspect crops according to their preferences, providing weekly or even daily pictures to show changes over time, thus revealing possible "trouble spots" and subsequently improving crop management and production in those areas by making better crop management decisions [68]. In addition to monitoring plant growth, crop surveillance, and scouting, UAVs are used for pesticide spraying, seeding, pollination, fertilizer spreading, and damage assessment (flood, drought, cyclone, etc.) [69–71]. The use of UAVs for crop monitoring saves farmers time and money by allowing them to target problem areas more precisely with GPS technology. China has employed UAVs for pesticide spraying in agriculture since 2010 [70]. By 2020, 70,344 UAVs were treating 14.48 million hectares of cropland in China. Chinese farmer's decision to adopt UAVs for pesticide application is primarily influenced by arable land size, with a 2-hectare threshold [72]. A survey of 2,000 farmers across 11 Chinese provinces revealed that UAV adoption boosted per-hectare revenue by approximately USD 434–USD 488 and reduced pesticide application time by 14.4–15.8 h per hectare [73].

5.1 Various applications of UAV in agriculture

5.1.1 Assessment of seedling emergence

Monitoring seedlings in the early stage of crop growth is challenging due to their small size and lack of distinctive morphological traits. Manually counting and identifying seedlings at the species level is labor-intensive, time-consuming, and extremely difficult [74]. Therefore, technological approaches are needed to quickly monitor large areas in the early stages of crop growth to provide timely recommendations to farmers. UAV field mapping offers a novel approach to seedling monitoring. The use of low-altitude, high-resolution imagery combined with automated object-based image analysis (OBIA) enables the detection and monitoring of small objects even in challenging terrain [75]. In agriculture, this approach is utilized to map areas with unsuccessful germination, providing farmers with critical information about the total area requiring gap filling, the number of seeds needed, and the specific locations where gap filling is necessary.

Buters et al. [69] achieved 80% accuracy in detecting and counting seedlings using low-altitude UAV imagery and automated OBIA software. However, the accuracy of classification decreases with higher flight altitudes (resulting in lower image resolution) and more complex background surfaces, such as increased coverage of nontarget grasses and varied substrate textures. The necessary spatial resolution depends on the plant's leaf size postemergence, with crops featuring thin, wispy leaves requiring higher spatial resolution than those with larger leaves [76]. Lin et al. [77] developed an efficient real-time peanut video counting model combining improved YOLOv5s, DeepSort, and OpenCV programs to accurately distinguish peanut seedlings from weeds. The model achieved an accuracy of 98.08%, comparable to human counting, but required only one-fifth of the time. This video-based model outperformed image-based target detection algorithms, making it more suitable for practical investigations of the germination rate in peanut production.

5.1.2 Weed detection and mapping

UAVs equipped with RGB, multispectral, and hyperspectral sensors and cameras provide high-resolution aerial imagery to precisely identify and locate weeds. The images captured by UAVs are processed using sophisticated algorithms to distinguish between crops and weeds. For mapping individual grassy weeds, a higher resolution of < 0.5 cm/pixel is required [78]. Gašparović et al. [79] collected UAV data using a low-cost RGB camera and tested four classification algorithms for weed mapping. They employed both automatic and manual methods, as well as object-based and pixel-based techniques, on two data subsets. The automatic object-based classification method achieved the highest accuracy, with 89.0% for subset A and 87.1% for subset B. Campos et al. [80] reported a 45% reduction in herbicide usage with site-specific herbicide spray using a UAV in a vineyard without compromising weed control efficacy. High-precision GPS allows drones to navigate accurately and apply herbicides with minimal drift, further enhancing the precision of the operation. Weeds were detected with 92% accuracy at a spatial resolution of 5.42 mm/pixel when the sensor was maintained at a 10 m altitude. However, the accuracy decreased to 84% at a spatial resolution of 20.31 mm/pixel when the altitude increased to 30 m above ground level [81]. Table 3 provides details on the successful use of UAVs for weed mapping in different crops.

5.1.3 Livestock monitoring

UAVs are also utilized for livestock monitoring by capturing high-resolution images of animals and tracking their movements, which helps identify areas of concern such as injured or sick animals, and track animal behavior patterns. Livestock monitoring using UAVs aids farmers in improving animal welfare and optimizing feeding and grazing practices [82]. UAV images were combined with vision algorithms for detecting changes in animals posture, for lameness detection within a herd. A study by Krul et al. [33] explored the performance of two visual simultaneous localization and mapping (VSLAM) algorithms, ORB-SLAM and LSD-SLAM using small commercial drones for indoor livestock monitoring, where GPS signals are typically unavailable. The findings indicated that drones equipped with an aerial VSLAM algorithm could achieve accurate positioning and waypoint navigation in indoor livestock environments with small position errors.

Table 3 Weed mapping using different sensors and algorithms for different crops

Crop	Sensor	Algorithum	Accuracy	Remarks	References
Oat	RGB	Pixcel-based RF, Object-based RF.	87–89%	Classification accuracy is highest for the automatic object-based classification method	[79]
Maize	RGB, Thermal, Multispectral,	RF, SVM, NBC. Among three, SVM performed best.	96%	Fusion of textural, structural, and thermal features achieved the best performance	[85]
Maize & Sunflower	RGB	OBIA by SVM, k-means, clustering, object-refining	~ 90%	Various statistical, spatial, and texture metrics offer significant potential for weed mapping between and within crop rows and work well when combined with OBIA.	[86]
Maize	Multispectral	Pixel-based weed and crop classification using a U-Net	90%	Low-cost system for weed mapping.	[87]
Sunflower	RGB, Multispectral	OBIA algorithm	100% for multispectral, 60% for RGB	Only 3–23% of the field was treated with herbicide instead of treating the entire field.	[88]
Rice	RGB	FCN, CNN (Patch-based and Pixel-based)	FCN outperformed (93%) other algorithms.	FCN is a fully supervised algorithm that relies on a large amount of labelled images for training and updating, requiring extensive manual labelling. This limits its application.	[89]
Silybum marianum	Multispectral	OC-SVM, OC-SOM, Autoencoders and OC-PCA	OC-SVM–96%	One class novelty detectors can be applied operationally for mapping *S. marianum* with UAV	[90]
Maize	Multispectral	OBIA	86%	Area free of weeds was 23%, and the area with low weed coverage (< 5% weeds) was 47%.	[91]

FCN Fully convolutional network; NBC naive Bayes classifier; OBIA Object-based image analysis; OC-SVM One class support vector machine; OC-SOM One class self-organizing maps; OC-PCA One class principal component analysis; RF random forest; SVM support vector machine

Bastos et al. [83] validated the feasibility of using UAV to collect zootechnical data in tropical cattle feedlots. UAV-captured images across 110 pens with up to 150 animals over 21 days, showed almost perfect agreement with conventional methods for feed trough levels (kappa = 0.901), and substantial agreement for fecal score (kappa = 0.785) and pen surface conditions (kappa = 0.737). While animal counts and water quality showed only fair agreement, the findings confirm UAV viability as an accurate, efficient, and cost-effective alternative for monitoring key zootechnical indices, promising improved animal management, welfare, and yield. Li and Xing [84] optimized UAV deployment strategy for tracking GPS-collared livestock in pastures, focusing on minimizing the average UAV-animal distance while accounting for animal mobility. The authors introduce a two-phase approach: first, a "sweep coverage" procedure by UAVs to acquire initial animal locations, followed by real-time UAV redeployment using a streaming K-means clustering algorithm that incorporates updated GPS data. Their method demonstrates superior performance in reducing the average UAV-animal distance compared to standard K-means, highlighting its potential for efficient livestock monitoring.

5.1.4 Pesticide spraying

UAVs equipped with tanks fly in proximity to fields, maintaining a consistent pesticide application rate and covering 20–33 hectares per day. This speed is 30–60 times faster than that of manual spraying [70]. Another study reported that UAV spraying cut the pesticide use by 30–505 and saved labor cost by 40–60% [92]. A UAV spray volume of 30 L/ha achieved weed control efficiency statistically comparable to that of a manual knapsack sprayer using 500 L/ha, highlighting an impressive ~ 15 times less water usage [93]. Quan et al. [73] found that UAV adoption increased revenue by $434 to $488 per hectare and reduced pesticide spraying time by 14.4 to 15.8 h per hectare based on a survey of 2000 farmers across 11 Chinese provinces. Crop spraying using UAVs also improves worker safety by preventing labor exposure to harmful pesticides [66, 94]. The intelligent spraying system of UAVs enhances pesticide application precision and reduces pesticide residue. However, fine droplets (< 50 μm) tend to drift easily and lose kinetic energy quickly after release, causing external winds (> 5 m/sec) to direct them into the drift zone. In contrast, coarser droplets (> 400 μm) substantially reduce drift compared to finer droplets but encounter difficulties in achieving penetration [95].

5.1.5 Water stress mapping

Soil moisture sensors provide point data on soil moisture depletion but lack field-scale assessments at the desired spatial and temporal resolutions. Modern variable rate irrigation systems offer tailored water distributions to different sections of the field based on their unique needs. However, information about soil moisture is needed at higher spatial (0.3 m pixel) and temporal resolutions [96]. Drones have the potential to enhance irrigation systems by providing high spatial and temporal crop water stress maps across diverse environmental conditions [97]. Images obtained at 13.00 h show a maximum correlation with crop water stress [71, 98]. For water stress mapping, thermal cameras are more commonly used than other types of sensors. Table 4 provides details on the successful use of UAVs for water stress mapping in different crops.

Table 4 Crop water stress detection using UAV thermal and multispectral images

Crop	Sensor	Parameters	Remarks	References
Maize	Multispectral	Nine vegetation indices	TCARI, RDVI, and SAVI had the best correlations with CWSI	[99]
Vineyard	Thermal	Canopy temperature, leaf water potential	0.3 m pixel resolution is needed for precise CWSI mapping. The optimal time for obtaining thermal images is 12:30 h, as CWSI correlates with leaf water potential.	[96]
Cotton	Thermal	Leaf stomatal conductance, CWSI	Canny edge detection algorithm effectively eliminates the soil background in a thermal infrared image	[98]
Cotton	Thermal	Canopy temperature histogram, stomatal conductance, transpiration rate	Simplified CWSI was used to diagnose water stress for cotton. Soil background pixels of thermal images were eliminated using the Canny edge detection.	[71]

TCARI-transformed chlorophyll absorption in the reflectance index; RDVI - renormalized difference vegetation index, SAVI- soil-adjusted vegetation index; CWSI- crop water stress index.

5.2 Challenges to the adoption of UAVs

Despite the numerous benefits of using UAVs in agriculture, several bottlenecks hinder their large-scale adoption (Fig. 4). The high cost of UAVs, sensors, hardware, and software brings a significant financial burden to farmers [100]. Without the UAV, the cost of a single multispectral camera can reach up to 4,500 euros [101]. UAVs produce very fine spray droplets (25–500 microns) that are highly susceptible to drift. The risk of drift increases with increasing spray height and wind speed. It is generally recommended to spray at heights less than 3 m and wind speeds less than 3 m/sec to minimize drift. Droplets smaller than 200 µm can drift considerably off-target when subjected to a crosswind of 5 km per hour [102]. Although UAVs cover large areas with small volumes of spray fluid, the spray is prone to rapid drying in hot weather. This shortens the window for weeds or plants to absorb pesticides, potentially reducing their efficiency.

Currently, apart from mapping drones, most drones have a flight endurance ranging from 7 to 15 min with a single battery. Additional spare batteries are required for extended operation hours, which increases overall costs [68, 103]. UAVs used in agriculture typically have a payload capacity of 10–25 kg, resulting in frequent reloading of spray fluid or seeds/fertilizers. The use of low spray volumes may affect pest control efficiency. Yan et al. [104] compared aerial and ground spraying methods for controlling thrips on cowpeas. UAV spray volumes of 22.5, 30, and 37.5 L/ha achieved thrips control rates of 69.79%, 80.15%, and 80.58%, respectively, demonstrating that lower spray volumes were less effective.

The UAV spray units currently available on the market do not support automatic site-specific application of herbicides based on GPS input. These units utilize the waypoint for herbicide applications, which is not capable of auto-triggering spray applications at a prespecified location [105]. Site-specific weed management operations using existing UAV spray platforms depend solely on the remote pilot's skillset to manually trigger applications at a required location. While this approach may work for small areas, it is not feasible for spot applications over a large farm. The use of UAVs is subject to various regulations related to aviation, privacy, and safety, which are complex and vary across countries, making adoption challenging for farmers [106]. The lack of supporting

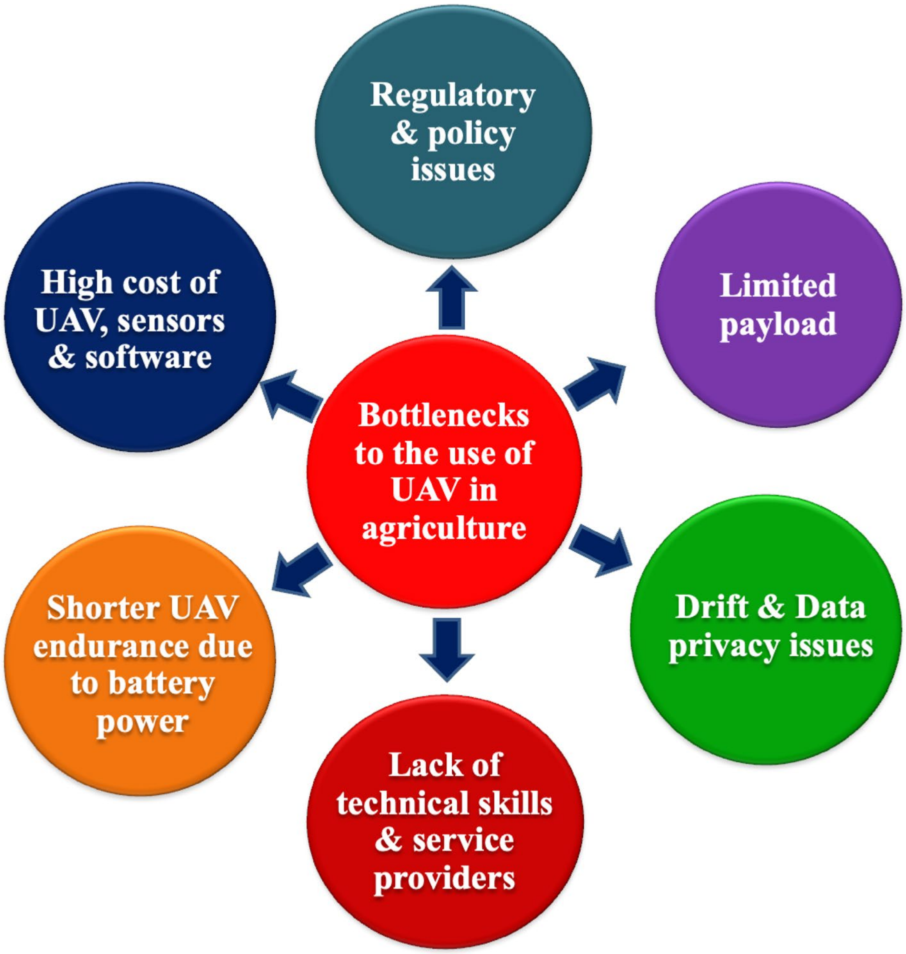

Fig. 4 Bottlenecks for UAV technology adoption in agriculture

infrastructure, such as charging stations and maintenance services, further hinders large-scale adoption. Moreover, using UAV technology requires technical knowledge and skills not readily available among farmers or farmworkers, making it difficult to interpret and act on the data collected [65, 107].

The large amount of data generated by UAVs could be overwhelming and require specialized skills for management and analysis [61]. Farmers need access to data management and analysis tools for effective use. Concerns about privacy and data protection may arise, as UAVs equipped with cameras may capture images and videos of people without consent [108]. Technology providers often claim data ownership due to their platforms and sensors. Farmers frequently cede control of their valuable operational data through complex contracts. Consequently, their aggregated insights can be sold to third parties, often without their explicit knowledge or fair compensation. Large corporations can leverage aggregated farm data for market analysis, price discrimination, or even to create new products that are then sold back to the very farmers who supplied the data, sparking concerns about fair value exchange and potential exploitation. Contracts are often lengthy, filled with technical jargon, and difficult for non-legal experts to fully comprehend. Farmers may not understand the full implications of what they are agreeing to. Additionally, if UAV data are not properly secured, they may be vulnerable to unauthorized access or theft, especially when transmitted wirelessly to ground control stations [109].

5.3 Intervention to overcome the challenges of UAVs

Strict adherence to standard operating protocols, such as spraying at lower heights during periods of lower wind speeds, can minimize the problem of drift hazards [102]. To ensure maximum uptake, it is advisable to spray when the weather is cooler. Spraying early in the morning or late in the evening is advised to prevent rapid drying of spray droplets. Additionally, wind speeds during these times are typically weaker than those at midday, reducing the risk of drift [105]. The invention of multipurpose UAVs, capable of performing diverse tasks such as seed spreading, fertilizer application, spraying, and mapping, has significantly enhanced the appeal of UAV technology for farmers. This versatility has facilitated increased adoption and mitigated the high initial investment costs associated with UAV technology [110]. Moreover, UAV adoption is rapidly increasing in many developing Asian countries, including India, driven by the availability of more affordable agricultural drone rental services. Similarly, the development of fast-charging intelligent batteries has made this technology more viable and acceptable. Intelligent batteries can be charged in less than 20 min and have approximately 300 to 400 recharge cycles.

Establishing nationwide drone pilot training and certification centers could equip many agrarian populations with the knowledge and skills required to become UAV pilots [103]. Policymakers, industry players, and development agencies must collaborate to develop solutions that reduce the cost and complexity of UAV technology, improve access to finance and infrastructure, ensure technical support, and enforce regulatory compliance [100, 107]. To ensure a more ethical smart farming, we must establish clear legal frameworks and industry standards for data ownership, access, and usage, strongly emphasizing farmer data sovereignty [105]. Ethical considerations like fairness, accountability, and privacy need to be integrated into the design of agricultural AI systems from the outset. Furthermore, implementing user-friendly, transparent, and comprehensible consent processes will truly empower farmers to control their data.

6 Big data analysis

Data is one of the most valuable resources in modern agriculture, driving innovations and enhancing decision-making processes. Forbes estimates that the world generates approximately 2.5 quintillion bytes of data daily, highlighting the vast scale of this resource. Big data analysis in agriculture refers to the process of collecting extensive information on weather patterns, soil conditions, crop yields, pest dynamics, livestock health, and market trends and applying advanced analytical techniques, including ML and predictive modeling, to extract valuable insights and patterns, enabling farmers to interpret past events, predict future outcomes, and make more precise, timely decisions through targeted investigations [34, 111]. Big data in agriculture is defined by five key characteristics: volume, velocity, variety, veracity, and value (Fig. 5).

The decreasing cost of sensor technology is empowering farmers to monitor crucial factors such as animal movement, soil physio-chemical properties, and soil moisture in nearly real-time. With accessible and affordable computing power, analyzing these data has become feasible, leading to the development of decision-support tools such as

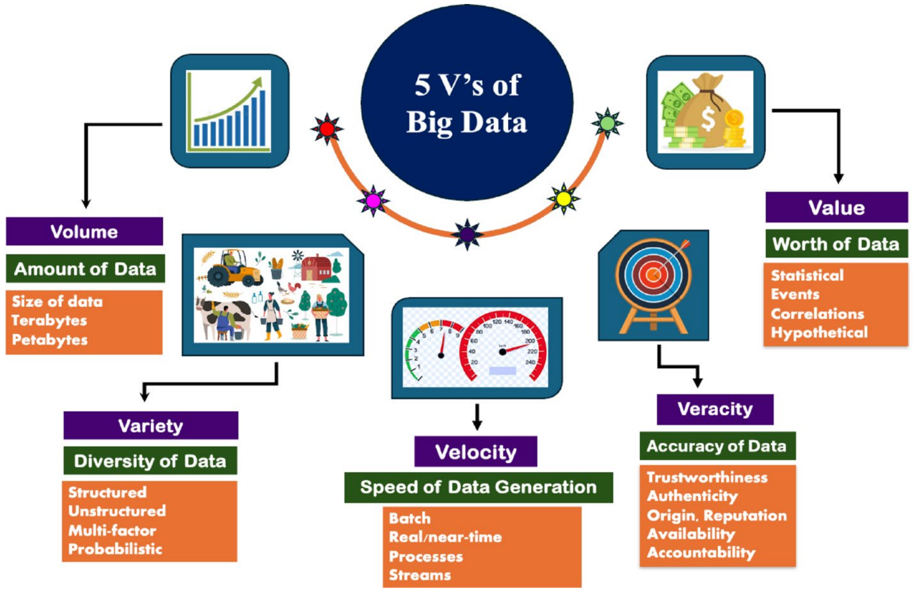

Fig. 5 The Five Vs (volume, velocity, variety, veracity, and value) of big data analytics

Table 5 Mobile-based big data advisory system for agriculture

Tool	Developer	Purpose
aAQUA and Agro Advisory System	IIT Bombay	Provide a solution to farmers queries related to crops. Multilingual question and answer forum.
m-Krishi	TCS	Mobile-based agro advisory system provides the farm-specific soil and crop data, and expert's advice to farmers in audio and video format.
Agrovoc	FAO	AGROVOC is a comprehensive thesaurus on food and agriculture, published as linked open data and accessible for public use (https://www.fao.org/agrovoc/). AGROVOC consists of 41,000 concepts and 1,151,000 terms in up to 42 languages.
Green phablet	ICRISAT in collaboration with NUNC Systems	Real-time information sharing between farmers and researchers helps farmers enhance crop productivity and enables researchers to gather accurate, practical data. Priced at US$ 299.
Agropedia	ICAR- National Agricultural Innovation Project	Online repository of agricultural information of nine crops, viz., rice, wheat, chickpea, pigeon pea, vegetable pea, lychee, sugarcane, groundnut, and sorghum (http://agropedia.iitk.ac.in/)
CropInfo	Arun Gulbadher	Website & android-based application provide crop production, protection and compendium information in multiple language (https://cropinfo.in/)
mKisan	Department of Agriculture and Cooperation, India	Give information/services/advisories to farmers by SMS (text/voice) in their language (https://mkisan.gov.in/Home/copyright). A total of 106,738 advisories were sent to 53 million registered users.

on-tractor dashboards and mobile applications (Table 5). These tools assist farmers in implementing more precise management practices, particularly with input applications. m-Krishi is a mobile-based agricultural platform developed by Tata Consultancy Services that provides management advice to farmers in audio and video formats based on soil and crop conditions. The mKisan is an Android application available on the Google Play Store that offers an advisory to registered farmers through SMS, IVRS, etc. Similarly, Krishimitra is an Android-based application that provides an advisory to Gujarat cotton growers using RESTful services. By proposing an agro advisory system, this open-source, cost-effective, and scalable big data analytics architecture narrows the technological gap between rural communities and information. This transformation is largely attributable to emerging Big Data analytical platforms, including cloud computing and ML algorithms, which drive AI in agriculture [111].

6.1 Tools and platforms for big data analysis and visualization

Numerous tools and platforms are available for data preparation, transformation, and modeling to extract valuable insights. Algorithms such as MapReduce enable the processing and generation of large datasets with massive scalability through parallel, distributed computing. Hadoop clusters exemplify this approach, handling vast amounts of unstructured data. Knime offers an open platform for data-driven innovation, while OpenRefine facilitates working with unstructured data. The R-Project supports data mining and statistical analysis. Orange provides open-source ML and data visualization. Microsoft's Power BI delivers interactive visualization and business analytics, and Tableau supports data preparation, analysis, and collaboration. Infograms help create engaging infographics and reports for data visualization. Olam Farmer Information System (OFIS) is a big data analytics technology that allows field staff to survey and record, on the spot, thousands of farms, the surrounding landscape, and the farmer's social circumstances. The collected information is used to create detailed models that advise farmers and supply chain participants on maximizing effort, identifying risks and opportunities, and focusing resources such as training or infrastructure investment. The OFIS was initially launched in 2014 in Côte d'Ivoire as an initiative to understand the farm landscape of Olam's cocoa suppliers. Since then, the platform has been rolled out across eight product categories, including coffee, cashew, cotton, and rice, in 30 countries, including Brazil, Ghana, Indonesia, Mexico, Turkey, and Vietnam. By the end of 2018, 550,000 farmers had been registered on the platform.

The big data pipeline comprises several crucial stages to transform raw data into valuable insights (Fig. 6). Initially, data extraction involves gathering data from various sources, such as sensors, databases, and social media, ensuring a comprehensive dataset. These raw data are then stored in scalable storage solutions, such as data lakes or distributed file systems, to accommodate the large volumes and varied formats. Next, data processing and integration standardize and clean the data, and different data sources are merged into a cohesive dataset ready for analysis. Following this, data analysis employs advanced algorithms and ML techniques to uncover patterns, trends, and actionable insights [34]. Finally, data visualization presents the analyzed data in an intuitive and accessible manner using charts, graphs, and dashboards, enabling stakeholders to make informed decisions swiftly and effectively. This structured approach ensures that data flows seamlessly from collection to actionable insights, driving strategic decision-making.

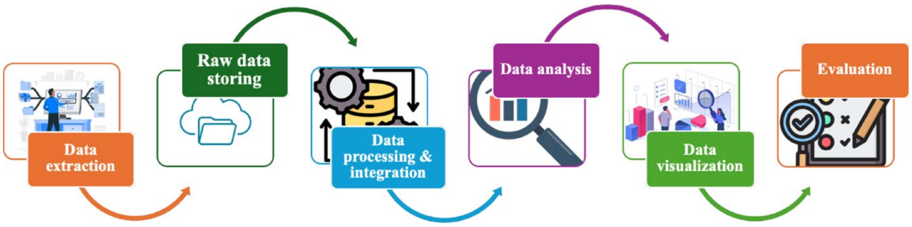

Fig. 6 Stages of the big data pipeline

6.2 Various applications of big data analytics in agriculture

Big data analytics is used in various agricultural processes, including agricultural machinery problem analysis, personalized production recommendations, price forecasts, agro-advisories, pest and disease identification, and autonomous robots and tractors (Table 6).

6.2.1 Digital agro-advisory

Shah et al. [115] developed and implemented a big data analytic prototype for cotton crop advisory in the Ahmedabad district, Gujarat, India. Farmers who utilized real-time agricultural advisory services experienced economic benefits ranging from 22 to 379% greater [116]. Similarly, the "intelligent agricultural systems advisory tool– iSAT" decision support tool integrates past climate data, current weather conditions, and forecasts to provide pre- and in-season agro-advisories to farmers. These advisories have impacted both strategic and tactical decisions, leading to evidence of crop diversification in treated villages versus in control villages. Approximately 80% of the farmers utilized the information for harvesting decisions, 79% for sowing, and 65% for land preparation. Crop productivity in climate-informed villages increased by 1–56% compared to that in uninformed villages [117]. Digital advisory services play a crucial role in promoting technology adoption among smallholder farmers. Asante et al. [118] reported that digital advisory services substantially increased the chances of embracing climate-smart agricultural methods such as row planting, zero tillage, and drought-tolerant seeds by 12.4%, 4.2%, and 4.6%, respectively. Various factors impact farmers' decisions to utilize digital advisory services, including age, gender, education, perceived pest and disease prevalence, and perceived drought pressure.

6.2.2 Disease identification and management

Digital image processing and model-based approaches accurately identify pests and diseases. Integrating ML and image processing further enhances this by automating feature extraction, enabling cost-effective, early-stage detection, classification, and prediction of crop issues [119]. Kaur et al. [119, 120] developed a big data analytics framework to identify diseases based on symptom similarity and recommend solutions accordingly. The data are collected from various sources, such as laboratory reports and websites, and then cleansed and normalized to extract relevant information and features. The normalized data are stored in the Hadoop Distributed File System and processed using HiveQL, an SQL-like query language, to analyze agricultural data. By matching crop disease symptoms, the framework identifies disease names and proposes solutions in graphical form based on evidence from historical data [119].

The Big Data Analytics system architecture for pest and disease identification is presented in Fig. 7. The Smarter Pest Identification Technology (SPIDTECH) Android app was created to digitally identify and monitor insect pests and diseases in nine crops (coffee, cacao, soybean, corn, banana, sugarcane, tomato, coconut, and rice) in the Philippines. It can recognize 71 insects and 63 diseases and provides management strategies both in English and Filipino. Identification utilizes a trained MobileNetV2 convolutional neural network, achieving accuracy rates ranging from 55.7 to 73.3% with a dataset containing 104 insects and 89 diseases [121].

Table 6 Different applications of big data analytics in agriculture

Purpose	Country	Technology used	Information/Services provided	Advantage	Developers & References
Agricultural machinery failure analysis	China	Internet and big data analytics. MapReduce data analysis engine, Spark engine and Hadoop technology.	Machinery failure causes. Timely warning for maintenance requirements.	Reduce or eliminate number of breakdowns. Prevent loss of productivity and quality. Reduced maintenance cost and time.	[112]
Personalized production recommendations	Italy	esiFARM web portal, big data analytics, Arduino MKR FOX 1200	Automated irrigation system. Information on weather and plant health.	Save water. Prevent losses due to weather hazards. Increased yield of fruits and vegetables.	FaMoSA (Farm Monitoring Systems for Agriculture)
Multipurpose wireless mobile robot	India	IoT, Raspberry Pi 2 model B hardware	Moisture sensing, scaring birds and animals, spraying pesticides and switching ON/OFF electric motor.	Reduce labor requirements. Real-time monitoring.	[113]
Smart Assistant	Japan	GPS antennas and other associated communication terminals	Visual surveillance, automation of agricultural machinery.	Increase production efficiency and operation status management.	Yanmar
Smart agricultural machinery information service	China	Internet, wireless communication and big data	Machinery positioning, dispatching, working area calculation and statistics.	Enhance efficiency, safety, and productivity.	Ningbo Agricultural Machinery Station cooperated with Ningbo China Mobile Branch
Agricultural Machinery Operation Management	China	Beidou Satellite Navigation System, circuit system, data transferring and remote monitor and control	Positioning monitoring, locomotive management, area statistics and soil temperature and humidity and locomotive speed in real time.	Enhance efficiency, safety, and productivity.	Jointly developed by Zhengcheng Technology Company Ltd. and Jiangsu Beidou Satellite Application Industry Research Institute [114].
iFarming: Providing scientific management and business decisions	China	Internet of Things and big data	Measure basic farmland data, collect location information, and match with intelligent agricultural machinery.	Improve productivity, production efficiency, and minimized production cost.	Revo Apos Group

6.2.3 Automated decisions on irrigation and fertilization

A big data platform called esiFARM was developed in Italy and has four core components: a data warehouse, a data transmission system, a data engine system, and a user panel. Real-time temperature, humidity, and crop volume data are collected by using

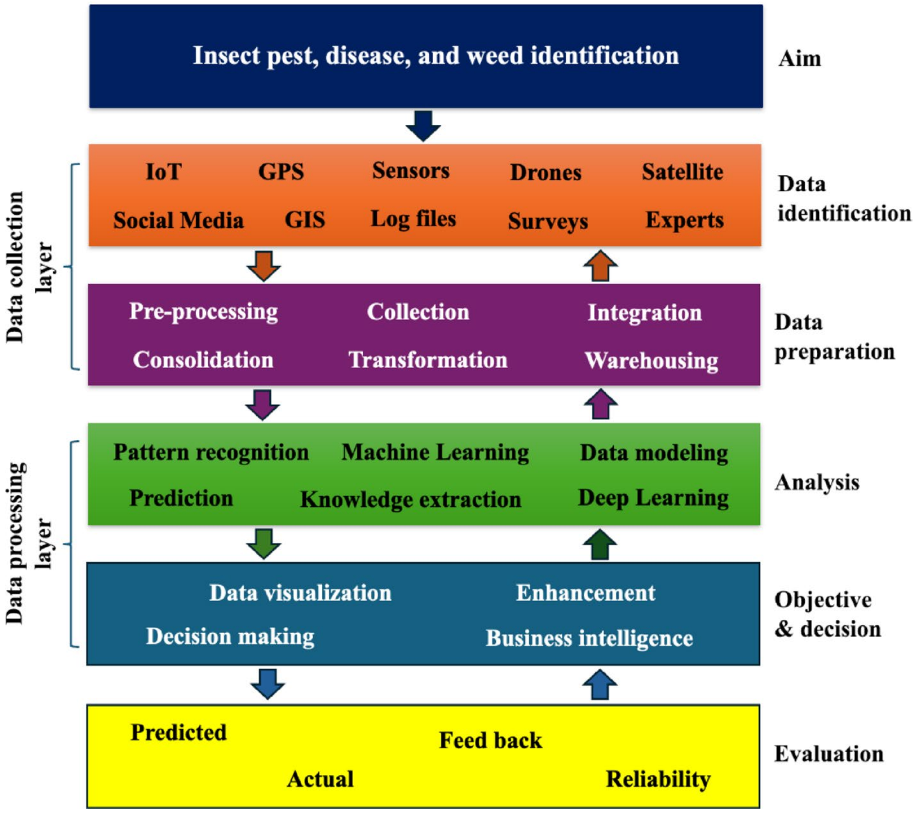

Fig. 7 The architecture of a big data analytics system

ground sensors and sensors on drones and satellites. These data are transmitted to the data warehouse via the LPWAN, GPRS/GSM, and Wi-Fi networks. The data engine system employs parallel calculations to create custom atmospheric evolution and plant growth models, facilitating personalized production recommendations [34]. Furthermore, irrigation systems automatically adjust external inputs to enhance agricultural productivity [112]. Zhang et al. [122] developed a system that utilizes the IoT and other technologies to monitor crop growth in real time, automatically collecting data and uploading it to Shandong Agricultural University's central big data database. This database intelligently stores, screens, calibrates, mines, and extracts monitoring data to establish a crop growth model based on big data. This model predicts and forecasts the water requirements of crops during different growth stages, enabling automated decisions regarding irrigation and fertilization.

6.2.4 Price forecast

Agricultural market prices are dynamic and nonlinear, posing challenges for accurate forecasting. Effective price prediction enables farmers to choose crops that maximize income [123], yet traditional models like ARIMA perform well only with linear trends, which is rarely the case in agriculture. This calls for more advanced approaches, such as ML models. Wang et al. [124], for instance, found that the SVM model effectively captures these nonlinear relationships in the garlic prices forecast. Notably, the ARIMA-SVM hybrid model surpasses both standalone ARIMA and SVM in short-term price forecasting, demonstrating superior accuracy. Similarly, in Pakistan, the ML model

Long-Short-Term Memory (LSTM) outperformed ARIMA and Random Forest with a higher R^2 value of 0.8 in the spinach prices forecast [123].

6.2.5 Enhancing food supply chain transparency and traceability

Concerns about food adulteration have been increasing, with incidents such as the intentional mislabeling of lower-quality food. Horsemeat was discovered in ground beef in the European Union [125], and 25% of seafood sold in Canada is mislabeled as more expensive varieties [126]. Big data analytics, in combination with DNA barcoding, significantly enhances the transparency and traceability of global food supply chains. DNA barcoding and mini barcoding are increasingly used to verify the origins of food, thereby identifying mislabeled or adulterated foods [127, 128]. Big data analytics tools, such as ML and data mining, can efficiently process and analyze the large dataset generated by DNA barcoding (a technique that uses short genetic sequences to identify species), enabling the rapid identification of patterns, anomalies, and trends that may indicate food fraud. By combining the power of DNA barcoding and big data analytics, we can build a more robust and transparent food supply chain.

Gorini et al. [128] examined 212 food samples from various categories: seafood, plants, agricultural products, spices, and probiotics. Their analysis revealed that DNA barcoding accurately identified nearly 89% of the samples and confirmed its status as a fast and reliable method for ensuring quality and safety in the food field. Xing et al. [127] assessed the authenticity of 52 meat, poultry, and fish products from Chinese markets using mini- and full-barcoding. Nearly 23% of these samples were mislabeled or contained undeclared species. Mini-barcoding, a streamlined DNA sequencing technique, proved effective in detecting food fraud, especially in processed foods. Combining mini-barcoding with next-generation sequencing (NGS) offers a promising approach to identifying mislabeled food products. AI, leveraging ML algorithms, is transforming foodgrain quality assessment. It enables rapid and accurate identification of product quality by evaluating characteristics like color, texture, and kernel integrity across various grains [119].

6.2.6 Precision weed control

Big data analytics automates the process of weed control in agriculture through systems that integrate autonomous vehicles with advanced GPS systems, drones, and digital libraries [105]. The IoT, cloud computing, mobile applications, and big data storage are technologies used to accomplish functions. The data sources are diverse and include official government surveys and reports, weather stations, sensors, satellites, news feeds, social media, etc. The sensors are IoT-enabled and transmit live data to remote cloud servers, where they are studied and analyzed via machine learning applications in neural networks and logistics regression.

6.2.7 Detection of agricultural machinery failure

A novel platform for agricultural machinery failure analysis was developed in China by collecting and analyzing floor data from agricultural engineering machinery and leveraging the internet and big data technologies. The platform offers intuitive information on mechanical parts, failure causes, and maintenance requirements. It has access to

100 million data points, and its practical application has been demonstrated on numerous farms across various provinces in China [112].

6.2.8 Soil physio-chemical property analysis

A Big Data environment for agricultural soil analysis from computed tomography images has been developed, incorporating three layers: source, big data environment, and applications. This system utilizes the Hadoop framework for processing computed tomography images and 3D reconstruction and includes statistical analysis of soil samples. The developed system serves as a comprehensive soil analysis tool to address agricultural soil-related issues [129].

6.3 Challenges to the adoption of big data analytics

Big data comes with big challenges. The success of big data analysis in agriculture hinges heavily on the availability of accurate data and precise assessments of variability in space and time [130]. More data is not always better. Regularly collecting a targeted set of data streams is more valuable than aimlessly gathering a broad array of data. Therefore, when discussing big data, it is essential to emphasize the importance of high-quality data. Data safety and privacy are the other major concerns [111, 131]. The data collected by smart farming is valuable to competitors, hackers, or other malicious actors. Data breaches or unauthorized access to smart farming systems and devices could lead to the loss of sensitive information, such as financial data or personal information of farmers, or data manipulation, leading to significant financial and reputational damage [132, 133]. The ownership and control of data generated by smart farming technologies could be a contentious issue. Farmers need to ensure that they retain control over their data and that it is not shared with third parties without their consent [134]. Smart farming technologies need to comply with various legal and regulatory frameworks related to data privacy and security. Farmers and their service providers should ensure that they comply with applicable laws and regulations related to data collection, storage, and sharing and implement appropriate data security measures to protect sensitive data and maintain the trust of their stakeholders.

6.4 Intervention to overcome the challenges of big data analytics

Several guidelines are already in use in ASEAN and European countries to address data privacy and security issues. The Association of Southeast Asian Nations (ASEAN) framework for personal data protection provides guidelines for ASEAN member countries. In 2018, ASEAN Telecommunications and Information Technology Ministers adopted a framework on personal data protection for digital data governance. Similarly, the European Union introduced the General Data Protection Regulation on 25 May 2018, which outlines six key data processing/protection principles (Fig. 8). Inadequate encryption of data in transit or at rest could leave data vulnerable to interception or theft. Farmers and their service providers should ensure that data are encrypted and secured at all stages of collection, storage, and transmission [135]. The problem of high capital investment can be partially addressed by using low-cost sensors and monitoring systems to collect data on soil moisture, temperature, and other factors [136, 137]. For example, low-cost multispectral sensors offer a viable alternative for automated weed control applications, providing accurate results. Although some misclassifications were observed in images

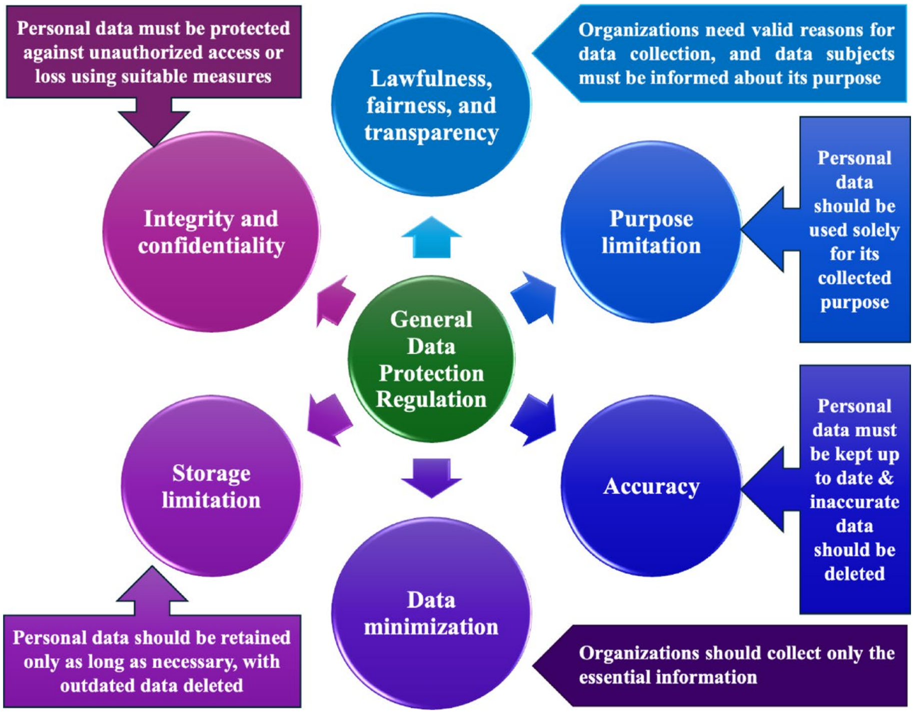

Fig. 8 General data protection regulation for big data

of small weeds and overlaps, along with minor over-segmentation, the overall accuracy (90%) demonstrated their potential [87]. Similarly, mobile app-based software platforms provide farmers with access to real-time data and analytics, helping them make more informed decisions about when to plant, irrigate, and harvest crops [5, 138].

7 Common challenges to the adoption of smart farming

The technology-specific challenges are discussed above individually under each respective technology. Here, we focus on common barriers to the adoption of smart farming, regardless of the specific technology. Many of the smart farming technologies currently available on the market are designed for larger commercial farms and may not be suitable for small-scale family farms due to their higher acquisition and maintenance costs [139, 140]. Many farmers, especially smallholders in developing countries, lack access to financial support for acquiring smart farming equipment. The heterogeneity of cropping systems and land fragmentation makes it infeasible for small landholding farmers to invest in smart farming technologies. The movement of machinery is restricted by small land holdings [140]. Cultural perceptions, resistance to adopting new technologies, and a lack of compelling success stories pose significant challenges for farmers considering investment in smart farming. Without clear and immediate benefits, farmers may hesitate to take risks and adopt new technologies, seeking evidence of their potential returns. Many smart farming technologies are still in the early stages of development, and it may take several years for them to become fully equipped.

An algorithm optimized solely for yield maximization, without considering local ecological contexts or long-term sustainability, could inadvertently recommend practices that lead to environmental degradation in certain areas. Over-reliance on algorithms can devalue the generational knowledge and practical intuition of farmers. If they cannot understand or challenge the algorithm's decisions, their agency and critical thinking skills may diminish. As AI systems take over more decision-making processes, there's a risk of "deskilling" farmers, reducing their active role in farm management to simply following automated instructions. Algorithms are only as good as the data they are trained on. If historical agricultural datasets predominantly reflect large-scale commercial farms in specific regions, an AI model trained on such data might generate recommendations that are unsuitable or even detrimental for smallholder farmers, those in different climates, or those practicing organic methods [105].

8 Interventions to overcome the challenges of smart farming

Traditional farming practices have a strong connection with farmers, and the transition to smart farming may not be easy for them. Farmers and other farmworkers require proper knowledge, information, and skills to effectively use smart farming tools [61, 141]. Thus, farmers need training to enhance their digital literacy and understanding of smart farming technologies and their implications. Governments and development partners should provide training and education programs on smart farming technologies to help farmers adopt new technologies [65, 142]. Regarding the willingness to adopt modern tools in agriculture, young farmers show more positive attitudes than older farmers [143]. Thus, capacity-building programs should target young farmers. Timpanaro et al. [141] found that public incentives and digital infrastructure are key to the adoption of innovative agricultural technologies. The high initial costs of equipment such as UAVs and robots can be managed through subsidies, tax exemptions, and other financial support to minimize investment costs. Farmers can also access these technologies through custom hiring or rental services provided by service providers [144]. Since most of this equipment is imported and thus expensive, encouraging local manufacturing could significantly reduce costs. Nevertheless, the cost of technology decreases with time [145].

It's crucial to develop "explainable AI" tools that let farmers understand algorithmic recommendations, fostering trust and enabling them to combine their expertise with technological insights. Each country should formulate national strategies to promote the automation of farming using robotics, data analytics, and sensor technology. Also, need to develop advanced agricultural technology parks in different parts of the country to train progressive farmers and early adopters, expose neighboring nonparticipating farmers to new technologies, and show the usefulness of the technology for short- and long-term management [140]. Governments and development partners should invest in research and development to improve smart farming technologies. This could involve developing technologies that are affordable, easy to use, and tailored to local conditions. A sustainable transition to smart farming requires an integrated approach that combines targeted incentives, training, and enhanced infrastructure [141]. Future research should investigate collaborative efforts between farms and technology providers and assess the impact of public policies on the widespread, informed adoption of smart farming technologies [141].

8.1 Policy interventions

(i) *National Agriculture 4.0 strategy and roadmap*: Create a comprehensive national strategy with clear goals, timelines, and measurable targets for Agriculture 4.0

adoption. This should include specific sub-strategies for different farm sizes and types (e.g., smallholder vs. large-scale, crop vs. livestock).

(ii) *Invest in rural digital infrastructure*: Prioritize and fund the expansion of reliable, high-speed internet (broadband) access to all rural farming communities. This includes incentivizing private sector investment in underserved areas. This will enable connectivity for IoT devices, cloud computing, and real-time data transfer.

(iii) *Establish robust data governance frameworks*: Enact legislation and regulations that clearly define data ownership (prioritizing farmer sovereignty), data access rights, usage permissions, and sharing protocols. Mandate transparent, understandable data agreements for all agri-tech providers. Conduct independent research on the ethical implications of data and AI in agriculture.

(iv) *Create financial incentives and support programs*: Implement grants, subsidies, low-interest loans, and tax credits specifically for farmers adopting Agriculture 4.0 technologies. This will reduce the high upfront cost barrier, encourage investment in new technologies, and de-risk adoption for farmers. Tailor programs to be accessible to small and medium-sized farms. Develop tailored financial products (e.g., green loans, digital agriculture loans, pay-per-use models for technology) that consider the unique investment cycles and risks in agriculture. Work with farmers to assess the return on investment (ROI) of smart farming investments.

(v) *Fund research, development, and extension services*: Increase public funding for R&D in agricultural AI, robotics, and sustainable precision farming practices. Focus R&D on practical, scalable, and affordable Agriculture 4.0 solutions for local contexts, especially for smallholders. Strengthen and modernize agricultural extension services to become hubs for Agriculture 4.0 knowledge transfer, offering hands-on training and technical support.

(vi) *Promote digital literacy and capacity building*: Develop and fund national digital literacy programs specifically designed for farmers, covering basic digital skills, understanding smart farming technologies, data interpretation, and cybersecurity best practices. Integrate these into existing agricultural training curricula.

(vii) *Integrate sustainability and climate resilience*: Design policies and incentives that link Agriculture 4.0 adoption with environmental benefits, such as reduced water and fertilizer use, lower greenhouse gas emissions, and enhanced biodiversity. Support the use of these technologies for climate change adaptation.

9 Conclusion

The evolution of agriculture, from the First Agricultural Revolution to today's Fourth, has been transformative, reshaping production methods with each phase. The Fourth Agricultural Revolution represents a profound transformation, leveraging technologies like IoT, AI, big data analytics, UAVs, and agricultural robots to create a data-driven approach to farming. By automating farming practices and optimizing input usage through site-specific crop management, smart farming tailor's practices to the spatial and temporal variability of agricultural production, boosting resource use efficiency, farm profitability and reducing external input use and environmental impact. Additionally, it bolsters food quality, traceability, safety, climate resilience, and ultimately sustainability. However, many developing nations and small landholders face barriers to adopting smart farming due to limited access to advanced agro-science technologies and the digital divide between developed and developing countries, and between large-scale and smallholder farmers.

Challenges including high initial costs, fragmented land holdings, diverse cropping patterns, limited awareness and access to technology, skill deficits, inadequate infrastructure, poor internet connectivity, and issues surrounding data privacy and ethical concerns, absence of supportive government regulations and policies, along with a lack of high-quality data for robust model creation, impede its widespread adoption. Nonetheless, the adoption of specific components, such as UAVs, robots, smart irrigation, mobile-based decision support systems, and precision fertilizer applications, often in combination, both in developed and developing nations, is evident. Smart farming technologies like big data and AI remain in limited use and are still in developmental stages. Factors like labor shortages, higher wages, credit availability, well-developed infrastructure, higher education levels, and favourable government policies contribute to the uptake of smart farming in developed countries.

To increase smart farming adoption globally and ensure its equitable distribution, a holistic approach is essential. Crucially, establishing strong infrastructure, fostering public and private sector investments, providing comprehensive skill transfer training for farmers, and implementing supportive government policies, regulations, subsidies, and tax exemptions are all vital steps toward accelerating global adoption and achieving a more productive, sustainable, and resilient agricultural future. Therefore, future research should focus on developing affordable sensors, open-source software solutions, context-specific AI model development, and multipurpose equipment specifically tailored for small-scale family farms. Also, investigating the socio-economic impacts and equitable adoption strategies and assessing the long-term environmental sustainability of integrated smart farming systems are important. By focusing on these areas, future research can bridge the existing gaps, mitigate barriers, and pave the way for a more inclusive, efficient, and sustainable global agricultural landscape driven by the Fourth Agricultural Revolution.

Acknowledgements
We express our heartfelt gratitude to all the researchers, scholars, and experts whose valuable work has made this review article possible.

Author contributions
Shanmugam Vijayakumar - Conceptualization, image creation, literature collection, writing original draft and editing; Varunseelan Murugaiyan, Rapolu Mahender Kumar, and S Ilakkiya - writing original draft, Image creation; Virender Kumar - writing original manuscript, revision and editing; Raman Meenakshi Sundaram - Overall review & editing. All authors have read and agreed to the published version of the manuscript.

Funding
This review received no external funding.

Data availability
No datasets were generated or analysed during the current study.

Declarations

Consent for publication
Required permission has been taken from the PME cell of ICAR-IIRR.

Competing interests
The authors declare no competing interests.

Language
Published in English.

Relevance
Directly addressed agricultural robots, UAVs in agriculture, or Big Data Analysis applications in agriculture.

Focus
Provided insights into applications, challenges, or required interventions for large-scale adoption within the specified domains.

Conflict of interest
The authors declare no conflicts of interest.

Ethical approval and consent to participate
Not applicable.

Received: 7 February 2025 / Accepted: 30 July 2025

References

1. Skoglund P, Malmström H, Raghavan M, Storå J, Hall P, Willerslev E, et al. Origins and genetic legacy of neolithic farmers and hunter-gatherers in Europe. Sci (1979). 2012;336(6080):466–9. https://doi.org/10.1126/SCIENCE.1216304.
2. Padhiary M, Kumar R, Enhancing Agriculture Through AI. Vision and machine learning: the evolution of smart farming. Advancements in intelligent process automation. IGI Global Scientific Publishing; 2024. pp. 295–324. https://doi.org/10.4018/979-8-3693-5380-6.CH012.
3. Gupta AK. Origin of agriculture and domestication of plants and animals linked to early holocene climate amelioration on JSTOR. Curr Sci. 2004;87(1):54–9.
4. Simpson J. European farmers and the British 'agricultural revolution.' exceptionalism and industrialisation: Britain and its European rivals. Cambridege, UK: Cambridge University Press; 2004. pp. 69–85. https://doi.org/10.1017/CBO9780511523830.004.
5. Zhai Z, Martínez JF, Beltran V, Martínez NL. Decision support systems for agriculture 4.0: survey and challenges. Comput Electron Agric. 2020;170:105256. https://doi.org/10.1016/J.COMPAG.2020.105256.
6. Rose DC, Wheeler R, Winter M, Lobley M, Chivers CA. Agriculture 4.0: making it work for people, production, and the planet. Land Use Policy. 2021;100:104933. https://doi.org/10.1016/J.LANDUSEPOL.2020.104933.
7. Sharma V, Tripathi AK, Mittal H. Technological revolutions in smart farming: current trends, challenges & future directions. Comput Electron Agric. 2022;201:107217. https://doi.org/10.1016/J.COMPAG.2022.107217.
8. Pingali PL. Green revolution: impacts, limits, andthe path ahead. Proc Natl Acad Sci U S A. 2012;109(31):12302–8. https://doi.org/10.1073/PNAS.0912953109.
9. Das RJ. The green revolution and poverty: a theoretical and empirical examination of the relation between technology and society. Geoforum. 2002;33(1):55–72. https://doi.org/10.1016/S0016-7185(01)00006-9.
10. Pimentel P D. Green revolution agriculture and chemical hazards. Sci Total Environ. 1996;188(SUPPL 1):S86–98. https://doi.org/10.1016/0048-9697(96)05280-1.
11. Sharma N, Singhvi R. Effects of chemical fertilizers and pesticides on human health and environment: A review. Int J Agric Environ Biotechnol. 2017;10(6):675–80. https://doi.org/10.5958/2230-732X.2017.00083.3.
12. Vijayakumar S, Gobinath R, Kannan P, Murugaiyan V. Optimizing potassium mining in rice-wheat system: strategies for promoting sustainable soil health - A review. Farming Syst. 2024;2(3):100099. https://doi.org/10.1016/J.FARSYS.2024.100099.
13. Singh RB. Environmental consequences of agricultural development: A case study from the green revolution state of haryana, India. Agric Ecosyst Environ. 2000;82(1–3):97–103. https://doi.org/10.1016/S0167-8809(00)00219-X.
14. Du T, Kang S, Zhang X, Zhang J. China's food security is threatened by the unsustainable use of water resources in North and Northwest China. Food Energy Secur. 2014;3(1):7–18. https://doi.org/10.1002/FES3.40.
15. Mallareddy M, Thirumalaikumar R, Balasubramanian P, Naseeruddin R, Nithya N, Mariadoss A, et al. Maximizing water use efficiency in rice farming: A comprehensive review of innovative irrigation management technologies. Water (Basel). 2023;15(10):1802. https://doi.org/10.3390/W15101802.
16. Vijayakumar S, Rajpoot SK, Manikandan N, Varadan RJ, Singh JP, Chatterjee D, et al. Extreme temperature and rainfall event trends in the middle gangetic plains from 1980 to 2018. Curr Sci. 2023;124(11):1300–7. https://doi.org/10.18520/CS/V124/I11/1300-1307.
17. Vijayakumar S, Nayak A, Manikandan N, Pattanaik S, Tripathi R, Swain C. Extreme weather events and its impacts on rice production in coastal Odisha region of India. Oryza-An Int J Rice. 2023;60(3):406–21. https://doi.org/10.35709/ORY.2023.60.3.4.
18. Som S, Burman RR, Sharma JP, Padaria RN, Paul S, Singh AK. Attracting and retaining youth in agriculture: challenges and prospects. J Community Mobilization Sustainable Dev. 2019;13(3):385–95.
19. Liu J, Fang Y, Wang G, Liu B, Wang R. The aging of farmers and its challenges for labor-intensive agriculture in china: A perspective on farmland transfer plans for farmers' retirement. J Rural Stud. 2023;100:103013. https://doi.org/10.1016/J.JRURSTUD.2023.103013.
20. Kimiywe J. Food and nutrition security: challenges of post-harvest handling in Kenya. Proc Nutr Soc. 2015;74(4):487–95. https://doi.org/10.1017/S0029665115002414.
21. FAO. International Year of Family Farming 2014 - Master Plan [Internet]. 2013. http://www.fao.org/fileadmin/user_upload/oek/oekr/pdf/UN_Resolution_Internacional_Year_Family_Farming. Accessed 22 Jun 2025.
22. Dobermann A, Witt C, Dawe D, Abdulrachman S, Gines HC, Nagarajan R, et al. Site-specific nutrient management for intensive rice cropping systems in Asia. Field Crops Res. 2002;74(1):37–66. https://doi.org/10.1016/S0378-4290(01)00197-6.
23. Ncoyini Z, Savage MJ, Strydom S. Limited access and use of climate information by small-scale sugarcane farmers in South africa: A case study. Clim Serv. 2022;26:100285. https://doi.org/10.1016/J.CLISER.2022.100285.
24. Santos Valle S, Kienzle J. Agriculture 4.0 - Agricultural robotics and automated equipment for sustainable crop production [Internet]. Rome, Italy; 2020.

25. Pivoto D, Waquil PD, Talamini E, Finocchio CPS, Dalla Corte VF, de Vargas Mores G. Scientific development of smart farming technologies and their application in Brazil. Inform Process Agric. 2018;5(1):21–32. https://doi.org/10.1016/J.INPA.2017.12.002.
26. Chuang JH, Wang JH, Liou YC. Farmers' knowledge, attitude, and adoption of smart agriculture technology in Taiwan. Int J Environ Res Public Health. 2020;17(19):7236. https://doi.org/10.3390/IJERPH17197236.
27. Dhanaraju M, Chenniappan P, Ramalingam K, Pazhanivelan S, Kaliaperumal R. Smart farming: internet of things (IoT)-Based sustainable agriculture. Agriculture. 2022;12(10):1745. https://doi.org/10.3390/AGRICULTURE12101745.
28. Yadav VS, Singh AR, Raut RD, Mangla SK, Luthra S, Kumar A. Exploring the application of industry 4.0 technologies in the agricultural food supply chain: A systematic literature review. Comput Ind Eng. 2022;169:108304. https://doi.org/10.1016/j.cie.2022.108304.
29. Yong L, Xiushan L, Degui Z, Fu L. The main content, technical support and enforcement strategy of digital agriculture. Geo-Spatial Inform Sci. 2002;5(1):68–73. https://doi.org/10.1007/BF02863497.
30. Saiz-Rubio V, Rovira-Más F. From smart farming towards agriculture 5.0: A review on crop data management. Agronomy. 2020;10(2):207. https://doi.org/10.3390/AGRONOMY10020207.
31. Janssen SJC, Porter CH, Moore AD, Athanasiadis IN, Foster I, Jones JW, et al. Towards a new generation of agricultural system data, models and knowledge products: information and communication technology. Agric Syst. 2017;155:200–12. https://doi.org/10.1016/J.AGSY.2016.09.017.
32. Muhuri PK, Shukla AK, Abraham A. Industry 4.0: A bibliometric analysis and detailed overview. Eng Appl Artif Intell. 2019;78:218–35. https://doi.org/10.1016/J.ENGAPPAI.2018.11.007.
33. Dayioğlu MA, Türker U. Digital transformation for sustainable Future - Agriculture 4.0: A review. J Agric Sci (Belihuloya). 2021;27(4):373–99. https://doi.org/10.15832/ANKUTBD.986431.
34. Roy P, Padhiary M, Hoque A, Sahu B, Roy D, Kumar K. Machine learning for precision agriculture and crop yield optimization: techniques and applications. The artificial intelligence in advancing applied life sciences. IGI Global Scientific Publishing; 2025. pp. 189–234. https://doi.org/10.4018/979-8-3693-9208-9.CH007.
35. Linaza MT, Posada J, Bund J, Eisert P, Quartulli M, Döllner J, et al. Data-Driven artificial intelligence applications for sustainable precision agriculture. Agronomy. 2021;11(6):1227. https://doi.org/10.3390/AGRONOMY11061227.
36. Ponnusamy V, Natarajan S. Precision agriculture using advanced technology of iot, unmanned aerial vehicle, augmented reality, and machine learning. Smart sensors for industrial internet of things. Springer International Publishing; 2021. pp. 207–29. https://doi.org/10.1007/978-3-030-52624-5_14.
37. Walter A, Finger R, Huber R, Buchmann N, Opinion. Smart farming is key to developing sustainable agriculture. Proc Natl Acad Sci U S A. 2017;114(24):6148. https://doi.org/10.1073/PNAS.1707462114.
38. Haque A, Islam N, Samrat NH, Dey S, Ray B. Smart farming through responsible leadership in bangladesh: possibilities, opportunities, and beyond. Sustainability. 2021;13(8):4511. https://doi.org/10.3390/SU13084511.
39. Obaideen K, Yousef BAA, AlMallahi MN, Tan YC, Mahmoud M, Jaber H, et al. An overview of smart irrigation systems using IoT. Energy Nexus. 2022;7:100124. https://doi.org/10.1016/J.NEXUS.2022.100124.
40. Javaid M, Haleem A, Singh RP, Suman R. Enhancing smart farming through the applications of agriculture 4.0 technologies. Int J Intell Networks. 2022;3:150–64. https://doi.org/10.1016/J.IJIN.2022.09.004.
41. Carolan M. Publicising food: big data, precision agriculture, and Co-Experimental techniques of addition. Sociol Ruralis. 2017;57(2):135–54. https://doi.org/10.1111/SORU.12120.
42. Ullah R, Abbas AW, Ullah M, Khan RU, Khan IU, Aslam N, et al. EEWMP: an IoT-Based Energy-Efficient water management platform for smart irrigation. Sci Program. 2021;2021(1):5536884. https://doi.org/10.1155/2021/5536884.
43. Widianto MH, Juarto B. Smart farming using robots in IoT to increase agriculture yields: A systematic literature review. J Rob Control. 2023;4(3):330–41. https://doi.org/10.18196/JRC.V4I3.18368.
44. Said Mohamed E, Belal AA, Kotb Abd-Elmabod S, El-Shirbeny MA, Gad A, Zahran MB. Smart farming for improving agricultural management. Egypt J Remote Sens Space Sci. 2021;24(3):971–81. https://doi.org/10.1016/j.ejrs.2021.08.007.
45. Ali A, Hussain T, Tantashutikun N, Hussain N, Cocetta G. Application of Smart Techniques, Internet of Things and Data Mining for Resource Use Efficient and Sustainable Crop Production. Agriculture. 2023;13(2):397. https://doi.org/10.3390/AGRICULTURE13020397
46. Keresztes B, Germain C, Da Costa J-P, Grenier G, Beaulieu XD. Vineyard Vigilant & INNovative Ecological Rover (VVINNER): an autonomous robot for automated scoring of vineyards. Proceedings of the International Conference of Agricultural Engineering. Zurich, Switzerland; 2014. pp. 6–10.
47. Mandhare P. The future of food production: robots revolutionising agriculture. FarmBiz. 2018;(3):41.
48. Hoque A, Padhiary M, Prasad G, Kumar K. Real-Time data processing in agricultural robotics. Computer vision techniques for agricultural advancements. IGI Global Scientific Publishing; 2025. pp. 431–68. https://doi.org/10.4018/979-8-3693-8019-2.CH014.
49. Fountas S, Mylonas N, Malounas I, Rodias E, Santos CH, Pekkeriet E. Agricultural robotics for field operations. Sensors. 2020;20(9):2672. https://doi.org/10.3390/S20092672.
50. Epée Missé PT, Werner A, Almond P. Developing automated and autonomous weed control methods on vegetable crops in new Zealand. SSRN Electron J. 2020. https://doi.org/10.2139/SSRN.3745319.
51. Sanchez J, Gallandt ER. Functionality and efficacy of Franklin robotics' tertill™ robotic weeder. Weed Technol. 2021;35(1):166–70. https://doi.org/10.1017/WET.2020.94.
52. Raja R, Slaughter DC, Fennimore SA, Siemens MC. Real-time control of high-resolution micro-jet sprayer integrated with machine vision for precision weed control. Biosyst Eng. 2023;228:31–48. https://doi.org/10.1016/J.BIOSYSTEMSENG.2023.02.006.
53. Aravind KR, Raja P, Pérez-Ruiz M. Task-based agricultural mobile robots in arable farming: A review. Span J Agricultural Res. 2017;15(1). https://doi.org/10.5424/SJAR/2017151-9573. e02R01-e02R01.
54. Sai MMV, Babu UH, Krishna NH. Multipurpose Agricultural Robot Using IoT. AIP Conf Proc. American Institute of Physics Inc.; 2022. pp. 2653–40004. https://doi.org/10.1063/5.0110673/2831725
55. Rahimi Azghadi M, Olsen A, Wood J, Saleh A, Calvert B, Granshaw T, et al. Precision robotic spot-spraying: reducing herbicide use and enhancing environmental outcomes in sugarcane. Comput Electron Agric. 2025;235:110365. https://doi.org/10.1016/J.COMPAG.2025.110365.

56. Mohanty T, Pattanaik P, Dash S, Tripathy HP, Holderbaum W. Smart robotic system guided with YOLOv5 based machine learning framework for efficient herbicide usage in rice (Oryza sativa L.) under precision agriculture. Comput Electron Agric. 2025;231:110032. https://doi.org/10.1016/J.COMPAG.2025.110032.
57. Grimstad L, From PJ. The Thorvald II agricultural robotic system. Robotics. 2017;6(4):24. https://doi.org/10.3390/ROBOTICS6040024.
58. Sparrow R, Howard M. Robots in agriculture: prospects, impacts, ethics, and policy. Precision agriculture. Online first. Precis Agric. 2021;22(3):1–16. https://doi.org/10.1007/s11119-020-09757-9.
59. Cubero S, Marco-noales E, Aleixos N, Barbé S, Blasco J, RobHortic:. A field robot to detect pests and diseases in horticultural crops by proximal sensing. Agriculture. 2020;10(7):276. https://doi.org/10.3390/AGRICULTURE10070276.
60. Gil G, Casagrande DE, Cortés LP, Verschae R. Why the low adoption of robotics in the farms? Challenges for the establishment of commercial agricultural robots. Smart Agricultural Technol. 2023;3:100069. https://doi.org/10.1016/J.ATECH.2022.100069.
61. Jellason NP, Robinson EJZ, Ogbaga CC. Appl Sci. 2021;11(12):5750. https://doi.org/10.3390/APP11125750. Agriculture 4.0: Is Sub-Saharan Africa Ready?.
62. Ghalazman EA, Das GP, Gould I, Zarafshan P, Rajendran SV, Heselden J, et al. Applications of robotic and solar energy in precision agriculture and smart farming. Solar energy advancements in agriculture and food production systems. Academic Press, Elsevier; 2022. pp. 351–90. https://doi.org/10.1016/B978-0-323-89866-9.00011-0.
63. Spykman O, Gabriel A, Ptacek M, Gandorfer M. Farmers' perspectives on field crop robots– Evidence from Bavaria. Ger Comput Electron Agric. 2021;186:106176. https://doi.org/10.1016/J.COMPAG.2021.106176.
64. Bechar A, Vigneault C. Agricultural robots for field operations: concepts and components. Biosyst Eng. 2016;149:94–111. https://doi.org/10.1016/J.BIOSYSTEMSENG.2016.06.014.
65. Scuderi A, La Via G, Timpanaro G, Sturiale L. The Digital Applications of Agriculture 4.0: Strategic Opportunity for the Development of the Italian Citrus Chain. Agriculture 2022, Vol 12, Page 400. 2022;12(3):400. https://doi.org/10.3390/AGRICULTURE12030400
66. Gayathri Devi K, Sowmiya N, Yasoda K, Muthulakshmi K, Kishore B. Review on application of drones for crop health monitoring and spraying pesticides and fertilizer. J Crit Reviews. 2020;7(6):667–72. https://doi.org/10.31838/JCR.07.06.117.
67. Vijayakumar S, Madireddy H, Bhusarapu SC, Kumar RM, Sundaram RM. Drone application in rice cultivation: experiences from ICAR-IIRR trails. Indian Farming. 2022;72(12):03–6.
68. Nayak SVK, Poonam AK, Khanam ASA. Unmanned aerial vehicle and its application in Indian agriculture: A perspective. Indian Farming. 2020;70(8):34–7.
69. Buters T, Belton D, Cross A. Seed and seedling detection using unmanned aerial vehicles and automated image classification in the monitoring of ecological recovery. Drones. 2019;3(3):53. https://doi.org/10.3390/DRONES3030053.
70. Zheng S, Wang Z, Wachenheim CJ. Technology adoption among farmers in Jilin province, china: the case of aerial pesticide application. China Agricultural Economic Rev. 2019;11(1):206–16. https://doi.org/10.1108/CAER-11-2017-0216.
71. Bian J, Zhang Z, Chen J, Chen H, Cui C, Li X, et al. Simplified evaluation of cotton water stress using high resolution unmanned aerial vehicle thermal imagery. Remote Sens (Basel). 2019;11(3):267. https://doi.org/10.3390/RS11030267.
72. Chen Q, Wachenheim C, Zheng S. Land scale, cooperative membership and benefits information: unmanned aerial vehicle adoption in China. Sustainable Futures. 2020;2:100025. https://doi.org/10.1016/J.SFTR.2020.100025.
73. Quan X, Guo Q, Ma J, Doluschitz R. The economic effects of unmanned aerial vehicles in pesticide application: evidence from Chinese grain farmers. Precis Agric. 2023;24(5):1965–81. https://doi.org/10.1007/S11119-023-10025-9.
74. Liu T, Li R, Jin X, Ding J, Zhu X, Sun C, et al. Evaluation of seed emergence uniformity of mechanically sown wheat with UAV RGB imagery. Remote Sens (Basel). 2017;9(12):1241. https://doi.org/10.3390/RS9121241.
75. Sankaran S, Khot LR, Carter AH. Field-based crop phenotyping: multispectral aerial imaging for evaluation of winter wheat emergence and spring stand. Comput Electron Agric. 2015;118:372–9. https://doi.org/10.1016/J.COMPAG.2015.09.001.
76. van der Merwe D, Burchfield DR, Witt TD, Price KP, Sharda A. Drones in agriculture. Adv Agron. 2020;162:1–30. https://doi.org/10.1016/BS.AGRON.2020.03.001.
77. Lin Y, Chen T, Liu S, Cai Y, Shi H, Zheng D, et al. Quick and accurate monitoring peanut seedlings emergence rate through UAV video and deep learning. Comput Electron Agric. 2022;197:106938. https://doi.org/10.1016/J.COMPAG.2022.106938.
78. Gao J, Liao W, Nuyttens D, Lootens P, Vangeyte J, Pižurica A, et al. Fusion of pixel and object-based features for weed mapping using unmanned aerial vehicle imagery. Int J Appl Earth Obs Geoinf. 2018;67:43–53. https://doi.org/10.1016/J.JAG.2017.12.012.
79. Gašparović M, Zrinjski M, Barković Đ, Radočaj D. An automatic method for weed mapping in oat fields based on UAV imagery. Comput Electron Agric. 2020;173:105385. https://doi.org/10.1016/J.COMPAG.2020.105385.
80. Campos J, Llop J, Gallart M, García-Ruiz F, Gras A, Salcedo R, et al. Development of canopy vigour maps using UAV for site-specific management during vineyard spraying process. Precis Agric. 2019;20(6):1136–56. https://doi.org/10.1007/S11119-019-09643-Z.
81. Che'Ya NN. Site-Specific weed management using [internet]emote sensing [Internet]. The University of Queensland; 2016. https://doi.org/10.14264/UQL.2016.821.
82. Behjati M, Mohd Noh AB, Alobaidy HAH, Zulkifley MA, Nordin R, Abdullah NF. LoRa communications as an enabler for internet of drones towards Large-Scale livestock monitoring in rural farms. Sensors. 2021;21(15):5044. https://doi.org/10.3390/S21155044.
83. Bastos KM, Barcelos JP, Orioli GF, Nascimento ST. Use of drones for trough reading, animal counting, and production monitoring in feedlot systems. AgriEngineering. 2024;6(4):4460–75. https://doi.org/10.3390/AGRIENGINEERING6040253.
84. Li X, Xing L. Use of unmanned aerial vehicles for livestock monitoring based on streaming K-Means clustering. IFAC-PapersOnLine. 2019;52(30):324–9. https://doi.org/10.1016/J.IFACOL.2019.12.560.
85. Xu B, Meng R, Chen G, Liang L, Lv Z, Zhou L, et al. Improved weed mapping in corn fields by combining UAV-based spectral, textural, structural, and thermal measurements. Pest Manag Sci. 2023;79(7):2591–602. https://doi.org/10.1002/PS.7443.
86. Pérez-Ortiz M, Peña JM, Gutiérrez PA, Torres-Sánchez J, Hervás-Martínez C, López-Granados F. Selecting patterns and features for between- and within- crop-row weed mapping using UAV-imagery. Expert Syst Appl. 2016;47:85–94. https://doi.org/10.1016/J.ESWA.2015.10.043.

87. Seiche AT, Wittstruck L, Jarmer T. Weed detection from unmanned aerial vehicle imagery using deep Learning—A comparison between High-End and Low-Cost multispectral sensors. Sensors. 2024;24(5):1544. https://doi.org/10.3390/S24051544.
88. López-Granados F, Torres-Sánchez J, Serrano-Pérez A, de Castro AI, Mesas-Carrascosa Fco -J, Peña J-M, et al. Early season weed mapping in sunflower using UAV technology: variability of herbicide treatment maps against weed thresholds. Precis Agric. 2016;17(2):183–99. https://doi.org/10.1007/S11119-015-9415-8.
89. Huang H, Deng J, Lan Y, Yang A, Deng X, Zhang L. A fully convolutional network for weed mapping of unmanned aerial vehicle (UAV) imagery. PLoS ONE. 2018;13(4):e0196302. https://doi.org/10.1371/JOURNAL.PONE.0196302.
90. Alexandridis TK, Tamouridou AA, Pantazi XE, Lagopodi AL, Kashefi J, Ovakoglou G, et al. Novelty detection classifiers in weed mapping: Silybum Marianum detection on UAV multispectral images. Sensors. 2017;17(9):2007. https://doi.org/10.3390/S17092007.
91. Peña JM, Torres-Sánchez J, de Castro AI, Kelly M, López-Granados F. Weed mapping in Early-Season maize fields using Object-Based analysis of unmanned aerial vehicle (UAV) images. PLoS ONE. 2013;8(10):e77151. https://doi.org/10.1371/JOURNAL.PONE.0077151.
92. Borah SK, Padhiary M, Sethi LN, Kumar A, Saikia P. Precision farming with drone sprayers: A review of auto navigation and Vision-Based optimization. J Biosystems Eng 2025. 2025;50(2):2. https://doi.org/10.1007/S42853-025-00263-2.
93. Paul RAI, Palanisamy MA, Peramaiyan P, Kumar V, Bagavathiannan M, Gurjar B, et al. Spray volume optimization with UAV-based herbicide application for effective droplet deposition and weed control in direct-seeded rice. Front Agron. 2024;6:1491842. https://doi.org/10.3389/FAGRO.2024.1491842.
94. Shahrooz M, Talaeizadeh A, Alasty A. Agricultural Spraying Drones: Advantages and Disadvantages. Virtual Symposium in Plant Omics Sciences. Institute of Electrical and Electronics Engineers Inc.; 2020. https://doi.org/10.1109/OMICAS52284.2020.9535527
95. Hussain S, Cheema MJM, Arshad M, Ahmad A, Latif MA, Ashraf S, et al. Spray uniformity testing of unmanned aerial spraying system for precise agro-chemical applications. Pak J Agric Sci. 2019;56(4):897–903. https://doi.org/10.21162/PAKJAS/19.8594.
96. Bellvert J, Zarco-Tejada PJ, Girona J, Fereres E. Mapping crop water stress index in a 'Pinot-noir' vineyard: comparing ground measurements with thermal remote sensing imagery from an unmanned aerial vehicle. Precis Agric. 2014;15(4):361–76. https://doi.org/10.1007/S11119-013-9334-5.
97. Gago J, Douthe C, Coopman RE, Gallego PP, Ribas-Carbo M, Flexas J, et al. UAVs challenge to assess water stress for sustainable agriculture. Agric Water Manag. 2015;153:9–19. https://doi.org/10.1016/J.AGWAT.2015.01.020.
98. Zhang Z, Bian J, Han W, Fu Q, Chen S, Cui T. Diagnosis of cotton water stress using unmanned aerial vehicle thermal infrared remote sensing after removing soil background. Trans Chin Soc Agricultural Mach. 2018;49(10):250–60. https://doi.org/10.6041/J.ISSN.1000-1298.2018.10.028.
99. Zhang L, Zhang H, Niu Y, Han W. Mapping maize water stress based on UAV multispectral remote sensing. Remote Sens (Basel). 2019;11(6):605. https://doi.org/10.3390/RS11060605.
100. Idoje G, Dagiuklas T, Iqbal M. Survey for smart farming technologies: challenges and issues. Comput Electr Eng. 2021;92:107104. https://doi.org/10.1016/J.COMPELECENG.2021.107104.
101. De Oca AM, Arreola L, Flores A, Sanchez J, Flores G. Low-cost multispectral imaging system for crop monitoring. International Conference on Unmanned Aircraft Systems. Institute of Electrical and Electronics Engineers Inc.; 2018. pp. 443–51. https://doi.org/10.1109/ICUAS.2018.8453426
102. Liu Q, Chen S, Wang G, Lan Y. Drift evaluation of a quadrotor unmanned aerial vehicle (UAV) sprayer: effect of liquid pressure and wind speed on drift potential based on wind tunnel test. Appl Sci. 2021;11(16):7258. https://doi.org/10.3390/APP11167258.
103. Rohan A, Rabah M, Talha M, Kim SH. Development of intelligent drone battery charging system based on wireless power transmission using hill climbing algorithm. Appl Syst Innov. 2018;1(4):44. https://doi.org/10.3390/ASI1040044.
104. Yan X, Zhou Y, Liu X, Yang D, Yuan H. Minimizing occupational exposure to pesticide and increasing control efficacy of pests by unmanned aerial vehicle application on Cowpea. Appl Sci. 2021;11(20):9579. https://doi.org/10.3390/APP112095 79/S1.
105. Vijayakumar S, Shanmugapriya P, Saravanane P, Ramesh T, Murugaiyan V, Ilakkiya S. Precision weed control using unmanned aerial vehicles and robots: assessing feasibility, bottlenecks, and recommendations for scaling. NDT 2025. Page 10. 2025;3(2):10. https://doi.org/10.3390/NDT3020010.
106. Shanmugam Vijayakumar, Aravindan S, Saravanane, Pasoubady, Sivashankari Manickam. Unmanned aerial vehicles: policies evaluation and suggestion to boost its agriculture application in India. Kerala Karshakan. 2021;8(7):1–4.
107. Kamilaris A, Kartakoullis A, Prenafeta-Boldú FX. A review on the practice of big data analysis in agriculture. Comput Electron Agric. 2017;143:23–37. https://doi.org/10.1016/J.COMPAG.2017.09.037.
108. Ayamga M, Tekinerdogan B, Kassahun A. Exploring the challenges posed by regulations for the use of drones in agriculture in the African context. Land (Basel). 2021;10(2):164. https://doi.org/10.3390/LAND10020164.
109. Yaacoub JP, Noura H, Salman O, Chehab A. Security analysis of drones systems: attacks, limitations, and recommendations. Internet Things. 2020;11:100218. https://doi.org/10.1016/J.IOT.2020.100218.
110. Hafeez A, Husain MA, Singh SP, Chauhan A, Khan MT, Kumar N, et al. Implementation of drone technology for farm monitoring & pesticide spraying: A review. Inform Process Agric. 2023;10(2):192–203. https://doi.org/10.1016/J.INPA.2022.02.002 .
111. Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big data in smart Farming– A review. Agric Syst. 2017;153:69–80. https://doi.org/10.1016/J.AGSY.2017.01.023.
112. Li D, Zheng Y, Zhao W. Fault analysis system for agricultural machinery based on big data. IEEE Access. 2019;7:99136–51. https://doi.org/10.1109/ACCESS.2019.2928973.
113. Lokesh Krishna K, Silver O, Malende WF, Anuradha K. Internet of Things application for implementation of smart agriculture system. Proceedings of the International Conference on IoT in Social, Mobile, Analytics and Cloud, I-SMAC. 2017. 2017;54–9. https://doi.org/10.1109/I-SMAC.2017.8058236
114. Meng F, Yang D, Wang Y, Zhang Y, Study of Agricultural Machinery Operating System Based on Beidou Satellite Navigation System. Adv Intell Syst Comput. 2018;686:268–73. https://doi.org/10.1007/978-3-319-69096-4_37.

115. Shah P, Hiremath D, Chaudhary S, Big Data Analytics Architecture for Agro Advisory System. 23rd international conference on high performance computing workshops (HiPCW). Institute of Electrical and Electronics Engineers (IEEE); 2017. pp. 43–9. https://doi.org/10.1109/HIPCW.2016.015
116. Ramachandrappa BK, Thimmegowda MN, Krishnamurthy R, Babu PNS, Savitha MS, Srinivasarao C, et al. Usefulness and impact of Agromet advisory services in Eastern dry zone of Karnataka. Indian J Dryland Agricultural Res Dev. 2018;33(1):32. https://doi.org/10.5958/2231-6701.2018.00005.2.
117. Ramaraj AP, Rao KPC, Kumar GK, Ugalechumi K, Sujatha P, Rao SA, et al. Delivering context specific, climate informed agro-advisories at scale: A case study of iSAT, an ICT linked platform piloted with rainfed groundnut farmers in a semi-arid environment. Clim Serv. 2023;31:100403. https://doi.org/10.1016/J.CLISER.2023.100403.
118. Asante BO, Ma W, Prah S, Temoso O. Promoting the adoption of climate-smart agricultural technologies among maize farmers in ghana: using digital advisory services. Mitig Adapt Strateg Glob Chang. 2024;29(3):1–24. https://doi.org/10.1007/S11027-024-10116-6.
119. Ajith S, Vijayakumar S, Elakkiya N. Yield prediction, pest and disease diagnosis, soil fertility mapping, precision irrigation scheduling, and food quality assessment using machine learning and deep learning algorithms. Discover Food 2025. 2025;5(1):1. https://doi.org/10.1007/S44187-025-00338-1.
120. Kaur R, Garg R, Aggarwal H. Big data analytics framework to identify crop disease and recommendation a solution. International Conference on Inventive Computation Technologies. Institute of Electrical and Electronics Engineers Inc.; 2016. pp. 1–5. https://doi.org/10.1109/INVENTIVE.2016.7824791
121. Guiam AC, Gutierrez RD, Gapasin CVD, Matalog RP, Ebuenga MD. Smarter pest identification technology (SPIDTECH): a mobile application for digital identification and remote monitoring of insect pests and diseases of major crops in the Philippines. Philipp J Sci. 2021;150(6B):1811–21. https://doi.org/10.56899/150.6B.17.
122. Zhang P, Zhang Q, Liu F, Li J, Cao N, Song C. The Construction of the Integration of Water and Fertilizer Smart Water Saving Irrigation System Based on Big Data. International Conference on Computational Science and Engineering and International Conference on Embedded and Ubiquitous Computing. Institute of Electrical and Electronics Engineers Inc.; 2017. pp. 392–7. https://doi.org/10.1109/CSE-EUC.2017.258
123. Rana H, Farooq MU, Kazi AK, Baig MA, Akhtar MA. Eng Technol Appl Sci Res. 2024;14(1):12652–8. https://doi.org/10.48084/ETASR.6468. Prediction of Agricultural Commodity Prices using Big Data Framework.
124. Wang B, Liu P, Chao Z, Junmei W, Chen W, Cao N, Computers, et al. Mater Continua. 2018;57(2):283–96. https://doi.org/10.32604/CMC.2018.03791.
125. Walker MJ, Burns M, Burns T. Horse meat in beef Products-Species substitution. J Assoc Public Anal. 2013;41:67–106.
126. Wong EHK, Hanner RH. DNA barcoding detects market substitution in North American seafood. Food Res Int. 2008;41(8):828–37. https://doi.org/10.1016/J.FOODRES.2008.07.005.
127. Xing RR, Hu RR, Han JX, Deng TT, Chen Y. DNA barcoding and mini-barcoding in authenticating processed animal-derived food: A case study involving the Chinese market. Food Chem. 2020;309:125653. https://doi.org/10.1016/J.FOODCHEM.2019.125653.
128. Gorini T, Mezzasalma V, Deligia M, De Mattia F, Campone L, Labra M, et al. Check your shopping cart: DNA barcoding and Mini-Barcoding for food authentication. Foods. 2023;12(12):2392. https://doi.org/10.3390/FOODS12122392.
129. Alves GM, Cruvinel PE. Big Data Environment for Agricultural Soil Analysis from CT Digital Images. 10th International Conference on Semantic Computing. Institute of Electrical and Electronics Engineers Inc.; 2016. pp. 429–31. https://doi.org/10.1109/ICSC.2016.80
130. Lioutas ED, Charatsari C. Smart farming and short food supply chains: are they compatible? Land Use Policy. 2020;94:104541. https://doi.org/10.1016/J.LANDUSEPOL.2020.104541.
131. Jakku E, Taylor B, Fleming A, Mason C, Fielke S, Sounness C, et al. If they don't tell Us what they do with it, why would we trust them? Trust, transparency and benefit-sharing in smart farming. NJAS - Wageningen J Life Sci. 2019;90–91100285. https://doi.org/10.1016/J.NJAS.2018.11.002.
132. Demestichas K, Peppes N, Alexakis T. Survey on security threats in agricultural IoT and smart farming. Sensors. 2020;20(22):6458. https://doi.org/10.3390/S20226458.
133. Amiri-Zarandi M, Dara RA, Duncan E, Fraser EDG. Big data privacy in smart farming: A review. Sustainability. 2022;14(15):9120. https://doi.org/10.3390/SU14159120.
134. Schönfeld Mv, Heil R, Bittner L. Big data on a Farm—Smart farming. In: Hoeren T, Kolany-Raiser B, editors. Big data in context. Cham: Springer; 2018. pp. 109–20. https://doi.org/10.1007/978-3-319-62461-7_12.
135. Barreto L, Amaral A, Smart Farming. Cyber Security Challenges. International Conference on Intelligent Systems (IS). Institute of Electrical and Electronics Engineers Inc.; 2018. pp. 870–6.
136. Cornejo-Velazquez E, Acevedo-Sandoval OA, Romero-Trejo H, Toriz-Palacios A. Low-cost technological strategies for smallholders sustainability: A review. J Technol Manage Innov. 2020;15(1):105–13. https://doi.org/10.4067/S0718-27242020000100105.
137. Schwamback D, Persson M, Berndtsson R, Bertotto LE, Kobayashi ANA, Wendland EC. Automated Low-Cost soil moisture sensors: Trade-Off between cost and accuracy. Sensors. 2023;23(5):2451. https://doi.org/10.3390/S23052451.
138. Vijayakumar S, Choudhary AK, Deiveegan M, Thirumalaikumar R, Kumar RM. Android based mobile application for rice crop management. Chron Bioresource Manage. 2022;6(1):019–24.
139. Mizik T. How can precision farming work on a small scale? A systematic literature review. Precis Agric. 2023;24(1):384–406. https://doi.org/10.1007/S11119-022-09934-Y.
140. Mondal P, Basu M. Adoption of precision agriculture technologies in India and in some developing countries: scope, present status and strategies. Prog Nat Sci. 2009;19(6):659–66. https://doi.org/10.1016/J.PNSC.2008.07.020.
141. Timpanaro G, Foti VT, Cascone G, Trovato M, Grasso A, Vindigni G. Living lab for the diffusion of enabling technologies in agriculture: the case of Sicily in the mediterranean context. Agriculture 2024. Page 2347. 2024;14(12):2347. https://doi.org/10.3390/AGRICULTURE14122347.
142. Paltasingh KR, Goyari P. Impact of farmer education on farm productivity under varying technologies: case of paddy growers in India. Agricultural Food Econ. 2018;6(1):1–19. https://doi.org/10.1186/S40100-018-0101-9.
143. Tey YS, Brindal M. Factors influencing the adoption of precision agricultural technologies: A review for policy implications. Precis Agric. 2012;13(6):713–30. https://doi.org/10.1007/S11119-012-9273-6/METRICS.

144. Kadaraiah A, Jirli B, Yarazari SP, Nandini HM, Chaubey PN. Perception of farmers towards custom hiring service centres in Tumakuru district of Karnataka. Indian J Ext Educ. 2022;58(2):209–12. https://doi.org/10.48165/IJEE.2022.58232.
145. Vijayakumar S, Gurjar B, Bagavathiannan M, Kumar V. The Role of Unmanned Aerial Vehicles and Sensor Technology in Site-Specific Weed Management. In: Chauhan, B.S., Mahajan, G, editors Recent Advances in Weed Science. Springer, Cham. Chapter 4, 2025. pp. 89–123. https://doi.org/10.1007/978-3-031-91014-2_4

Publisher's note