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REVIEW

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Modern tools for sustainable agriculture: a review of intelligent crop protection technologies

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Abstract

Modern agriculture is under increasing pressure due to rising global food demand and the intensifying effects of climate change. Traditional crop protection methods often struggle to meet the current demands for higher productivity, reduced environmental impact, and long-term sustainability. This review highlights the importance of intelligent crop protection as a timely and necessary approach to address these challenges. There is a clear need for advanced Technologies and strategies to enable efficient, sustainable, and precise crop management. Intelligent crop protection integrates several modern technologies to enhance decision-making, minimize resource utilization, and protect crops more effectively. We review the application of technologies such as the Internet of Things (IoT), artificial intelligence (AI), machine learning (ML), robotics and automation, remote sensing, precision agriculture tools, and genome editing in crop protection. IoT devices, such as soil sensors, weather stations, and drones, real-time monitoring of field conditions. AI and ML assist in detecting pests and diseases early through image analysis and predictive models. Robotics enhances the accuracy and efficiency of tasks such as spraying and weeding. Genome editing techniques, such as CRISPR, are used to develop crop varieties with enhanced resistance to pests and diseases. By integrating these technologies, intelligent crop protection systems can reduce chemical use, conserve labor and resources, and promote more sustainable farming practices. This review demonstrates how adopting these innovations can help farmers enhance productivity and resilience while addressing the environmental and social challenges of modern agriculture.

Keywords Artificial intelligence, Automation, Genome editing, Internet of things, Machine learning, Robotics

1 Introduction

Traditional crop protection practices have long served as the foundation of agricultural production, relying on approaches such as calendar-based pesticide applications, manual field scouting, cultural practices (crop rotation, intercropping, and tillage), and the use of resistant cultivars [1, 2]. While these methods have historically supported global food security, they depend heavily on human observation and reactive decision-making. As a result, they often lead to delayed pest or disease detection, inconsistent management outcomes, and high labor demands. Moreover, the widespread use of broad-spectrum pesticides has contributed to environmental contamination, pesticide resistance, and negative impacts on non-target beneficial organisms [3, 4]. Climate change further exacerbates these limitations by altering pest dynamics, disease pressure, and the optimal environmental conditions required for healthy plant growth [5]. These challenges collectively highlight why traditional methods alone are no longer adequate to meet the rising demand for sustainable and efficient crop protection. In response to these limitations, there has been a global shift toward intelligent, technology-assisted crop protection systems capable of delivering precise, timely, and resource-efficient interventions [6, 7].

Modern intelligent tools are designed to establish and maintain optimal plant conditions through continuous monitoring, early stress detection, predictive analytics, and targeted management. These technologies aim to improve agricultural resilience, reduce unnecessary chemical inputs, and enhance overall sustainability. Intelligent crop protection systems represent a transformative advancement in modern agriculture, offering innovative responses to urgent challenges related to sustainability, food security, and resource efficiency [8, 9]. With growing global populations and growing climate-related constraints, traditional agricultural practices are increasingly inadequate to meet rising food demands while ensuring environmental sustainability [10]. Consequently, emerging intelligent technologies are being progressively integrated into agricultural systems to overcome the drawbacks of traditional approaches and optimize plant health conditions [11]. In response, emerging technologies such as the Internet of Things (IoT), artificial intelligence (AI), machine learning (ML), robotics and automation, precision agriculture, and genome editing are being rapidly integrated into agricultural systems to enhance productivity, resilience, and ecological sustainability [12].

Among these, the IoT is foundational, enabling real-time monitoring of environmental and crop conditions through devices such as soil moisture sensors, weather stations, and drones [13]. These tools support precise irrigation scheduling, early detection of plant stress, and data-informed decision-making, contributing to more efficient resource use and improved crop outcomes [14]. However, fully integrating IoT-generated data into comprehensive farm management platforms remains a technical challenge requiring further research and innovation [15]. AI and ML complement IoT by analyzing large datasets to generate actionable insights. For example, predictive models can forecast pest and disease outbreaks based on environmental and historical data, enabling timely and targeted interventions that reduce chemical use and crop losses [16, 17]. These data-driven approaches align with the broader objectives of sustainable agriculture by minimizing environmental impact and improving system efficiency.

Robotics and automation further transform crop protection by enabling high-precision operations such as targeted pesticide application, automated weeding, and pest surveillance. AI-powered robotic systems can reduce labor costs and environmental harms by delivering inputs only where needed, enhancing both ecological outcomes and farm profitability [18, 19]. In parallel, remote sensing technologies employing satellite, aerial, and drone-based imaging provide critical data for monitoring crop health, detecting stressors, and assessing soil moisture across large areas. Multispectral and hyperspectral imaging, in particular, provide detailed insights into vegetation plant condition, facilitating early intervention and reducing reliance on manual field inspections [20, 21]. Precision agriculture tools integrate remote sensing data with geospatial technologies such as Geographic Information Systems (GIS), Global Positioning Systems (GPS), and Variable Rate Technology (VRT) [22]. These tools enable site-specific management of inputs, optimizing the application of water, fertilizers, and pesticides, thereby increasing efficiency and reducing waste [23, 24]. In parallel, genome editing, particularly via CRISPR/Cas9, represents a breakthrough in developing pest- and disease-resistant crop varieties. By allowing precise genetic modifications, genome editing reduces the need for chemical interventions while enhancing crop productivity and resilience [25, 26].

Despite the promise of these innovations, several challenges hinder the widespread adoption of intelligent crop protection systems. These include technical challenges to data integration, limited access for smallholder farmers, economic feasibility concerns, and uncertainties about long-term ecological impacts [27]. Addressing these challenges is essential to fully harness the potential of intelligent technologies in agriculture. Intelligent crop protection systems thus offer a compelling pathway to transforming agriculture into a more sustainable and resilient enterprise. By combining real-time monitoring, predictive analytics, robotics, and genetic innovations, these systems have the potential to enhance global food security while preserving vital natural resources [8, 28]. Accordingly, this review systematically examines the role of intelligent crop protection technologies in addressing major agricultural challenges. It highlights the applications, benefits, and limitations of IoT, AI, ML, robotics, remote sensing, precision agriculture, and genome editing, while outlining future research priorities critical for promoting sustainable agricultural development.

2 Internet of things (IoT)

The IoT is a transformative technology that connects physical devices and systems, enabling continuous data exchange over digital networks. First introduced by Kevin Ashton in 1999, IoT has since become a foundational element in modern agricultural practices [29]. IoT devices such as sensors, weather stations, and drones collect real-time environmental and biological data. In a typical IoT workflow, sensors first measure physical parameters (e.g., moisture, temperature, pH), which are then transmitted via wireless communication protocols such as Wi-Fi, LoRaWAN, Bluetooth, or cellular networks [30, 31]. The collected data reach a cloud server or an edge-computing unit, where algorithms process and convert raw sensor values into meaningful indicators (e.g., soil dryness level, pest risk index). Finally, the processed information is displayed on mobile apps or dashboards, enabling farmers to make data-driven decisions or trigger automated actions such as irrigation and spraying [32]. One of the most significant applications of IoT in agriculture is its role in intelligent crop protection. based crop protection systems operate through a closed loop: (1) sensing of plant and environmental parameters; (2) transmission of real-time data; (3) automated analysis of stress signatures; and (4) activation of responses such as alarms, spraying, or irrigation [33]. This system uses advanced technologies to monitor crops for signs of pests, diseases, and environmental stress, enabling farmers to intervene quickly and efficiently. By facilitating early detection and precise intervention, intelligent crop protection helps to minimize pesticide use, reduce crop damage, and promote sustainable farming practices [34].

In addition to crop protection, IoT-enabled crop monitoring systems provide a comprehensive view of crop health. Soil-embedded sensors such as the Teros 12 measure key parameters like soil moisture, temperature, and nutrient levels, which are essential for optimal crop growth. These sensors transmit data wirelessly to cloud platforms where it is analyzed in real-time, providing farmers with actionable insights to improve irrigation scheduling, fertilization, and pest control [35]. Moreover, IoT-integrated weather stations, like Vantage Weather Station, offer precise local weather data, such as rainfall, humidity, and temperature, helping farmers prepare for extreme weather conditions and protect crops from potential damage [36]. With this information, farmers can make smarter decisions, improving crop yield and reducing environmental impact [37].

Another key application of IoT in agriculture is pest and disease management. IoT-enabled systems can monitor pest populations through sensors placed in traps or on plants, allowing farmers to track pest activity in real-time and respond promptly [38]. These systems collect data on the presence and behavior of pests, which helps farmers determine the best time and place for pesticide application. This targeted application reduces the use of chemicals and minimizes environmental pollution [34]. Additionally, IoT sensors can detect early signs of diseases, enabling farmers to act on time and prevent widespread diseases. This proactive disease and pest control approach increases crop protection efforts and promotes more sustainable agricultural practices [39]. For example, systems like Trapview® provide real-time pest monitoring with cloud-based alerts, enabling precise pesticide applications [40].

Beyond ground-level monitoring, aerial drone surveillance has become an essential tool in modern agriculture. The DJI Agras T40, for example, is a high-performance agricultural drone capable of spraying and spreading tasks with advanced obstacle avoidance and RTK precision mapping. It is frequently used for large-scale crop spraying and field monitoring [41]. Drones, equipped with high-resolution cameras and linked to IoT networks, provide detailed images of crops, revealing stress symptoms, nutrient deficiencies, or pest infestations that might go unnoticed from the ground [42]. These drones can rapidly and efficiently survey large areas, providing farmers with insights that guide timely interventions and targeted resource allocation (Fig. 1). By integrating drone technology with ground sensors, farmers can enhance crop health management and optimize the use of resources [43].

Soil health monitoring is another critical aspect where IoT plays a vital role. IoT sensors in the soil measure moisture levels, pH, and other key parameters influencing plant growth. These sensors provide real-time data on soil health, allowing farmers to adjust irrigation, fertilization, and crop rotation practices to ensure optimal soil health [44]. Netafim's Precision Irrigation system, widely used in vineyards and maize fields, integrates soil moisture sensors and weather data to automate smart drip irrigation, ensuring precisely timed and volume-optimized water applications [45, 46]. This system enhances soil fertility over the long term while improving crop yield and sustainability (Figure I). The integration of IoT into agriculture equips farmers with the tools needed to monitor, manage, and protect their crops more efficiently than ever before [47]. By combining soil sensors, weather stations, drones, and automated pest monitoring systems, IoT facilitates real-time decision-making that enhances productivity, reduces resource waste, and

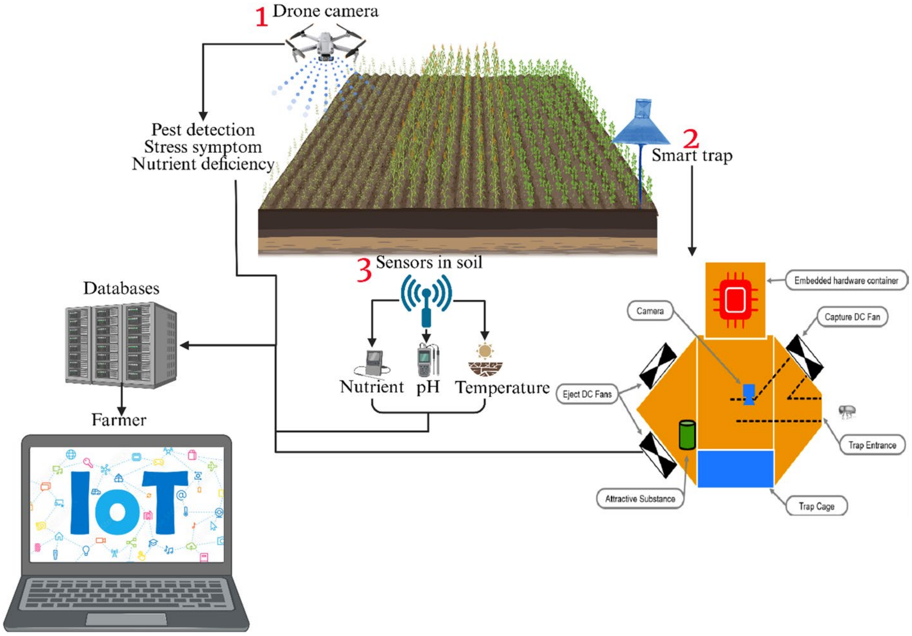

Fig. 1 IoT-based crop protection system. This system uses drone cameras (1) for pest detection, smart traps (2) for pest monitoring, and soil sensors (3) to measure nutrients, pH, and temperature. Data is sent to cloud databases for real-time analysis, helping farmers make informed decisions on pest control, irrigation, and resource management

promotes sustainable farming practices. As IoT technology advances, its role in agriculture will grow, driving innovation and improving operational efficiency in farming globally.

3 Artificial intelligence and machine learning

Artificial Intelligence (AI) is an interdisciplinary domain focused on replicating human intelligence, particularly in areas like learning, problem-solving, and simulating human-like cognitive functions. In agriculture, AI has rapidly emerged as a powerful tool, increasing crop production, pest control, and disease management [48, 49]. ML, a core subset of AI, enables efficient crop protection by analyzing large datasets to predict, monitor, and manage agricultural challenges (Fig. 2). Given that pests and diseases account for approximately 15–20% of global crop losses annually, AI and ML offer critical innovations for improving farm productivity and long-term sustainability [50]. Early identification and swift intervention are crucial to minimizing these losses. AI, especially when integrated with uncrewed aerial vehicles (UAVs) and drones, provides farmers with real-time monitoring capabilities to detect early signs of pest infestations, diseases, or environmental stress. AI predictions can automatically trigger IoT-enabled interventions, creating a closed-loop system for precision crop management [51]. Farmers can quickly pinpoint problematic zones and take necessary actions by using AI to process this data, improving crop health and yield.

ML enhances crop protection by analyzing data from environmental sensors, satellites, and UAVs. These systems measure essential variables such as soil moisture, temperature, humidity, and crop growth indicators like leaf coloration and size [52]. ML models can integrate real-time field data with historical weather patterns and soil profiles to predict pest outbreaks and disease events, supporting proactive management strategies [53]. AI-based detection systems also contribute significantly to pest control. These systems

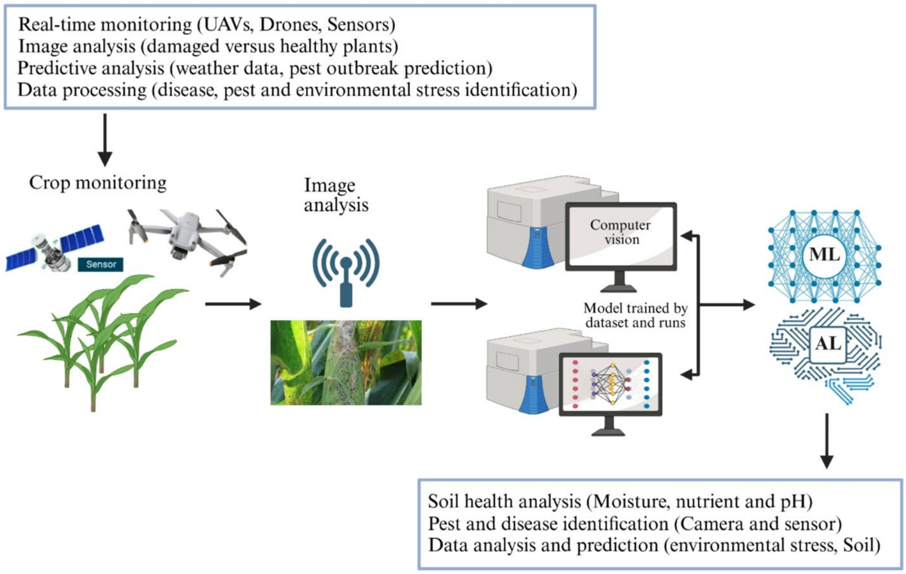

Fig. 2 AI and ML-based crop protection system. Real-time data from drones and sensors is processed using computer vision and trained models to detect pests, diseases, and environmental stress. The system supports soil analysis, image recognition, and predictive forecasting for targeted, data-driven crop management

detect movement, heat, and sound linked to pest activity. The collected data is compared with large datasets using AI algorithms to identify pests and recommend appropriate treatment measures [54]. For example, the Anticimex SMART Digital Rodent Control System uses Smart traps and environmental sensors to monitor rodent populations, predict infestation trends, and support efficient pest management [55]. Similarly, AI-driven UAVs can forecast insect population dynamics over extended periods, enabling the implementation of proactive and preventive pest control strategies [56].

Another groundbreaking application of AI is computer vision. AI-powered systems analyze high-resolution crop images to detect early signs of disease or pest damage. By comparing real-time imagery with comprehensive databases of healthy plants, these systems can detect subtle abnormalities that may be overlooked by human observation [57]. Early detection enables rapid interventions, minimizing crop losses and preventing disease spread. Moreover, advanced AI models can distinguish among various pests and diseases, facilitating more accurate and targeted management strategies [55]. Soil health, another crucial aspect of crop protection, also benefits from AI and ML. Through data from soil sensors, AI systems can analyze parameters such as soil pH, nutrient levels, and moisture content, offering insights into the soil's health and helping farmers optimize their fertilizer and irrigation practices. This, in turn, promotes healthier crops and reduces the need for excessive inputs [58, 59].

Additionally, integrating AI with weather station data can help predict changes in environmental conditions that could increase the risk of pest or disease outbreaks. By harnessing AI's predictive capabilities, farmers can prepare for adverse weather and adjust their crop management strategies accordingly [60]. UAVs equipped with AI technologies also monitor aerial crop health by capturing high-resolution images and data. These collected data are processed using AI algorithms to identify any damage to crop health, and AI systems can pinpoint areas requiring intervention, enabling farmers to focus resources precisely where they are most needed [61]. These approaches ensure that pest and disease control efforts are more efficient and minimize pesticide overuse, making crop protection practices more sustainable and environmentally friendly [62].

The integration of AI and ML also optimizes pesticide application. Rather than applying pesticides across an entire field, AI systems help farmers use pesticides only where necessary, based on real-time data. By analyzing factors like pest activity, crop health, and weather conditions, AI models give farmers precise recommendations on when and where to apply pesticides, reducing waste, labor costs, and environmental impact [63]. This targeted approach to pest control makes the entire process more efficient and sustainable, aligning with the growing emphasis on environmentally responsible farming practices. By enabling more efficient, precise, and sustainable agricultural practices, these technologies help farmers enhance productivity while reducing environmental impact. Moreover, AI contributes to the development of precision agriculture, where resource inputs are optimized to minimize waste and environmental damage. This targeted approach to pest control makes the entire process more efficient and sustainable, aligning with the growing emphasis on environmentally responsible farming practices. By enabling more efficient, precise, and sustainable agricultural practices, these technologies help farmers enhance productivity while reducing environmental impact. Moreover, AI contributes to the development of precision agriculture, where resource inputs are optimized to minimize waste and environmental damage.

4 Robotics and automation

Robotics and automation play a key role in modern agricultural production by addressing critical challenges such as labor shortages, inefficient resource use, and the growing demand for sustainable practices. Recent advancements in robotics have revolutionized agriculture, especially crop protection, enabling more precise, efficient, and environmentally friendly farming systems [64]. These technologies offer accurate, efficient, and environmentally friendly alternatives to traditional methods, particularly in managing pests and diseases. Robotics now enables targeted crop protection, replacing broad-spectrum pesticide use, which minimizes chemical application and promotes sustainable farming practices. For example, autonomous robotic weeders, unlike conventional hand-weeding or blanket herbicide application, can reduce pesticide usage by up to 30% while maintaining crop yields [65]. By integrating robotics and AI technologies, resources such as water, fertilizers, and pesticides can be applied with greater accuracy and efficiency, reducing waste and environmental footprint. These systems can collect and analyze real-time data on crop health, enabling early detection of pest infestations, disease outbreaks, and nutrient deficiencies [66, 67].

Autonomous drones and ground robots can monitor vast agricultural fields and provide high-resolution images, enabling farmers to intervene precisely where necessary [62]. Drones with multispectral sensors and AI algorithms autonomously scan large fields to identify pest outbreaks, disease symptoms, and plant stress zones. They provide high-resolution, real-time data that enables precise, site-specific interventions, improving treatment efficiency and reducing chemical use [68]. AI systems analyze this data to identify specific pests or diseases, enhancing the efficiency of crop management. For example, a study demonstrated that AI-powered robots can detect insect damage early, enabling prompt action to prevent further crop loss [69]. Beyond crop protection, robotics and automation contribute to other critical aspects of modern agricultural production, such as soil preparation, planting, and weeding. For example, autonomous tractors and robotic seeders precisely prepare land and plant seeds, ensuring optimal spacing and depth [70, 71]. Robotics-based weeding systems, like the Ecorobotix and Naïo Technologies' Oz, use computer vision to distinguish crops from weeds and mechanically remove or spray weeds with minimal herbicide use, reducing chemical input while improving field hygiene [72, 73].

Autonomous spraying systems represent a significant advancement in crop protection. Using GPS technology and sensor-based targeting to apply pesticides and fertilizers exclusively where needed. Unlike traditional sprayers that cover entire fields, autonomous systems identify and treat specific zones affected by pests or diseases and reducing chemical usage, lowers environmental impact, and enhances the overall efficiency of crop treatment [74]. For example, In vineyards, robotic sprayers precisely apply fungicides and herbicides to areas with high pest activity, improving treatment efficiency and reducing chemical exposure in the surrounding regions [65]. In addition, robotic systems also support innovative irrigation solutions. AI-integrated robotic irrigation units analyze soil moisture data and weather forecasts to precisely deliver water to crops, thereby conserving water and preventing over-irrigation. Systems such as IrrigBot and Solar-powered drip irrigation robots have proven effective in smallholder and large-scale farming [75, 76].

Robotic automation has substantially lowered labor costs in agriculture by reducing dependence on seasonal workers. Autonomous robots such as sprayers, harvesters, and monitoring units perform repetitive and labor-intensive tasks with minimal human input. These systems can operate continuously, even in challenging conditions, ensuring consistent productivity and mitigating the impact of labor shortages [77]. For example, the AHPPEBot, a robotic tomato harvester, can detect the ripeness of tomatoes and pick them without causing damage, outperforming manual labor in both speed and precision [78]. Robotic systems improve crop protection by enabling precise, data-driven pest and disease management. AI and ML analyze real-time field data to optimize the timing and location of interventions, enhancing efficiency and reducing environmental impact [79]. The integration of robotics in agriculture enhances efficiency, supports sustainability, and improves cost-effectiveness across various farming operations [69].

In conclusion, robotics and automation are redefining crop protection through precise monitoring, targeted intervention, and reduced chemical use. These technologies improve efficiency, support sustainable practices, and address key challenges such as labor shortages and food security. As AI and robotics advance, they will become essential to scalable, environmentally responsible agriculture [80]. The integration of robotics in agriculture enhances efficiency, supports sustainability, and improves cost-effectiveness across various farming operations, including planting, irrigation, weeding, harvesting, and crop protection, making it a cornerstone of modern agricultural transformation (Fig. 3). To maximize efficiency, these robotic systems should be integrated through centralized platforms that allow interoperability among drones, ground robots, autonomous sprayers, and irrigation units. Data from multiple sensors and machines can be aggregated in a single dashboard, enabling coordinated decision-making and real-time interventions. Standardized communication protocols and APIs are essential for seamless data exchange, ensuring that all robotic components work in harmony across diverse farm operations.

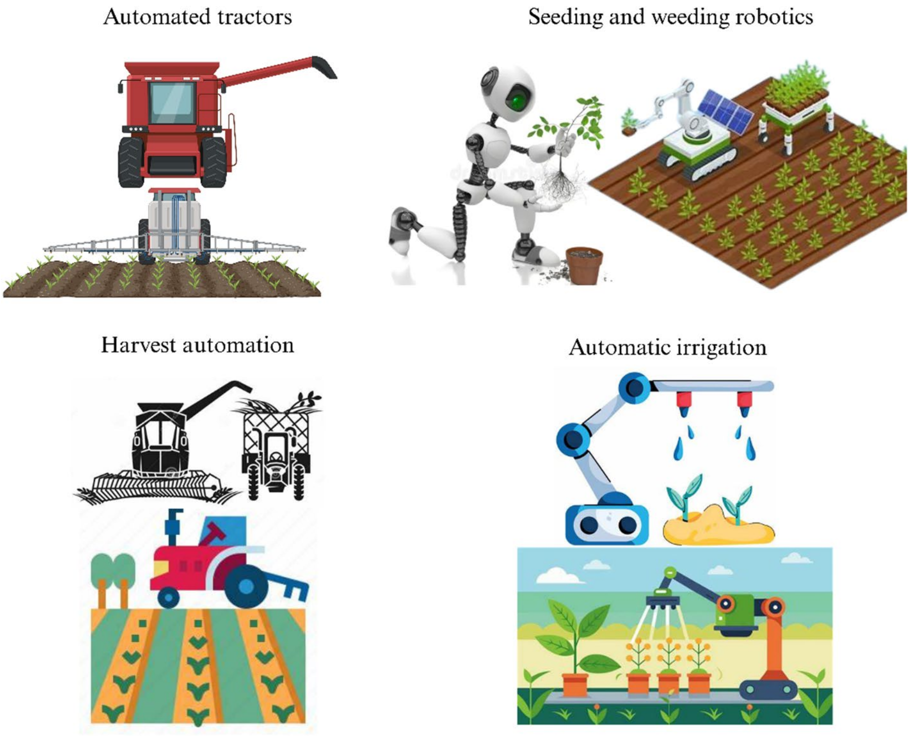

Fig. 3 Robotics and automation in modern agriculture. Key applications include automated tractors for soil preparation, seeding, and weeding robotics for precise planting and weed control, harvest automation to reduce labor dependency, and automatic irrigation systems for optimized water use. These technologies enhance productivity, reduce chemical and water usage, and support sustainable, efficient farming practices

5 Remote sensing and satellite imagery

Advancements in remote sensing and satellite imagery have revolutionized crop protection by enabling precise monitoring, early detection of pests and diseases, and optimized resource management [81]. These technologies provide farmers with real-time, high-resolution data on crop health, reducing reliance on traditional field scouting methods that are time-consuming and labor-intensive. Satellite imagery enables large-scale, frequent monitoring of agricultural conditions, supporting timely decisions and promoting more sustainable and efficient farming practices [82]. A range of remote sensing technologies enhances crop protection, including satellite-based, aerial, and ground-based systems. Satellite platforms such as Landsat, Sentinel, and MODIS offer large-scale monitoring through multispectral and thermal data, enabling the detection of plant stress, soil moisture levels, and pest outbreaks [83].

Multispectral and hyperspectral imaging are vital for early pest and disease identification (Fig. 4). Multispectral imaging captures data from 5 to 10 spectral bands, including the red-edge band (700–800 nm), which detects plant stress before visible symptoms appear, enabling timely intervention and reducing potential crop losses [82]. Hyperspectral imaging captures data across hundreds of narrow spectral bands, generating detailed spectral signatures of crops. This high-resolution method detects subtle changes in reflectance associated with pest infestations or disease onset, enabling early, accurate diagnosis and timely interventions to safeguard crop yields [84]. Drones equipped with multispectral and hyperspectral sensors detect subtle variations in plant health, enabling precise, targeted interventions [85].

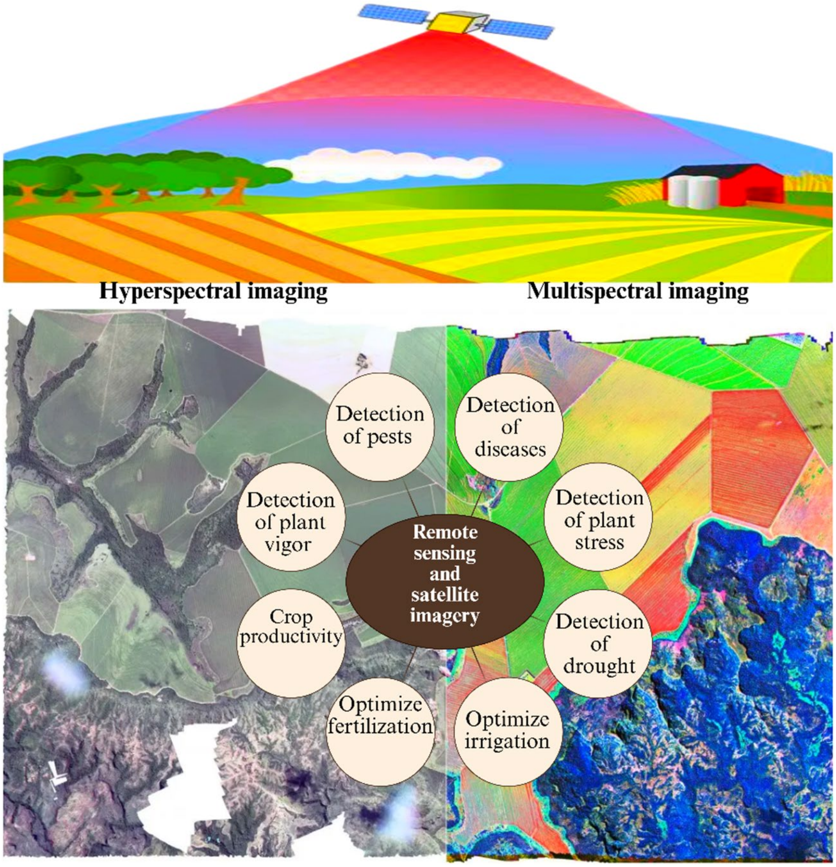

Fig. 4 Application of remote sensing and satellite imagery in agriculture. Hyperspectral and multispectral imaging technologies enable the detection of pests, diseases, plant stress, drought, and plant vigor. These tools support optimized fertilization and irrigation, enhance crop productivity, and improve decision-making through large-scale monitoring and analysis

Vegetation indices are mathematical formulas that interpret satellite or drone imagery to assess plant health, density, and coverage. They work by analyzing how vegetation reflects light in different parts of the electromagnetic spectrum, particularly in the red, blue, and near-infrared (NIR) wavelengths. Healthy plants reflect more NIR light and absorb red light due to their chlorophyll content. Studies show that using RS reduces crop loss by up to 25% compared to conventional methods due to earlier detection of pests and diseases [86, 87]. Vegetation indices derived from remote sensing data are essential for assessing crop health and stress. The Normalized Difference Vegetation Index (NDVI) measures the contrast between near-infrared and red reflectance to indicate plant vigor and detect early stress. The Enhanced Vegetation Index (EVI), designed for high-biomass regions, improves sensitivity in dense canopies, providing more accurate assessments in areas where NDVI may saturate [88]. Chlorophyll Indices evaluate plant health by estimating chlorophyll concentration, a key indicator of photosynthetic activity and nutrient status. Thermal infrared imaging complements this by detecting drought stress through canopy temperature variations. Together, these indices support data-driven decisions for optimizing irrigation, fertilization, and pest control, enhancing crop productivity while conserving vital resources [89].

Beyond monitoring, remote sensing is integral to early warning systems and predictive analytics in crop protection. Satellite imagery enables the early detection of pest and disease outbreaks before widespread impact occurs, allowing for timely, preventive action and minimizing crop loss [90]. These models recognize patterns in vegetation health, generate risk assessments and provide early alerts that help farmers take preventive measures. This predictive strategy reduces dependence on reactive pesticide applications, minimizing crop damage while promoting agricultural sustainability [91]. Automated irrigation systems, guided by remote sensing, ensure water distribution aligns with actual crop requirements, minimizing waste and strengthening resilience against drought [92]. Similarly, satellite-guided pesticide applications restrict chemical use to affected zones, minimizing environmental impact. Integrating satellite data with farm management systems provides farmers with detailed remote insights, enabling data-driven decisions. This synergy exemplifies precision agriculture, maximizing resource efficiency and improving farm productivity [93].

Satellite data is also integral to crop health monitoring systems, providing extensive, real-time evaluations of large agricultural areas. These systems process satellite imagery to assess crop health indicators, stress levels, and environmental conditions [94]. Platforms like EOSDA Crop Monitoring utilize time-series satellite imagery to detect fluctuations in crop conditions, identifying issues such as nutrient deficiencies and disease outbreaks earlier than traditional methods. The advantages of satellite-based monitoring are substantial, offering real-time data that supports more accurate decisions in resource allocation, pest control, and overall crop protection strategies [94]. Moreover, satellite imagery significantly reduces the need for frequent manual inspections, lowering labor costs and boosting efficiency. Remote sensing technologies significantly enhance crop protection through early detection, optimized resource management, and data-driven precision farming.

Integrating satellite and UAV imagery with farm management systems allows seamless coordination with robotic sprayers, VRT systems, and AI-based decision support platforms. Centralized dashboards aggregate these data streams, enabling predictive pest management, optimized irrigation, and precision pesticide application. Ensuring interoperability through standard data formats and APIs enhances the effectiveness of precision agriculture.

6 Precision agriculture tools

Precision agricultural tools have become vital in modern farming, especially for intelligent crop protection. These technologies allow for site-specific input application, real-time crop monitoring, and targeted responses to pests, diseases, and weeds, minimizing resource waste while maximizing effectiveness and sustainability [95, 96]. Key tools in precision agriculture include GPS-guided equipment, Variable Rate Technology (VRT), and drones (UAVs). GPS-guided machinery accurately applies fertilizers, herbicides, and other inputs, ensuring efficient coverage and reducing waste [97]. Farmers can minimize overlap and missed areas during input application by utilizing GPS technology, ensuring pesticides are applied only where needed. This precision reduces chemical waste, lowers costs, and mitigates the environmental impact of overapplication [98]. GPS-guided sprayers adjust flow rates of chemicals based on field positions, ensuring precise coverage and minimizing drift [99]. In addition to improving application efficiency, GPS technology supports pest detection by enabling the generation of precise geospatial maps of infestation patterns across agricultural fields. Crop advisors can utilize GPS-enabled data collection devices to pinpoint areas affected by pests or diseases, facilitating correct decision-making and the targeted application of control measures [100]. This data-driven approach allows farmers to implement targeted control strategies, optimizing crop health and maximizing yields.

VRT further enhances precision agriculture by enabling farmers to apply inputs such as seeds, fertilizers, and pesticides at varying rates based on specific field conditions [101]. VRT systems analyze factors like soil fertility, moisture content, and historical yield data to create prescription maps that guide optimal input application across different field zones. This customized approach minimizes resource waste, reduces environmental harm, and ensures that crops receive the necessary inputs [102]. Moreover, based on field conditions, VRT systems can adjust pesticide applications in real time. For example, if remote sensing detects a disease or pest outbreak in a specific area, the system can increase pesticide application in that zone while reducing it in unaffected areas. VRT adjusts seed, fertilizer, and pesticide application based on soil fertility, moisture, and historical yield data. Studies indicate VRT can reduce chemical use by 20–35% while maintaining or improving yield, compared to conventional uniform application [103]. This capability improves pest control and promotes sustainable farming by reducing overall chemical usage.

Uncrewed Aerial Vehicles (UAVs), commonly known as drones, represent a transformative component of precision agriculture, particularly in pest monitoring and management. Equipped with advanced imaging technologies, such as multispectral and hyperspectral cameras, drones can rapidly survey large agricultural areas and capture high-resolution imagery to assess crop health and detect pest-infested zones with precision [104]. Unlike satellite imagery, drones provide greater flexibility and can detect stress indicators related to disease or pest damage before they become visible to the naked eye. In addition to monitoring, drones are increasingly used for targeted pesticide applications [81]. Automated drones can be programmed to apply pesticides only where infestations are detected, significantly reducing chemical usage and minimizing risks to non-target organisms [105].

Integrating these precision tools with Integrated Pest Management (IPM) practices further enhances sustainable crop protection (Fig. 5). By combining data-driven technologies with IPM principles, farmers can reduce pesticide use, promote biodiversity, and implement more environmentally friendly pest control methods [106]. These technologies enable precise input application based on localized field conditions, improve pest detection and monitoring, and facilitate targeted interventions that support efficient and sustainable farming [36]. By reducing chemical usage, minimizing environmental impact, and enhancing crop yields, precision agriculture is paving the way for a more sustainable and productive agricultural future. To fully realize the potential of precision agriculture tools, these technologies should be integrated into unified platforms that allow seamless communication among GPS-guided machinery, VRT systems, UAVs, and soil sensors. User-friendly interfaces, mobile apps, and dashboards are essential for presenting actionable insights to farmers, enabling them to make timely and informed decisions without requiring extensive technical knowledge. This integration maximizes efficiency, reduces resource waste, and ensures coordinated pest and input management across fields.

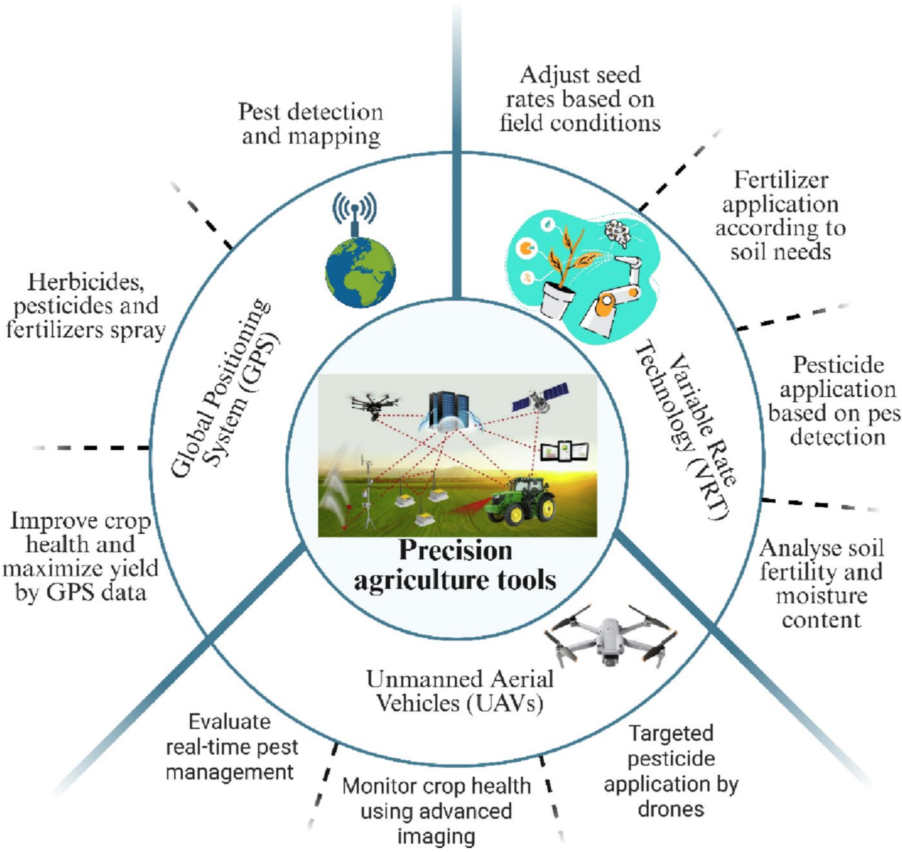

Fig. 5 Precision agriculture tools integrating GPS, UAVs, and Variable Rate Technology (VRT). These tools enable pest detection, real-time crop monitoring, targeted pesticide application, and site-specific management of seeds, fertilizers, and irrigation. The system enhances crop health, optimizes input use, and maximizes yield through data-driven decision-making

7 Integrating genome editing into intelligent crop protection systems

Genome editing technologies, especially CRISPR/Cas9, have transformed crop protection by enabling precise genetic modifications that enhance agricultural sustainability and resilience. These tools allow scientists to accurately alter plant genomes, accelerating the development of crops resistant to biotic stresses like pests and diseases [107]. Unlike conventional breeding, which is slower and less accurate, genome editing provides a faster, targeted approach to enhancing desirable traits. CRISPR/Cas9, derived from a bacterial immune system, surpasses older technologies such as ZFNs and TALENs in simplicity, affordability, and precision [108]. The system functions through three stages: adaptation, where bacterial cells integrate viral DNA fragments into CRISPR arrays; expression, where these sequences guide Cas9 enzyme synthesis; and interference, where Cas9 cleaves invading viral DNA, neutralizing threats. Adapted for plants, this mechanism allows precise editing of genes linked to disease susceptibility, revolutionizing crop protection strategies [109, 110].

A key application of genome editing in crop protection involves targeting host susceptibility genes essential for pathogen invasion. For example, eukaryotic translation initiation factors such as eIF4E play a critical role in viral replication. CRISPR/Cas9-mediated modification of eIF4E genes disrupts interactions with viral proteins, thereby inhibiting replication and conferring resistance to pathogens such as Turnip Mosaic Virus

(TuMV) [111]. Multiplex gene editing further broadens this potential by simultaneously modifying multiple genes or pathways. In cucumbers, editing several eIF4E alleles conferred resistance to various Potyviridae viruses, including Zucchini yellow mosaic virus (ZYMV) and Cucumber vein yellowing virus (CVYV), showcasing its utility in developing crops with durable, broad-spectrum resistance [112].

Beyond biotic stresses, genome editing enhances tolerance to abiotic challenges like drought, salinity, and extreme temperatures, critical traits as climate change intensifies. By editing genes regulating stress responses, researchers have improved drought resilience in rice and wheat, enabling growth in water-scarce regions [113]. Similarly, modifying salt tolerance genes offers promise for cultivating crops in saline soils, a growing issue in agriculture. These advancements highlight CRISPR's role in sustaining productivity under environmental duress [114]. Genome editing also reduces reliance on chemical pesticides, promoting eco-friendly farming. Crops engineered for innate pest or disease resistance minimize pesticide use, lowering environmental harm and preserving biodiversity [115]. For example, genetically modified corn and tomato varieties exhibit enhanced insect resistance, curbing insecticide needs. Likewise, fungal and bacterial-resistant crops reduce fungicide and bactericide applications, aligning with sustainable practices [116].

Integrating genome editing with intelligent agricultural systems amplifies its impact. Coupling CRISPR with IoT sensors, AI, and remote sensing enables real-time crop monitoring, precise pest detection, and timely interventions (Fig. 6). Drones equipped with multispectral imaging, for example, can swiftly identify stress signals in edited crops, allowing targeted management [117]. However, the widespread adoption of genome-edited crops and other novel agricultural technologies requires clear, streamlined regulatory frameworks. Policymakers must establish science-based approval processes that

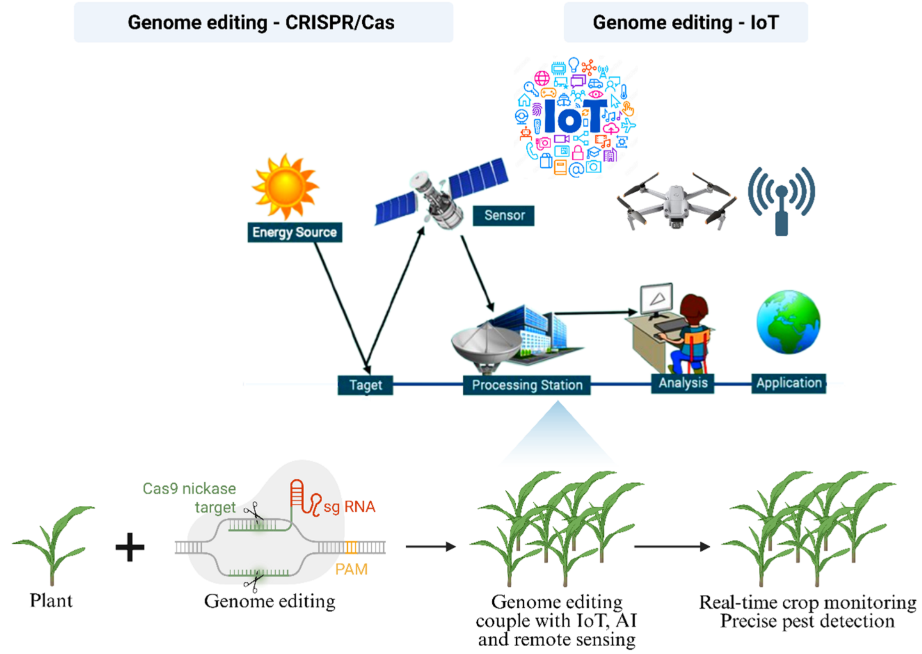

Fig. 6 Integration of genome editing with IoT and remote sensing. CRISPR/Cas-based genome editing enhances crop traits, while IoT, AI, and remote sensing technologies enable real-time crop monitoring and precise pest detection. This combined system improves crop resilience, productivity, and targeted agricultural interventions

ensure the safety, efficacy, and traceability of edited crops, while minimizing bureaucratic delays and ensuring transparency [118]. Harmonized national and international regulations can facilitate the adoption of genome editing by farmers and reduce trade barriers. Additionally, transparent guidelines will help build public trust, support innovation, and encourage private-sector investment in sustainable crop protection technologies [119].

CRISPR/Cas9 and related technologies are redefining crop protection through precise genetic enhancements that combat biotic and abiotic stresses while promoting sustainability [120]. These tools address urgent agricultural challenges by editing susceptibility genes, multiplexing defenses, and improving stress tolerance. Their integration with innovative farming systems further optimizes efficiency and environmental stewardship [121]. As research unravels plant-pathogen dynamics and resistance genetics, genome editing will remain pivotal in building resilient, sustainable food systems. Harnessing these innovations alongside intelligent technologies offers a pathway to global food security amid climate uncertainties, ensuring a future of adaptive agriculture. In parallel with technical integration, clear and streamlined regulatory frameworks are crucial to ensure the safe, efficient, and widespread adoption of genome-edited crops. Harmonized approval processes, transparent safety guidelines, and traceability standards facilitate farmer adoption, encourage private-sector investment, and allow genome-edited crops to be seamlessly incorporated into integrated crop protection platforms alongside AI, IoT, and precision agriculture tools.

8 Case studies and practical applications of intelligent crop protection systems in modern agriculture

The intelligent crop protection system, a key component of contemporary agriculture, has recently garnered significant attention, with several successful implementations. While these technologies offer precise pest and disease management, their high investment costs and technical complexity can limit adoption, particularly for smallholder farmers. The following case studies illustrate not only the effectiveness of these systems but also strategies to enhance economic feasibility and accessibility (Table 1).

8.1 Case study 1: IoT-driven pest management

The integration of IoT and AI technologies led to a 25% reduction in pesticide use and enabled precise irrigation scheduling, resulting in a 35–40% decrease in water consumption and associated environmental impact. The working principle involves sensors monitoring environmental parameters (soil moisture, temperature, humidity) and pest activity, transmitting real-time data to cloud or edge-computing platforms. AI algorithms analyze this data to generate alerts or trigger automated interventions such as irrigation or spraying. In Sub-Saharan Africa, IoT sensors were deployed to track locust swarm movements, enabling timely interventions that reduced crop losses by approximately 30%. Early detection of pest outbreaks improved crop resilience and contributed to a 20% increase in yield. Economic feasibility was enhanced by using low-cost sensors and community-shared IoT networks, making the system accessible to smallholder farmers [122–124].

Table 1 Case studies of applications of intelligent crop protection technologies in modern agriculture

Technology	**Description**	**Application**	**Impact**	**Case Study Example**	**References**
IoT-Driven Pest and Environment Monitoring	IoT sensors are deployed to continuously collect environmental data (e.g., soil moisture, temperature, humidity) to monitor pest activity and optimize irrigation and soil conditions.	AI and cloud computing analyze real-time data for early pest detection and precise irrigation control, improving farm resource management.	25% reduction in pesticide use and Improved crop yield by 20%.	Sub-Saharan Africa: IoT applications reduced locust-related crop damage by 30%.	[122, 123]
Artificial Intelligence (AI) and Machine Learning (ML)	AI algorithms analyze complex environmental data to predict pest outbreaks and optimize pest management strategies based on past and current data.	AI-driven decision-making systems allow farmers to anticipate pest behavior, forecast outbreaks, and time pesticide applications effectively.	– 85–90% accuracy in pest prediction- 40% reduction in pesticide use- Increased crop resilience and yield.	Australia: AI models in greenhouse environments predicted pest outbreaks with 85–90% accuracy, reducing pesticide consumption by 40%.	[125, 178]
Robotics and Autonomous Systems	Robotics, powered by AI and machine vision, enable precise weed and pest control by autonomously identifying and removing pests or weeds with minimal environmental disruption.	Autonomous robots are deployed for precise pest removal and weed control in large-scale farming operations, significantly reducing chemical inputs.	30% reduction in pesticide use- Increased operational efficiency- Improved soil health through reduced chemical exposure.	USA: Autonomous AI-powered robots for weed removal reduced pesticide use by 30% while maintaining soil health.	[129, 130]
Remote Sensing and Satellite Imagery	Satellite imagery, coupled with AI models, is used to monitor large agricultural fields for early signs of pest infestations, crop stress, and nutrient deficiencies.	Remote sensing provides real-time monitoring of pest damage, enabling proactive interventions to minimize losses and optimize crop management.	25% reduction in crop loss Improved yield forecasting and pest management coordination. Reduced need for manual field inspections.	Asia (Rice Fields): Sentinel-2 satellite imagery identified early pest damage, preventing up to 25% crop loss and improving yield predictions.	[61, 134, 179]
Precision Agriculture	Precision farming tools, including drones, sensors, and GPS technologies, enable targeted pest control and nutrient management based on real-time data from the field.	Drones and sensors collect data on soil conditions and pest presence, allowing for precise pesticide and fertilizer application, minimizing waste.	20–35% reduction in pesticide use- Improved crop yield- Enhanced soil health and resource efficiency.	Australia: Drones with multispectral cameras identified pest hotspots, reducing pesticide use by 20–35% while preserving crop health.	[135–137]
Genome Editing (e.g., CRISPR-Cas9)	Genetic engineering techniques such as CRISPR-Cas9 are used to develop pest resistant crops, reducing the need for chemical pesticides and promoting sustainable agricultural practices.	CRISPR-based crops are bred to enhance natural pest resistance, reducing pest pressure and improving crop resilience.	70% reduction in pest infestations Reduced pesticide Improved crop yield and sustainability.	China (Tomatoes): CRISPR-edited tomatoes with increased resistance to aphids and whiteflies showed a 70% reduction in pest infestations, leading to a decrease in pesticide usage.	[139, 141, 142]

8.2 Case study 2: AI and machine learning for pest prediction

ML and AI have shown significant potential in forecasting and controlling pest outbreaks. High-tech greenhouses in Australia used AI models and IoT devices to predict insect outbreaks. The basic principle involves ML models analyzing environmental and crop data (temperature, humidity, light intensity) to forecast pest infestations. Real-time alerts allow farmers to apply targeted interventions efficiently. These models achieved 85–90% accuracy [125, 126]. For smallholders, open-source ML models and mobile-based AI applications enable predictive pest management without expensive hardware investments. This AI-powered method decreased the greenhouse industry's environmental impact while increasing crop quality. Machine learning algorithms are very successful in real-time insect identification and pest population forecasts [127]. Research done in Zambia, in which a deep learning model, MobileNet v2, achieved 91% precision for *Locusta migratoria* and 85% for *Nomadacris septemfasciata*, integrated with real-time environmental data collection to enhance early warning and pest control strategies in the agricultural sector of Zambia [128].

8.3 Case study 3: robotics and automation in pest and weed control

Recent advancements in AI and machine vision have enabled robots to differentiate between crops and weeds with high precision, allowing for targeted weed removal without the need for chemical herbicides. The working principle involves cameras and sensors capturing images of the field, while AI algorithms process the data to distinguish weeds from crops. Actuators or robotic arms then mechanically remove weeds, minimizing chemical use and soil disturbance. An American study illustrated the efficiency of AI-powered robotic weeders with machine vision capabilities. With minimum soil disturbance and a 30% reduction in pesticide use and labor costs, these robots precisely located and mechanically pulled weeds [129]. For smallholder farmers, economic feasibility can be improved through shared or cooperative robotic services, renting equipment, or using smaller-scale robotic weeders adapted to limited field sizes [130]. Thus, robotics and automation have become vital instruments for large-scale farming operations, encouraging ecologically friendly agricultural methods while lowering dependency on manual labor and chemical herbicides.

8.4 Case study 4: remote sensing and satellite imagery

Satellite imaging combined with remote sensing technology has made them essential tools for managing and monitoring pests on a large scale. The basic principle involves satellites or UAVs capturing high-resolution images of crops, which are then analyzed using AI or ML algorithms to detect stress indicators caused by pests or diseases. Vegetation indices, such as NDVI, NDWI, and NDMI, are calculated to identify affected areas for targeted interventions. Sentinel-2 satellite images combined with AI models were used in an Asian project to identify early signs of insect damage in rice crops [131–133]. This strategy enabled early intervention, enhancing yield estimate accuracy and preventing up to 25% crop losses. Furthermore, using satellite data made it easier to coordinate pest management across regions, enhancing agricultural sustainability and resilience [61, 134]. Smallholder farmers can access this technology cost-effectively through government-supported remote sensing platforms, free satellite data services, or community-based advisory programs. To enhance accuracy in managing pests and diseases, remote sensing technology continues to develop, using ML algorithms and high-resolution UAV images. These developments illustrate a move toward data-driven, sustainable, and scalable farming methods accessible to both large and small-scale farmers.

8.5 Case study 5: precision agriculture tools for targeted interventions

Pest control has been transformed by precision agricultural tools, including drones with multispectral cameras and ground-based sensors, which allow for focused treatments. The working principle involves drones or sensors detecting pest hotspots through spectral imaging or environmental measurements. AI algorithms analyze these data to guide targeted pesticide application, reducing unnecessary spraying. Research in Australia showed that multi-spectral sensors on drones could locate insect hotspots and apply pesticides to targeted areas. With this focused strategy, pesticide consumption decreased by 20–35% while crop yields remained high [61, 135]. Studies employing UAV-mounted sensors for spatial soil-plant interaction research have shown that this method increased soil health and production [136]. The effectiveness of precision agricultural machines in modern farming was further supported by the significant cost savings and enhanced crop quality that farmers experienced [137]. The future of sustainable agriculture is still being shaped by precision agricultural tools, which encourage effective, data-driven decision-making. For smallholders, cooperative drone services, modular drones, or government-supported rental programs can overcome high investment costs, making precision agriculture accessible and economically feasible.

8.6 Case study 6: genome editing for pest resistance

Genome editing technologies have transformed the breeding of pest-resistant crops by enabling precise modifications to genes to strengthen systemic defenses. The working principle involves using tools like CRISPR to edit specific genes that confer resistance to pests, enhancing natural plant defenses without chemical inputs [138]. Researchers in China have effectively developed tomato plants that have been CRISPR-edited to have increased resistance to aphids and whiteflies [139, 140]. Pesticide usage significantly decreased due to these genetically engineered crops and 70% drop in insect infestations. Research demonstrates that heritable pest resistance characteristics may be introduced by genome editing, providing long-term protection without the need for chemical treatments [141]. Scientists have shown that genome editing can modify plant metabolic pathways to provide natural defenses against pests, thus lowering the need for chemical inputs [142]. Economic feasibility for smallholder farmers can be improved through government or NGO-supported seed distribution programs, public-private partnerships, and low-cost access to CRISPR-edited seeds. These genetically modified crops demonstrate how modern technologies may increase food security and encourage environmentally friendly agricultural practices. These case studies demonstrate that modern intelligent crop protection systems not only improve precision and sustainability but can also be adapted for smallholder farmers through cooperative approaches, low-cost tools, shared services, and government-supported programs. Widespread adoption depends on overcoming regulatory, technical, and financial barriers while ensuring access for farmers at different scales [143, 144].

9 Challenges and limitations

Implementing intelligent crop protection systems in modern agriculture has several benefits, including increased efficiency, lower pesticide usage, and greater sustainability. However, various hurdles and restrictions impede these technologies, including general acceptance and efficacy [145]. One of the primary challenges in adopting intelligent crop protection is ensuring seamless integration and interchangeability among various technological components [146]. For example, IoT devices, AI-driven platforms, robotics, and precision agricultural tools must work together effectively to collect, process, and interpret data in a coordinated manner. Ensuring this level of interoperability is crucial for optimizing efficiency and maximizing the benefits of innovative agricultural solutions [147]. Research has shown that adopting integrated farm systems encounters incompatibility challenges with previously installed older agricultural technology, particularly where hardware and software are involved [148].

Furthermore, these systems must be compatible. Technologies must interact fluidly across several devices and platforms. However, it is sometimes challenging due to the usage of various data formats and standards [149]. Sensors and AI systems produce large volumes of data, demanding sophisticated data management and processing. Agricultural systems risk being overwhelmed by unstructured information, making real-time decision-making tough [150]. Another major challenge includes the scalability of these systems. Though effective, intelligent crop protection systems have already demonstrated their use in small-scale pilot farms, scalability to large-scale remains uncertain [151]. This is especially true for scalability, since integrating multiple devices may complicate data management and analytics with large datasets from varied farming conditions [152].

In the long term, intelligent crop protection systems offer the potential for higher yields and resource efficiency, but economic hurdles frequently hinder these benefits [153]. High investment costs and financial uncertainty regarding potential long-term benefits present a significant barrier for farmers to adopt this technology. The upfront expenses of implementing intelligent crop protection systems are often extremely substantial [154]. Regulatory organizations must to establish clear guidelines to help increase productivity and reduce costs over the long term. Moreover, the return on investment (ROI) may not be immediately evident, making opposition among farmers who cannot justify the initial cost [155]. In Europe, attention has been drawn to the high cost of precision agricultural technologies and small farmers financial challenges when adopting them. Although technologies such as variable rate irrigation and advanced fertilization systems are highly effective in reducing resource consumption, their initial investment and ongoing maintenance costs remain very high [156]. Ongoing operational costs, such as cloud-based data storage and processing, can accumulate significantly over time. According to research, investment through public and private partnerships or government incentives for farmers to use these new technologies might ease other financial constraints [151, 157]. However, such funding is difficult for a small farming operation because preparing and submitting a funding proposal requires specific technical knowledge.

Intelligent crop protection systems must be aligned with legal and environmental requirements to ensure they are practical, sustainable, and comply with national and international legislation [158]. Controlling and managing pesticide applications is a key aspect of intelligent crop protection. Crop protection systems that employ AI technology to monitor crop health and determine pesticide applications must comply with strict regulations on their use [159]. AI-based systems must have a mechanism that prevents over- or misapplication of the chemical due to the potentially hazardous environmental effects. These systems must ensure that their recommendations do not exceed the legally permissible limitations for pesticide use; over-application causes soil degradation, water pollution, and harms non-target species [160]. Precision agricultural tools like remote sensing and AI-powered irrigation systems might help farmers optimize resource utilization while lowering water, fertilizer, and pesticide consumption. Conversely, these tools must be managed to avoid detrimental environmental consequences [161]. Improper use of precision agricultural technologies might result in resource overexploitation, such as water, or disrupt local ecosystems, such as the groundwater table [162].

Regulatory bodies should establish clear guidelines for implementing such systems to ensure long-term viability. Furthermore, because Intelligent Crop Protection Systems create a large amount of data regarding crop health, pesticide usage, and farm activities, data privacy and security concerns are becoming increasingly relevant [163]. Data among farmhouse operators, service providers, and third-party cloud platforms must be transmitted via secure channels following data protection regulations such as the General Data Protection Regulation (GDPR in Europe) [164]. Ensuring that collected data is retained and used only for the purpose it was collected is critical to trust and the long-term adoption of these technologies [165]. The large-scale implementation of intelligent crop protection technologies holds significant potential for the agricultural revolution. Acceptance is challenging due to issues with integration, scalability, financial accessibility, and regulatory compliance. Addressing these obstacles would unlock the real potential of intelligent crop protection systems for agricultural sustainability, efficiency, and equity.

10 Future directions and recommendations

The future of intelligent crop protection will transform agriculture by integrating advanced technologies with sustainable practices. As global food demand increases, the need for efficient and eco-friendly solutions becomes more urgent [8]. Emerging technologies such as sensors, AI, gene editing, and automated decision support systems are changing crop protection. For example, modern sensors provide real-time soil and plant health data, including moisture, nutrient levels, and insect activity [166]. When connected to the IoT, these sensors optimize resource utilization, increase yields, and enable targeted insect responses, reducing broad pesticide use and environmental impact [167]. AI and ML have transformational potential since they analyze large amounts of data to forecast pest outbreaks. AI-driven models use drones, satellites, and sensor data to allow preventative pest control techniques [151, 168]. ML techniques enhance accuracy with fresh data, while AI applications, such as projecting pest outbreaks based on climate and historical trends, enable more effective pest control [169]. CRISPR Cas, a genome editing technique, accelerates the development of pest-resistant crops by altering genes that enhance pest susceptibility. These crops reduce dependency on chemical pesticides, supporting environmentally friendly practices [141]. Automated decision support systems enhance pest control by integrating big data analytics with real-time inputs. These systems identify crop stressors by analyzing data from soil sensors, weather stations, and satellite imagery and recommend targeted interventions. This precision maximizes resource efficiency while minimizing environmental impact [79]. Despite these advances, it is essential to evaluate the long-term effects of these technologies on soil health, biodiversity, and ecosystem services. Although tools like AI and sensors help reduce pesticide use, they must be carefully evaluated to prevent unintended environmental consequences [95]. Integrating different technologies, such as AI, IoT, drones, and gene editing, into coherent systems creates new obstacles. Frameworks that enable smooth coordination among technologies are critical for comprehensive pest management. User-friendly interfaces are also necessary, as many farmers lack technological knowledge [170]. Apps and dashboards are intuitive technologies that assist with data understanding and decision-making. Farmers can justify using these technologies with research regarding their economic feasibility [171]. Long-term studies that demonstrate financial benefits, such as lower pesticide costs and increased yields, will encourage broad adoption [95].

Policymakers should provide resources and incentives, such as subsidies or grants, to encourage adoption. Training programs to improve farmers' technical skills and increased funding for agricultural research are essential [172]. In parallel, clear regulatory frameworks are necessary to ensure the safe implementation of innovations, particularly genome editing and novel agricultural advances. Streamlining approval processes while maintaining safety standards will promote development [173]. Collaboration among academics, businesses, and government is critical to improving intelligent crop protection. Public-private collaborations can boost innovation by combining knowledge and resources. Together, stakeholders can encourage the adoption of innovative technology, providing farmers with the tools they need to meet current food production concerns [174]. Sensors, AI, genome editing, and decision support systems will improve agriculture's sustainability and efficiency. Addressing research gaps and promoting supporting policies will enable these technologies to reach their full potential, ensuring food security for future generations.

To ensure the effective uptake of intelligent crop protection systems, several strategies are recommended. User-friendly interfaces, mobile applications, and intuitive dashboards should be developed to support farmers with limited technological knowledge, simplifying data interpretation and decision-making. Long-term studies should evaluate the effects of these technologies on soil health, biodiversity, and ecosystem services to prevent unintended environmental consequences [175]. Data privacy and security frameworks must be established to ensure the safe transmission, storage, and use of agricultural data. Public-private partnerships, government subsidies, and incentive programs can encourage innovation and facilitate adoption among smallholder farmers who face financial challenges. Targeted training programs and extension services are essential to improve farmers' technical skills, enabling the proper and efficient use of IoT devices, AI tools, and genome-edited crops [176, 177]. By addressing technological accessibility, economic feasibility, ecological sustainability, and policy support, these recommendations aim to maximize the benefits of intelligent crop protection systems and promote their widespread, safe, and sustainable adoption.

11 Conclusion

Intelligent crop protection represents a transformative approach to modern agriculture, tackling key challenges related to food security, environmental sustainability, and climate resilience. By integrating technologies like IoT, AI, machine learning, and robotics, intelligent crop protection systems enable real-time monitoring, predictive analyses, and automated interventions that improve input use, minimize reliance on chemical pesticides, and enhance overall efficiency. Adopting these technologies not only improves yields and resource management but also supports the goals of sustainable agriculture by minimizing environmental impact and protecting human health. However, to fully harness these technologies, it is essential to address infrastructural limitations, economic constraints, and educational barriers, particularly among smallholder farmers. Future initiatives should focus on improving AI-driven platforms' scalability, interoperability, and cost-effectiveness, alongside clear regulatory guidelines and targeted training capacity-building programs. Ongoing research, technological innovation, and stakeholder collaboration are key essentials for intelligent crop protection that can drive agriculture's more resilient, efficient, and sustainable future.

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The authors have nothing to report.

Declarations

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