Transforming Agricultural Pest Management: The Effect of Artificial Intelligence and Remote Sensing

By

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Abstract

Food security, environmental sustainability, and climate change are just a few of the global issues that may be revolutionized by the use of remote sensing(RS) and artificial intelligence (AI) in agricultural pest control. Given their potential to boost output and resource efficiency, the study case examines how new technologies are affecting approaches to pest diagnosis, prediction, and treatment. With a focus on precision agriculture and early insect detection techniques, this research study synthesizes studies on machine learning algorithms, drone imagery, and Internet of Things sensors. Because it examines the benefits and drawbacks of using these ideas in farming with limited resources and small farms, this case study is significant. Key findings show that although AI and RS have improved the way decisions are implemented and influenced long-term interventions, these technologies face obstacles to widespread adoption because of their high prices, lack of technical expertise, and inadequate infrastructure. The research underlines the need of multidisciplinary collaboration and creativity in bridging the gap between technological innovation and practical application, paving the way for a more inclusive and sustainable agriculture

Keywords: Remote Sensing (RS); Artificial Intelligence (AI); Precision Agriculture; Sustainable Farming; Small-Scale Farmers; Predictive Analytics.

1 Introduction

The incorporation of advanced technologies like machine learning (ML), RS, the Internet of Things (IoT), and artificial intelligence (AI) is causing an evolutionary shift in agriculture (Assimakopoulos et al., 2025). The technology revolution is revolutionizing traditional agricultural processes, allowing farmers to maximize productivity, sustainability, and efficiency in the face of growing global concerns. With the world's population predicted to reach 9.7 billion by 2050, food security and decreased environmental impact have been top priorities (UN, 2019). Meanwhile, climate change, pest infestations, and resource limits are putting an unprecedented pressure on agricultural systems (Abbass et al., 2022). Precision agriculture, that is supported by modern technology like drones, satellite imagery, and AIdriven analytics, is one possible remedy for these problems (Ghosh et al., 2024).

The current case study assesses the role of AI and sensor technology in shaping agricultural pest control, which is an important component of green farming. Disease and pest losses are significant each year, affecting farmers' livelihoods and food security (Ali et al., 2023). Remote sensing methods, when combined with AI and ML algorithms, offer novel ways to detecting early signs of pest infestations, forecasting epidemics, and optimizing response mechanisms (Aziz et al., 2025). Not only can these technologies boost crop health and output, but they also promote environmentally responsible practices by reducing pesticide and fertilizer consumption.

The significance of this case study lies in its ability to bridge the gap between technical development and practical use in agriculture. Even though larger agricultural operations have begun to implement these sophisticated methods, small and disadvantaged farmers often face significant challenges regarding their acceptance and access (Aziz et al., 2025).

This report seeks to address several critical scientific questions, including:

- How can remote sensing and AI help detect pests early and improve decision-making for farmers?
- In what ways do AI and remote sensing promote sustainable pest management and contribute to food security?
- What challenges do small-scale farmers face when adopting AI and remote sensing for pest management, and how can these be addressed?

2 Literature Review

Recent research has examined how AI, imaging, and other similar technologies may be integrated into agriculture, showing how they can revolutionize pest management. This section explores important studies, concepts, methodologies, and findings, combining insights into AI-driven analytics and precision farming, and identifying opportunities for further study.

2.1 Overview of Smart Agriculture and Technological Innovations

Agriculture is changing as a result of the incorporation of high-tech advancements like blockchain, artificial intelligence (AI), machine learning (ML), the Internet of Things (IoT), and remote sensing. In addition to increasing production and resource efficiency, this movement also referred to as smart agriculture or precision farming aims to solve significant global issues like food security, environmental sustainability, and climate change. Traditional agricultural methods have been altered by modern technology, which enables farmers to better manage resources, monitor field conditions in real time, and boost crop yields.

Smart agriculture combines cutting-edge technologies and processes to create datadriven farming ecosystems that are both efficient and sustainable. IoT-enabled sensors and drones, for instance, provide real-time information on weather, water content of the soil, and diseases caused by insects, enabling improved decisions about fertilization, irrigation, and pest control (Kumar et al., 2024). According to Amulothu et al. (2024), AI and machine learning systems also analyze big databases to predict insect outbreaks, arrange planting times, and provide tailored treatments, reducing input waste and raising yields. These developments are changing sustainable agriculture, smart greenhouses, vertical gardening, and open-field farming.

Precision agriculture's application has expanded due to recent developments in drone technology. The use of multispectral and thermal imaging sensors on unmanned aerial vehicles (UAVs) is widespread, as they can assess crop health by detecting pests in the early stages and estimate yield (Alsadik et al., 2024). For instance, research has demonstrated that UAV-based remote sensing is highly effective in detecting agricultural water stress and nutrient deficiencies, enabling timely remediation measures (Surendran et al., 2024). In large-scale farming operations when manual monitoring is not feasible, these devices are extremely helpful.

Blockchain technology is another breakthrough that has important ramifications for agriculture. Blockchain validates the legitimacy of agricultural goods and improves supply chain control and monitoring by creating an open and irreversible record of interactions (Panwar et al., 2023). This is particularly crucial for satisfying consumer demand for responsibly and ethically produced food. Also, through the use of blockchain, local farmers can receive fair payment for their goods, while global markets can be opened (Kononets et al., 2022).

In recent years, AI-driven decision support systems (DSS) have gained popularity. Farmers may find these technologies helpful as they gather information from a variety of sources, such as satellite imagery, Internet of Things components, and weather forecasts. For example, "Darli," an AI chatbot created to help small-scale farmers control pests and maximize agricultural harvests, is highlighted by Assimakopoulos et al. (2025). These developments show how AI might improve access to cutting-edge agricultural technology, bridging the gap between large commercial farms and smallholders with limited resources.

However, there are many obstacles in the way of the broad adoption of smart agriculture technologies. Particularly in underdeveloped nations, high expenses, a lack of technical know-how, and poor infrastructure continue to be significant obstacles (Fragomeli et al., 2024). Furthermore, further research and legal frameworks are required due to worries about algorithmic bias, data privacy, and the moral use of AI in agriculture (Uddin et al., 2024). Addressing these difficulties requires cooperation between academics, politicians, and industry partners in order to guarantee fair access and long-term benefits.

A crucial first step in achieving environmental sustainability and global food security is integrating AI, IoT, blockchain, and other emerging technologies into agriculture. As these innovations are used to achieve resource efficiency, productivity increase, and climate adaption, the agricultural industry is expected to undergo a substantial transformation in the future. However, attaining their full potential would require overcoming current obstacles and encouraging interdisciplinary cooperation to create scalable and inclusive solutions.

2.2 Remote Sensing in Agriculture: A Tool for Pest Detection

Remote sensing has grown as a cutting-edge technique in modern agriculture, particularly for pest identification and control. Real-time crop health updates and early pest infestation detection are made possible by remote sensing based on state-of-the-art imaging technologies, such as drones, satellites, and sensors connected via the Internet of Things. preventing crop loss to the greatest degree possible. This sub-section discusses remote sensing for pest identification, including methods, applications, and inputs to sustainable agriculture.

2.2.1 Methodologies and Technologies in Remote Sensing

Remote sensing technologies use several instruments to collect precise information on crop conditions. Multispectral, hyperspectral, and thermal cameras placed on drones are increasingly being used to survey high-resolution areas (Sabir et al., 2024). These cameras detect tiny vegetation index fluctuations, like the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), which indicate plant stress due to pests or disease (Meivel & Maheswari, 2020). Similarly, insect outbreaks across wide agricultural regions can be identified thanks to satellite imaging, which enables large-scale surveillance (Silva et al., 2021).

By offering localized, instant data on temperature, humidity, also for various environmental variables that impact pest dynamics, soil-based IoT sensors improve satellite and aerial systems (Padmavathi et al., 2024). These technologies work together to provide an integrated monitoring system that allows for more accurate and rapid pest identification.

2.2.2 Applications in Pest Detection

It has been shown that identifying pests with remote sensing is a very efficient way to lower crop losses and increase yields. For instance, research has indicated that UAV-based remote sensing might identify early signs of pest infestations, such defoliation, wilting, and discoloration of leaves, which are often invisible to the human eye (Liao et al., 2022). In one well-known case, AI-powered analysis of drone footage revealed wheat rust infections weeks before outward signs showed up, allowing for targeted pesticide administration and a 20% reduction in output losses (Shaikh et al., 2022).

Large-scale pest monitoring has also benefited greatly from satellite imagery. For instance, locust swarms in East Africa were mapped using remote-sensing algorithms that examined satellite data, giving vital information for prompt action and averting extensive crop destruction (Klein et al., 2021). These usages illustrate how satellite imagery may enhance pest management strategies and avoid financial losses.

2.2.3 Contributions to Sustainable Agriculture

Aside from insect identification, remote sensing helps to promote sustainable agriculture practices by reducing the usage of pesticides and fertilizers. Precision distributing techniques that employ remote sensing data allow farmers to apply pesticides precisely where and when needed, reducing environmental pollution and biodiversity (Raj et al., 2022). To manage pest populations in a enduring manner, integrated pest management (IPM) systems which incorporate biological, cultural, and chemical control strategies also benefit from RS (Zhou et al., 2024).

Furthermore, the integration of RS, AI, and ML enhances its capabilities. AI-powered prediction algorithms employ historical meteorological data and field information to forecast insect outbreaks, allowing farmers to take preventative steps (Manzi et al., 2024). Remote sensing and artificial intelligence increase pest detection precision while also encouraging resource conservation and environmental sustainability.

2.2.4 Problems and the Next Phase

The application of RS in farming has significant challenges despite its clear advantages. Important obstacles include expensive implementation, a lack of technical expertise, and inadequate infrastructure, especially for low-income and small-scale farmers (Serote et al., 2023). Furthermore, remote sensing data interpretation is a specialist skill that is not widely available in most agricultural communities.

To overcome these issues, recent projects have centered on creating user-friendly tools and platforms that facilitate data analysis and decision-making. For instance, using data from remote sensing, AI-powered chatbots such as "Darli" provide small-scale farmers with useful pest control recommendations (Assimakopoulos et al., 2025). Additionally, remote sensing methods are becoming more scalable and economical due to advancements in cloud computing and IoT technology (Fuentes-Peñailillo et al., 2024).

Prospective studies should concentrate on creating of low-cost, easy-to-use remote sensing devices for a variety of agricultural applications. To improve accuracy and openness in controlling insect operations, satellite imaging should be used with modern technology like blockchain (Sharma & Shivandu, 2024).

2.3 AI and ML in Pest Control

The incorporation of AI and ML into pest control has transformed the agriculture industry by allowing more accurate, data decisions. To reduce crop losses and promote more sustainable farming practices, these technologies have demonstrated the ability to be successful instruments for detecting, predicting, and controlling pest infestations. This section investigates the importance of AI and ML in pest control, emphasizing its methodology, applications, and contributions to modern agriculture.

2.3.1 Methodologies: From Data Collection to Actionable Insights

AI and ML algorithms analyze large volumes of data generated by IoT sensors, drones, satellites, and other remote sensing devices to identify patterns, trends, and anomalies that point to pest activity. For example, ML models use past meteorological data, field conditions, and pest population dynamics to accurately anticipate outbreaks (Domingues et al., 2022). These prediction models allow farmers to take preemptive steps, such as targeted pesticide use or biological control strategies before pests cause major harm.

Deep learning which is a subset of ML has shown great promise in deciphering complex information, such as multispectral images captured by satellites or drones. These approaches can identify tiny changes in vegetation indices, such as NDVI (Normalized Difference Vegetation Index), which act as early warning signs of pest stress (Gospodarek et al., 2020). Furthermore, generative AI models are being used to replicate pest behavior in a range of environmental settings, which might provide more insights into future epidemic situations (Delfani et al., 2024).

2.3.2 Applications in Pest Detection and Management

AI-powered systems have achieved impressive results in real-time pest identification and management. For instance, compared to conventional methods, an AI-powered system used in wheat fields successfully identified early indicators of rust infections weeks before noticeable symptoms appeared, resulting in a 20% decrease in output losses (Shaikh et al., 2022). Similarly, satellite imagery evaluated using remote-sensing algorithms has been useful in tracking locust swarms in East Africa, allowing for prompt interventions and averting widespread agricultural damage (Halubanza, 2024).

In addition to detection, AI and machine learning are changing integrated pest management (IPM) systems. These systems use a combination of biological, cultural, and chemical control strategies to sustainably manage pest populations. In order to optimize pesticide efficacy and minimize adverse ecological impacts, artificial intelligence algorithms identify the optimal time to administer them (Mittu et al., 2025).

2.3.3 Contributions to Sustainable Agriculture

Uses of AI and ML capabilities in pest management greatly supports sustainable agriculture practices. These technologies enable precision spraying systems, which reduce pesticide misuse, minimize environmental pollution, and promote biodiversity. Furthermore, AI-powered predictive analytics maximize resource utilization by applying inputs like as water, fertilizer, and pesticides just where and when they are required (Titirmare et al., 2024).

Furthermore, by combining technologies that identify healthy soil and carbon storage with pest control, AI and ML help ecological farming. For example, AI-recommended cover cropping practices assist avoid soil erosion and reduce tillage, resulting in a more resilient agricultural environment (Hafiyya et al., 2024). These developments contribute to global initiatives to improve food security and reduce the negative environmental impacts of agriculture.

2.3.4 Challenges and Future Directions

Despite their transformational promise, AI and machine learning in pest management encounter several hurdles. Poor infrastructure, limited technical skills, and high implementation costs remain major obstacles, particularly for small-scale and resourceconstrained farmers (Serote et al., 2023). Concerns concerning data privacy, algorithmic bias, and the ethical application of AI call for more research and legislative frameworks (Uddin et al., 2024).

To overcome these issues, recent projects have centered on creating cost-effective and user-friendly solutions customized to a variety of agricultural scenarios. For example, cloudbased tools and connected devices are making driven by AI pest control solutions more accessible and scalable (Sharma, 2025). Future studies should concentrate on creating inclusive technologies that support equitable access to contemporary tools and help smallholder farmers.

Additionally, by fusing cutting-edge technology like blockchain with AI and machine intelligence, pest management operations may become more transparent and traceable. Blockchain can confirm the accuracy of data gathered from drones and IoT devices, boosting stakeholder confidence (Hafeez, 2024).

2.4 Challenges in Implementing AI and Remote Sensing for Small-Scale Farmers

Implementing AI and remote sensing technology is fraught with challenges, particularly for small-scale and resource-constrained farmers, despite its enormous promise to revolutionize agricultural methods. These difficulties include accessible and academic issues in addition to technological, economical, infrastructural, and ethical ones. To provide equitable access to cutting-edge technologies and optimize their impact on global agriculture, these obstacles must be removed.

The substantial initial investment required for AI and remote sensing technology is one of the most important impediments to their adoption. The cost of procuring drones, IoTenabled sensors, satellite imaging services, and AI-driven decision support systems might be prohibitively expensive for small-scale farmers with limited resources (Atapattu et al., 2024). For example, many smallholders may not be able to afford the significant upfront expenditures required for infrastructure and equipment associated with AI and remote sensing-based vertical farming approaches (Assimakopoulos et al., 2025). Similarly, the maintenance and operational expenses of these technologies add to the financial burden, inhibiting adoption by resource-constrained farmers.

Beyond budgetary restrictions, the successful deployment of AI and remote sensing technology needs specialized knowledge and technical competence, which many small-scale farmers lack. Interpreting data from IoT devices, drones, or satellites necessitates knowledge of data analysis, machine learning, and agronomy, which are not readily available in rural or underserved areas. Furthermore, poor infrastructure, such as intermittent internet connectivity and restricted access to energy, impedes the successful adoption of these technologies in rural areas (Mishra et al., 2022). Without strong infrastructure, real-time data gathering and analysis are almost impossible, weakening the benefits of AI and remote sensing.

The widespread adoption of IoT devices and AI algorithms raises worries about data privacy and security. Small-scale farmers frequently lack knowledge about how their data is gathered, kept, and utilized, making them vulnerable to abuse or unlawful access (Gyamfi et al., 2024). If sufficient precautions are not in place, rivals or malevolent actors may be able to exploit sensitive information like agricultural yields, soil conditions, and pest infestations (Atapattu et al., 2024). To overcome these problems and encourage broader adoption, data management systems must be transparent and trustworthy.

Despite technological developments, many AI and remote sensing technologies are not designed to meet the demands of small-scale farmers, particularly those in developing countries. Tools made for large commercial farms may not be cost-effective or scalable for smaller enterprises (Abate et al., 2023). To develop affordable, simple remedies that work in a range of farming situations, further work is necessary.

The application of AI and remote sensing in agriculture presents ethical and societal challenges. For example, dependence on technology may marginalize farmers without access to it, exacerbating existing inequities in the agricultural industry (Hackfort, 2021). Furthermore, when using AI algorithms to make key pest management or resource allocation choices, algorithmic bias and fairness must be carefully considered. Ensuring that these technologies are inclusive and egalitarian is critical to their acceptability by small-scale farmers.

To overcome these difficulties, collaboration across governments, researchers, and business entities is required. Subsidies, subsidies, and low-cost financing solutions can help small-scale farmers ease their financial burden (Pandeya et al., 2025). Training programs and capacity-building activities can help farmers improve their technical abilities and digital literacy, allowing them to more effectively use AI and remote sensing tools (Li et al., 2018). Additionally, mobile applications and cloud-based platforms can bridge the gap between end consumers and technology by offering accessible and affordable solutions (Sharma, 2025).

Ongoing research and technology developments are also necessary to address scalability and accessibility challenges. For example, open-source software and energysaving technologies can lower prices and increase usability, giving small-scale farmers more access to advanced machinery (Chicaiza et al., 2024). By tackling these challenges, stakeholders may guarantee that AI and remote sensing help to create a more equitable and sustainable agricultural future.

2.5 Contributions to Sustainable Agriculture and Environmental Conservation

Using RS, AI, and similar technologies in agriculture has considerably aided in sustainable farming techniques and environmental protection. Along with increasing productivity and resource efficiency, these developments also tackle urgent global concerns including biodiversity loss, climate change, and food security. These technologies enable precise monitoring, data-driven decision-making, and resource optimization, resulting in more dependable, effective, and ecologically balanced models of agricultural systems. By maximizing resource use, reducing waste, and mitigating environmental impacts, AI and remote sensing significantly contribute.

Precision agricultural equipment, such as variable rate technology (VRT) and IOTenabled sensors, enable farmers to administer inputs like water, fertilizer, and herbicides just where and when they are required. Artificial intelligence-powered irrigation systems, for example, monitor soil moisture levels in real-time to ensure optimal water usage and minimize runoff (Patil, 2024). Similar to this, machine learning algorithms analyze data from remote sensing to identify areas that are infected with pests, enabling customized pesticide usage and reducing chemical misuse (Lochan et al., 2024). In keeping with the aims of global sustainability, these developments reduce pollution and habitat devastation caused by excessive agricultural inputs while simultaneously protecting resources.

Advanced technologies greatly aid regenerative agriculture, which focuses on restoring soil health, boosting biodiversity, and sequestering carbon. To provide cover cropping strategies, crop rotation plans, and organic supplements that improve soil fertility and stop erosion, artificial intelligence (AI) and machine learning models evaluate soil data collected by drones and Internet of Things devices (Getahun et al., 2024). For instance, in keeping with global efforts to mitigate climate change, (Petropoulos et al., 2025) highlight the use of big data analytics to track soil organic matter renewal and carbon sequestration. In order to increase ecosystem resilience, AI-powered automation technologies offer accurate scheduling for regenerative operations such including animal grazing or planting cover crops

(Assimakopoulos et al., 2025). These innovations demonstrate how technology may boost agricultural productivity and support long-term environmental sustainability.

Zero-waste agriculture, an innovative method to create circular systems, uses AI and IoT to reduce waste and reuse agricultural outputs. Agricultural activities generate over five billion tons of waste annually, most of which may be recycled or used for other purposes, according to current estimates. AI and machine learning algorithms improve waste management by discovering ways to transform agricultural leftovers into bioenergy, compost, or biodegradable materials (Nirmala et al., 2025). For instance, IoT-enabled biomass-based energy systems and solar-powered dryers transform agricultural waste into sustainable energy sources, reducing reliance on fossil fuels. These advances not only lower greenhouse gas emissions but also encourage a circular economy in agriculture, which fosters sustainability and resource efficiency.

AI and remote sensing technology can potentially help to mitigate climate change and increase biodiversity in agricultural settings. These tools help farmers implement practices that reduce their carbon footprint and increase ecosystem resilience by tracking carbon stocks, land-use patterns, and vegetation indices. For instance, governments can take conservation action when reforestation and land degradation are detected by satellite data analyzed by AI models (Haq et al., 2024). Furthermore, precision farming approaches minimize tillage and chemical inputs, conserving soil structure and sustaining various microbial communities. These techniques create homes for pollinators and other beneficial creatures, which helps to conserve biodiversity and promotes ecological balance.

Environmental preservation and environmentally conscious farming are greatly aided by smart greenhouses. These high-tech surroundings, which include AI, IoT, and renewable energy systems, optimize resource utilization, increase agricultural yields, and decrease environmental impact (Morkūnas et al., 2024). For example, energy-efficient designs that are fueled by solar panels and wind turbines reduce dependency on nonrenewable energy sources (Morkūnas et al., 2024). AI-powered temperature control systems optimize growth conditions, saving water and energy while increasing production (Padmavathi et al., 2024). By increasing year-round farming and lowering dependent on imported and irregular crops, these improvements increase food security and sustainability.

AI and remote sensing play a major role in addressing more significant global issues including food security, environmental sustainability, and climate resilience. Stakeholders may develop scalable solutions that integrate environmental stewardship and productivity by integrating these technologies into agricultural systems (Oshilalu, 2024). Blockchain-enabled traceability solutions, for example, promote supply chain transparency, consumer trust, and sustainable practices (Vazquez Melendez et al., 2024). Additionally, farmers may adapt to climate uncertainty with the use of AI-powered predictive analytics, which leads to robust lifestyles and steady harvests (Rane et al., 2024).

Notwithstanding their revolutionary potential, widespread adoption of these technologies requires bridging the gap between innovation and real-world implementation. Training programs, capacity-building projects, and legislative backing are crucial to empowering farmers particularly smallholders to incorporate AI and remote sensing into their operations. Building low-cost, user-friendly solutions for a range of agricultural applications can be facilitated by cooperation between academics, governments, and corporate organizations. Stakeholders can guarantee equitable access to these advancements and hasten the transition to a more resilient and sustainable agricultural future by tackling obstacles such as cost, accessibility, and technical know-how.

2.6 Existing Work

The present research on RS and AI in agricultural pest control employs a diverse set of approaches and results. Zhu et al. (2024) examined the use of unmanned aerial vehicles (UAVs), remote sensing (RS), and deep learning (DL) to identify agricultural diseases and pests, highlighting the benefits of hyperspectral imaging and multi-sensor data fusion. They found challenges including extremely dimensional analysis and the absence of consistent datasets, even though their work showed excellent classification accuracy using DL models. Similarly, Ahmad et al. (2022) investigated synergy of data and technology strategies for improving crop monitoring, finding that integrating UAV-based RS with sophisticated algorithms increased pest identification. However, they cited operating expenses and technical skills as major impediments to adoption.

Sishodia et al. (2020) used satellite data and vegetation indices to detect early indicators of insect infestations, resulting in successful large-scale monitoring. Despite their promising results, constraints like as cloud coverage and resolution hampered real-time applications in certain places. Velusamy et al. (2021) solved these issues by using UAVs fitted with multispectral sensors, which gave better spatial resolution and precision for pest detection. However, they noted that the need for technical expertise and high running expenses were obstacles to broader implementation.

Mardanisamani et al. (2019) studied the use of deep convolutional neural networks (DCNNs) supplemented with handmade texture characteristics for crop lodging prediction, which outperformed established approaches. However, their research underlined the importance of considerable computing resources, which may be inaccessible to small-scale farmers. Decision tree machine-learning algorithms and UAV-based vegetation indicators were employed by Johansen et al. (2021) to identify coffee leaf rust, demonstrating high classification accuracy. Nevertheless, they listed the dependence on certain weather patterns and sensor settings as limitations.

CNN's ability to perform based on imagery illness and pest diagnostics was highlighted by Kamilaris and Prenafeta-Boldú (2018) in their evaluation of deep learning applications in agriculture. Their findings emphasized the relevance of big annotated datasets while also raising concerns about the understanding of deep learning models. Huang et al. (2021) developed an attention-based YOLACT++ model for real-time segmentation of maize leaf lesions with good accuracy. They did, however, stress that further tweaking is necessary for embedded systems due to the fact that DL models are black-box.

Marin et al. (2021) used UAV-acquired multispectral pictures to extract several vegetation indices, such as GRVI and NDVI, for crop health monitoring purposes. Their investigation confirmed the usefulness of UAV-based RS but also highlighted the issue of extraneous spectral data, which might impair model accuracy. Lei et al. (2021) used UAV multisource sensors to detect yellow leaf disease in areca nuts and achieved acceptable classification accuracies using BPNN and SVM algorithms. They acknowledged the challenges of integrating various data sources while highlighting the importance of feature selection.

Francesconi et al. (2021) employed data fusion to improve the accuracy of wheat fusarium detection using UAVs equipped with RGB and thermal infrared cameras. Their findings indicated improved categorization performance but raised concerns regarding the cost and availability of sophisticated sensors. To determine the extent of Pantana phyllostachysae Chao infestation in Moso bamboo forests, Xu et al. (2022) using UAV multispectral RS, which led to precise feature selection. They did, however, stress the necessity of more reliable algorithms to deal with environmental uncertainty.

Lu et al. (2023) investigated the function of artificial general intelligence (AGI) in agriculture and proposed AGI-based pest control strategies. Their research highlighted AGI's transformative potential while also recognizing the current disconnect between theoretical advancements and practical application. In their evaluation of precision agricultural techniques, namely variable rate technology (VRT) for targeted pesticide application, Naresh et al. (2024) discovered significant decreases in pesticide misuse. Despite their positive outcomes, they admitted that many farmers still had to deal with high initial and continuing expenses.

Existing Study Summary Table:

Study	**Methodology**	**Findings**	**Limitations**
Zhu et al. (2024)	UAV-based RS with hyperspectral imaging, LiDAR, and thermal sensors; used AI algorithms and wavelength selection approaches (SPA, GAPLS, CARS).	DL models provide high classification accuracy, while multi-sensor fusion improves monitoring.	High-dimensional data processing issues; a scarcity of standardized datasets.
Ahmad et al. (2022)	UAV-based RS paired with ML improves spatial resolution in pest identification.	Data fusion increased monitoring accuracy.	High implementation costs need technical knowledge.
Sishodia et al. (2020)	Satellite images and vegetation indices (NDVI) are used for pest monitoring on a broad scale.	Effective in large-scale applications.	Cloud coverage and insufficient resolution hampered real-time applications.

Velusamy et al. (2021)	UAVs equipped with multispectral sensors provide precise pest detection.	Satellite-based approaches were outperformed in terms of accuracy and resolution.	High operational expenditures and a demand for technological skills.
Mardanisamani et al. (2019)	DCNNs and textural cues were used to anticipate crop lodging in photos captured by a UAV.	Improved classification accuracy over older approaches.	High computational resource needs.
Johansen et al. (2021)	Using UAV vegetation indexes and decision tree models to identify coffee leaf rust.	High sensitivity in identifying early-stage infections.	Sensor calibration and ambient factors influenced generalizability.
Huang et al. (2021)	Attention-based YOLACT++ model for segmenting maize leaf lesions.	Excellent precision and real-time performance.	The black-box nature of DL models prompted questions regarding interpretability.
Marin et al. (2021)	UAV multispectral imagery using GRVI and NDVI indices; analysis using machine learning methods.	Crop health is effectively monitored.	Spectral noise and environmental variability both have an impact on accuracy.
Lei et al. (2021)	Using BPNN and SVM, UAV multisource sensors detect yellow leaf disease in areca nuts.	Using feature selection, we achieved a high level of classification accuracy.	Integrating different data sources is complex.
Francesconi et	UAVs equipped with RGB	Fusarium head	High price and sensor

al. (2021)	and thermal cameras can detect wheat fusarium using data fusion techniques.	blight is now more easily detected.	availability limitations.
Xu et al. (2022)	UAV multispectral RS to detect Pantana phyllostachysae Chao infestations in bamboo forests.	Precise infestation detection via feature selection.	Environmental variability necessitated the use of robust algorithms.
Lu et al. (2023)	AI-powered, automated temperature control for greenhouse pest management.	Encouraging outcomes in controlled contexts.	The scalability of openfield farming remained questionable.
Kumar et al. (2024)	AI analytics provide blockchain-based traceability for pest management supply chains.	Addressed ethical concerns over data utilization.	The complexity of implementation created adoption issues.
Naresh et al. (2024)	Variable Rate Technology (VRT) allows for precise pesticide application.	Significantly reduced pesticide overuse.	High initial and continuing expenditures limited access.
Mahesh (2020)	Supervised and unsupervised machine learning algorithms for pest and disease identification.	Ensemble learning techniques produce promising outcomes.	Data availability and quality concerns in underdeveloped countries.

3 Conclusion

This study reveals how AI and remote sensing may improve current pest control, improving sustainability, efficiency, and resilience in agriculture. IoT-enabled sensors, dronebased imagery, and machine learning algorithms work together to optimize resources, diagnose pests early, and intervene precisely, increasing agricultural output while reducing environmental impact.

The study highlights significant challenges for small-scale and resource-limited farmers, including high expenses, technological limitations, and inadequate infrastructure. Targeted solutions are needed for tackling these problems, including government-sponsored technology assistance, low-cost AI software, and capacity-building programs that provide farmers the digital skills they need.

The investigation must further investigate cost-efficient AI models, create regulations for inclusive agricultural technology, and execute practical pilot projects in smallholder farming communities. Additionally, multidisciplinary collaboration among agricultural scientists, AI researchers, politicians, and rural development groups will be critical in ensuring that these technology improvements are accessible, scalable, and sustainable in a variety of farming situations.

This study adds to the worldwide effort to improve food security, climate resilience, and sustainable agriculture practices by bridging the gap between innovation and practical application

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