Review of AI methods in precision agriculture

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Abstract. This review analyzes the increasing adoption of Artificial Intelligence (AI) in precision agriculture, paying special attention to the advances in crop management brought by machine learning and deep learning technologies. From scouting to pest and disease detection, weeding, irrigation, and crop quality estimation, tasks traditionally plagued by human error and excessive manual work are now being addressed by AI solutions which are quicker, precise, and easily scalable. This review also examines the use of drones and sensors integrated with the Internet of Things and robotics, alongside real-time monitoring, predictive analytics, and automated decision-making, the foreseen and observable enhancements of AI in agriculture, particularly in reducing chemical use and improving efficiency alongside AI techniques such as Support Vector Machines, Random Forest, Convolutional Neural Networks, and Vision and Hybrid Transformers. Nonetheless, there are still significant challenges such as the high computational demands and limited availability of large high-quality datasets, the expense to smallholder farmers, and privacy concerns. We believe that AI specialists and agricultural scientists collaborating on affordable, reliable, and field-ready innovations would have the greatest impact on stimulating widespread adoption. In essence, the review reinforces the idea that AI technologies can boost the resiliency, productivity, and sustainability of agriculture.

1 Introduction

Precision Agriculture (PA) is a farm management approach that relies on technology to optimise crop production while limiting negative effects on the environment [1, 2]. In its early development, PA mainly utilised tools such as Global Positioning Systems (GPS), Geographic Information Systems (GIS) and different types of sensors to collect and process

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field data [3]. Today, with the development of Artificial Intelligence (AI), the discipline has gone beyond simple data collection and is now moving toward predictive and prescriptive practices. In this context, AI is increasingly considered as a potential answer to global challenges related to food security, limited natural resources and climate change, as well as to the need to reduce health and environmental risks associated with conventional agricultural systems [1, 4, 5].

AI techniques make it possible to interpret large and complex datasets gathered from a variety of sources, including drones [1, 6], satellites [1, 5] and ground-based sensors [3, 7] . They also provide real-time results that support decision-making at the field level. Consequently, these tools help overcome the constraints of traditional approaches, which are often labour-intensive, costly and subject to error, particularly in tasks such as crop disease detection, pest identification or weed management [4, 8]. The objective of this review is therefore to bring together the main AI methods used in precision agriculture and to examine how machine learning and deep learning improve both productivity and sustainability [1, 3, 8, 9]. The review specifically discusses applications in areas such as pest and disease detection [1, 8, 9], targeted weed control [1, 4] and crop quality estimation [3], while also highlighting current limitations and future opportunities for wider integration of these technologies.

2 The Growing Importance of AI in Precision Agriculture

Artificial intelligence (AI) is rapidly transforming the domain of precision agriculture by offering more effective and dependable approaches than traditional practices. Perhaps the most notable difference is in the methods of detection. Conventional methods rely heavily on skill and in-depth taxonomic knowledge; in contrast, AI methods depend on automated systems that synergize machine learning, deep learning, and computer vision. With these technologies, pests, plant diseases, and weeds can be identified far more quickly and accurately than through manual observation [1,8,9].

This advancement provides clear benefits concerning time and labor. Examiners need relative specialists for manual scanning tasks as they are specialized, often slow and repetitive. Decision-making and labor spending are often better with AI-based tools, as they automate much of the work, substantially improving efficiency and time resources. AI systems also offer greater reliability. Unlike humans whose performance often varies due to expertise or fatigue, AI models are capable of the identifying subtle and intricate patterns in large datasets, which results in greater dependability [8,9]. Another key benefit of AI tools is the scalability. AI eases the challenges of broad spatial and temporal extensiveness which is often encountered with remote sensors or drones, large scale monitoring platforms, and traditional methods due to the former's ease of embedding into the tools. Such AI capabilities ensure extensive coverage and unbroken surveillance. These systems also help the environment. AI enhances early detection and precise targeting of issues which reduces the need for generalized pesticide use, thereby supporting green farming and more ecologically sustainable methods [1,4]. Even though the upfront costs of AI infrastructure surpass that of traditional approaches, long-term expenses are typically balanced out by automation, boosted efficiency, and increased productivity. However, there are still challenges. The most pressing ones include the lack of high-quality labeled datasets which are essential for training the models, and the limited funding models which pose obstacles for smallholder farmers. Table 1 illustrates the key differences between Traditional and AI-Driven Approaches in Precision Agriculture.

Table 1. Key Differences Between Traditional and AI-Driven Approaches in Precision Agriculture.

Aspect	Conventional Methods	AI-Based Methods
Detection process	Relies on human observation and taxonomic knowledge	Automated analysis using ML, DL, and computer vision
Time efficiency	Slow and time-consuming	Rapid and real-time detection
Labor requirement	High (manual identification, expert knowledge needed)	Low (system automates most of the process)
Accuracy	Variable, depends on human expertise	High, with ability to detect subtle patterns and features in large image datasets
Scalability	Limited (difficult to apply across large areas quickly)	Highly scalable, can be integrated with drones, sensors, and large-scale monitoring
Cost	Lower initial costs but high labor costs over time	Higher initial investment, but reduced long-term costs due to automation
Environmental impact	Frequent pesticide spraying due to delayed/uncertain ID	Reduced pesticide use through precise and early pest detection
Challenges	Human error, slow response	Data scarcity, need for high-quality labeled datasets, affordability issues

3 AI Methods in Precision Agriculture

Artificial Intelligence (AI) is recognized as a powerful tool for precision farming since it enhances crop monitoring, yield prediction, resource optimization and stress detection. Varieties of AI applications are categorized into machine learning and deep learning models, computer vision, hybrid and reinforcement learning models, as well as IoT and data-driven frameworks. Classification, yield prediction, and stress assessment in crop farming use machine learning techniques such as Support Vector Machines (SVMs), Random Forest (RF), Gradient Boosting, Decision Trees, K-Nearest Neighbors (KNN), and Multilayer Perceptrons (MLP). RF has been successful in estimating yield as well as detecting droughts with UAV-based multispectral data [1, 5, 7, 9]. Moreover, SVMs are effective in detecting salinity and drought stress in crops like citrus and cucumber. Fuzzy logic and optimization-based models also assist in irrigation scheduling aiming at enhancing water use efficiency [6]. The use of deep learning (DL), and more specifically, Convolutional Neural Networks (CNNs), has increased immensely for agricultural tasks. Architectural breakthroughs, such as Faster R-CNN, SSD, RetinaNet, YOLO and its versions (YOLOv3, YOLOv5, etc.), DenseNet, GoogLeNet, and ResNet, have proven useful for pest recognition, plant disease diagnosis, and weed identification [4, 8, 9]. Further developed stress monitoring and early warning systems for plant disorder detection include more advanced CNN-LSTM hybrids, Vision Transformers (ViTs), and Mask R-CNNs [5]. These models have become more useful and adaptable with the use of Transfer learning, especially in situations where agricultural datasets are sparse[9]. Deep learning relies on computer vision and image processing to extract visual features such as Histograms of Oriented Gradients (HoG), segmentation, alignment, and annotation. These methods have enabled UAVs, drones, and ground platforms to garner imagery for detecting nutrient deficiencies, assessing weed classification, and evaluating plant health [1, 4, 7, 8]. Such imagery aids robotics and autonomous machines to perform targeted spray and precise navigation tasks with the use of GPS, RTK-GPS, SLAM, and other such technologies [4, 10].

Stress detection, yield prediction, and even resource allocation are more accurately managed with the use of hybrid AI frameworks integrating different models, like RF-SVM, CNN-LSTM, and CNN-ViT, compared with single-algorithm solutions [5, 9]. In addition, more focused resource management, like adaptive resource management, supports irrigation interval optimization through reinforcement learning models like Deep Q learning [6, 9]. Another significant development is the use of AI in conjunction with the IoT, sensor fusion, and big data analytics. With IoT, realtime monitoring of irrigation, pest, and stress factor overlaps is possible with deep learning models [5–8, 10]. Further, the use of UAVs, and thermal and multispectral imaging cameras for sensor fusion have enhanced the detection of complex phenomena, like the progression of drought stress and diseases [4, 5, 11].
The range of applications is rapidly expanding, from weeding, harvesting, and precision spraying, all performed by UAV and drone-operated systems. Actionable insights with AI-based decision support tools for sustainable and proactive management are now available for farmers [7, 10, 12].

AI in precision agriculture encompasses a spectrum of methods, from traditional machine learning classifiers to advanced deep learning and hybrid models, integrated with IoT, robotics, and remote sensing. Together, these innovations facilitate early pest and disease detection, precise stress prediction, optimized irrigation, and efficient resource management contributing significantly to productivity and resilience in agriculture[1, 3–10]. fig.1 summarizes the artificial intelligence approaches applied to precision agriculture.

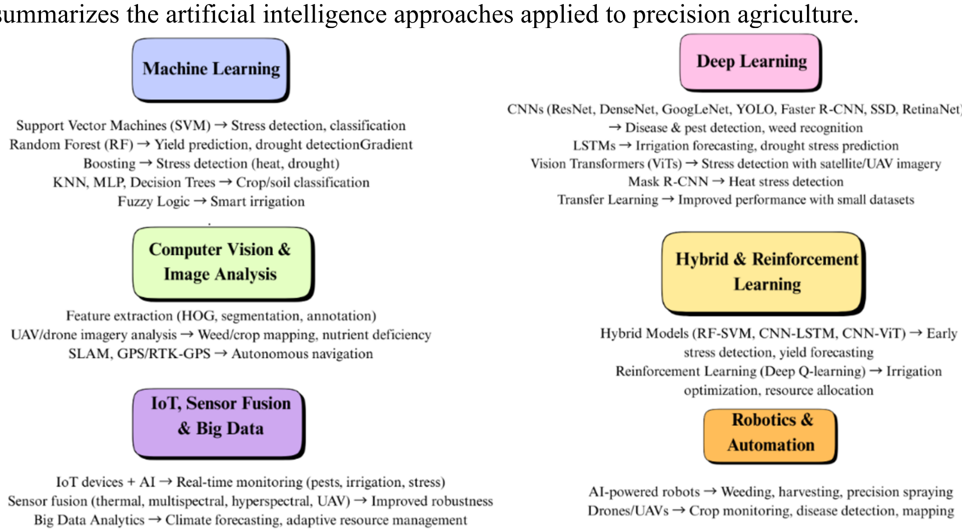

Fig. 1. Artificial intelligence in Agriculture Precision .

Fig.2 shows how AI models for insect detection have developed from 2012 up to 2025. The timeline starts with early computer vision methods, such as Support Vector Machines (SVM) in 2012. A couple of years later, in 2014, deep learning became more prominent with networks like VGGNet and GoogleNet. By 2016, models such as R-CNN and Random Forest appeared, marking an important step forward. A real breakthrough came with the YOLO family of models, which went through many versions (from YOLOv1 to YOLOv12) and steadily improved real-time object detection. More recently, in 2022, architectures like Vision Transformers (ViT) and Detection Transformers (DETR) gained attention. The last entries on the timeline, Insect-mamba and the Pyramid Vision Transformer in 2024–2025, represent the latest efforts to push performance even further. Overall, the figure highlights how techniques have quickly moved from simple classifiers to advanced and highly specialized detection systems in entomology.

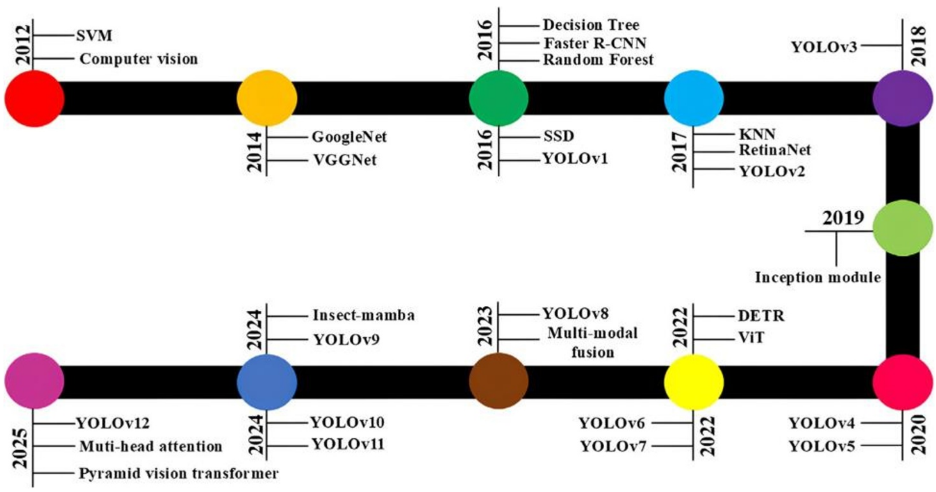

Fig. 2. Chronology of AI-based object detection models applied for insect identification (Sourav Chakrabarty et al).

4 Applications of AI in Precision Agriculture

4.1 Pest and Disease Detection and Management

The capabilities of artificial intelligence are beneficial in managing crop threats as it enables precision and automation. AI technologies are applied in more advanced directions as well, such as for discovering dangerous pests, and more recently, both traditional and deep learning methods have been explored for such goals [8]. Moreover, AI is capable of detecting diseases at an early stage, such as tomato diseases linked to Tuta absoluta [9]. Besides, the combination of AI and drones have been proven to be effective in the accurate detection of crop diseases [1]. AI can replace the human operation of insect identification, as is the case in the example shown in Fig.3, where cameras are used to capture the images and are further processed in the feature extraction and classification layers. Contrary to the system, the human eye uses thinking and sight to interpret the image. The system successfully recognizes Athalia in the example provided.

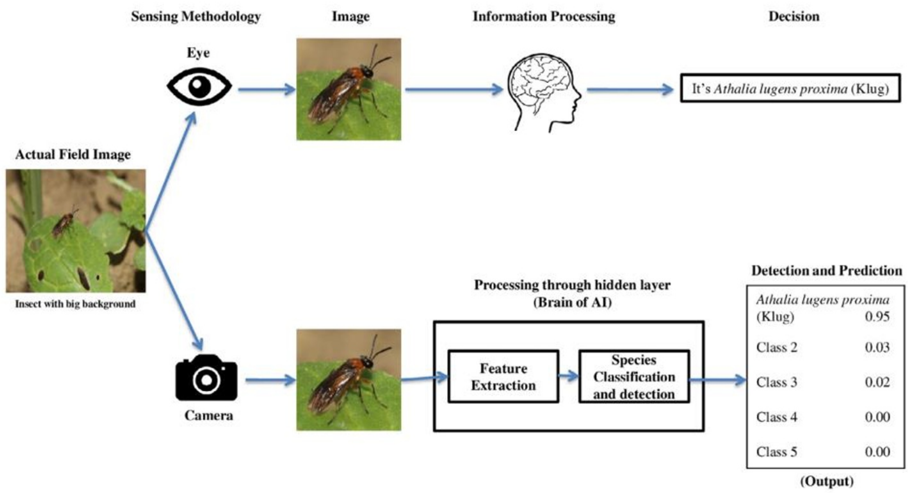

Fig. 3. Comparative pipeline of human learning and artificial intelligence humans process information through the brain, while machines rely on artificial neural networks (Sourav Chakrabarty et al).

Fig.4 shows the overall steps taken in implementing AI models in pest detection. The first step involves understanding the specific insects of concern and gathering relevant images, which is succeeded by curation, annotation, and the necessary pre-processing steps. The data is then split into training, validating, and testing subsets, and model evaluation is performed using designated performance metrics. The model, after being validated, can be integrated in applications enabling real-time pest detection in precision agriculture, thus proving its usefulness.

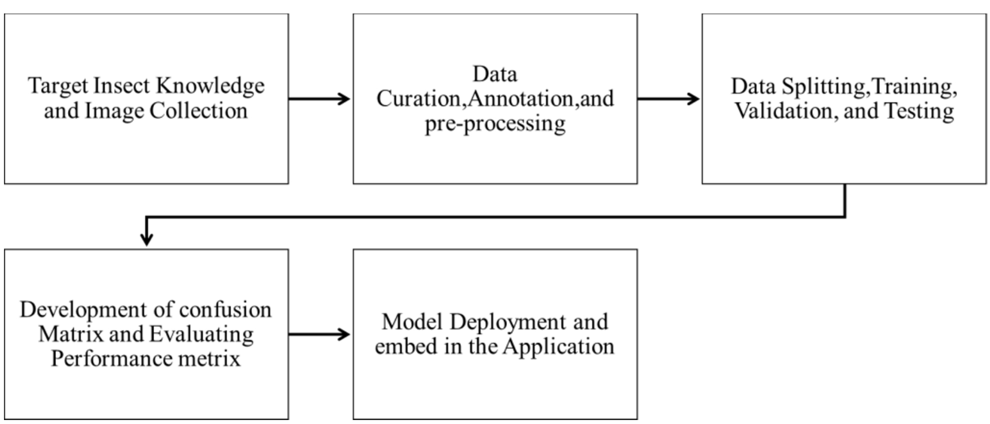

Fig. 4. A General Overview of Detection and Identification of Insect Species Using Artificial Intelligence Models (Sourav Chakrabarty et al).

4.2 Weed Management

With the growth of technology, unmanned aerial vehicles and unmanned ground vehicles are now equipped with AI, and therefore, are used to identify and remove weeds with a high precision. This reduces the need for unskilled workers as well as the need for heavy manual spraying of herbicides [1, 4]. One of the reviews showed great results with the use of UGVs for weeding, especially in the navigation and detection models implementation [4]. In the same manner, AI integration with drones is designed to support UAV-based operations and and weed control [1].

4.3 Crop Quality and Fruit Maturity Estimation

AI technology is employed to assess the quality of fruit before the harvest using non-invasive methods. A review has shown that using machine learning methods like SVM, k-NN, and even neural networks, coupled with spectrometry and imaging, can estimate the fruit's maturity, sugar level, and even its firmness. To enhance precision, non-destructive sensors are being supplemented with advanced AI algorithms from various non-destructive sensors **[3]**.

4.4 Other Applications

AI assists with many other parts of precision agriculture. Irrigation management: The real-time and remote measurement capabilities provided by digital technologies are being utilized for more efficient water use, shifting towards more sophisticated, Agriculture 4.0 methods **[6]**. Crop stress detection: AI is being utilized to create advanced early warning and predictive systems to identify abiotic stresses like drought in fruit trees **[5]**. Agricultural automation: The productivity and efficiency of farming operations is greatly enhanced AI in combination with computer vision is utilized in the automation of all-terrain vehicles (ATVs) **[7]**.

5 Challenges and Future Research Directions

While artificial intelligence has the potential to significantly change agriculture, several challenges still hinder its widespread adoption. One of the primary challenges revolves the collection and variety of datasets. Any AI model's performance will depend on the quality, diversity, and the representation of the data. Scholars have emphasized how insufficient data diversity and representativeness not only weakens model AI model robustness, but also leads to overfitting [9]. In addition, the model's complexity and its practical application is another challenge. Some advanced AI architectures, like R-FCN and RPN-VGG, are computationally intensive, making them difficult to deploy at farms [8]. Furthermore, the lack of field testing of many systems demonstrates the necessity for collaboration beyond AI experts and agronomists. It is crucial to develop tools that are both innovative and practical [4]. Ease of accessibility is another challenge. The cost of such systems, technologies, and tools is still disproportionately high for small to medium scale farmers, making adoption difficult [10, 12]. Future research should focus on new ways for small and medium-scale farmers to access innovative financing and collaboration models to address the cost barriers. Potential options to lessen the cost of entry include shared AI service platforms, cooperative-structured equipment ownership, and subsidies from the government. Developed infrastructures underpinned by public-private partnerships and open access digital resources can further democratize the access to AI-powered agriculture instruments used in farming and broaden AI adoption in underdeveloped farming regions. The proposed public and private financing collaboration makes farming precision and advanced agriculture technologies readily available. In order to achieve precision agriculture, affordable substitutes need to be developed. More importantly, AI and agronomy professionals need to develop systems that are both effective and easy to use. Lastly, data privacy and trust issues[13–17].

6 Conclusion

To sum up, this review shows that artificial intelligence is already changing the way agriculture is practiced. With methods such as machine learning and deep learning, important progress has been made. Farmers now have tools that help them recognize pests and diseases with better accuracy, manage weeds in a more targeted way, and even check fruit maturity without damaging the crops. These applications prove that AI can improve efficiency while also supporting a more careful use of natural resources[18, 19]. Still, the road to full adoption is not simple. The lack of diverse and reliable datasets remains a serious obstacle, and some of the more advanced models are too demanding in terms of computation to be practical in the field[20–24]. Added to this are the high costs, which make it difficult for small farmers to benefit, and the ongoing worries about data privacy and trust. For the future, research needs to move in the direction of simpler, more affordable, and better-tested AI tools. What seems most important is stronger collaboration between AI experts and agricultural scientists, so that solutions are not only technically advanced but also realistic in real farming conditions. If these challenges are tackled, AI could play a key role in shaping a food system that is more productive, efficient, and sustainable for future generations.

References

1. I. Anam, N. Arafat, M.S. Hafiz, et al. A systematic review of UAV and AI integration for targeted disease detection, weed management, and pest control in precision agriculture. Smart Agricultural Technology **9**, 100647 (2024). https://doi.org/10.1016/j.atech.2024.100647
2. T. Chikte, T. Kopta, V. Psota, et al. A Comprehensive Review of Low- and Zero-Residue Pesticide Methods in Vegetable Production. Agronomy **14**:2745 (2024). https://doi.org/10.3390/agronomy14112745
3. M. Islam, S. Bijjahalli, T. Fahey, et al. Destructive and non-destructive measurement approaches and the application of AI models in precision agriculture: a review. Precision Agric **25**. 1127–1180 (2024). https://doi.org/10.1007/s11119-024-10112-5
4. E.K. Wiafe, K. Betitame, B.G. Ram, X. Sun. Technical study on the efficiency and models of weed control methods using unmanned ground vehicles: A review. Artificial Intelligence in Agriculture **15**, 622–641 (2025). https://doi.org/10.1016/j.aiia.2025.05.003
5. M.A. Mushtaq, M. Ateeq, M. Ikram, et al. Securing fruit trees future: AI-driven early warning and predictive systems for abiotic stress in changing climate. Plant Stress **17**, 100953 (2025). https://doi.org/10.1016/j.stress.2025.100953
6. I.A. Lakhiar, H. Yan, C.Zhang, et al. A Review of Precision Irrigation Water-Saving Technology under Changing Climate for Enhancing Water Use Efficiency, Crop Yield, and Environmental Footprints. Agriculture **14**, 1141 (2024). https://doi.org/10.3390/agriculture14071141
7. M. Padhiary, D. Saha, R. Kumar, et al. Enhancing precision agriculture: A comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation. Smart Agricultural Technology **8**, 100483 (2024). https://doi.org/10.1016/j.atech.2024.100483

8. S. Chakrabarty, C.K. Deb, S. Marwaha, et al. Application of artificial intelligence in insect pest identification - A review. Artificial Intelligence in Agriculture **16**, 44–61 (2026). https://doi.org/10.1016/j.aiia.2025.06.005
9. H.A. Shehu, A. Ackley, M. Mark, O.E. Eteng. Artificial intelligence for early detection and management of Tuta absoluta-induced tomato leaf diseases: A systematic review. European Journal of Agronomy **170**, 127669 (2025).https://doi.org/10.1016/j.eja.2025.127669
10. M. Roy, A. Medhekar. Transforming smart farming for sustainability through agri-tech innovations: Insights from the Australian agricultural landscape. Farming System 3, 100165 (2025). https://doi.org/10.1016/j.farsys.2025.100165
11. X. Zhu, D. Li, Y. Zheng, et al. A YOLO-based model for detecting stored-grain insects on surface of grain bulks. Insects **16**, 210 (2025).https://doi.org/10.3390/insects16020210
12. E.-C. Oerke. Crop losses to pests. J. Agric. Sci. 144, 31–43 (2006).https://doi.org/10.1017/S0021859605005708
13. M. Xiang, M. Qu, G. Wang, et al. Crop detection technologies, mechanical weeding executive parts and working performance of intelligent mechanical weeding: A review. Front. Plant Sci. **15**, 1361002 (2024). https://doi.org/10.3389/fpls.2024.1361002
14. T. Jin, X. Han. Robotic arms in precision agriculture: A comprehensive review of the technologies, applications, challenges, and future prospects. Comput. Electron. Agric. **221**, 108938 (2024). https://doi.org/10.1016/j.compag.2024.108938
15. W. Jiang, L. Quan, G. Wei, et al. A conceptual evaluation of a weed control method with post-damage application of herbicides: A composite intelligent intra-row weeding robot. Soil Tillage Res. **234**, 105837 (2023).https://doi.org/10.1016/j.still.2023.105837
16. G. Gil, D.E. Casagrande, L.P. Cortés, R. Verschae. Why the low adoption of robotics in farms? Challenges for the establishment of commercial agricultural robots. Smart Agricultural Technology **3**, 100069 (2023).https://doi.org/10.1016/j.atech.2022.100069
17. S.M. Talley. Public acceptance of AI technology in self-flying aircraft. JAAER 29, Article 3 (2020). https://doi.org/10.15394/jaaer.2020.1822
18. R. Raja, T.T. Nguyen, D.C. Slaughter, S.A. Fennimore. Real-time robotic weed knife control system for tomato and lettuce based on geometric appearance of plant labels. Biosyst. Eng. **194**, 152–164 (2020).https://doi.org/10.1016/j.biosystemseng.2020.03.022
19. V. Choudhary, R. Machavaram, P. Soni. Optimizing mat quality and transplanter performance using soil mix with vermicompost and farmyard manure in paddy tray nursery: A sustainable smart farming approach in India. Farming System **1**, 100046 (2023).https://doi.org/10.1016/j.farsys.2023.100046
20. Y. Cao, C. Yi, G. Wan, et al. An analysis on the role of blockchain-based platforms in agricultural supply chains. Transp. Res. Part E **163**, 102731. https://doi.org/10.1016/j.tre.2022.102731
21. K. Paul, S.S. Chatterjee, P. Pai, et al. Viable smart sensors and their application in data-driven agriculture. Comput. Electron. Agric. **198**, 107096 (2022) https://doi.org/10.1016/j.compag.2022.107096
22. P.C. Ndayisaba, S. Kuyah, C.A.O. Midega, et al. Push-pull technology enhances resilience to climate change and prevents land degradation: Perceptions of adopters in western Kenya. Farming System **1**, 100020 (2023).https://doi.org/10.1016/j.farsys.2023.100020

23. M. Pramuka, L. Van Roosmalen. Telerehabilitation technologies: Accessibility and usability. Int. J. Telerehab. **1**, 85–98 (2009). https://doi.org/10.5195/ijt.2009.6016
24. U. Debangshi, A. Sadhukhan, D. Dutta, S. Roy. Application of smart farming technologies in sustainable agriculture development: A comprehensive review on present status and future advancements. IJECC **13**, 3689–3704 (2023).https://doi.org/10.9734/ijecc/2023/v13i113549