CHAPTER-4

Applications of Artificial Intelligence and Robotics in Plant Sciences: From Precision Monitoring to Data-Driven Decision Making

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Summary

Rapid advancements. The fast development of artificial intelligence, robotics and digital sensing technologies has transformed the current day plant sciences as it allowed a transition to be no longer based on awareness processes to massively automated and data-intensive systems. The integration is explored in this chapter of remote sensing with AI, machine learning, phenotyping, robotics-assisted farming, and evidence-based decision models throughout the agricultural systems. Emphasizing the origin of multimodal data streams of satellites, UAVs, IoT networks, and proximal sensors are fused algorithmically, providing continuous plant performance, early biotic and abiotic stress detection, and predictive yield modeling. The chapter also evaluates the introduction of self-directed field robots in planting, irrigation, nutrient delivery, weeding and harvesting, which will emphasize their contribution to bottlenecks of labor decreased and improving operational precision. Also, the growing dependency on big data analytics and decision support platforms is discussed as one of the key motivators of efficient utilization of resources and climate-adaptive crop management. Artificial intelligence in agriculture has ethical, economic and regulatory consequences, as discussed to put in perspective the shift to automated, intelligent farming ecosystems. In general, the chapter is a prospective overview of the social transformation of AI and robotics in plant sciences and paves the further innovations of sustainability, efficiency, and resilience of crop production systems.

Keywords: Artificial Intelligence in Plant Sciences, AI in Agriculture, Agricultural Robotics, Precision Agriculture, Smart Farming, Digital Agriculture, Machine Learning in Agriculture, Deep Learning for Crop Monitoring, Computer Vision in Agriculture, Data-Driven Agriculture

1 Introduction

Artificial intelligence (AI) and robotics are still transforming the modern agricultural. and plant sciences, which allow new possibilities to enhance productivity, resource utilization, and sustainability (Eissa, 2024). Feeding the 9 billion by 2050 in a sustainable manner is a big problem in the world since there are limited natural resources to support this population, and disparity in regions and increasing reliance on unsustainable resources. This requires place-based policies, better planning instruments and robust food systems that are resistant to extreme events and interruption in world trade (Wang, 2022).

1.1 Intelligent Automation in Crop Management

The conventional practices of farming that require extensive use of manual labor and regular inspections cannot match the volume and the intricacy of the existing farming issues (Jouzi et al., 2017). It is on this background that AI-driven systems and autonomous robots are a paradigm shift; they allow unremitting surveillance, interventions, and high-throughput data collection of plant systems (Kaya, 2025). At the same time, the development of sensing technologies, including multispectral cameras, LiDAR (Light Detection and Ranging) , or hyperspectral imaging, has further enhanced the realization of AI in the integration of plant sciences (Eltner et al., 2022). These sensors, when placed on drones or ground vehicles, gather high-resolution information regarding the health of crops, their nutrient status, and their reaction to stress (El-Tabakh et al., 2024). This information is processed with the machine learning models and can predict the growth patterns, diagnose a disease, and estimate a yield on a more detailed scale than before in a field (Domingues et al., 2022). These characteristics will reduce the utilization of periodic manual scouting and subjective observations and make monitoring more objective, scalable and timely (Khan et al., 2022). At the same time, robotics have expanded to perform a wide range of farming tasks single-handedly and also seeding and weeding and even fertilization and selective harvesting. Modern robots have an adequate locomotion system, a sense of the environment, and manipulators, enabling them to operate in the unstructured field environment (Wijayathunga et al., 2023). These robots are not only used to solve the problem of labor-intensive work; they also result in the reduction of the use of agrochemicals (Balaska et al., 2023) and such an intervention should now be made site-specific and is now precise (Molin et al., 2020). These systems are capable of making smart decisions, including the location of where and when to apply inputs that will save resources and have less impact on the environment by incorporating AI (Pedersen & Lind, 2017).

1.2 Advances and Practical Outreach

The latest developments aiming for modernized solutions have left no challenges related to the implementation of AI and robotics in agriculture. There are a lot of barriers to its deployment due to high capital costs, energy consumption, and the complexity of system integration (Shafik, 2024). Moreover, the agricultural robots have to work in dynamic and uncertain conditions, which necessitate strong navigation, localization, and perception functions (Xie et al., 2022). Interoperability and standardization of data: combining the data of dissimilar sensors, platforms, and decision-support systems is not that easy, particularly when one has to go beyond the experimental to commercial scale (Marco-Ruiz et al., 2016). The other important category of challenges is associated with socio-economic and ethical aspects of using AI and robotics in plant sciences. Employing the automation in rural areas can lead to job displacement, raising the issue of the loss of jobs and equity (Bilic et al., 2023). Besides that, the AI-based decision-making must be trusted; the farmers and other stakeholders must trust in the quality, transparency, and fairness of such systems (Gardezi et al., 2024a). Most jurisdictions also have inadequately developed laws on autonomous farm equipment, data privacy, and liability, thus making it hard to roll out in a large scale (Wiseman et al., 2018).

2 Artificial Intelligence in Crop Monitoring and Assessment

The modern agriculture industry is being improved using Agriculture 5.0 tech interventions, which can provide predictive analytics, automated pest detection, and robotic monitoring solutions that can make the industry more precise and less labor-intensive (Taha et al., 2025). At the same time, the agriculture industry continues to struggle with such major issues as water scarcity, soil erosion, and the environmental impact of excessive use of the chemicals as fertilizers (Adedibu, 2023). Through the use of AI-powered sensory devices to monitor key variables (Qinxia et al., 2021) like temperature, soil moisture, rainfall, and pH, farmers can be in a position to make informed and real-time decisions on irrigation and nutrient management (David et al., 2020). This intelligent monitoring does not only conserve resources or contribute to the preservation of soil health, it also contributes to the development of smarter crop-planting strategies, which ultimately makes the agricultural production system more resilient, sustainable and efficient (Mallik et al., 2025).

2.1 Remote Sensing and Image-Based Crop Monitoring

When used together with AI and machine learning models, remote sensing platforms such as satellites, unmanned aerial vehicles (UAVs), and ground-based sensor networks generate enormous data flows of spectral, spatial, and temporal information (Panda et al., 2024), which can be used to give detailed information on crop health, biomass distribution, nutrient imbalances, and early stress patterns (Zhang et al., 2024). Along with it, image processing has become an indispensable part of precision agriculture, where it is possible to accurately monitor crop development, livestock, and the quality of produce without the participation of an expert (Mavridou et al., 2019). The farmers can evaluate the health of their plants, detect nutrient deficiencies, track livestock, and classify fruits and vegetables, as well as detect defects and diseases through image segmentation, disease detection, and three-dimensional growth analysis (Soltani Firouz and Sardari, 2022). The reduced use of the manual visual check will help AI-based remote sensing to enhance the amount of monitoring and the accuracy of the measurements, i.e., heterogeneous fields will be assessed in a regular and objective way (Chawla & Singh, 2025). Deep learning (DL) approaches, and, in particular, convolutional neural networks (CNNs) can be used to further complement the capabilities to conduct automated phenotyping of plants (Chawla and Singh, 2025). The recent investigations have shown that the DL models are better than the conventional ML techniques in canopy architecture mapping, lesion sensing, and segmentation of plants and organs on a fine scale (K. Xie et al., 2024). This possibility has been confirmed in the field; as UAV-mounted cameras and CNNs have been used to identify disease and pest damage in the field, using RGB and thermal imaging (Alsadik et al., 2024). These innovations enable DL systems to encode more complicated phenotypic characteristics leaf morphology, dynamics of texture, and canopy geometry - that can be used in early diagnosis and adaptive crop control (Maraveas, 2024). In addition to motionless images, AI can also be used to predict the future on the basis of predictive modeling structures (Suo et al., 2023).

2.2 Predictive Modeling for Crop Performance

Predictive modeling builds the power of machine learning and deep learning to make the most accurate forecasts of yield using complex interactions between soil, weather and crop variables. These models discover the nonlinear patterns that traditional methods tend to miss hence producing more scalable and accurate predictions. The predictive frameworks can improve the decision-making process and the performance of crops significantly because of a combination of various datasets. Deep reinforcement learning also contributes to predictive ability by integrating deep and reinforcement-based learning to directly process raw environmental, soil, water, and crop data. The suggested Deep Recurrent Q-Network can well predict sequential crop behavior and optimize the actions to reduce error and attains a prediction accuracy of 93.7% without altering the original data distribution, which is more effective than the existing models (Elavarasan & Vincent, 2020). The combination of machine learning and crop modeling can be instrumental in predicting yields on a large scale, based on agro-ecological principles. Machine learning methods collectively are able to combine soil, weather, management, and historical yield information and the predictive power is very high with a small error (~9% RRMSE). Furthermore spatial error analysis also drew attention to the impact of cropland ratios, soil variability, and extreme weather events and made it possible to make more reliable forecasts at the county to field levels (Sajid et al., 2022). Machine learning also enhances predictive modeling by converting farm-level data into practical information that maximizes the utilization of resources and crop development as shown in Figure 1. Other algorithms like Bayes Net and Naive Bayes perform highly and hence, they provide very robust predictions of crop status, trend of performance, and disease occurrences with accuracy exceeding 99 percent. These models combined with the real-time data of the IoT can be used to predict yields more accurately and reduce production losses better, making the crop management system more sustainable and robust (Elbasi et al., 2023). Hybrid modeling, specifically the integration of Multiple Linear Regression and Artificial Neural Networks is more stable and efficient in prediction. Initialization of ANN weights based on MLR-obtained coefficients improves the performance of learning, whereby the hybrid MLR-ANN model is chosen over ANN, MLR, SVR, and KNN and RF algorithm to provide better accuracy and reduced computational time in the prediction of paddy yields. This organized start-up will enhance predictability in the models and a more reliable predictive framework (Gopal and Bhargavi, 2019).

Further developments in the deep learning architecture, primarily hybrid CNN based models are additions that would take the predictive crop performance modeling to a higher level by modeling the multifactorial or complex soil-weather interactions. The CNN-DNN model has shown to have a better predictive accuracy with a lower error rate as compared to CNN-XGBoost, CNN-RNN, CNN-LSTM, and control XGBoost models. The CNN-DNN model can potentially give better and more stable predictions of soybean yield because the XGBoost results are more rapid but less consistent and predictable (Oikonomidis et al., 2022). In general, predictive modeling is highly instrumental to the agricultural planning process because it can deliver credible information that helps in making informed decisions in time. Its implementation into agricultural systems helps to increase productivity, decrease the uncertainty, and resource inefficiencies. As data becomes more and more available, predictive modeling will keep developing as one of the primary instruments of sustainable and resilient crop production.

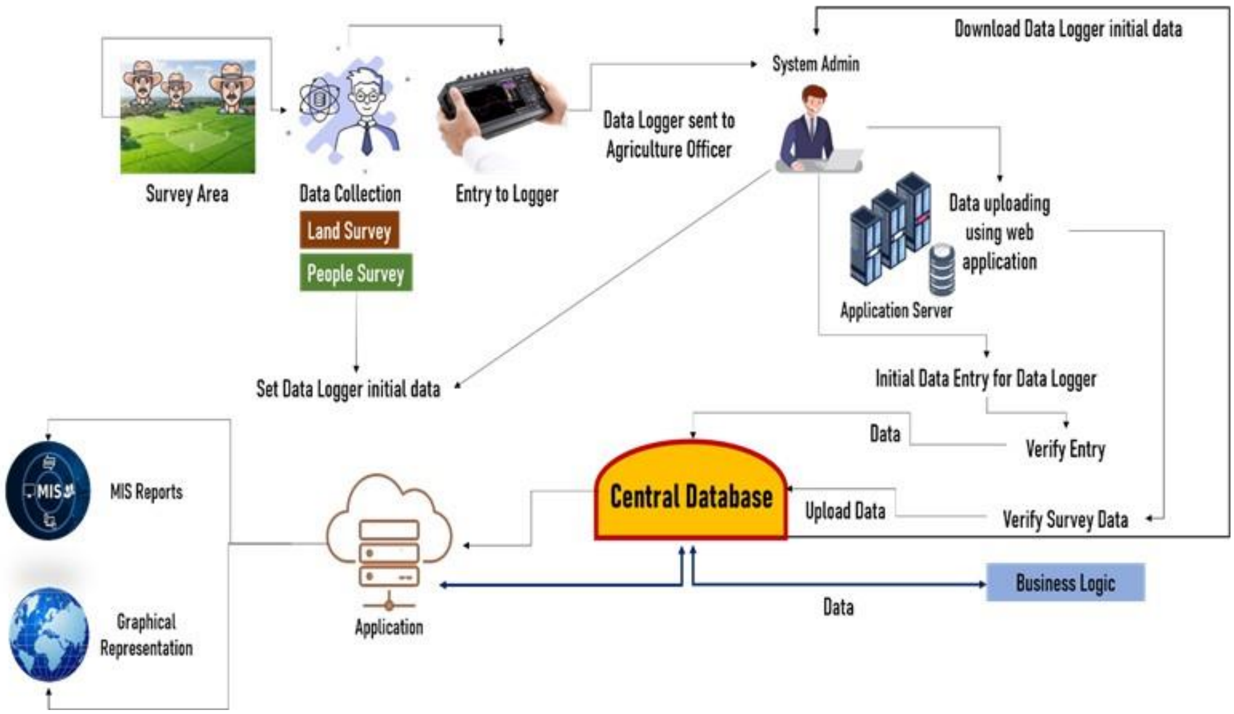

Figure 1. Agriculture-based data smart operations for Crop improvements

3 Robotic Revolution in Field Operations

Robotics in agriculture have revolutionized the conventional way of farming practices, bringing more precision, efficiency, and sustainability in the farming processes in terms of planting, cultivation, and harvesting (Jobe et al., 2025). Agronomic tasks can be done with great precision by autonomous robots fitted with sophisticated perception systems, which are able to navigate complex and unstructured field environments (Botta et al., 2022). They are based on computer vision, LiDAR, GPS, and inertial measurement units (IMUs) to detect obstacles, detect crop rows, and implement planting tasks with the minimal human participation (Agelli et al., 2024).

3.1 Autonomous Planting and Seeding Systems

Through adopting robotics in planting activities, the farmers will be able to record the correct seed planting, ideal depth planting, and the right density of the planting, which is very important in the increase of plant germination and the subsequent yields of the crops (Gammanpila et al., 2024). Large scale operations can also be scaled with autonomous systems of seeding and planting. As an example, to implement an automated planter of row crops (maize and soybean) in real-time, real-time data feeds are used to realign the position of seeds based on soil factors, topography, and moisture dynamics (Duckett et al., 2018). Accurate planting robots eliminate seed waste, maximize the population of the plant, and the even population of crops, which has a direct impact on yield stability. In addition, robots decrease the reliance on human labor, and workforce deficits that are increasingly prevalent in the agricultural industry because of demographic changes and population urbanization tendencies (Bechar & Vigneault, 2016; Koirala et al., 2022). Other than planting, robotics have been widely used in taking care of the crops as indicated in Table 1, such as automated weeding, irrigation, and nutrient management.

Figure 2. Smart robotics for precision agriculture

3.2 Robotics in Irrigation, Weeding, and Nutrient Management

Robotic machine vision weeding systems have the ability to identify crops and weeds and eliminate unwanted plants mechanically, thermally, or with chemicals (Slaughter et al., 2021). Such a focus results in reduced herbicide usage, lower production costs, and minimum environmental impacts. Equally, irrigation robots with soil moisture sensors and artificial intelligence programs can apply site-specific water, enhancing water-use efficiency and minimizing the unnecessary water usage (Li, Zhao, Wang, et al., 2020). Fertigation robots, that combine nutrient sensing with targeted delivery, also improve the health of plants by delivering nutrients as well as targeted pesticides to crops in a more precise manner, lowering the nutrient leaching with mechanized protection, enhancing the beneficial effects contributing to safety measures and climatic upregulations (Kassim et al., 2020).

3.3 Harvesting and Post-Harvest Automation

Another area that robotics has brought about revolutionary change is the harvesting industry. Robotic systems that are used in harvesting high-value crops (fruits, vegetables, nuts) can identify ripe products and harvest using robotic arms, multi-modal sensing, and computer vision, without damaging the plants (Bac et al., 2014; Hameed et al., 2021). AI-based advanced robotics in farming also increases productivity, decreases human labor requirements, and lowers environmental effects through the use of AI-controlled robots to carry out economic activities such as planting, irrigation, harvesting, and pesticide application in a highly precise manner, as shown in Figure 2, (Rai et al., 2023). Such systems allow the maintenance of constant functioning, loss reduction, and efficiency, including packaging robots that can pick up to 80 percent of fruit without any decline in quality (Hayashi et al., 2014). Although the initial cost is high, the long-run advantages have shown as reduction in the operational costs, increased yields, and long-term food production (Hayashi et al., 2014).

Table 1. Technological Frameworks for Data-Driven Crop Management

Platform	Working Mechanism	Operational Advantages	References
Big Data Analytics	Processing large-scale heterogeneous farm datasets from satellites, sensors, machinery, and weather stations.	Predictive crop management, yield forecasting, stress detection, resource optimization.	Wolfert et al., 2017; Kamilaris & Prenafeta-Boldú, 2018
IoT Sensors	Soil moisture, temperature, nutrient, and microclimatic sensors connected via wireless networks.	Real-time monitoring, automated irrigation/fertilization, precise input application.	Farooq et al., 2020; Patel et al., 2022
Decision Support Systems (DSS)	Platforms integrating multi-source data with AI models to provide actionable crop management recommendations.	Optimized planting, irrigation, pest management, adaptive strategies under climate variability.	(Yi et al., 2024)
Predictive Modeling	Machine learning (ML), AI, and recurrent neural networks (RNN, LSTM) applied to crop growth and yield forecasting.	Early warning for stress/disease, 'what-if' scenario analysis, improved resource allocation.	Victor et al., 2022; Kamilaris & Prenafeta-Boldú, 2018
Smart Irrigation Systems	Automated irrigation using sensor feedback and ML algorithms.	Water savings up to 40%, optimal plant growth, reduced labor.	Patel et al., 2022; Li et al., 2020

Moreover, robotics ensures longer harvesting hours since it can operate at night or during low seasons to enhance the supply chain. With these developments, robotics usage in agriculture is still facing a number of challenges. The outlay investment, energy costs, and technicality make it inaccessible to small- to medium-scale farms (Duckett et al., 2018; Slaughter et al., 2021). Moreover, field robots will have to deal with the changing properties of the environment, including rough topography, climatic conditions, intricate crop structures, and others, which can diminish working stability. Other challenges are also a persistent problem with maintenance, sensor calibration, and inter-platform data integration. Lastly, social-economic consequences of the labor displacement and necessity to train operators must be discussed in order to make the process of robots implementation fair and sustainable (Hameed et al., 2021; Koirala et al., 2022).

4 Data-Driven Decision Making in Plant Sciences

4.1 Big Data Analytics in Agriculture

The research and decision-making in the agricultural sector has been changed through the application of big data analytics, which is allowing the integration and analysis of large, multidimensional datasets produced on farms. Current accuracy regimes regularly gather data on remote sensing platforms, soil and atmospheric sensors, automated machinery, and long-term management records to make up a data ecosystem which underlies evidence-based crop management (Wolfert et al., 2017). These non-homogeneous streams of data enable predictive models to identify new stresses, future yield curves, and resource optimization with specific interventions in irrigation, nutrient supply, and pest control (Kamilaris et al., 2017; Yi et al., 2024). An example is that disease prediction algorithms created in machine learning may give growers a warning of upcoming outbreaks, minimizing loss of money in production, and increasing sustainability (Amulothu et al., 2024).

4.2 Integration of IoT, Sensors, and Smart Systems

An addition of IoT devices and sensor networks have also enhanced the principles of data-driven agriculture (Yadav et al., 2021). Measured real-time by distributed sensors, the variables include soil moisture, temperature, nutrient content, and microclimate where the algorithm gets adjusted to optimize the irrigation or fertilization frequency with the minimum human input to cloud-based systems or edge-processing systems (Farooq et al., 2020; Li, Zhao, & Wang, 2020). Specifically, smart irrigation systems have shown over 40% water savings with the need to grow optimally in response to the needs of the plant (Patel et al., 2022). The result of such sensor rich environments is also rich longitudinal data that can enhance predictive model accuracy as time progresses as well as enabling adaptive management techniques (Hero & Cochran, 2011). The growing integration of IoT, AI and remote sensing has reduced farms to integrated digital ecosystems with the ability to continuously monitor and automatically take decisions. Rapid development of single-sensor to multi-sensor fusion systems in agricultural navigation has been further advanced to a vision-based approach and INS-GNSS integration, which have been most successfully used in field navigation under multifaceted conditions. The Kalman filter-based fusion and the optimized path-planning algorithms can be used to help give strong and effective guidance to future autonomous farming systems (Yang et al., 2025). It is estimated that by 2030, smart crop monitoring could unlock a value between USD 130 billion and USD 175 billion globally, with the use of enhanced connectivity allowing for accurate soil, equipment, and crop surveillance (Latorre et al., 2025). These advancements highlight the transformative potential of digital technologies in reshaping the agricultural landscape and boosting global GDP (Goedde et al., 2020). Multispectral and hyperspectral observatories and thermal sensors used in drone systems are able to produce high-resolution geospatial data to measure crop health, canopy stress, soil moisture gradient and presence of pests or diseases. They can precisely map the fields, apply variable rates of input and spray in specific areas with minimum drift because of their autopilot flight and GPS controlled navigation. Drones may be helpful in effective and rapid delivery of anomalies, evapotranspiration forecasting, and enhancement of spatial decision support platforms via integration of sensor data with analytical algorithms. Combined, these capabilities will eliminate inefficiency in input-use as well as variability of operation and the overall yield performance through data driven crop management (Joshi & Pandey, 2024). Use of modern technologies in agriculture is an important development in the field that is likely to make the industry more efficient and profitable. Such innovations are not just an incremental innovation; they are a significant jump into a different direction of dealing with farming (Sachs, 2016).

4.3 Decision Support Systems (DSS) for Crop Management

The analytical heart of this digital transformation is decision support system (DSS) because it integrates numerous sources of data as shown in figure 3., In order to recomment on field operations (Zhai et al., 2020). Current DSS systems are a collision of satellite data, weather forecast, soil analysis, and historical data on the context of the planting date, fertilizer date, and irrigation date, and harvesting date (Singh & Sharma, 2013). Increasingly such systems rely on machine learning models, which are updated as new observations are generated enhancing the quality and reliability of management decisions (Kamilaris et al., 2017). In addition to strategic planning, DSS tools can also be used in real-time decision-making in the pest surveillance and nutrient management field, which can strengthen resilience towards climate variability (Duraimurugan et al., 2025). They have also been combined with autonomous implements such as robotic sprayers or harvesters that have increased their capacity to support intelligent, semi-autonomous farming operations.

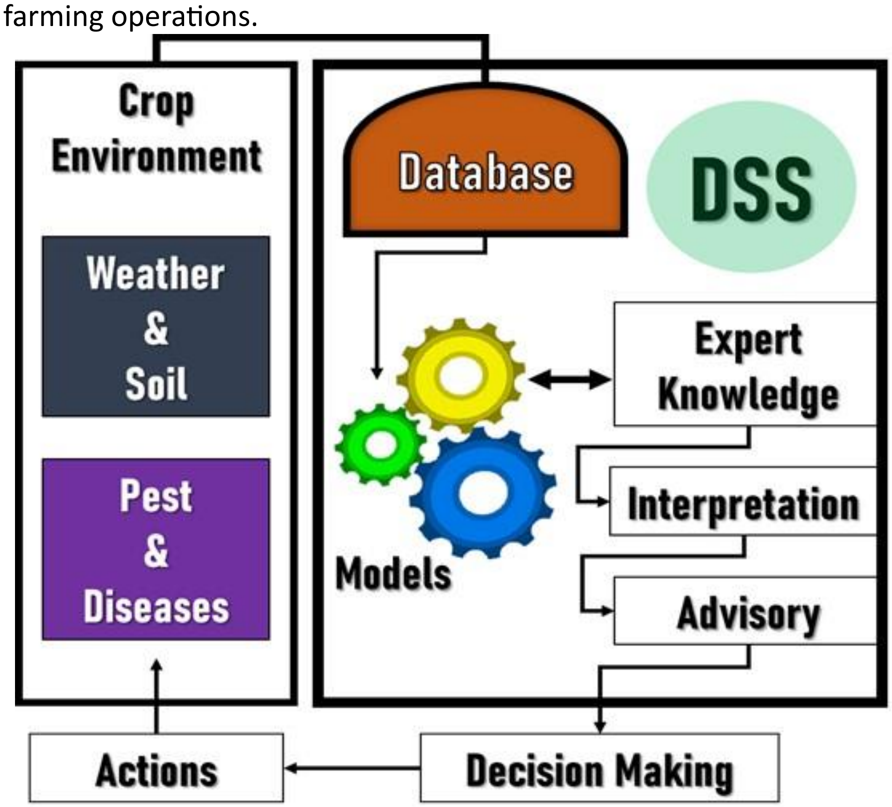

Figure 3. Decision support intelligence for agricultural automation

Along with these developments, there are still some shortcomings that are limiting the wide use of big data and intelligent farming systems. The quality of data is also one of the major concerns because the absence of values, inappropriate formats, and sensor failures undermine the functionality of the model (Patel et al., 2022; Wolfert et al., 2017). There is still limited interoperability among devices, platforms, and proprietary systems that allows data to be easily exchanged and integrated to analyze it (Dave & Mittapally, 2024). There is additional adoption hindrance due to cost barriers and uneven digital infrastructure especially in smallholder farming areas. Such ethical and governance issues as the ownership of data, their privacy, and fair access to AI-based services should be also taken into consideration to guarantee inclusive digital transformation (Zhai et al., 2020). In the future, edge computing can be used with cloud analytics, low-power sensor design must be improved, and federated learning can be used to maintain data privacy, which are promising opportunities (Dave & Mittapally, 2024). Moreover, data-intensive agriculture should be scaled by democratizing access to DSS and making it affordable to access by all, which will help create more resilient, sustainable, and efficient landscapes in agriculture in the long run (Michael & Ogunsola, 2021).

5 Ethical, Economic, and Social Considerations

The application of AI in agricultural decision-making may lead to unwanted effects as algorithms have biases or predictive models may lack transparency (Kovari, 2024). Explainable AI (XAI) models have been suggested so that it can be ensured that the farmers and the stakeholders are aware of the creation of the predictions, which will lead to trust and accountability (Arcuri et al., 2022). Moreover, the ethical use of autonomous robots must also be related to safety criteria, liability in the event of failure in the operation, and the environmental costs of introducing resource-consuming robot platforms (Bechar & Vigneault, 2016; Wolfert et al., 2017). Developers and policymakers need to set up effective regulatory frameworks to make sure that AI and robotics use is in a responsible manner, risks to human beings and the environment are minimal, economic consequences of adopting AI and robotics are also relevant. Even though the technologies have the potential to increase productivity, lower input expenses, and increase yield stability, the large capital investment is a detriment to small- and medium-scale farms (Duckett et al., 2018; Koirala et al., 2022). The cost-benefit analysis shows that the income of investment is situational and depends on the type of crops, the size of the farm, and the supply of labor. Moreover, the automation can also increase economic inequality in the rural areas, benefiting small-scale business that is capable of implementing the changes. The mechanisms proposed to democratize the access to advanced agricultural technologies are government incentives, cooperative models, as well as shared-access robotic services (Hameed et al., 2021).

The social aspect of robotics and AI adoption includes the labor displacement, requirements of skills, and rural labor employment. Also, autonomous systems decrease the number of people working in the plants, harvesting, and monitoring crops, which may drive the displacement of vulnerable community members (Pramanik, Bisht, and Thapliyal, 2022). Nevertheless, high-skilled positions of robot operation, maintenance, and data analytics emerge as a result of these technologies as well. Participatory approaches, reskilling and training are necessary to achieve fair benefits and alleviate adverse social effects. It has been demonstrated that involving local stakeholders in technology design and deployment increases the levels of acceptance and sustainability of AI-based agricultural systems in the long term (Ristovska, Georgieva, and Kirovski, 2021).

Table 2. Navigating the AI and Data Driven based Agricultural Monitoring

Challenge Category	Specific Challenges	Impact & Implications	Research Sources
Data Quality & Availability	Fragmented data sources, data scarcity, inconsistent phenotyping protocols, heterogeneous agricultural data across regions, inadequate data availability, low replicability due to field variability	Limited model training, reduced prediction accuracy, difficulty in building robust AI systems. No two fields are exactly alike, making systematic data gathering challenging.	(Linaza et al., 2021; Sahoo et al., 2024; Wójcik-Gront et al., 2024)
Infrastructure & Technology Limitations	Limited digital infrastructure in developing regions, high implementation costs, inadequate technological resources, connectivity challenges, and bandwidth limitations.	Uneven AI adoption between developed and developing nations, small-scale farmers unable to access technologies, limited 5G/6G deployment in rural areas.	(Gul, 2017; Sharma & Shivandu, 2024)
Model Interpretability & Transparency	Lack of model explainability, black-box algorithms, insufficient transparency in AI decision-making, limited interpretability of deep learning models.	Farmers who are unable to understand recommendations are more likely to reduce their trust in AI systems and experience difficulty in adopting complex models.	(Cheng et al., 2021; Gardezi et al., 2024; Thalpage, 2023)
Model Robustness & Performance Issues	Variable performance across different crops and regions, failures in transfer learning, object occlusion challenges, algorithmic bias, model overfitting	Inconsistent prediction accuracy, reduced effectiveness in resource-constrained environments, and potential perpetuation of inequalities through biased algorithms	(Ahmed et al., 2021; Cunningham & Delany, 2021)
Deployment & Scalability Challenges	High computational requirements, difficulty deploying models in resource-constrained settings, scalability constraints for small/medium farms, real-time deployment limitations	Limited practical applicability in developing regions, computational cost barriers, challenges in achieving fully autonomous farms	(Liu et al., 2024; Sunindyo & Theodore, 2025)
Environmental & Operational Constraints	Varying lighting conditions, complex agricultural backgrounds, weather variability impacting sensor performance, diverse climatic conditions affecting system accuracy.	Reduced accuracy of computer vision systems, need for robust models adaptable to changing conditions.	(Kadmon et al., 2003; Lee et al., 2010)
Data Privacy & Security Concerns	Data ownership issues, privacy violations, cybersecurity threats, inadequate data protection frameworks, concerns over unauthorized data access.	Farmer hesitancy in adopting AI systems, loss of competitive advantage, need for encrypted data management systems.	(Gupta et al., 2020; Kapoor, 2024)
Technical Expertise & Knowledge Gaps	Lack of specialized technical skills, insufficient farmer literacy in AI/ML technologies, training deficiencies, and a knowledge gap	Difficulty in adopting and managing AI systems, reduced effectiveness of technology implementation, need for	(El-Sagheer et al., 2025; Songol et al., 2021)

	between farmers and technology.	continuous training programs.	
Economic & Financial Barriers	High implementation costs, expensive sensors and hardware, significant initial investment requirements, affordability for small-scale farmers, ongoing maintenance expenses.	Unequal access to technology based on farm size and economic capacity, digital divide widening.	(Hennessy et al., 2016; Kerras et al., 2022)
Integration & Interoperability Issues	Lack of standardized protocols, incompatible systems between different manufacturers, difficulty integrating diverse datasets, and proprietary systems limiting connectivity.	Reduced system flexibility, vendor lock-in, and challenges in creating unified agricultural platforms.	(Jeyaseelan, 2025; Thomasson et al., 2018)
Regulatory & Policy Frameworks	Inadequate regulatory standards, unclear governance structures, customization challenges for different regions, lack of ethical guidelines	Uncertainty in technology adoption, inconsistent implementation across different regions, potential misuse of AI systems.	(Pöhler et al., 2024; Tzachor et al., 2022)

Policies and regulations can have a key role in determining the ethical and social consequences of AI and robotics implementation in agriculture. The safety practices should be standardized, autonomous systems should be certified, and the liability should be well defined in order to secure the interests of farmers, workers, and consumers (Arcuri et al., 2022). Moreover, the problem of data privacy and its ownership is also confronted in the case of massive usage of IoT sensors and cloud-based decision-support systems. The policies of who is allowed to have access, usage, and benefit of farm-generated data need to be clear to avoid misuse and establish trust between the stakeholders (Jakkua et al., 2018). Responsible AI and robotics innovation in the agricultural field can also be encouraged by cross-national joint venture and knowledge exchange platforms (Bhimavarapu, 2025). AI and robotic agriculture can be made sustainable in the long term by ensuring the balance between technological efficiency and social justice and environmental sustainability (Prakash, 2025). By incorporating ethical issues into the design, deployment, and governance models, it is possible to make sure that the technologies will positively influence food security and avoid intensifying social disparities (Kamilaris et al., 2017). In order to incorporate these developments in the field level mitigating all the potential limitations and challenges are needs focused approach as illustrated in Table 2. Moreover, involvement of multi-stakeholders such as farmers, policymakers, researchers and civil society is of paramount importance to ensure that the adoption of technology is aligned to the societal objectives. With the development of the field, the success of sustainable agricultural innovation will be comprised of incorporating the ethics, economic equity, and social responsibility into the very fabric of AI and robotic applications.

6 Conclusion

The fast development of artificial intelligence, robotics, and information-based systems is redefining the contemporary plant sciences to make the traditional labor-intensive practices to be converted into intelligent, automated production ecologies. Throughout the chapter, it becomes evident that remote sensing, machine-learning-driven phenotyping, and AI-based predictive modeling have become the key instruments of high-resolution performance monitoring of crops, providing opportunities to detect stress early in the growth of crops and implement the necessary interventions in a resource-efficient manner. Robotics also increase the efficiency of planting, weeding, irrigation, and harvesting processes by cutting down on the human manpower, and also increasing precision, uniformity, and efficiency of work. The IoT networks, sensor fusion, and smart platforms with the help of big data analytics have transformed the way plant sciences are managed as management has become more predictive than reactive. With these systems, there is the ability to optimize nutrient management, scheduling of irrigation and disease prevention due to continuous data streams. The Decision Support Systems to be mentioned in the chapter can help to understand the way, in which the combination of environmental, physiological, and operational data provides an actionable intelligence capable of serving farmers, agronomists, and researchers. However, AI and robotics have also brought in worthwhile ethical, socioeconomic and sustainability challenges, including data ownership, equal access, job losses and sustainability. To rise above such challenges, research, policy makers, technology and farming community developers are the ones expected to collaborate so as to bring about responsible and inclusive innovation. Overall, it is evident that artificial intelligence, robotics, and data science are not only a technological breakthrough but a paradigm shift in the plant sciences, which will lead to resilient agricultural systems, food production that is climate-sensitive as well as sustainable intensification in the whole world picture.

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