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Artificial intelligence for smarter, sustainable and climate-resilient farming

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Intricacies of the subject

Artificial intelligence (AI) is reshaping agricultural decision-making by linking field observations with rapid data analysis and site-specific management. Sensors, satellite and drone imagery, machine learning, computer vision and automated machinery can support timely decisions on soil, water, crop health, farm inputs and operations. This article reviews the practical role of AI in precision farming, smart irrigation, crop-health surveillance, autonomous machinery, yield and market decision support, and sustainable resource management. Particular attention is given to the complete decision chain from sensing and data integration to prediction, recommendation, field action and feedback. AI can improve the spatial and temporal precision of farm operations, but its value depends on reliable local data, sensor calibration, affordable delivery models, connectivity, farmer skills and transparent recommendations. Recent developments in generative AI may further improve farmer-facing advisory services by converting complex datasets into accessible, multilingual explanations, although inaccurate or fabricated outputs remain a serious concern. AI should therefore complement, rather than replace, agronomic knowledge and field verification. When locally validated and combined with extension support, digital infrastructure and responsible data governance, AI can contribute to productive, resource-efficient and climate-resilient farming.

Introduction

Agriculture must increase productivity while facing climate variability, labour constraints, rising input costs and pressure on soil and water resources. At the same time, farms increasingly generate data from weather stations, soil sensors, machinery, mobile devices, satellites and unmanned aerial vehicles. Artificial intelligence provides computational methods for converting these heterogeneous data into predictions, classifications and management recommendations. Machine-learning approaches are now used in crop, soil, water and livestock management, while deep-learning methods have expanded image-based applications such as disease diagnosis, crop recognition and weed detection (Liakos *et al.*, 2018; Kamilaris and Prenafeta-Boldú, 2018; Benos *et al.*, 2021). The practical value of AI lies not in automation alone but in improving the timing, location and accuracy of farm decisions. A farmer may use AI-supported tools to identify which part of a field requires irrigation, detect plants showing early disease symptoms, estimate yield, select a spraying

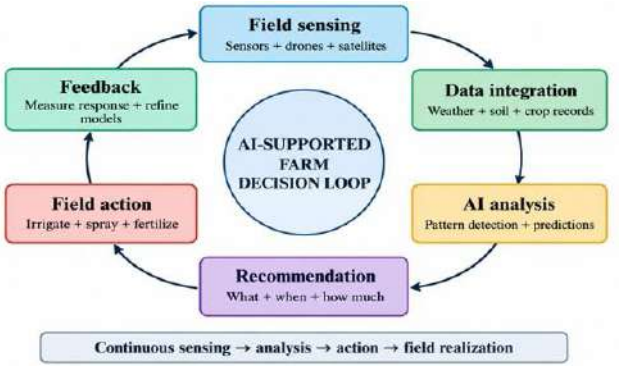
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window or prioritize areas for field scouting. Smart-farming systems increasingly connect data acquisition, analysis, decision support, field execution and feedback into a continuous management cycle (Saiz-Rubio and Rovira-Más, 2020). This human-in-the-loop approach is important because agronomic decisions must account for local soil, crop, weather, economic and management conditions that may not be fully represented in a model.

Precision farming: turning field variability into better decisions

Agricultural fields are rarely uniform. Soil texture, nutrient status, moisture, crop vigor, weed density and pest pressure can vary substantially within short distances. Precision farming treats this variability as actionable management information. The resulting maps or recommendations can guide variable-rate seeding, fertilization, irrigation and crop protection. Machine-learning systems are particularly useful when several interacting variables influence crop performance. Soil moisture, nutrient supply, canopy temperature, rainfall, growth stage and previous management can be analyzed together, enabling recommendations to change as new data arrive. Reviews show that machine learning has been used extensively for yield prediction, crop quality assessment, weed detection, water management and soil management (Liakos *et al.*, 2018; Benos *et al.*, 2021). However, prediction accuracy is only one measure of usefulness. A practical system must also provide recommendations at the right time, explain the major factors behind them and allow farmers to compare model output with field observations.

Fig. 1. Circular AI-supported farm decision loop



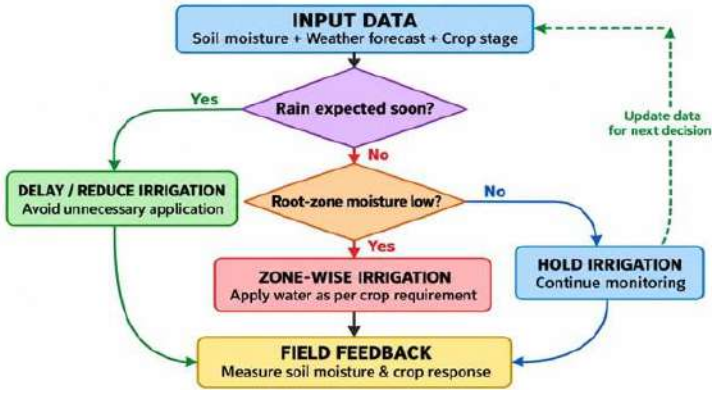
Smart irrigation: applying water according to crop need

Water management is one of the most direct applications of AI in agriculture. Conventional irrigation schedules may rely on fixed intervals or field averages even when soil moisture and crop demand vary across time and space. Smart irrigation combines root-zone moisture measurements with weather information, crop stage, evapotranspiration estimates requirement and support decisions on when, where and how much water to apply (Talaviya *et al.*, 2020; Ercan Oğuztürk, 2025). The benefit comes from responsiveness. Forecast rainfall may justify delaying irrigation; rapidly drying field zones may need additional water; and adequate root-zone moisture may indicate that irrigation can be postponed. Recent synthesis of AI-driven irrigation research reports improvements in water-use efficiency across multiple systems, but the magnitude of benefit depends on sensor placement, calibration, crop type, irrigation uniformity and local weather data (Ercan Oğuztürk, 2025). For this reason, automated

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recommendations should operate within agronomically defined limits and retain an override option for the farmer or irrigation manager.

Fig. 2. Decision-tree pathway



Crop health, disease, pest and weed detection

Timely diagnosis is essential because many crop problems are easier and less costly to manage at an early stage. Computer vision and deep learning can classify images of leaves, canopies or field patches and identify visual patterns associated with diseases, nutrient disorders, weeds or insect damage. Ferentinos (2018) demonstrated the strong potential of convolutional neural networks for image-based plant disease recognition across numerous plant disease combinations. Such systems can support field scouting by rapidly directing attention to suspicious plants or zones. AI-based detection should nevertheless be treated as decision support rather than automatic diagnosis. Symptoms may vary with variety, growth stage, light conditions, nutrient status and environment, and a model trained on curated images may perform differently in a farmer's field. Reliable systems therefore require representative local datasets, independent field validation and periodic recalibration. A robust workflow combines automated screening with agronomic confirmation: AI indicates where a problem may exist, while the farmer, agronomist or extension professional verifies the cause and selects an appropriate intervention. Weed management is another important application. Machine vision can distinguish crop plants from weeds and guide targeted mechanical or chemical control. Robotic weed-control research has emphasized four linked functions guidance, weed detection, precision treatment and mapping (Slaughter *et al.*, 2008). Newer AI models improve recognition, yet overlapping canopies, variable weed growth stages, dust and changing illumination remain field challenges.

Autonomous machinery and targeted input application

AI is increasingly integrated into tractors, sprayers, harvesters and field robots. Navigation systems can maintain accurate field paths, computer vision can recognize plants and obstacles, control algorithms can adjust machine operation in real time. These capabilities reduce overlap during seedling, fertilizer application and spraying, and they enable sensing and site-specific treatment to occur during the same field pass. Automation is particularly useful for repetitive operations that require consistency or fine spatial control. Economic suitability differs among farming systems. The value of autonomous machinery depends on farm size, crop type, annual utilization, service availability and downtime

costs. For small or fragmented farms, shared machinery, custom-hiring centers, cooperatives or service-based platforms may be more practical than individual ownership. Appropriate automation should therefore be adopted where it provides a clear agronomic, economic or environmental advantage.

Prediction, market intelligence and integrated decision support

AI can help farmers anticipate production and market conditions. Yield models combine production history, weather, crop condition and management data, while market-support systems integrate price, supply and weather-related signals to support harvesting, storage and marketing decisions. Because such forecasts are uncertain, useful systems should communicate assumptions and uncertainty rather than present a single prediction as certain. At farm level, integrated platforms are often more useful than isolated digital tools. A single dashboard can prioritize weather, irrigation, crop-health and operational information, reducing the need to interpret disconnected applications. This connected human–machine approach is central to Agriculture 5.0 (Saiz-Rubio and Rovira-Más, 2020).

Generative AI and farmer-facing advisory services

Generative AI is extending digital agriculture

from prediction toward natural-language interaction. Large language models and related systems can summarize farm records, retrieve technical information, explain model recommendations and potentially deliver multilingual advisory messages through conversational interfaces. Recent reviews describe emerging applications in precision farming, pest and disease management, decision support and agri-food information systems (Krupitzer, 2024; Pallottino *et al.*, 2025). This may lower the technical barrier for farmers who cannot directly interpret sensor dashboards or statistical outputs. The same technology introduces new risks. Generative systems can produce confident but inaccurate or fabricated information, and general-purpose models may not reflect local pesticide regulations, cultivar responses, weather conditions or region-specific agronomy. Agricultural advisory applications should therefore use verified knowledge sources, show the origin and date of critical information, flag uncertainty, and route high-risk recommendations for expert review. In this context, generative AI is most valuable as a communication layer over validated agronomic data and models not as an unsupervised authority for crop management decisions (Pallottino *et al.*, 2025).

AI for sustainable and climate-resilient agriculture

AI contributes to sustainability mainly by improving resource-use efficiency. Better irrigation scheduling can reduce avoidable water use; targeted spraying can limit unnecessary pesticide or herbicide application; variable-rate nutrient management can reduce over-application; and early diagnosis can prevent local problems from becoming field-wide losses. AI can also support soil-health monitoring, crop rotation planning and climate-risk assessment when integrated with sound agronomic practices. Climate resilience is strengthened when models combine weather forecasts with crop and soil data to warn of heat, drought, excess rainfall or disease-conducive conditions. Farmers can then adjust irrigation, sowing, crop protection or harvest operations. However, transferred models may perform poorly where local weather networks are sparse or agro-climatic conditions differ, making local data infrastructure and recalibration essential.

Practical challenges and responsible adoption

Despite rapid progress, adoption is constrained by high initial costs, weak rural connectivity, unreliable electricity, sensor maintenance, incompatible data platforms and limited technical support. Data quality is equally important: advanced models cannot compensate for poorly calibrated sensors, missing field records or biased training data. Farmers also need to understand why a recommendation was generated and when it may be unreliable, making explainable and auditable systems preferable for high-stakes decisions. Farm data may include production history, input use, finances and precise field locations, so clear agreements are needed on ownership, storage, sharing and reuse. Extension services, universities, farmer-producer organizations and technology providers can jointly evaluate tools, build digital skills and develop interoperable standards. Responsible adoption should also prevent exclusion of smallholders because of device cost, language, literacy or connectivity.

Future prospects

The next phase of AI in agriculture will likely combine edge computing, low-cost sensors, high-resolution remote sensing, robotics, digital twins and conversational advisory systems. More processing may occur directly on farm devices, while interoperable systems connect machinery, weather feeds, sensors and records. Research should evaluate these tools across seasons, crops and farm sizes using profitability, usability, environmental outcomes, model drift and farmer trust not prediction accuracy alone. For wider adoption, technology development must move from demonstration to dependable service through locally calibrated models, affordable delivery options, transparent recommendations, maintenance support and farmer participation in system design. Long-term success will depend as much on data stewardship, institutional capacity and human–technology interaction as on advances in algorithms.

Conclusion

Artificial intelligence is becoming an important component of modern agricultural management because it can convert large and diverse datasets into timely, site-specific information for irrigation, crop monitoring, input management, automation and planning. Used carefully, AI can help improve productivity while reducing avoidable use of water, chemicals, labour and energy. Recent generative AI tools may make digital advisory systems easier to access, but their outputs require verification and clear safeguards against inaccurate recommendations. Successful adoption ultimately depends on reliable local data, agronomic validation, farmer-friendly design, affordable delivery models and responsible data governance. AI should therefore support, not replace, farmers' experience and professional agronomic judgment. Combining digital intelligence with practical crop and soil management provides the most credible pathway toward smarter, suitable and climate-resilient farming. In the coming years, integrating AI with remote sensing, the Internet of Things (IoT) and precision agriculture could further strengthen real-time decision-making and resource-use efficiency.

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