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Review Article

Artificial Intelligence, Genome Editing and Precision Agronomy for Climate-Resilient Crop Production: A Global Synthesis

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Abstract

Artificial intelligence, genome editing and precision agronomy are converging into a new paradigm for crop production under climate change. This review synthesises global evidence on remote sensing, machine learning, CRISPR-based trait improvement, site-specific nutrient and water management, and digital advisory systems, and evaluates how their integration affects yield, yield stability, resource-use efficiency, profitability and environmental outcomes. The central finding is that sensing, learning, editing and management must be developed together: accurate data improve models, models improve decisions, improved genotypes raise the ceiling on what management can achieve, and precision management allows new genotypes to express their potential in farmers fields. Across regions and crops, integrated systems consistently outperform isolated technologies, with reported water savings of 30 to 50 percent in AI-driven irrigation, nitrogen reductions of 6 to 35 percent under precision management, and substantial gains in drought, heat, salinity and disease tolerance from targeted gene editing. The review also examines data bias, model transferability, regulatory divergence, seed-system bottlenecks, cost, equity and trust, and proposes a five-stage Sense-Learn-Edit-Manage-Deliver framework to guide research, investment and policy. It concludes that the next advance in agronomy will come not from a single tool, but from responsible integration of biological and digital innovation with farmer knowledge and inclusive institutions.

Keywords: artificial intelligence; CRISPR; genome editing; precision agronomy; remote sensing; climate resilience; nitrogen-use efficiency; digital agriculture

1. Introduction

Feeding a growing population under a changing climate is now the defining challenge of agronomy (Porter et al., 2014; IPCC, 2022; FAO, 2022). Heatwaves, erratic rainfall, floods, salinity, pests and diseases are reducing yield stability, while soil degradation, water scarcity, fertiliser price volatility and labour shortages raise the cost of production (Lipper et al., 2014; Pretty et al., 2018). Conventional agronomy, based on uniform recommendations, average weather and a small number of broadly adapted varieties, is no longer sufficient. Farmers need varieties that tolerate specific stresses, information that is specific to their field and season, and management that adjusts as conditions change. Three technological revolutions now make that possible: sensing and artificial intelligence (AI), genome editing, and precision agronomy. Each is powerful alone. Together, they change what agronomy can do.

AI and remote sensing allow crops, soils and weather to be observed at spatial and temporal resolutions that were unimaginable a generation ago (Weiss et al., 2020; Kamilaris and Prenafeta-Boldu, 2018). Satellites revisit fields every few days, unmanned aerial vehicles capture centimetre-scale canopy detail, soil sensors report moisture and nutrients continuously, and weather stations and models provide short-term forecasts and seasonal outlooks. Machine learning converts these streams into predictions of yield, nutrient stress, disease risk, irrigation need and harvest timing (Jin et al., 2021; Chlingaryan et al., 2018). Genome editing, especially CRISPR-Cas systems, base editors and prime editors, allows precise modification of genes that control drought, heat, salinity, disease resistance, nutrient-use efficiency and grain quality (Chavhan et al., 2025; Kumar et al., 2023; Raza et al., 2022). Precision agronomy translates sensing, prediction and improved genetics into field-specific decisions on variety, sowing date, density, fertiliser, water, pest control and harvest (Gebbers and Adamchuk, 2010; Balafoutis et al., 2017; Basso and Antle, 2020).

This review has three aims. First, it synthesises evidence on sensing and AI, genome editing, and precision nutrient, water and pest management, and their effects on yield, stability, efficiency, economics and the environment. Second, it explains why integration outperforms isolated technologies, and where data, biological, institutional and social constraints limit impact. Third, it proposes a Sense-Learn-Edit-Manage-Deliver framework that links biological innovation to digital innovation and to delivery systems that farmers can use. The review is global in scope, draws on meta-analyses, systematic reviews, field trials and modelling studies, and gives equal weight to high-income commercial systems and smallholder systems in Africa, Asia and Latin America, where the need is greatest and the delivery challenge is hardest.

2. Sensing and Learning: Remote Sensing, IoT and Artificial Intelligence

Modern agronomy begins with observation. Satellite platforms such as Sentinel-2 and Landsat provide multispectral imagery that can be used to estimate leaf area, chlorophyll, biomass, nitrogen status and water stress (Weiss et al., 2020). Unmanned aerial vehicles add thermal, hyperspectral and LiDAR data at field scale, enabling detection of early disease, nutrient deficiency, waterlogging and weed patches before they are visible to the eye (Sharma et al., 2024). Ground sensors measure soil moisture, temperature, electrical conductivity and nutrient ions, while weather stations and Internet-of-Things devices record microclimate, irrigation flow and machinery operations (Wolfert et al., 2017; FAO, 2022). Together, these sources create a digital representation of the field that can be updated daily or even hourly.

Machine learning is the engine that turns observation into decision. Convolutional neural networks classify disease and weed images with high accuracy, recurrent networks and transformers model temporal patterns in weather and growth, and ensemble models combine satellite, soil, weather and management data to predict yield (Kamilaris and Prenafeta-Boldu, 2018; Jin et al., 2021). In tree-crop and cereal systems, machine-learning yield prediction has achieved accuracy ranging from 50 to 99 percent depending on crop, data quality, lead time and validation design, with the best results coming from multi-source models validated across locations and seasons. Figure 1 summarises reported performance across major AI applications in agronomy. The pattern is clear: disease and weed identification, where images are rich and labels are abundant, perform best, while yield prediction and nitrogen management, where weather and management interact in complex ways, remain harder.

The most important lesson from the AI literature is that data quality, representativeness and validation matter more than algorithm choice. A model trained on irrigated wheat in one region will not transfer automatically to rainfed maize in another, or to a different variety, soil or season (Jin et al., 2021; Weiss et al., 2020). Models trained on data from large, well-resourced farms may systematically underperform for small, intercropped, heterogeneous fields that are under-represented in training data. Explainable AI, uncertainty quantification, and local calibration with farmer observations and on-farm

trials are therefore essential, not optional. When AI is embedded in advisory systems that are localised, timely and linked to input access, it can change decisions. When it is a black box, disconnected from markets or based on biased data, it will be ignored or will mislead.

Figure 1. Reported performance of AI applications in agronomy

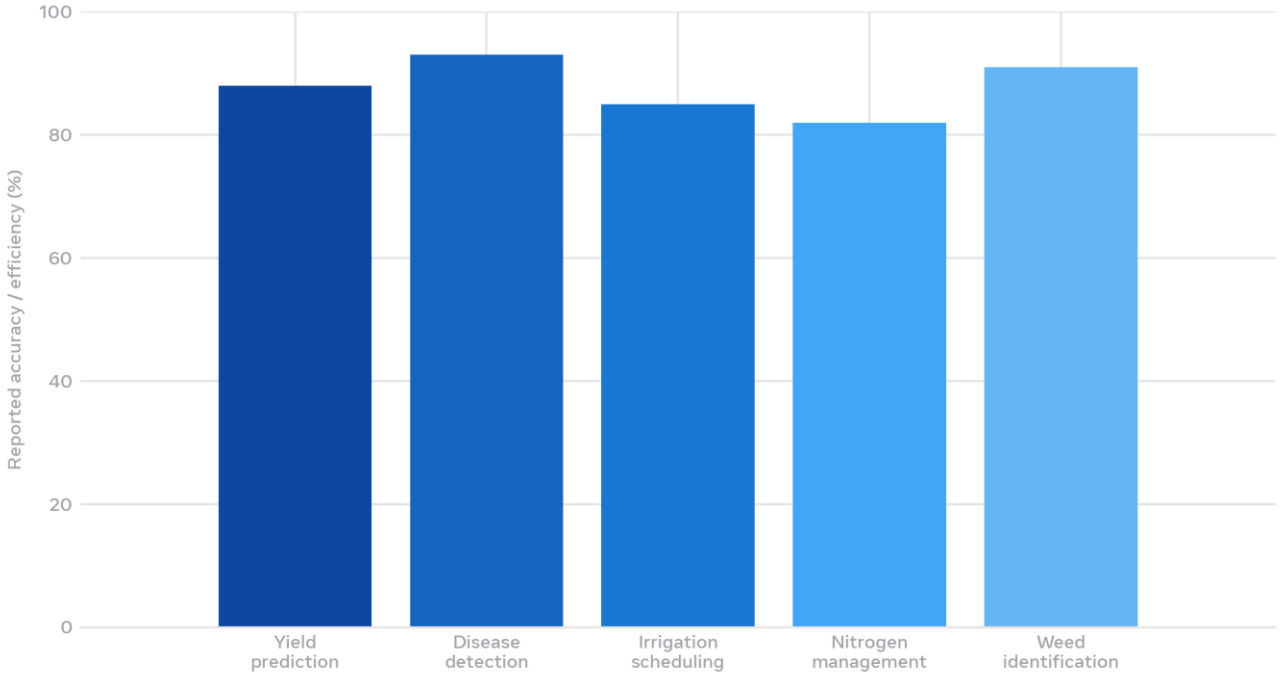

Figure 1. Reported accuracy and efficiency across major AI applications, synthesised from the reviews cited in Section 2.

3. Editing and Breeding: CRISPR and Climate-Resilient Traits

Genome editing has transformed crop improvement by allowing precise, predictable changes to specific genes without necessarily introducing foreign DNA (Chavhan et al., 2025; Kumar et al., 2023). CRISPR-Cas9 creates targeted double-strand breaks that can knock out susceptibility genes or modify regulatory regions. Base editors change single nucleotides, enabling fine-tuning of protein function. Prime editors can write short, precise edits. These tools complement conventional breeding and marker-assisted selection by shortening the time from trait discovery to improved variety, and by enabling changes that would be difficult to achieve through crossing alone (Hickey et al., 2019; Bailey-Serres et al., 2010).

Climate-resilient traits are the most urgent target. Editing transcription factors in the DREB, NAC, MYB, WRKY and bHLH families can improve drought and heat responses by regulating osmotic adjustment, antioxidant defence and stomatal behaviour (Chavhan et al., 2025; Zhu, 2016). Editing transporter and ion-homeostasis genes, such as SOS and NHX families, can improve salinity tolerance. Knocking out susceptibility genes, such as MLO for powdery mildew and ERF922 for rice blast, can confer broad-spectrum disease resistance without continuous fungicide use (Kumar et al., 2023; Raza et al., 2022). Editing genes that control root architecture, such as DRO1, can improve water capture from deep soil layers. Editing genes for nitrogen uptake and assimilation can improve nitrogen-use efficiency, while editing for grain quality, cooking time and micronutrient content can improve nutrition (Dhankher and Foyer, 2018). Figure 2 shows the distribution of edited-trait studies across major stress and efficiency targets, with drought tolerance and disease resistance dominating.

Genotype by environment by management interactions remain central. An edited drought-tolerant variety that performs well under controlled drought may not outperform a local variety under combined heat, low nitrogen and pest pressure in farmers fields (Cairns et al., 2013; Asseng et al., 2015). Pleiotropy, where one gene affects multiple traits, can create trade-offs: a gene that improves drought tolerance by closing stomata may reduce photosynthesis and yield in a good year. Epigenetic regulation, polygenic architecture and soil microbiome interactions add further complexity. High-throughput phenotyping, multi-location trials and on-farm evaluation are therefore needed to validate edited lines under real agronomic conditions. Speed breeding, genomic selection and gene editing together can

accelerate progress, but only if phenotyping and field testing keep pace with genotyping and editing.

Figure 2. Distribution of genome-editing studies by trait target

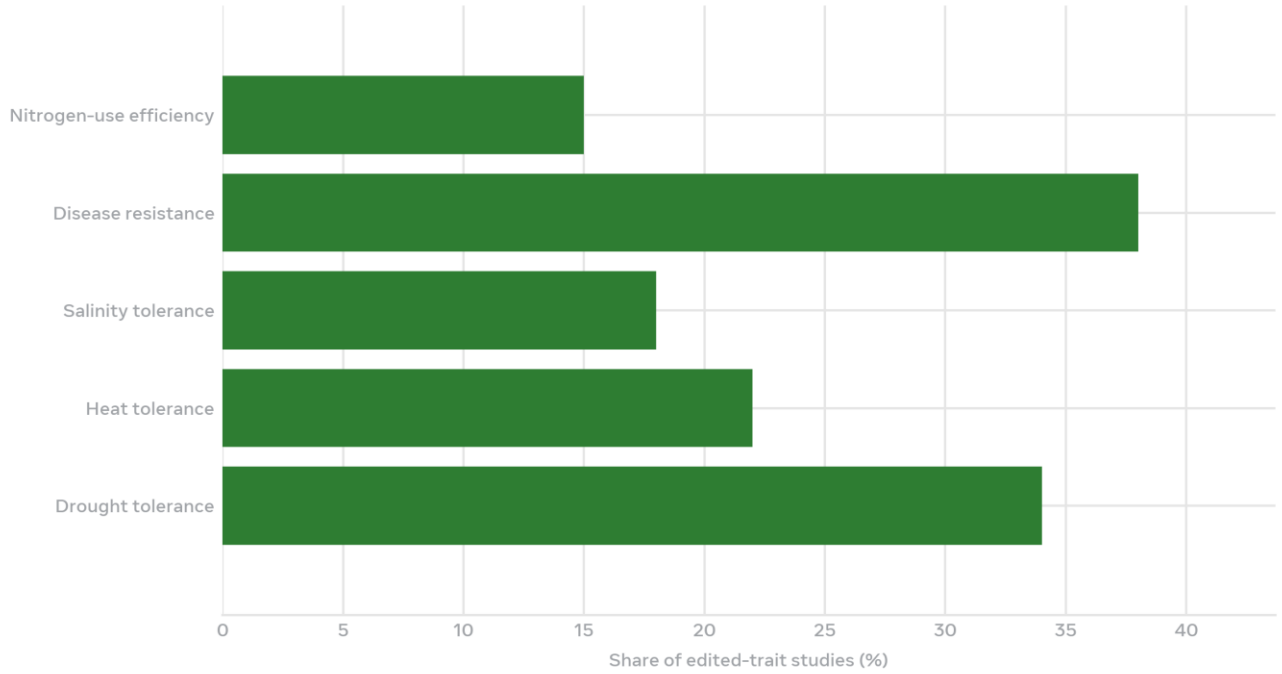

Figure 2. Share of edited-trait studies across drought, heat, salinity, disease and nitrogen-use targets reviewed in Section 3.

4. Precision Nutrient, Water and Pest Management

Nutrient management is where AI, sensing and precision agronomy deliver immediate, measurable gains. Site-specific nutrient management uses soil tests, crop demand, omission trials and increasingly remote sensing and crop models to set field-specific rates and timing (Dobermann et al., 2002; Vanlauwe et al., 2010). In maize, precision nitrogen management based on crop models, remote sensing and machine learning reduced nitrogen rates by 6 to 16 percent and increased nitrogen-use efficiency by 8 to 18 percent while maintaining yield and economic return (Li et al., 2023). Sensor-based nitrogen management in maize and wheat has reduced fertiliser use by 20 to 35 percent in several reviews while sustaining or improving yields. Integrated nutrient management, which combines mineral fertiliser with organic inputs, biological nitrogen fixation and soil pH correction, remains essential because mineral fertiliser alone does not rebuild soil organic matter and organic inputs alone often cannot meet the nutrient demand of high-yielding crops (Sutton et al., 2013; Vanlauwe et al., 2010). Table 1 organises precision technologies by their sensing, decision and application functions.

Water management shows even larger gains. AI-driven irrigation, which combines soil-moisture sensors, weather forecasts, satellite evapotranspiration and machine-learning scheduling, has achieved water savings of 30 to 50 percent and yield improvements of 20 to 30 percent in a recent systematic review and meta-analysis (Zhang et al., 2024). Alternate wetting and drying in rice, drip irrigation, deficit irrigation and rainwater harvesting each have a role, depending on crop value, water price, energy cost, soil and farmer capacity. The key is not the technology alone, but the decision rule: when to irrigate, how much, and how to adjust for rainfall, crop stage and soil moisture. Digital scheduling that is linked to reliable water supply and to maintenance support outperforms hardware alone.

Pest, disease and weed management are being transformed by image-based detection, forecasting models and variable-rate application. Early detection allows targeted, timely control, reducing pesticide use and slowing resistance development. Push-pull systems, resistant varieties, biological control and cultural practices remain the foundation of integrated pest management, and AI can strengthen them by improving monitoring, forecasting and threshold-based decisions (Khan et al., 2014). In weed management, AI-guided spot spraying can reduce herbicide use substantially by spraying only where

weeds are detected, rather than the whole field. The risk is over-reliance on chemical control and on models trained on limited pest populations. Integrated, ecologically grounded pest management, supported by digital tools, is more durable than digital control alone.

Table 1. Precision technologies: sensing, decision and application functions

Function	Sensing and data	Decision tool	Field application
Sensing	Satellite, UAV, soil sensors, weather	Data fusion, calibration	Canopy, soil and weather monitoring
Learning	Multi-source time series	Machine learning, crop models	Yield, disease and nutrient prediction
Actuation	Variable-rate maps	Prescription maps	Variable-rate fertiliser and irrigation
Verification	Yield monitors, sensors	Performance analytics	Outcome, efficiency and profit audit

5. Integration: The Sense-Learn-Edit-Manage-Deliver Framework

The most important finding in this review is that integration outperforms isolation. Sensing without learning produces data, not decisions. Learning without editing leaves the genetic ceiling unchanged. Editing without management means new varieties do not express their potential in farmers fields. Management without delivery means innovations stay on research stations. The Sense-Learn-Edit-Manage-Deliver framework, shown in Figure 3, links these stages into a continuous loop. Sensing collects satellite, UAV, soil, weather and farmer data. Learning builds models that predict yield, stress, nutrient need and irrigation timing. Editing and breeding create varieties matched to those stresses and management systems. Management translates predictions and genetics into field-specific decisions. Delivery ensures that seed, advisories, finance and markets reach farmers, and that farmer feedback returns to improve sensing, models and breeding.

Table 2 presents a practical checklist for designing an integrated programme. It asks what limits yield most, what data and models are available, what traits are needed, what management can be changed, and what delivery systems exist. A programme for rainfed maize in a drought-prone region might combine drought-tolerant edited or bred varieties, soil-moisture sensing, AI-based planting-date and nitrogen advice, legume intercropping and index insurance. A programme for irrigated rice might combine submergence- and salinity-tolerant varieties, alternate wetting and drying, site-specific nitrogen management, disease forecasting and digital advisories. In each case, the components reinforce one another, and the whole is greater than the sum of its parts.

Integration also creates new research opportunities. Phenotyping data from precision fields can feed genomic selection and gene-editing target discovery. Model predictions can guide trial design, reducing the number of locations and seasons needed to validate a new variety. Farmer-generated data, with consent and privacy protection, can improve model transferability to heterogeneous smallholder fields. Digital twins, which simulate a field or farm under different weather and management scenarios, can help test combinations before they are deployed. These opportunities require open data standards, interoperable platforms and collaboration across disciplines that have traditionally worked apart: genetics, agronomy, data science, engineering, economics and social science.



Figure 3. The five-stage framework linking sensing to delivery, applied in Section 5.

Table 2. Checklist for designing an integrated AI, editing and precision agronomy programme

Question	What to assess	Why it matters
What limits yield?	Soil, climate, pests, markets	Targets the binding constraint
What data exist?	Satellite, sensors, trials	Determines model feasibility
What traits are needed?	Stress profile, farmer traits	Guides editing and breeding
What can be managed?	Water, nutrients, pests	Defines precision options
What delivery exists?	Seed, advisory, finance	Ensures adoption and equity

6. Adoption, Equity, Regulation, Economics and Risk

Adoption is the decisive test of innovation. A technology that works in a trial but is not adopted has not yet solved the problem (Giller et al., 2021; Pretty et al., 2018). Adoption depends on perceived benefit, risk, cost, labour, complexity, compatibility with existing systems, and access to inputs, credit, extension and markets. Digital tools face additional barriers: connectivity, device access, digital literacy, language, trust and data privacy. Genome-edited crops face regulatory divergence: some jurisdictions regulate edited crops as conventional varieties when no foreign DNA remains, others apply GMO-style regulation, and still others are revising frameworks (Chavhan et al., 2025). This divergence affects trade, seed development, investment and farmer access, and it creates uncertainty that disproportionately harms public-sector breeding for orphan crops and smallholder systems.

Equity must be designed in, not assumed. Women farmers, youth, tenants and remote smallholders often face the greatest constraints in land, credit, extension and digital access, even though they provide a large share of agricultural labour (Giller et al., 2021). If AI models are trained on data from large farms, advisories are delivered only in one language or on expensive phones, or edited seed is priced for commercial growers, inequalities will widen. Participatory design, gender-responsive extension, affordable pack sizes, local-language advisories, community-based seed systems and farmer data rights are essential. Trust is also critical: farmers will not follow a model they do not understand, use seed they do not trust, or share data they fear will be used against them. Transparent, explainable, locally validated systems build trust; opaque, extractive systems destroy it.

Economics must be calculated from the farmers perspective. Partial budgets that include seed, fertiliser, water, energy, labour, machinery, data and subscription costs, as well as risk and yield variance, are more informative than yield alone. AI-driven irrigation and precision nitrogen can save inputs and raise profit, but only if hardware, connectivity and service costs are affordable and if savings are not offset by higher fixed costs (Balafoutis et al., 2017; Zhang et al., 2024). Genome-edited seed may command a premium, but it must deliver a clear, stable benefit in farmers fields to justify that premium. Public investment, blended finance, insurance and time-bound subsidies can help farmers take on the short-term risk of trying a new system, but subsidies should support learning and market development, not permanent dependence.

7. Conclusions and Future Research Priorities

This review concludes that artificial intelligence, genome editing and precision agronomy together offer a credible pathway to climate-resilient, productive and sustainable crop production, but that their impact is conditional on integration, validation and inclusive delivery (Chavhan et al., 2025; Basso and Antle, 2020; Pretty et al., 2018). Where sensing, learning, editing, management and delivery are linked, the evidence shows higher and more stable yields, substantial water and nitrogen savings, improved stress tolerance and disease resistance, and reduced environmental losses. Where they are developed in isolation, or where data, seed, finance and trust are missing, even powerful technologies can disappoint or widen inequality.

Future research should prioritise five areas. First, robust, multi-location, multi-season validation of AI models and edited varieties under farmers management, including for orphan crops, pulses, roots and vegetables that matter for nutrition. Second, low-cost, low-connectivity sensing and advisory tools that work for smallholders, with local languages, explainable recommendations and farmer feedback loops. Third, systems research on genotype by environment by management interactions, including soil health, microbiome and intercropping, to ensure that new varieties and digital tools work together. Fourth, rigorous studies of adoption, equity, data governance, regulation and scaling, including gender, youth, tenure and collective action. Fifth, integrated modelling and monitoring that link field, farm, landscape and food-system outcomes, so that agronomic, economic, climate, nutrition and biodiversity outcomes can be judged together (IPCC, 2022; FAO, 2022). Agronomy has always been an integrative science. Its next advance will come from integrating biological and digital innovation with farmer knowledge and inclusive institutions.

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Conflict of Interest

The authors declare no conflict of interest.

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