



ARTIFICIAL INTELLIGENCE AND REMOTE SENSING TECHNOLOGIES IN SMART AGRICULTURE: RECENT ADVANCES, APPLICATIONS, CHALLENGES, AND FUTURE PERSPECTIVES

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ABSTRACT

Artificial intelligence (AI) and remote sensing technologies have emerged as a transformative tool for addressing the growing challenges of global food security, climate change, resource scarcity, and sustainable agricultural production. The integration of machine learning, deep learning, Internet of Things (IoT) devices, unmanned aerial vehicles (UAVs), satellite remote sensing, and advanced sensor networks has significantly improved the efficiency, accuracy, and automation of agricultural management through data-driven decision-making. This review critically examines recent advances in AI-enabled remote sensing technologies and their applications in smart agriculture, including crop monitoring, yield prediction, disease and pest detection, precision irrigation, nutrient management, weed identification, and climate risk assessment. The review further evaluated the integration of AI algorithms with multisource remote sensing data for precision agriculture and highlights emerging technologies such as explainable artificial intelligence (XAI), edge AI, digital twins, federated learning, and autonomous agricultural systems. In addition, the paper discussed major technical, economic, and institutional barriers limiting large-scale adoption, particularly in developing countries, including inadequate digital infrastructure, high implementation costs, limited technical expertise, poor data interoperability, and concerns regarding data governance and privacy. Finally, the review identifies current research gaps and proposes future research directions to enhance the accessibility, scalability, and sustainability of AI-driven smart agriculture. The findings demonstrated that, although AI and remote sensing technologies are reshaping modern agricultural systems, their successful implementation will require interdisciplinary collaboration, supportive policies, affordable technological innovations, and improved capacity building to ensure sustainable and climate-resilient food production worldwide.

Keywords: Artificial, Intelligence; Remote, Sensing; Smart, Agriculture.

INTRODUCTION

Feeding a global population expected to near 10 billion by 2050 is already a tall order, and doing it while shrinking agriculture's environmental footprint makes the challenge even steeper. The FAO has been clear that production needs to rise substantially in the coming decades, but the old playbook — uniform management, decisions made largely by eye and experience — simply wasn't built for farming systems this variable and this complex (FAO, 2022; IPCC, 2022). Climate change hasn't made things easier. Droughts, floods, heat waves, pest outbreaks, rainfall that no longer follows any predictable pattern — all of it chips away at productivity and raises the stakes for farmers, especially in developing regions where rain-fed agriculture and thin technological infrastructure leave little room for error (IPCC, 2022). At the same time, decades of heavy fertilizer use, pesticide application, and irrigation have taken their own toll: degraded soils, polluted waterways, rising emissions, and biodiversity loss. Between the two pressures, the case for climate-smart, sustainable practices has never been more urgent (Basso & Antle, 2020). Digital technology has started to shift how farming actually gets done. What used to run on tradition and gut instinct is increasingly running on data. Agriculture 4.0 — the umbrella term for this shift — has pulled artificial intelligence, remote sensing, robotics, cloud computing, IoT devices, big data, and autonomous machinery into the day-to-day of farm management. The result is that growers can now track crop growth, soil conditions, weather variables,



and field operations more or less continuously, which sharpens both the precision and the sustainability of the decisions they make (Javaid *et al.*, 2022; Saiz-Rubio & Rovira-Más, 2020).

Two technologies sit at the center of this shift: AI and remote sensing. AI gives machines the ability to work through enormous, messy agricultural datasets — spotting patterns, generating predictions, and increasingly making decisions with minimal human input — through machine learning, deep learning, computer vision, and predictive analytics. Remote sensing, meanwhile, covers everything from satellites and UAVs to airborne sensors, hyperspectral cameras, LiDAR, and ground-based sensor networks, all feeding back continuous, high-resolution, non-destructive readings on crop health, soil, water status, and vegetation. Put the two together and you get real gains in crop classification, yield forecasting, disease detection, weed identification, irrigation scheduling, nutrient management, and early warning for both abiotic and biotic stress (Benos *et al.*, 2021; Linaza *et al.*, 2021; Zhang *et al.*, 2023). None of this comes cheap or easy, though. Adoption is still held back by high upfront costs, patchy digital infrastructure, datasets that don't talk to each other, sensing platforms with poor interoperability, a shortage of people who know how to run these systems, black-box algorithms, cybersecurity risk, and policy environments that haven't caught up — all of which hit low- and middle-income countries hardest (Klerkx *et al.*, 2019). Add to that the ongoing unease around data ownership, privacy, and how ethically these tools are actually deployed, and it's easy to see why stakeholder buy-in is still uneven. Plenty has been written on AI, remote sensing, and precision agriculture — usually one at a time. What's missing is a synthesis that pulls the three together and reflects where things stand now, including newer developments like explainable AI, foundation models, edge computing, digital twins, and multimodal sensing platforms, none of which existing reviews have really caught up with yet.

This review sets out to close that gap: it draws together recent progress in sensing technology, AI algorithms, and intelligent decision-support systems, weighs current applications against the obstacles to implementation, flags emerging trends, points out where the research still falls short, and lays out where the field needs to go next — toward agricultural systems resilient and data-driven enough to hold up food security as the climate keeps changing.

METHODOLOGY

A structured narrative review approach was adopted to evaluate recent advances in artificial intelligence (AI) and remote sensing applications in smart agriculture. Relevant peer-reviewed articles were retrieved from major databases, including Scopus, Web of Science, ScienceDirect, SpringerLink, IEEE Xplore, Wiley, Taylor & Francis, and MDPI, using keywords related to AI, machine learning, remote sensing, precision agriculture, digital agriculture, UAVs, crop monitoring, and smart farming. Studies published between **2017 and 2026** were considered, with emphasis on recent advances from 2021 onward. Articles focusing on AI applications, remote sensing technologies, and their integration in agricultural systems were included, while irrelevant, duplicate, non-English, and non-peer-reviewed studies were excluded.

The selected studies were analysed thematically, covering smart agriculture development, AI techniques, remote sensing applications, technological challenges, emerging innovations, and future research directions.

Here's the humanized version:

Smart Agriculture: Concepts and Evolution

Smart agriculture is essentially what happens when digital technologies such as; AI, remote sensing, IoT, robotics, data analytics get woven directly into how farms are run, with the goal of squeezing more productivity and sustainability out of the same resources. It builds on precision agriculture but goes further, using interconnected cyber-physical systems to enable real-time monitoring, predictive analytics, and decisions that increasingly make themselves (Wolfert *et al.*, 2017; Klerkx *et al.*, 2019; Javaid *et al.*, 2022).

The move from precision agriculture toward what's now called Agriculture 4.0 didn't happen overnight, it's been pushed along by steady advances in GPS, GIS, IoT, cloud computing, big data, and AI. Together, these tools let farmers keep tabs on crops, soils, weather, and field operations more or



less continuously, and that steady stream of information is what's turning agricultural management from something reactive — responding to problems after they show up — into something predictive.

At its core, smart agriculture leans on a handful of key pieces: AI-based predictive models, remote sensing, IoT monitoring systems, cloud computing, robotics, and decision-support tools. Working together, these underpin better resource management, help farms adapt to a changing climate, and support food production that can actually hold up over time (Ayaz *et al.*, 2019; Wolfert *et al.*, 2017).

Remote Sensing Technologies in Smart Agriculture

Remote sensing has earned its place as one of the backbone technologies of smart agriculture, largely because it offers a way to monitor crops, soils, and environmental conditions quickly, non-destructively, and at scale. Pair it with AI, and it becomes even more useful — powering crop monitoring, yield prediction, disease detection, irrigation management, and precision farming more broadly (Mulla, 2018; Kamlaris & Prenafeta-Boldú, 2018; Benos *et al.*, 2021).

The platforms used for agricultural remote sensing generally fall into three categories — satellite, UAV, and ground-based — and each brings its own trade-offs in terms of spatial resolution, how often data can be collected, and how flexible the system is to operate.

Satellite-Based Remote Sensing

Satellite remote sensing provides continuous observations of agricultural landscapes through multispectral, hyperspectral, thermal, and radar imagery. Platforms such as Sentinel-1, Sentinel-2, Landsat, and MODIS support crop classification, biomass estimation, drought monitoring, and yield prediction (Drusch *et al.*, 2012).

Vegetation indices, including NDVI, EVI, SAVI, and NDWI, are widely used to assess crop vigour, water status, and vegetation dynamics (Xue & Su, 2017). However, limitations such as cloud interference, spatial resolution constraints, and challenges in monitoring smallholder farms remain significant. Recent advances in AI-based data fusion and image processing are improving the accuracy and availability of satellite-derived agricultural information (Zhang *et al.*, 2023).

UAV-Based Remote Sensing

Drones have become one of the more flexible tools in precision agriculture, largely because they can fly low, fly often, and capture imagery at a resolution satellites simply can't match. Fitted with RGB, multispectral, hyperspectral, thermal, or LiDAR sensors, UAVs let growers zoom in on crop health, catch nutrient deficiencies early, spot disease symptoms, track weed pressure, and check how well irrigation is actually performing across a field (Tsouros *et al.*, 2019; Zhang & Kovacs, 2019).

Where this really starts to pay off is when UAV imagery is fed into AI models — convolutional neural networks and other computer vision approaches have made it possible to automate disease detection and support decisions right down to the field level (Ferentinos, 2018; Benos *et al.*, 2021). That said, drones aren't a perfect solution. Battery life is still limited, regulations around flight vary and can be restrictive, bad weather grounds them entirely, and the operational costs add up quickly.

Ground-Based Sensing Technologies

Ground-based sensors take a different approach: instead of periodic flyovers, they sit in the field and measure soil moisture, temperature, nutrients, crop conditions, and weather continuously. This steady stream of real-time data is really what makes IoT-enabled agriculture possible in the first place — it's the raw material AI systems need to actually analyze and act on (Ayaz *et al.*, 2019).

The trade-off is that while ground sensors are excellent for capturing fine-grained changes over time, they come with real costs — installation, calibration, ongoing maintenance, powering the units, and keeping communication infrastructure running. Those costs are exactly why uptake has been slower in developing agricultural systems, where that kind of infrastructure often isn't in place yet.

Emerging Remote Sensing Technologies

Newer sensing technologies are pushing agricultural monitoring well beyond what was possible even a few years ago. Hyperspectral imaging can pick up fine-grained detail on plant physiology that ordinary cameras simply miss. LiDAR adds a three-dimensional layer, mapping crop structure rather than just a flat image. Thermal infrared sensing has gotten much better at catching water stress before it becomes visible to the eye, and synthetic aperture radar has the distinct advantage of working straight

through cloud cover, which matters a lot in regions where clear skies aren't guaranteed (Benos *et al.*, 2021).

Where all this is heading, most likely, is toward systems that don't rely on just one sensing platform but stitch several together — hyperspectral, LiDAR, thermal, SAR — and run the combined data through AI-driven analytical frameworks. The end goal is something close to a full digital representation of the farm itself, one detailed enough to sharpen prediction accuracy and genuinely support more sustainable farming decisions.

Table 1: Comparison of Major Remote Sensing Technologies Used in Smart Agriculture

Remote sensing technology	Major agricultural applications	Advantages	Limitations	Key references
Satellite Remote Sensing (e.g., Sentinel-2, Landsat-8/9, MODIS)	Crop classification, crop health monitoring, drought assessment, yield prediction, land-use mapping	Large-area coverage, long-term monitoring, frequent revisit time, relatively low operational cost	Cloud contamination for optical sensors, moderate spatial resolution, lower effectiveness for smallholder farms	Mulla (2018); Zhang <i>et al.</i> (2019); Li <i>et al.</i> (2020); Benos <i>et al.</i> (2021)
UAV (Drone)-Based Remote Sensing	Disease detection, weed mapping, nutrient deficiency assessment, precision spraying, crop phenotyping	Ultra-high spatial resolution, flexible data acquisition, rapid deployment, site-specific monitoring	Limited flight duration, weather dependence, regulatory restrictions, relatively high operational costs	Tsouros <i>et al.</i> (2019); Zhang & Kovacs (2019); Ferentinis (2018); Benos <i>et al.</i> (2021)
Ground-Based IoT Sensors	Soil moisture monitoring, irrigation scheduling, nutrient monitoring, environmental monitoring	Continuous real-time data collection, high measurement accuracy, supports automated farm management	Installation and maintenance costs, sensor calibration, limited spatial coverage	Ayaz <i>et al.</i> (2019); Ojha <i>et al.</i> (2019); Talaviya <i>et al.</i> (2020)
Thermal Infrared Imaging	Water stress detection, irrigation management, disease monitoring, canopy temperature assessment	Early detection of plant water stress, improved irrigation efficiency	Environmental sensitivity, expensive thermal sensors, requires calibration	Mahlein (2016); Li <i>et al.</i> (2020)
LiDAR (Light Detection and Ranging)	Canopy architecture analysis, biomass estimation, plant height measurement, orchard management	Accurate three-dimensional (3D) structural information, high measurement precision	High equipment cost, complex data processing, limited affordability for smallholders	Zhang <i>et al.</i> (2019); Li <i>et al.</i> (2020)
Synthetic Aperture Radar (SAR)	Soil moisture estimation, flood mapping, crop monitoring under cloudy conditions	Operates day and night, penetrates cloud cover, suitable for tropical regions	Speckle noise, specialized image processing, interpretation complexity	Zhang <i>et al.</i> (2019); Li <i>et al.</i> (2020)

Artificial Intelligence Applications in Smart Agriculture

Artificial intelligence has quickly become one of the main engines behind smart agriculture, largely because it can turn raw, scattered data into decisions that actually make sense. AI systems pull together information from remote sensing platforms, UAVs, IoT devices, weather stations, and on-farm sensors, and use it to sharpen crop management, squeeze more efficiency out of limited resources, and push farming toward something more sustainable (Benos *et al.*, 2021; Linaza *et al.*, 2021; Javaid *et al.*, 2022).

The toolkit here is broad — machine learning, deep learning, computer vision, and a handful of related techniques — and it's been put to work on everything from yield prediction and disease



detection to weed identification, irrigation optimization, soil assessment, livestock monitoring, and climate adaptation. None of this would work nearly as well without the parallel progress happening in big data analytics, cloud and edge computing, and higher-resolution sensing, all of which feed directly into how effective these AI models can be (Liakos *et al.*, 2018; Benos *et al.*, 2021).

Machine Learning Applications

At its simplest, machine learning gives computers a way to sift through agricultural data, pick out patterns humans might miss, and turn those patterns into predictions useful for precision farming. A handful of supervised learning algorithms show up again and again in the literature — Random Forest, Support Vector Machine, Artificial Neural Networks, Decision Trees, and Gradient Boosting — mostly for crop classification, yield forecasting, disease diagnosis, and estimating soil properties (Liakos *et al.*, 2018; Benos *et al.*, 2021).

Random Forest tends to be the go-to choice, and for good reason: it holds up well against nonlinear relationships and handles agricultural data pulled from multiple sources without much fuss. Support Vector Machine still has its place too, particularly for crop classification and disease detection when the dataset available is on the smaller side. And when the task calls for squeezing out extra predictive performance, ensemble methods like XGBoost and LightGBM have become the preferred option for more complex agricultural problems (Benos *et al.*, 2021; Linaza *et al.*, 2021).

That said, conventional machine learning isn't without its limits. It generally depends on features being extracted by hand, which becomes a real bottleneck once the datasets involved are large-scale imagery or multispectral data — and that limitation is a big part of why deep learning has been gaining ground.

Table 2. Comparison of Common Machine Learning Algorithms in Smart Agriculture

Algorithm	Major applications	Advantages	Limitations	Representative references
Random Forest (RF)	Yield prediction, crop classification, soil property estimation	High accuracy, resistant to overfitting, handles nonlinear data	Reduced interpretability; performance may decline with highly imbalanced datasets	Liakos <i>et al.</i> (2018); Benos <i>et al.</i> (2021)
Support Vector Machine (SVM)	Disease diagnosis, crop classification, weed detection	Effective with small datasets; high classification accuracy	High computational cost for large datasets; parameter tuning required	Liakos <i>et al.</i> (2018); Kamilaris & Prenafeta-Boldú (2018)
Decision Tree (DT)	Crop management decisions, land suitability analysis	Simple, interpretable, fast	Susceptible to overfitting when used alone	Benos <i>et al.</i> (2021)
Artificial Neural Network (ANN)	Yield prediction, irrigation scheduling, weather forecasting	Captures complex nonlinear relationships	Requires large datasets; limited interpretability	Liakos <i>et al.</i> (2018); Linaza <i>et al.</i> (2021)
XGBoost / Gradient Boosting	Yield prediction, climate-risk modelling, precision irrigation	High predictive performance, efficient computation	Hyperparameter tuning can be complex	Linaza <i>et al.</i> (2021); Javaid <i>et al.</i> (2022)

Deep Learning Applications

Deep learning takes machine learning a step further — instead of relying on hand-crafted features, these multilayer neural networks learn directly from raw images and data, pulling out complex patterns on their own. That shift has made a real difference in agricultural analysis, particularly for image recognition tasks where conventional methods used to struggle (Kamilaris & Prenafeta-Boldú, 2018).

Convolutional neural networks, in particular, have become something of a workhorse in agricultural computer vision — showing up in plant disease detection, weed identification, crop



classification, fruit counting, and nutrient assessment, drawing on UAV, satellite, and ground-level imagery alike (Ferentinos, 2018; Benos *et al.*, 2021). More recently, object detection models like YOLO, Faster R-CNN, and EfficientDet have pushed things further still, making it possible to spot weeds, pests, and diseases in real time — which in turn is what makes precision spraying and other automated operations feasible.

There's also a newer wave of transformer-based models, Vision Transformer and Swin Transformer among them, that handle complex agricultural imagery a bit differently, picking up on spatial relationships across the whole image rather than just local patterns. The catch is that they're computationally hungry and need a lot of annotated data to train properly, which limits how widely they've been adopted so far.

And accuracy aside, deep learning models still carry a well-known drawback: they're largely black boxes. It's often unclear why a model reached a particular conclusion, and that opacity is a real problem when farmers and agronomists are being asked to trust — and act on — the output. That's part of what's driving growing interest in Explainable AI, which aims to make these systems more transparent and easier to trust.

Integration of Artificial Intelligence and Remote Sensing Technologies in Smart Agriculture

Bring AI and remote sensing together and what you get is something closer to an intelligent decision-support system than a simple monitoring tool. Satellites, UAVs, and IoT sensors supply the raw spatial and temporal data at scale, while AI algorithms do the work of turning that data into something farmers can actually act on — for precision management, better resource use, and more sustainable production overall (Li *et al.*, 2020; Benos *et al.*, 2021; Javaid *et al.*, 2022).

This pairing supports ongoing monitoring of crop growth, soil conditions, water availability, pests, disease, and environmental stress. Machine learning and deep learning models are what make sense of it all — spotting hidden patterns, classifying crop conditions, forecasting outcomes, and flagging management actions early enough to matter. It's this shift, from reacting to problems after the fact to anticipating them beforehand, that really defines modern agricultural decision-making (Kamilaris and Prenafeta-Boldú, 2018; Linaza *et al.*, 2021).

Broadly, the AI-remote sensing pipeline follows a familiar path: data gets collected, then preprocessed and fused, then analyzed with AI, and finally translated into decision support. From there, it feeds directly into precision irrigation, fertilizer planning, pest control, yield forecasting, and assessing climate risk.

AI-Assisted Crop Health Monitoring

One of the more valuable applications is catching problems before they're visible to the naked eye crop stress, nutrient deficiencies, disease, pest damage through satellite and UAV imagery. Convolutional neural networks, in particular, have gotten quite good at reading spectral and visual signals early, often well before symptoms would otherwise show up in the field (Mahlein, 2016; Ferentinos, 2018).

Precision Irrigation and Water Management

On the irrigation side, AI and remote sensing work together by pulling in satellite imagery, thermal readings, weather data, and soil moisture measurements to estimate how much water a crop actually needs. Machine learning models process vegetation indices, canopy temperature, and other environmental variables to fine-tune irrigation schedules and cut down on water that would otherwise go to waste (Talaviya *et al.*, 2020; Linaza *et al.*, 2021).

Yield Prediction and Crop Productivity Assessment

Forecasting yield has also improved considerably by combining remote sensing data with weather variables, soil characteristics, and historical records. Algorithms like Random Forest, Artificial Neural Networks, Gradient Boosting, and LSTM networks are particularly good at untangling the complex relationships between environmental conditions and how a crop actually performs (Liakos *et al.*, 2018; Benos *et al.*, 2021).

Weed, Pest, and Disease Detection

Crop protection has become considerably more automated too. UAV imagery, run through deep learning models such as CNNs, YOLO, and Faster R-CNN, can now flag weeds, pests, and diseases



with real accuracy — which opens the door to targeted pesticide application instead of blanket spraying, cutting both chemical use and crop losses (Ferentinos, 2018; Benos *et al.*, 2021).

Variable-Rate Technology and Precision Input Management

Finally, this same AI–remote sensing combination underpins variable-rate technology, generating spatial maps that guide exactly where fertilizer, irrigation, pesticide, or soil amendments should go. By analyzing satellite and UAV data, machine learning can identify distinct management zones within a field and direct GPS-guided machinery to apply inputs precisely where they're needed — boosting productivity while keeping environmental impact in check (Finger *et al.*, 2019; Basso & Antle, 2020).

Table 3: Major Applications of AI–Remote Sensing Integration in Smart Agriculture

Application	AI techniques	Remote sensing data source	Major benefits	Representative references
Crop health monitoring	CNN, Random Forest	UAV multispectral imagery, Sentinel-2	Early stress detection, improved crop monitoring	Ferentinos (2018); Benos <i>et al.</i> (2021)
Yield prediction	ANN, Random Forest, XGBoost, LSTM	Satellite imagery, weather, soil data	Accurate production forecasting, harvest planning	Liakos <i>et al.</i> (2018); Linaza <i>et al.</i> (2021)
Disease detection	CNN, YOLO, Faster R-CNN	UAV RGB and hyperspectral imagery	Early disease diagnosis, reduced crop losses	Ferentinos (2018); Kamilaris & Prenafeta-Boldú (2018)
Precision irrigation	Machine learning, ANN	Thermal imagery, soil moisture sensors, IoT	Improved water-use efficiency	Talaviya <i>et al.</i> (2020); Javaid <i>et al.</i> (2022)
Weed detection	YOLO, CNN	UAV imagery	Reduced herbicide application	Benos <i>et al.</i> (2021)
Variable-rate fertilizer application	Random Forest, Decision Support Systems	Satellite and UAV imagery	Optimized fertilizer use, reduced environmental pollution	Finger <i>et al.</i> (2019); Basso & Antle (2020)
Climate risk assessment	Machine learning, LSTM	Weather, satellite, climate datasets	Improved adaptation and resilience	Linaza <i>et al.</i> (2021); Javaid <i>et al.</i> (2022)

Source: Adapted and synthesized from Finger *et al.* (2019); Basso and Antle (2020); Talaviya *et al.* (2020); Benos *et al.* (2021); Linaza *et al.* (2021); Javaid *et al.* (2022).

Critical Discussion and Opportunities of AI-Driven Smart Agriculture

For all the progress AI-integrated remote sensing has brought to agricultural monitoring, the challenges haven't gone away. Most AI models are only as good as the data they're trained on, and that data tends to be limited, patchy, and skewed toward certain regions. A model trained under one set of agroecological conditions can lose a lot of its accuracy the moment it's applied somewhere with different climate, soil, crops, or management practices. Closing that gap — building AI models that generalize well, stay interpretable, and actually transfer across different farming systems, especially in developing countries — is arguably where future research needs to focus.

Improved Crop Productivity and Yield Optimization

One of the clearer wins from AI-driven agriculture is better yield outcomes, achieved largely through predictive modeling and smarter farm-level decisions. Machine learning algorithms work through remote sensing data, weather patterns, soil properties, and past yields to figure out what's actually driving crop performance. Models like Random Forest, Support Vector Machines, Artificial Neural Networks, and gradient boosting have made yield prediction noticeably more reliable, which in turn helps farmers make better calls on planting, input use, and when to harvest (Liakos *et al.*, 2018; Benos *et al.*, 2021).



Efficient Resource Management and Sustainable Input Use

AI-based decision-support systems are also proving useful for tightening up how water, fertilizer, and pesticides get used, by pulling together remote sensing, IoT sensor data, and environmental information. That combination enables precision irrigation, variable-rate fertilizer application, and inputs targeted only where they're needed — which cuts costs, reduces waste, and eases the environmental burden all at once (Basso & Antle, 2020; Talaviya *et al.*, 2020).

Early Detection of Crop Diseases and Pests

Catching problems early is another area where AI has made a real difference. Image analysis powered by AI, combined with UAV and satellite data, can flag diseases, pests, and crop stress well before they'd otherwise be noticed. Convolutional neural networks in particular have shown strong accuracy in recognizing plant disease, and that early warning supports more targeted crop protection — less pesticide, fewer losses (Ferentinos, 2018; Kamilaris & Prenafeta-Boldú, 2018).

Climate-Smart Agriculture and Environmental Resilience

AI and remote sensing also have a role to play in climate adaptation, bringing together climate data, crop information, and environmental observations to anticipate risk and inform how farms respond. That shows up in practice as drought monitoring, better irrigation planning, soil assessment, and crop planning built around climate resilience — all of which feed into a more sustainable system overall.

Automation, Robotics, and Labour Reduction

Automation is reshaping farm operations too — autonomous machinery, robotic harvesting, intelligent weed control, automated monitoring. These tools improve efficiency, cut down on labor needs, and add a level of precision that's hard to match manually. That said, adoption is still far from universal; high costs, infrastructure demands, and the technical know-how required keep many regions on the sidelines for now.

Intelligent Decision Support and Farmer Advisory Services

Decision-support systems built on AI can pull together weather data, satellite imagery, soil information, and crop models to generate practical recommendations — when to plant, how to irrigate, when to fertilize, how to manage pests, what climate risks to watch for. Mobile-based advisory platforms, in particular, hold real promise for smallholder farmers, though affordability, connectivity, digital literacy, and the need for local adaptation remain genuine hurdles.

Challenges and Limitations of AI and Remote Sensing Technologies in Smart Agriculture

Even with all this progress, adoption is still being held back on several fronts — technical, economic, institutional, and social. The recurring barriers are high implementation costs, limited data, questions around model reliability, weak digital infrastructure, cybersecurity risk, and a shortage of technical capacity, particularly across developing countries (Klerkx *et al.*, 2019; Javaid *et al.*, 2022).

Cost and Economic Barriers

UAVs, sensors, computing infrastructure, AI platforms, automated machinery — none of it comes cheap, and that cost alone shuts a lot of smallholder farmers out. Much of what's currently on the market was designed with large-scale commercial farming in mind, which makes it a poor fit economically for farmers working with fewer resources. If adoption is going to be inclusive, the technology needs to get more affordable, scalable, and adapted to local conditions (Klerkx *et al.*, 2019; Javaid *et al.*, 2022).

Data Availability and Quality Challenges

AI is data-hungry — it needs datasets that are large, diverse, and dependable — but agricultural data rarely comes that way. It's usually fragmented, geographically narrow, and shaped by all the variation in climate, soil, crop type, and management practice from one place to the next. Remote sensing data has its own constraints too, from cloud cover to differences between sensors to resolution limits. What's really needed is standardized agricultural databases and open-access data platforms that can help AI models perform better and transfer more reliably across contexts (Kamilaris & Prenafeta-Boldú, 2018; Benos *et al.*, 2021).



Model Accuracy, Transferability, and Interpretability

AI models can be remarkably accurate, but a lot of deep learning systems still function as black boxes — which makes it hard for users to understand, let alone trust, what's driving a given recommendation. Explainable AI is starting to address that gap, aiming to make these systems more transparent and their outputs more reliable. On top of that, models trained under one set of environmental conditions often don't hold up as well elsewhere, which is really the crux of why adaptive, transferable AI models matter so much going forward (Arrieta *et al.*, 2020; Benos *et al.*, 2021).

Digital Infrastructure and Connectivity Limitations

None of this works without the basics being in place — reliable internet, a steady energy supply, cloud computing, functioning communication networks. And in a lot of rural areas, those basics simply aren't there, which shuts farmers out of AI-based agricultural services before they even get a chance to try them, particularly across developing regions. Edge computing, low-power networks, and AI that can run offline are emerging as ways around this, though they're still more promise than widespread practice at this point (Ayaz *et al.*, 2019).

Cybersecurity, Data Ownership, and Privacy Issues

The more digital agriculture becomes, the more questions come up around who actually owns the data, how private it is, and how secure it is. Sensors and AI platforms are generating farm-level data constantly now, and without clear, transparent governance around how that data gets used, farmers are left exposed in ways that matter — both for their privacy and for how responsibly their information ends up being handled (Wolfert *et al.*, 2017; Klerkx *et al.*, 2019).

Skills and Knowledge Gaps

Even the best AI tools are only as useful as the people who know how to use them, and that's where a lot of adoption stalls out. Farmers, extension agents, agricultural professionals — all of them need a baseline of digital skill that isn't always there, and that gap is especially pronounced in developing countries. Getting past this really comes down to investment: digital literacy programs, proper training, stronger extension support (Klerkx *et al.*, 2019).

Ethical and Social Challenges

There's a social dimension to all this too, and it's worth taking seriously. AI-driven agriculture raises real questions about jobs, about who gets access to the technology and who doesn't, and about bias baked into the algorithms themselves. A model trained on a narrow dataset may simply fail to represent the diversity of farming conditions out there, and that risks widening the gap between large commercial operations and smallholder farmers rather than closing it. Going forward, fairness, inclusiveness, transparency, and keeping the farmer at the center of design decisions need to be treated as priorities, not afterthoughts.

Emerging Technologies and Future Directions in AI-Enabled Smart Agriculture

Looking ahead, AI, remote sensing, and digital technology more broadly seem to be converging toward farming systems that are more integrated, more autonomous, and better able to adapt on their own. A handful of emerging technologies stand out as likely drivers of that shift — explainable AI, foundation models, generative AI, digital twins, edge computing, federated learning, and agricultural robotics — each expected to push future systems toward being smarter, more scalable, and more accessible.

Explainable Artificial Intelligence for Transparent Decision-Making

Accuracy alone hasn't been enough to win full trust in AI systems — interpretability is still the sticking point. Explainable AI tries to address that directly, using approaches like SHAP, LIME, feature importance analysis, and various visualization techniques to show what's actually driving a given prediction. In agriculture, that transparency matters: when a system flags crop stress or diagnoses a disease or recommends how to allocate resources, farmers are far more likely to trust — and act on — that recommendation if they can see the reasoning behind it (Arrieta *et al.*, 2020; Gunning *et al.*, 2019).

Generative AI and Large Language Models in Agriculture

Generative AI and large language models open up a different kind of opportunity — one centered less on image analysis and more on advisory and communication. Think intelligent extension support, disease diagnosis through conversation, help interpreting remote sensing data, farmer



education delivered in plain language. Combine that with satellite data, weather information, soil conditions, and expert agricultural knowledge, and an LLM-based system could, in principle, offer recommendations tailored to an individual farm. The catch is reliability — these models can and do produce inaccurate output, so any real-world deployment would need to be tightly integrated with validated agricultural databases and expert systems rather than left to operate on its own.

Foundation Models and Multimodal Artificial Intelligence

Foundation models — trained on enormous, wide-ranging datasets — are opening up a different kind of possibility for agriculture, mainly because they can be adapted across multiple tasks rather than built from scratch for each one: crop classification, land-use mapping, environmental monitoring, climate-risk assessment, and so on. Push this further with multimodal AI, which pulls together satellite imagery, sensor readings, weather data, and existing agricultural knowledge, and you start getting a much fuller picture of how a farming system actually behaves. That said, these models don't come without baggage — they're computationally expensive to run, prone to inheriting bias from their training data, and not always easy to adapt to a specific region's conditions (Jakubik *et al.*, 2023).

Digital Twins for Intelligent Farm Management

Digital twins take a different tack — building a live, virtual mirror of a farm by combining AI, IoT, remote sensing, and real-time analytics. The value is in simulation: being able to test how irrigation, fertilization, or crop management decisions might play out before actually committing to them in the field, and adjusting for climate risk along the way. It's still an emerging area more than an established one, but the direction it's heading — toward farming that's predictive and increasingly autonomous — looks promising (Verdouw *et al.*, 2021; Pylaniadis *et al.*, 2021).

Edge AI for Real-Time Agricultural Analytics

Edge AI flips the usual setup around — instead of sending data off to the cloud for processing, the analysis happens right on the device itself, whether that's a sensor, a UAV, a smartphone, or a piece of farm machinery. That local processing cuts out a lot of the lag and the dependency on connectivity, which matters for things like disease detection, smart irrigation, weed identification, and running autonomous machinery in real time. It's a particularly good fit for remote or smallholder farms where reliable connectivity isn't something that can be counted on (Shi *et al.*, 2016; Satyanarayanan, 2017).

Federated Learning for Agricultural Data Sharing

Federated learning solves a fairly specific problem: how do you train AI on data from many different farms without actually moving that raw data anywhere? The answer is to let each dataset contribute to training locally, keeping the underlying information where it started. That makes it a genuinely useful approach for collaborative work — crop disease prediction, yield forecasting, climate adaptation modeling — while sidestepping a lot of the data ownership and privacy concerns that come with more centralized approaches (McMahan *et al.*, 2017; Li *et al.*, 2020).

Robotics, Autonomous Systems, and Agriculture 5.0

What's being called Agriculture 5.0 puts the emphasis back on people — farming built around collaboration between humans and increasingly capable machines, rather than full automation for its own sake. AI-powered robots fitted with computer vision, GPS navigation, and various automation systems are already being developed for planting, spraying, harvesting, weed control, and ongoing crop monitoring. Still, broad adoption isn't happening overnight — the costs are high, the maintenance demands are real, safety concerns haven't been fully worked out, and adapting these systems to the sheer diversity of farming environments out there remains a genuine challenge (Saiz-Rubio & Rovira-Más, 2020; Shamshiri *et al.*, 2018).



Table 4: Emerging Technologies Shaping the Future of Smart Agriculture

Emerging technology	Principle	Potential agricultural applications	Key benefits	Major challenges
Explainable AI (XAI)	Makes AI decisions understandable	Crop diagnosis, yield prediction, decision support	Improves trust and transparency	Balancing accuracy and interpretability
Generative AI and LLMs	Generates and interprets human-like information	Digital extension services, agricultural assistants	Personalized knowledge delivery	Accuracy verification and hallucination risks
Foundation models	Large-scale pretrained AI models	Remote sensing analysis, crop mapping	Adaptability across multiple tasks	High computational requirements
Digital twins	Virtual representation of physical systems	Farm simulation and optimization	Predictive management	Complex data integration
Edge AI	Local AI processing	UAVs, sensors, autonomous machinery	Real-time decisions without cloud dependence	Limited computing power
Federated learning	Distributed model training	Collaborative agricultural intelligence	Data privacy protection	Communication and coordination challenges
Agricultural robotics	Autonomous intelligent machines	Planting, spraying, harvesting	Reduced labour and improved precision	High investment cost

Source: Synthesized from Gunning *et al.* (2019); Javaid *et al.* (2022); recent developments in AI-enabled digital agriculture.

Research Gaps, Policy Implications, and Future Outlook

For all the ground AI, remote sensing, and digital technology have covered, real gaps remain — around scalability, affordability, data quality, interoperability, governance, and, maybe most persistently, adoption among smallholder farmers. A lot of this comes back to the same underlying problem: AI systems are still leaning on datasets that are fragmented and skewed toward certain regions, which limits how well they translate to farming environments elsewhere. Where research needs to go from here is fairly clear — open, standardized agricultural datasets, better integration across multiple data sources, and AI models built to actually transfer across contexts, whether through transfer learning, multimodal AI, or foundation models. Alongside that, there's a growing case for putting more weight behind affordable, farmer-centered technology, explainable AI, ethical data governance, and digital solutions designed with local realities in mind rather than as one-size-fits-all products (Kamilaris & Prenafeta-Boldú, 2018; Benos *et al.*, 2021; Klerkx *et al.*, 2019; Javaid *et al.*, 2022; Arrieta *et al.*, 2020). None of this happens on its own, though — it needs backing. Governments and other stakeholders have a real role to play: investing in rural digital infrastructure, supporting research that crosses disciplines, improving digital literacy among farmers and extension staff, and pushing policy that actually secures equitable access to AI, protects data, and encourages public–private collaboration (Ayaz *et al.*, 2019; Wolfert *et al.*, 2017). Where all of this seems to be heading, eventually, is Agriculture 5.0 — a stage where AI, robotics, digital twins, advanced sensing, biotechnology, and renewable energy come together to make farming genuinely intelligent, autonomous, and sustainable. But the point of getting there shouldn't be lost along the way: the goal is still better productivity, resources used more carefully, stronger food security, better rural livelihoods, and technology that's actually within reach for every farmer, not just the ones who can already afford it (Saiz-Rubio & Rovira-Más, 2020).

CONCLUSION AND RECOMMENDATION

Bringing AI, remote sensing, IoT, and advanced analytics together is reshaping agriculture into something far more intelligent and predictive than it used to be — sharper crop monitoring, better yield forecasts, smarter resource use, and a real capacity to manage climate risk before it becomes a crisis.



But progress in machine learning, deep learning, and the newer technologies alongside them hasn't erased the underlying obstacles. Data limitations, high costs, weak infrastructure, and a shortage of technical capacity are still very much standing in the way of adoption at scale. Getting past that will take innovation that's genuinely affordable, built around the farmer rather than around the technology, handled ethically, and adapted to local conditions — because that's really what sustainable agriculture, climate resilience, and food security depend on going forward.

In practical terms, that means pushing smart agriculture technologies that people can actually afford and access, backed by dependable data infrastructure, rural connectivity, and AI systems transparent enough to be trusted. It also means investing in capacity building, encouraging collaboration across disciplines, and putting policy in place around data governance and ethical AI that actually holds. And perhaps most importantly, whatever comes next in this space needs to keep smallholder farmers and developing regions at the center — not as an afterthought, but as the starting point for building digital agricultural solutions that are affordable, locally grounded, and genuinely farmer-centered.

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