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Remote sensing and ai-driven innovations in contemporary agriculture and horticulture: A review for crop improvement

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Abstract

Remote sensing (RS) and artificial intelligence (AI) are driving a paradigm shift in modern agriculture and horticulture. This review examines how contemporary sensing platforms (satellites, UAVs, ground sensors) paired with data-driven AI techniques enable precision crop monitoring and management for improved yield and sustainability. We trace the historical development of RS and early AI applications in agricultural science, highlighting key contributors. The main body surveys current methods and technologies: satellite imagery (Landsat, Sentinel, Planet), aerial/drone imaging (RGB, multispectral, hyperspectral, thermal) and ground-based sensors, alongside AI/ML models including machine learning classifiers and deep learning networks. Future directions involve integrating high-resolution sensor networks, IoT, autonomous robotics and advanced AI (e.g. federated learning, explainable AI) to further enhance crop improvement. This exhaustive review provides a global perspective on the state-of-the-art of RS and AI in crop sciences, emphasizing their potential to address yield, resource and sustainability challenges in contemporary agriculture and horticulture.

Keywords: Remote sensing, artificial intelligence, precision agriculture, crop monitoring, yield prediction, horticulture, multispectral imaging, machine learning, vegetation indices, UAVs

Introduction

Global agriculture and horticulture face pressing challenges: feeding a growing population under climate change and resource constraints demands higher productivity, resilience and efficiency. Remote sensing (RS) and AI technologies have emerged as pivotal tools to meet these challenges ^[1]. *Remote sensing* collects data on crops and environments from a distance (satellites, drones, sensors) and has been applied for decades in Earth observation. *Artificial intelligence* (AI), particularly machine learning (ML) and deep learning, enables automated analysis of the vast data produced by RS to extract actionable insights. The fusion of RS and AI supports *precision agriculture* and *precision horticulture*, enabling field-specific management that optimizes inputs (water, fertilizer, pesticides) and maximizes yield while minimizing environmental impact ^[2]. Traditional agriculture relied on manual field scouting and random sampling. By contrast, modern digital agriculture uses sensors to continuously monitor crops in space and time. Advances in spectral imaging allow measurement of plant vigor (e.g. via NDVI), moisture content (e.g. using thermal or radar) and canopy structure (LiDAR) over large areas ^[3]. Simultaneously, AI algorithms analyze complex sensor data to predict crop performance or detect anomalies. This combination allows early warning of stress (drought, disease), detailed mapping of field variability and data-driven decision-making on irrigation, fertilization and pest control. In horticulture, high-value fruit and vegetable crops benefit from fine-scale monitoring (for example, drone-based yield estimation in orchards or automated greenhouse environment control) ^[4].

The use of remote imaging for agriculture has roots before World War II, but accelerated in the mid-20th century. In the 1930s and 1940s, aerial photography from planes became a practical tool for mapping soil types and crop conditions. Visionaries like Professor J. Ralph Shay

(Purdue University) recognised the potential of air and space sensing for agriculture. In 1960, the successful launch of TIROS-1 (Television Infrared Observation Satellite) demonstrated weather observation from space [5]. By 1958, the term “remote sensing” was introduced to describe this emerging discipline. In 1961, a U.S. National Research Council committee on “Aerial Survey Methods in Agriculture” was chaired by Professor Shay, bringing together experts. Early grants by NASA and USDA funded data collection and analysis projects. Robert N. Colwell (UC Berkeley) worked on manual photointerpretation for forests and crops, laying groundwork for image classification [6]. By 1966, Purdue’s Laboratory for Applications of Remote Sensing (LARS) was established (led by Shay, with Dr. K. S. Fu and Dr. David Landgrebe), an interdisciplinary team integrating engineering and plant science. K.S. Fu, a pioneer in pattern recognition, advocated using computer algorithms to analyze spectral data. Landgrebe’s early research pioneered the idea of using spectral signatures (rather than fine spatial detail) to identify vegetation foreshadowing modern multispectral analysis [7]. Simultaneously, artificial intelligence began to influence agricultural data analysis. Early AI research in the 1950s–60s (e.g. Frank Rosenblatt’s Perceptron in 1957) was not initially agricultural. However, by the 1970s–80s, specialists applied machine learning to crop data analysis. For example, Smith *et al.* in the 1980s used pattern recognition to classify crop types from imagery [8]. Guy Fayad, Qingshan Liu and others contributed to the use of neural networks and decision trees in crop yield estimation and disease identification. The field of *precision agriculture* emerged around 1990, integrating GPS and GIS with sensor data, in this era scientists like John L. Bennetts (CSIRO, Australia) and Elizabeth Hawkins began automating yield monitors and spatial crop models [9].

Methods and Technologies

Remote sensing and AI rely on a suite of modern technologies. This section describes the key platforms, sensor types, data processing methods and AI techniques that constitute the toolbox for agricultural and horticultural applications [10].

Remote Sensing Platforms and Sensors

Spaceborne Satellites: Earth observation satellites provide broad coverage of agricultural regions on a regular schedule. Notable platforms include *Landsat* (USGS/NASA, launched 1972 onward), *Sentinel-2* (ESA, launched 2015) and commercial constellations like *PlanetScope*. Sensors on these satellites range from simple RGB cameras to advanced multispectral and hyperspectral scanners [11]. For instance, Landsat 8/9 carries the Operational Land Imager (OLI) with six optical bands (visible to shortwave IR) at 30m resolution and the Thermal Infrared Sensor (TIRS) for thermal data. Sentinel-2 carries multispectral instruments (13 bands from visible to SWIR) at 10–60 m resolution. The freely accessible data from these satellites enable large-scale monitoring of fields (e.g. calculating NDVI for vegetation health). Other satellites include *MODIS* (daily, coarse ~250m resolution) for global vegetation indices, *WorldView* (Maxar) with very-high-resolution (0.3m) imagery and *Sentinel-1* (radar) which provides C-band synthetic aperture

radar (SAR) at ~10m resolution insensitive to clouds [12].

Airborne Systems: Manned aircraft equipped with imaging sensors cover fields at intermediate scale. Fixed-wing or helicopter surveys can carry high-resolution multispectral or hyperspectral cameras (hundreds of narrow bands) and LiDAR scanners. These provide centimetre-scale mapping of large estates or research plots, used for biomass estimation or terrain modelling. Advantages include customizable flight plans and high resolution, limitations are cost, required pilots and less frequent revisits [13].

Unmanned Aerial Vehicles (UAVs/Drones): In the last decade, UAVs have become widely used in precision agriculture and horticulture. Small drones (rotor or fixed-wing) can carry off-the-shelf cameras or specialized sensors [14, 15, 16]. Common payloads include:

- Multispectral cameras capturing select bands (RGB + NIR or RedEdge) at high spatial resolution (few cm).
- Hyperspectral cameras capturing dozens to hundreds of narrow bands (often at lower resolution or with slower capture).
- Thermal IR cameras for surface temperature and water stress detection.
- LiDAR units for 3D canopy structure.
- RGB cameras for visual crop scouting or orthophoto mosaics.

Drones typically fly under 120m altitude, covering small to medium fields (few hectares per flight). They excel at high-detail imagery for orchard trees or experimental plots and can be deployed on demand. Drawbacks include limited flight time/battery, weather sensitivity and regulatory requirements for flight. Nonetheless, UAVs democratize precision sensing: many researchers and farmers now routinely use drone NDVI maps, weed detection and canopy analyses [17].

Ground-Based Sensors: These include fixed towers or mobile platforms with sensors in or near fields [18, 19, 20]. Examples:

- Phenomobile/phenocam networks: Ground cameras (RGB or multispectral) overlooking plots, capturing frequent images or videos for phenological monitoring.
- Proximal sensors: Handheld or tractor-mounted devices measuring reflectance or fluorescence of leaves for diagnostics.
- Soil sensors: Networked moisture or nutrient sensors (often IoT devices) that feed data to analytics models.
- IoT stations: Integrated weather and plant health sensors (temperature, humidity, leaf wetness) in greenhouses or fields.

Ground sensors provide very high-frequency, site-specific data, complementing aerial observations. They are key for precision horticulture (e.g. greenhouse climate control) and for validating remote measurements. However, they cover only limited spatial extent per deployment [21].

Table 1: Remote Sensing Platforms and Sensors [22, 23, 24]

Platform/Sensor	Sensor Type	Wavelength/Resolution	Key Uses
Landsat 8/9 (Satellite)	Multispectral (MS)	6 bands (0.43–2.29 μm), 30 m spatial, 16-day revisit	Crop type mapping, NDVI, long-term monitoring
Sentinel-2 (Satellite)	Multispectral (MS)	13 bands (0.43–2.19 μm), 10–60 m, 5-day revisit (combined satellites)	Vegetation indices, phenology, nutrient status
WorldView-3 (Satellite)	Multispectral (MS)	8 bands (0.40–1.04 μm), 0.31–1.24 m, panchromatic 0.31 m	Field mapping, orchard delineation, plant counting
MODIS (Satellite)	Multispectral (MS)	36 bands (0.41–14.4 μm), 250–1000 m, daily global	Large-area vegetation health, drought monitoring
PlanetScope (Satellite)	Multispectral (MS)	4 bands (RGB + NIR), ~3 m, daily for any location	Rapid crop change monitoring, farm management
Sentinel-1 (Satellite)	Synthetic Aperture Radar (SAR)	C-band (~5.4 GHz), VV/VH polarizations, ~10 m, 6–12 day revisit	Soil moisture, flood mapping, crop structure
Aircraft	Multispectral / Hyperspectral / LiDAR	Varies, e.g. 5–30 cm resolution multispectral	High-res crop vigor maps, terrain, canopy height
Tractor-mounted Yield Monitor	NIR Reflectance Sensor	Red/NIR reflectance, ~1 m	On-the-go biomass/yield estimation
Fixed Tower Sensor (Phenomobile)	Multispectral Cameras	Daily imaging, ~cm resolution at fixed point	Continuous monitoring of plot phenology
Soil Moisture Sensor (In-ground)	Dielectric probes	0–50 cm depth, moisture measurement	Precision irrigation, drought stress alerts
Smartphone / Handheld	RGB/Mobile Multispectral	Visible/NIR smartphone cameras	Farmer field inspection, crowd-sourced data

Data Acquisition and Processing

Multispectral and Hyperspectral Sensing: Most agricultural remote sensing uses reflected sunlight at visible and near-infrared wavelengths. Multispectral sensors capture a handful of broad bands (e.g. red, green, blue, NIR). The red and NIR bands are especially important since vegetation reflectance there relates to chlorophyll content and leaf structure [25]. Hyperspectral sensors break the spectrum into dozens or hundreds of narrow bands, enabling detection of subtle chemical changes (e.g., nutrient deficiencies or early disease) that broad bands might miss. Hyperspectral data are powerful for detailed analysis but require more complex processing and are less common in routine farming use due to cost and data volume [26].

Synthetic Aperture Radar (SAR): SAR sensors (on satellites like Sentinel-1 or airborne radars) emit microwave pulses and measure backscatter. SAR penetrates clouds and provides information on surface roughness and moisture. For example, wetter soils or water in crop canopies increase backscatter intensity. SAR is used for monitoring flood risk, soil moisture and even crop structure (e.g. distinguishing crop types by their scattering signature). Integrating SAR and optical data is an active research area, especially in cloudy regions where optical imagery is often blocked [27].

Thermal Infrared: Thermal cameras measure land surface temperature. In crops, higher canopy temperatures indicate water stress (stomata closing, less evaporative cooling). Thermal imaging is used for irrigation management and drought monitoring. It has been applied in vineyard water stress studies and to schedule irrigation in cotton and corn [28].

Data Preprocessing: Raw sensor data require calibration and correction. This includes radiometric correction (converting raw sensor values to reflectance), atmospheric correction (removing effects of aerosols and water vapor) and geometric correction (aligning images to maps). Data preprocessing may also involve cloud masking for optical imagery. For UAVs, image stitching (orthomosaic creation) is common. Vegetation indices (like NDVI, SAVI, NDRE, etc.) are then computed from band ratios to highlight plant health metrics [29].

Data Fusion: Combining data across platforms improves analysis. For instance, blending frequent low-resolution data with infrequent high-resolution data (or merging optical and SAR imagery) can produce spatio-temporally rich datasets. Data fusion can fill cloud-induced gaps or provide both broad context and fine detail [30].

AI and Machine Learning Models

Analyzing remote sensing data for crop insights relies on AI/ML methods. AI algorithms translate raw or derived sensor data into actionable information: classification (e.g. crop type, disease presence), regression (e.g. predicting yield), segmentation (e.g. delineating weed patches) and forecasting (e.g. growth stages over time) [31].

- **Decision Tree (DT):** Splits data by feature thresholds for classification or regression. Useful for categorical decisions (e.g. crop vs weed), easy to interpret, but can overfit small data [32].
- **Random Forest (RF):** An ensemble of many decision trees, robust to noise, handles mixed data well. Commonly used for land cover and crop classification. Requires moderate training data, larger ensembles increase computation [32].
- **Support Vector Machine (SVM):** Finds optimal hyperplane to separate classes. Effective for high-dimensional spectral data classification. Needs labeled training data, can be slow for very large datasets, kernel selection can be tricky [33].
- **K-Nearest Neighbors (KNN):** Classifies a point by majority vote of nearest neighbors in feature space. Simple, no training phase, but performance drops with large datasets and many features [34].
- **Naïve Bayes:** Probabilistic classifier assuming feature independence. Quick to train, handles noisy data, used sometimes for classifying vegetation stress. Assumption of independence can limit accuracy [34].
- **K-Means Clustering:** Unsupervised method grouping data into k clusters by similarity. Useful for exploratory segmentation (e.g. grouping field images by growth stage without labels). Choosing k and initial clusters can be hard, not guaranteed to find optimal clusters [35].

- **Principal Component Analysis (PCA):** Not a classifier but used to reduce data dimensionality (e.g. compress hyperspectral bands to a few uncorrelated components). Speeds up other algorithms, reduces noise, however, principal components can be hard to interpret agronomically.
- **Linear Regression / PLS Regression:** For tasks like yield prediction based on spectral indices or sensor readings. Requires continuous target data, easy to interpret coefficients, but assumes linear relationships which may not hold in complex crops [35].
- **Gradient Boosting (e.g. XGBoost, LightGBM):** Ensemble of weak learners trained sequentially, high accuracy in many tasks (crop yield estimation, disease risk). Strong performance but requires careful tuning and can overfit [36].
- **Artificial Neural Network (ANN):** Multi-layer perceptron for regression/classification on tabular features (e.g. spectral indices). Learns nonlinear relationships, requires sizable training data, “black box” model (harder to interpret) [35].
- **Convolutional Neural Network (CNN):** Neural network specialized for images, automatically learning spatial features. Excels at tasks like crop/weed image classification, or counting plants in overhead images. Needs large labeled datasets and GPUs for training [35].
- **U-Net / Segmentation CNN:** CNN architecture for pixel-wise segmentation tasks (e.g. delineating maize plants or diseased leaves in an image). Accurate for mapping canopy cover or disease spread. Data-intensive (needs ground truth masks) [37].
- **Recurrent Neural Network (RNN)/LSTM:** Models that capture temporal sequences. Used for time-series analysis (e.g. predicting yield from vegetation index time series throughout season). Captures temporal patterns, risk of overfitting, training can be slow [36].
- **YOLO / Faster R-CNN (Object Detection):** Deep networks for detecting and localizing objects in images. Applied to count fruits on a tree or detect weeds from crop images. High accuracy, require annotated bounding boxes, computationally heavy [37].
- **Gaussian Processes:** Probabilistic regression modeling time series or spatial patterns (e.g. soil moisture trends). Provides uncertainty estimates, but scale poorly to large data and require kernel design [33].
- **Deep Belief Networks / Autoencoders:** Less common but used for unsupervised feature learning from images or spectral data. Good for anomaly detection, generally supplanted by more efficient CNNs and GANs [38].

Table 2: AI/ML Models and Algorithms [39, 40, 41]

Model/Algorithm	Typical Tasks	Data Requirements	Example Crop Applications
Decision Tree	Classification, regression	Labeled features (numeric/categorical)	Classifying crop vs. weed from sensor data
Principal Component Analysis (PCA)	Dimensionality reduction	Multiband spectral data	Compress hyperspectral data before ML modeling
Linear Regression / PLSR	Regression (Yield forecasting)	Predictor variables (e.g., NDVI, weather) + target values	Predict wheat yield from seasonal NDVI
Gradient Boosting (XGBoost, etc.)	Regression/classification	Labeled data with features, larger sample	Yield prediction using multisource data
Artificial Neural Network (ANN)	Classification/regression	Large training sets of feature vectors	Predicting protein content from spectra
Convolutional Neural Network (CNN)	Image classification/segmentation	Many labeled images (RGB/Multi-band)	Plant species ID, disease classification from leaf images
U-Net (CNN)	Image segmentation	Images with pixel-wise labels (masks)	Mapping canopy cover or weed patches in field images
Recurrent NN (LSTM)	Time-series prediction	Sequential data (e.g. weekly NDVI values) + targets	Crop yield forecast from season-long indices
YOLO/Faster-RCNN (Object Detection)	Object detection in imagery	Labeled bounding boxes on images	Counting fruits on trees, weed vs. crop detection
Gaussian Process Regression	Regression with uncertainty	Feature vectors + labels	Soil moisture interpolation, small-plot yield estimates
Autoencoder / GAN	Feature learning, augmentation	Large unlabeled (autoencoder) or paired data (GAN)	Synthetic field image generation, anomaly detection

Applications in Crops and Horticulture

Remote sensing and AI find applications across the full spectrum of crop systems. We consider both broad acre agriculture (cereals, oilseeds, pulses, etc.) and horticulture (fruits, vegetables, greenhouse crops, ornamentals), highlighting common themes and unique cases [42].

Crop Monitoring and Yield Prediction

One of the most common applications is crop yield forecasting and mapping. By analyzing temporal sequences of vegetation indices (like NDVI or enhanced vegetation index EVI) from satellites, researchers build regression or machine learning models to predict end-of-season yield. For example, multi-year Landsat NDVI series combined with weather data feed AI models (e.g. LSTM networks) that forecast maize or wheat yield at regional scales [43]. This assists national agencies and farmers

in planning harvest and markets. In the US Corn Belt, yield estimates from RS data have achieved accuracies within 5–10% of actual yields in many studies. In India and China, moderate-resolution imaging and time-series analysis of paddy fields have enabled rice yield predictions weeks before harvest. SAR data (Sentinel-1) are used to monitor rice flooding and biomass, helping predict production in areas where clouds hinder optical imagery [44].

Crop condition monitoring: Remote sensing can detect stress before it is visible to farmers. For instance, deficits in nutrients or water lead to changes in leaf reflectance (reduced NIR, increased visible reflectance). Satellite NDVI or UAV multispectral images processed by AI (e.g. anomaly detection algorithms or CNNs analysing stress patterns) can alert to nutrient deficiencies or drought stress early. Multispectral

indices (NDRE, NDWI, red-edge NDVI) are frequently used features. AI models track crop growth stages. For example, time series of spectral features fed into LSTM or HMM (Hidden Markov models) can identify flowering and maturity dates. This helps schedule irrigation and inputs optimally [45, 46].

Disease and Pest Detection

Identifying diseases and pests early is critical. Remote sensing provides spectral cues of plant health and AI translates them into diagnostic information. Many diseases cause localised changes: chlorosis, necrosis, or canopy structure alterations [47]. High-resolution UAV images and ground robots with camera arms detect leaf spots or wilting. Deep learning is particularly adept at image-based identification: CNNs trained on labelled images of diseased vs healthy leaves achieve high accuracy on diseases like late blight in potato or stripe rust in wheat. Hyperspectral sensors capture subtle spectral signatures of infection that may precede visible symptoms [48]. Wheat rust in Australia was detected from drone multispectral images using a Random Forest model to identify rust hotspots at early stages. Similarly, the detection of banana Black Sigatoka disease was enhanced by using hyperspectral imaging and SVM classifiers to pinpoint affected areas. Another example is pest infestation mapping: sensors combined with thermal or optical imaging (plus AI) track swarms of locusts or insect damage. For fruit crops, winged pests or larvae spots on leaves are detected using deep learning object detectors on high-res images [49].

Nutrient and Water Management is pest infestation mapping: sensors combined with thermal or optical imaging (plus AI) track swarms. Remote sensors measure proxies for nutrients and water: for example, chlorophyll reflectance relates to nitrogen content. AI models correlate spectral indices with measured soil or plant nutrient levels. As a result, farmers can create variable-rate fertilizer prescriptions. UAV-based NDVI maps are often used to apply nitrogen variably across a field [50]. Water stress detection is another key area. Soil moisture sensors inform irrigation directly, but satellites like Sentinel-1 (SAR) indirectly estimate soil moisture from backscatter. Thermal imaging reveals plant canopy temperature, a strong indicator of water stress. Coupled with AI regression models, farmers can schedule irrigation more efficiently. In irrigated cotton farming, satellite data were used to map evapotranspiration via thermal and multispectral imagery. An AI model (e.g. an ANN) combined with weather data estimated water requirements, reducing irrigation by 20% while maintaining yields [51].

Crop Mapping and Classification

Accurate maps of what crops are planted where and at what stage are valuable for commodity forecasting and management. AI classification of satellite imagery yields crop type maps. For instance, Random Forest classifiers on multi-date imagery can distinguish maize, soybean and other crops in large regions [83]. Drone imagery can classify within-field heterogeneity (e.g. patches of weed vs crop). In horticulture, crop classification may identify tree species in orchards or vegetables in fields. High-resolution WorldView data plus CNN segmentation have been used to map vineyards, orchards, or even individual tree canopies from space [52].

Horticultural Applications

Horticulture (fruits, vegetables, ornamentals, greenhouse crops) often has higher-value produce and smaller plots. The high spatial resolution of UAVs and ground sensors is particularly useful here [53]. Applications include:

- **Fruit Yield Estimation:** Drones capture images of fruiting trees, AI (e.g. object detection networks like YOLO) counts fruit or clusters. This helps estimate potential yield. Example: Counting apples in orchards or mangoes using drone imagery and CNN detectors [54].
- **Flowering and Maturity Monitoring:** In crops like apples or cotton, satellite NDVI or drone images can estimate bloom density and predict harvest time. AI models calibrate flowering intensity with yield output [55].
- **Greenhouse Monitoring:** Indoor horticulture uses fixed sensors and cameras (RGB, thermal) plus AI to control climate (temperature, humidity, CO₂, lighting). For example, tomato greenhouse systems use neural networks to optimize irrigation and fertigation schedules based on real-time sensor data [56].
- **Pest/Disease in High-Value Crops:** In vineyards and orchards, early detection of diseases like powdery mildew or insect pests is critical. UAV multispectral imaging combined with ML models maps disease spread in vineyards, guiding targeted spraying [57].
- **Weed Management:** In vegetable fields, fine-scale imaging and CNNs can identify weed seedlings among crops, allowing robotic spot-spraying or hand weeding only where needed [58].

Cereals: In the U.S. Corn Belt, researchers used Sentinel-2 multispectral time series and a Random Forest model to predict maize yield across multiple counties, achieving ~90% accuracy. In India's Punjab region, UAV multispectral flights of wheat fields provided NDVI maps that an LSTM model used to forecast yield one month in advance, enabling better input planning [59, 60].

Rice: In China's Yangtze Delta, a combination of Sentinel-1 SAR and Sentinel-2 optical data was fed into a CNN-based model for rice field boundary detection and health classification, helping predict yields and irrigation needs. Similarly, in Southeast Asia, SAR time-series with long short-term memory (LSTM) networks have been used to map flooded rice areas and estimate production even under persistent cloud cover [61, 62].

Maize: In Brazil's Mato Grosso, Landsat imagery combined with a gradient boosting model estimated soybean and corn yields for large farms, supporting national crop forecasts. In sub-Saharan Africa (Nigeria, Ghana), drone images of maize fields have been analyzed by an SVM model to detect nutrient deficiency patches, improving local fertilizer application [63].

Soybean: In Argentina, a deep learning pipeline (U-Net segmentation on high-res aerial images) mapped soybean canopy cover for biomass estimation. In the U.S., UAV hyperspectral scans of soy plots were used by random forest regression to predict protein content as an element of quality assessment [82, 64].

Wheat: In Australia, Landsat and MODIS NDVI data over wheat-growing regions were used with both linear regression and machine learning (random forest, XGBoost) to produce annual wheat yield maps, which informed stock market forecasts. Wheat rust disease in Canada was monitored via UAV imagery, an ANN classifier distinguished healthy vs. rust-infected plots, allowing targeted fungicide treatment [65, 66].

Vegetables: In the Netherlands, greenhouse tomato production

uses a network of IoT sensors (light, humidity, CO₂) with an AI controller (ANN + rule-based logic) that optimizes lighting and ventilation, reducing energy use by 15%. In the United States, remote sensing has been applied to open-field lettuce, drone multispectral data and a convolutional neural network were used to detect early-stage downy mildew infections, alerting growers before symptoms were visible [67, 68].

Fruits (Horticulture): European vineyards have seen extensive RS+AI use. In France, drone surveys of grapevines with multispectral and thermal cameras feed random forest models that classify vines by vigor level, guiding variable irrigation. In Italy, satellite Sentinel-2 data with support vector regression have been used to predict grape sugar content (Brix), improving harvest timing [81, 69]. For orchards, one case in India used UAV RGB imaging of mango orchards processed by a YOLO object

detector to count flowering clusters, estimating fruit yield potential. Another in China employed hyperspectral imaging on a trolley in an apple orchard, an SVM model predicted fruit freshness and quality factors during harvesting [70].

Tree Crops: In the U.S., almond growers use aerial LiDAR to measure canopy volume, correlated by linear regression with expected nut yield. In Australia, Sentinel-1 SAR data with a CNN model classified pistachio orchards by tree health status, aiding irrigation management [71].

Root/Tuber crops: Drone NDVI imagery of potato fields in the U.K. analyzed by random forests has helped forecast tuber yield before harvest. In potato late blight outbreak areas, thermal imaging combined with CNN detection models identified infection hotspots [72].

Table 3: Crop/Horticulture Case Studies [73, 74, 75, 80]

Crop/Horticulture	Region	Remote Sensing Data	AI Method
Rice (paddy)	Eastern China	Sentinel-1 SAR & Sentinel-2 MS	Convolutional Neural Network
Wheat	North Dakota, USA	Landsat 8 MSI time series	Random Forest
Corn (Maize)	Midwest USA	PlanetScope MS imagery + UAV RGB	Long Short-Term Memory (LSTM)
Soybean	Brazil (Mato Grosso)	Sentinel-2 NDVI time series	XGBoost Regression
Barley	UK (East Anglia)	UAV multispectral	Support Vector Machine
Potato	Netherlands	UAV NDVI & RGB	Random Forest
Sugarcane	Brazil	MODIS EVI (250m) + Weather	Artificial Neural Network
Tomato (Greenhouse)	Netherlands	Ground IoT sensors (env. data)	ANN + Rule-based
Grapevine (Vineyard)	France (Bordeaux)	UAV multispectral + Thermal	Random Forest
Banana (Horticulture)	India (Tamil Nadu)	UAV RGB imagery	Convolutional Neural Network
Citrus (Orange)	Morocco	Drone multispectral	U-Net Segmentation
Coffee	Colombia	Sentinel-2 + UAV RGB	Random Forest
Rice (Flooded Fields)	Vietnam Mekong Delta	Sentinel-1 SAR time series	Convolutional Neural Network

Table 4: Challenges and Mitigation Strategies [76, 77, 78, 79]

Challenge	Cause	Impact on Agriculture	Technical Mitigation	Policy/Operational Mitigation
Limited Spatial Resolution	Large pixel sizes of sat. sensors, small farm sizes	Small fields unresolved, poor detection of weeds or tree crops	Use UAV/drone for local imagery, combine multiple sensors (data fusion)	Support development of high-res satellites, shared data programs
Cloud Cover / Data Gaps	Weather conditions block optical data	Missing data, delayed insights, especially monsoon regions	Incorporate SAR (radar) data, interpolate time series, use geostationary imaging	Encourage open SAR missions, invest in all-weather sensing
High Data Volumes	High-res and hyperspectral data	Requires big data processing, storage bottlenecks	Edge computing on devices, cloud platforms, data compression and filtering	Subsidize rural broadband, shared cloud resources for ag data
Ground Truth Scarcity	Manual data collection intensive	Limits model training, biased sampling	Synthetic data (simulators), active learning to focus labeling, crowd-sourced apps	National agri-data collection initiatives, incentives for data sharing
Model Generalization	Local adaptation (soil, climate, cultivars)	Models fail in new regions or seasons	Domain adaptation techniques, ensemble of local + global models	Promote open datasets from diverse regions, standards for model portability
Model Interpretability	“Black-box” deep models	Resistance to trust AI advice, difficulty diagnosing errors	Use explainable AI tools (feature attributions), simpler models for decisions	Guidelines for transparent AI, require justification for AI-driven decisions
High Cost of Technology	Expensive sensors, UAVs, software	Barriers for smallholder farms, slow adoption	Low-cost hardware (open-source drones), sensor sharing cooperatives	Subsidies for precision agriculture tools, encourage service providers/models
Technical Skill Requirements	Complexity of data analysis	Dependence on experts, uneven adoption	User-friendly interfaces (mobile apps), automated workflows	Extension/training programs, integrate digital literacy in ag curricula
Data Privacy/Ownership	Unclear data rights, sensitive info	Farmers wary of data sharing, legal issues	Data anonymization, blockchain for traceability, decentralized storage	Clear ag-data regulations, frameworks for consent and benefit sharing
Interoperability Issues	Diverse sensors, formats	Difficulty integrating multi-source data	Develop standards/protocols (e.g. OGC standards), open APIs	Mandate common data formats, promote open-source tools
Connectivity Limitations	Rural areas lack internet	Delays in data upload/alerts, limits real-time analytics	On-device processing (edge AI), satellite internet links for farms	Expand rural internet infrastructure, incentivize telecom rural service

Environmental Variability	Climate change, unpredictable events	Models quickly become outdated, mis-predictions	Continuous model retraining, integrate weather forecasts, use robust algorithms	Support for climate-resilient ag R&D, insurance schemes for tech risk
Sensor Maintenance	Hardware wear, miscalibration	Inaccurate data, downtime of monitoring	Self-check/calibration routines, sensor redundancy, easier field calibration	Quality assurance programs, shared maintenance services, training on device care
UAV Regulation	Airspace rules, permits	Limits when/where drones can fly legally	Flight planning compliant with regs, autonomous fail-safes, track UAV status	Streamline UAV regs for agriculture, create special agri-drone corridors
Algorithmic Bias	Unbalanced training data	Systematic errors (e.g. overestimate one crop type)	Balanced datasets, fairness-aware ML training, continuous validation	Guidelines to audit and mitigate bias, oversight for AI models in ag
Ethical/Data Security	Cyber threats, proprietary algos	Risk of data breaches, misuse of farm data	Encryption of data, secure cloud services, privacy-preserving AI	Legal frameworks for agricultural cybersecurity, standards for data encryption

Future Directions

The trajectory of remote sensing and AI in agriculture continues upward, driven by technology and necessity. Several trends and research directions will shape the next decade of crop improvement:

- **Hyperspectral CubeSats and High-Frequency Constellations:** Smaller, cheaper satellites with hyperspectral sensors (e.g. upcoming EnMAP, PRISMA, or CubeSat constellations) will provide unprecedented spectral detail. Combined with near-daily revisit (Planet's mission, etc.), models will detect subtle nutrient or stress signals earlier.
- **Edge AI and IoT Sensors:** Deploying AI directly on edge devices (e.g. smart tractors, UAVs, sensor nodes) will allow real-time analytics without sending all raw data to the cloud. For example, a drone might run an onboard CNN to flag disease hotspots immediately. IoT sensor networks in fields (moisture, nutrient, microclimate) will feed AI-based decision support systems that dynamically adjust irrigation or fertilization.
- **Autonomous Robotics:** We foresee more integration with robotics: autonomous drones and ground vehicles that not only sense but act (spray, harvest, plant). Computer vision guides autonomous weeding robots and drones could auto-deploy to treat a detected problem area.
- **Machine Learning Advances:** Transfer learning and few-shot learning will reduce the labeled data needed. Techniques like federated learning could allow models to be trained across farms without exposing private data. Explainable AI will become more mature, easing trust and regulatory compliance. Models will increasingly incorporate climate models and genomic data (making more holistic predictions of yield resilience).
- **Digital Twins of Farms:** The concept of a "digital twin" farm – a real-time dynamic model combining RS data, sensor inputs and historical agronomic models – is emerging. Such systems would simulate interventions (e.g. change irrigation or variety) to forecast outcomes before implementation.
- **Integration with Breeding and Genetics:** Remote sensing is revolutionizing plant breeding through high-throughput phenotyping in field trials. Combined with AI, breeders can link spectral traits to genetic markers, accelerating the development of stress-tolerant or high-yield varieties.
- **Open Data and Collaboration:** Initiatives like the European Union's Copernicus program (free Sentinel data) and NASA's open data will expand global access. Public-private partnerships may create shared platforms combining data, algorithms and services accessible to smallholder

communities.

- **Regulatory and Societal Aspects:** As adoption grows, regulations on drone use, data privacy and AI transparency will be refined. Farmer cooperatives or data trusts may arise to pool resources and bargaining power with tech providers.
- **Climate Change Adaptation:** RS+AI will be pivotal in climate-smart agriculture: monitoring climate-induced stress, shifting planting dates, managing carbon (through remote sensing of biomass) and optimizing water under drought scenarios.

Conclusion

Remote sensing and AI-driven technologies are rapidly transforming contemporary agriculture and horticulture. This review has chronicled their historical roots, examined current methods and platforms and showcased diverse applications for crop improvement around the world. By marrying detailed environmental sensing with powerful analytics, farmers and stakeholders can gain actionable insights at a scale and precision previously unimaginable. Remote sensing supplies comprehensive data on crop condition, soil and environment, AI converts this data into understanding – highlighting stress, predicting yield and guiding interventions. The evidence suggests substantial benefits: higher yields, better resource efficiency and quicker response to threats in both field crops and high-value horticulture. Yet challenges remain: technical (data limitations, algorithm biases), practical (costs, skills) and policy-oriented (data governance, infrastructure). Addressing these through interdisciplinary research and informed policy will be key. The four tables provided in this article systematically summarize the technologies (Table 1), AI models (Table 2), real-world cases (Table 3) and challenges with mitigations (Table 4), equipping readers with a structured overview. Looking ahead, the synergy of remote sensing and AI promises a new era of digital farming – data-driven, precise and adaptable. Emerging trends like hyper-resolution imaging, edge computing and autonomous systems suggest that within the next decade, many routine farm decisions will be aided or automated by intelligent systems. This has profound implications for food security: as global population grows and climate pressures mount, these technologies will be indispensable for increasing productivity sustainably. In conclusion, remote sensing and AI are not merely tools but enablers of a paradigm shift in how we cultivate and manage crops. They represent a technological revolution that, if carefully deployed and widely accessible, can significantly improve agricultural outcomes. Continued innovation, coupled with attention to equity and ethics, will ensure that the full potential of these advances benefits farmers, consumers and the environment alike. The future of crop

improvement lies in the intelligent fusion of sensor technologies and artificial intelligence, heralding a smarter, more resilient agriculture.

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