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Remote sensing and AI based technologies in modern agriculture: A comprehensive review for crop improvement

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Abstract

Remote sensing and artificial intelligence have been used in agriculture, which has resulted in the creation of strong tools for crop development. These techniques have enabled large-scale monitoring and decision support that is driven by data. This paper presents an in-depth analysis of the various artificial intelligence (AI) approaches (machine learning and deep learning) and remote sensing platforms (satellites, airplanes, unmanned aerial vehicles, and ground sensors) that are applicable to current precision farming. We provide an overview of the historical evolution of agricultural remote sensing applications from Landsat to unmanned aerial vehicles (UAVs), highlighting the most important contributions. Methods such as multispectral and hyperspectral imaging, radar, LiDAR, and vegetation indices (such as the normalized difference vegetation index, or NDVI), as well as strategies for data fusion and preprocessing, are discussed here. Several significant artificial intelligence models, including as linear regression, random forests, support vector machines, CNNs, and RNNs, are summarized in tables, and a comprehensive review of sensors and platforms, such as Landsat, Sentinel, MODIS, PlanetScope, and ground devices based on unmanned aerial vehicles (UAVs), is provided. Public datasets that provide images and labels are examined by us. Some examples of these datasets are Landsat, Sentinel, USDA Cropland Data Layer, PlantVillage, and DeepWeeds. Applications for crop improvement are the primary focus of this study. These applications include yield prediction, disease and pest detection, high-throughput phenotyping, irrigation and fertilisation control, precision spraying, and breeding assistance. For each, performance data and stated accuracy ranges are provided (see Table 4 for further information). Case studies highlight real-world applications, such as aerial vehicle-based orchard monitoring in Tunisia and artificial intelligence-driven irrigation mapping in the United States. Following this, we take into consideration the obstacles (data quality, deployment, and costs) as well as the future possibilities (explainable artificial intelligence, multi-source fusion, and edge computing). The conclusion of the paper is that the combination of artificial intelligence and remote sensing has the potential to revolutionize agriculture. These technologies have the potential to considerably boost yields, cut inputs, and expedite breeding, all of which contribute to improvements in global food security. They do this by allowing accurate monitoring and prompt intervention.

Keywords: Remote sensing, precision agriculture, artificial intelligence, machine learning, crop yield prediction, disease detection, phenotyping, irrigation management, data sources, sensors, hyperspectral imaging

Introduction

Precision agriculture is a kind of farming that takes into consideration the variety of fields in order to maximize crop yield. The confluence of artificial intelligence (AI) and remote sensing (RS) lies at the heart of this idea ^[1, 2]. Continuous and extensive coverage of agricultural and environmental factors may be achieved via the use of remote sensing platforms, which include satellites (such as Landsat and Sentinel), unmanned aerial vehicles (UAVs or drones), and in-field sensors ^[3]. Spectral signals are used by these technologies to monitor plant health, identify water stress, map soil conditions, and perform a variety of other functions. AI, on the other hand,

has made fast progress because to improved algorithms and more data. Data in the field of agronomy may be handled using machine learning models, which can handle complicated and nonlinear interactions [4]. These models range from conventional regressions to deep neural networks. By combining satellite photos, meteorological data, soil samples, and genetic information, they are able to make predictions about the consequences and provide recommendations for actions [5]. A convolutional neural network (CNN) may, for instance, take a multi-spectral picture of a field and immediately output zones of nutrient deficit [6]. This was made possible by modern artificial intelligence, which permits end-to-end analysis. The purpose of this paper is to present a thorough and analytical assessment of the applications of RS and AI applications in crop development [7]. An overview of the historical background, methodology, and data is provided in the introduction. Our discussion includes the development of agricultural RS as well as the growth of artificial intelligence in crop science, with a focus on early initiatives and researchers [8, 9]. The most important technologies, including data gathering, pre-processing, indices, and modelling, are discussed, along with the sensor systems that are now in use. We classify the most well-known AI methods according to their appropriateness.

History

- Aerial photography and spectroscopy were used in the early stages of agricultural research. Airborne imaging was first used to forestry and agricultural analysis in the 1950s and 1960s by pioneers such as Robert N. Colwell, who worked at the University of California, Berkeley. It was a significant event when the first Landsat satellite, known as ERTS-1, was lifted into orbit in 1972. The multispectral scanner data from Landsat was soon investigated by research teams for the purpose of crop categorization [10].
- As an example, researchers from the USDA named Bauer and Cipra used early Landsat images to discriminate between maize and soybean crops in the Midwest of the United States. vast Area Crop Inventory Experiment (LACIE), a study conducted by the National Aeronautics and Space Administration (NASA), established in the 1970s that satellite data could be used to estimate wheat output across vast areas [11]. Throughout the 1970s and 1980s, universities (such as Purdue University under Donald Landgrebe, Kansas State University, and the University of California) and government organizations (such as the United States Department of Agriculture and the National Oceanic and Atmospheric Administration) constructed laboratory systems in order to calibrate spectral indices to crop condition, carry out crop area surveys, and predict yields [12].
- The development of specialized programs is one of the most important milestones. For example, the Corn Blight Watch in the 1970s used early RS to monitor disease, the Crop Identification Technology Assessment (CITARS) applied digital classification to imagery, and AgRISTARS in the 1980s utilized aircraft and satellites to monitor row crops in the United States [13]. The geographical coverage and the sorts of information that were gathered increased with each successive stage. There were a number of influential scientists working during this time period, including Don Jensen of NASA and others who created pixel-based categorization systems. In the early 21st century, the introduction of high-resolution commercial satellites and low-cost unmanned aerial vehicles (UAVs) made remote

sensing a common technique in agricultural operations [14].

- Artificial intelligence and computational approaches developed concurrently. For the purpose of irrigation scheduling and crop diagnostics, early expert systems and basic neural networks were put through their paces in the latter part of the 20th century. The dawn of the big data age, on the other hand, marked the beginning of the revolution [15, 16]. In the field of artificial intelligence, researchers such as Geoffrey Hinton, Yann LeCun, and Yoshua Bengio made significant advancements that made deep learning feasible. A number of agricultural research organizations started using machine learning and convolutional neural networks on sensor networks and field photographs respectively [17]. As an example, decision-tree ensembles and support vector machines were used in the 2010s for the purpose of performing yield prediction and classification tasks. Recent years have seen an increase in the investigation of generative models and transformers for the purpose of performing difficult tasks such as the generation of synthetic training pictures or the analysis of spatio-temporal patterns [18, 19].

Methods and Technologies in remote sensing along modern agriculture

Agricultural remote sensing measures light and other electromagnetic emissions from crops. Common techniques include:

- **Vegetation Indices:** Combinations of spectral bands that indicate plant properties. NDVI (Normalized Difference Vegetation Index) uses red and near-infrared bands to measure greenness, which correlates with biomass and health. Other indices (EVI, GNDVI, NDRE, NDWI) enhance sensitivity to chlorophyll, nitrogen content or water. These indices are often computed from satellite or drone images to track crop growth over time. For example, an NDVI time-series curve can reveal planting dates, peak biomass and stress events [20].
- **Spectral Analysis:** Beyond indices, using the full spectrum (multispectral or hyperspectral) allows discrimination of subtle features. Hyperspectral sensors (hundreds of bands) can detect nutrient deficiencies or disease symptoms that are invisible in RGB. For instance, specific near-infrared and shortwave-infrared features might indicate fungal infection before leaves yellow. Spectral unmixing and continuum removal techniques extract such signals [21].
- **Radar (SAR):** Synthetic Aperture Radar provides active microwave imaging that penetrates clouds and operates day/night. SAR backscatter intensity is sensitive to surface roughness, biomass and moisture. In farming, SAR (e.g. Sentinel-1 C-band) is used for soil moisture estimation, flood mapping and crop structure analysis. Data fusion combining optical indices with SAR features has improved crop classification and stress detection under all-weather conditions [22].
- **LiDAR:** Light Detection and Ranging uses laser pulses to generate 3D maps. Airborne or drone LiDAR produces detailed canopy height models. These are useful for estimating plant height and structural traits, important in phenotyping and yield estimation. LiDAR can also map terrain, aiding water flow and soil erosion studies [23].
- **Time-Series Analysis:** Modern analyses rely on sequences of images. Temporal features (time of green-up, length of season) are extracted from satellite archives. Fourier analysis or wavelets might decompose vegetation index

time series into growth cycles. Long Short-Term Memory (LSTM) networks and other recurrent models can predict yields or classify phenology stages from such sequences ^[24].

- **Preprocessing:** Raw data must be corrected and prepared. Images undergo radiometric calibration and atmospheric correction to ensure consistency. Cloud and shadow masking algorithms remove unusable pixels. Geometric correction aligns imagery to known coordinates. Gap-filling methods (e.g. spatio-temporal interpolation) handle missing data. For UAV data, orthomosaic stitching is required. Data fusion integrates multi-sensor inputs (e.g. co-registering SAR and optical images or combining multispectral and LiDAR data into a single dataset) ^[25].
- **Computation and GIS:** Recent cloud platforms (e.g.

- Google Earth Engine) allow large-scale analysis of satellite archives with built-in preprocessing. GIS and remote sensing software enable spatial overlays of soils, weather and yield maps. Geostatistical methods interpolate sparse field measurements (soil tests, weather stations) to continuous surfaces. These tools support the pipeline from raw data to farm management zones ^[26, 27].
- **AI-driven Automation:** Downstream applications may include automated decision support. For example, machine learning algorithms can ingest processed RS data to generate prescription maps (variable-rate irrigation/fertilizer), or run on tractors/drones for on-the-fly decisions (weed spraying robots using real-time vision and classification) ^[28].

Table 1: Remote sensing platforms and sensors ^[29, 30, 31, 32, 33, 34]

Platform (Example)	Sensor Type	Spectral Bands / Resolution	Typical Use Cases
Satellite Landsat 8 (OLI/TIRS)	Multispectral, Thermal	VIS-NIR-SWIR (30m), Thermal (100m)	Crop monitoring, vegetation index trend
Satellite Sentinel-2 (MSI)	Multispectral	13 bands (visible-NIR-SWIR) at 1060m	Field-level NDVI, crop classification
Satellite MODIS (Terra/Aqua)	Multispectral	36 bands (250m/1km)	Regional crop trends, global indices
Satellite Sentinel-1 (C-band SAR)	SAR (Radar)	C-band (10m, VH/VV polarizations)	Soil moisture, structure mapping, all-weather
Satellite PlanetScope	Multispectral	RGB + NIR (4 bands at ~3m)	Frequent high-res NDVI, field scouting
Satellite WorldView-3	Multispectral + Pan	RGB-NIR (8m @1.2m) + Pan (0.3m)	Very high-detail mapping (e.g. pest spots)
Satellite PRISMA/EnMAP	Hyperspectral	~200 bands (400-2500nm) @~30m	Crop stress and species ID
Satellite Thermal (e.g. Landsat TIRS)	Thermal Infrared	Thermal IR (~100m)	Evapotranspiration, water stress
Airplane (manned) Multispectral	Multispectral	410 band custom @110m	Large-area surveys (vineyards, fields)
Airplane Hyperspectral (e.g. AVIRIS)	Hyperspectral	~200 bands @14m	Research on plant physiology
Airplane LiDAR	LiDAR (3D)	Laser (dense point clouds)	Canopy height, biomass, terrain mapping

AI Techniques and Models

A wide range of AI methods are used in agriculture:

- **Regression Models:** Linear and logistic regression relate sensor-derived features to outcomes (e.g. yield or plant health scores). Gaussian Process Regression can also model yield with uncertainty. These are easy to interpret but may struggle with highly nonlinear data ^[35, 36].
- **Decision Trees and Ensembles:** Decision Trees split data by feature thresholds. Ensembles like Random Forests and Gradient Boosting (XGBoost, LightGBM) combine many trees for robust predictions. Inputs might be index values or extracted features, outputs are crop classes or continuous estimates. Strengths include handling mixed data and importance ranking, weaknesses include large model size and overfitting if not tuned ^[37].
- **Support Vector Machines (SVM):** Kernel SVMs classify or regress using high-dimensional boundaries. Useful with limited data (e.g. classifying disease presence from indices). They scale poorly on huge datasets and need kernel choices ^[38].
- **Nearest Neighbours & Clustering:** k-Nearest Neighbors classifies based on nearest training samples. Clustering (k-means, Gaussian Mixtures) groups data (e.g. unsupervised segmentation of farmland). Simple and intuitive but can be sensitive to noise and scaling ^[39].
- **Neural Networks (MLP):** Multi-layer perceptrons take numerical input features (e.g. index values) and learn

- complex relations. They can approximate nonlinear responses but require larger training sets ^[40].
- **Convolutional Neural Networks (CNN):** Key for image analysis. CNNs accept image patches (e.g. RGB or multispectral tiles) and output class maps (e.g. per-pixel weed/crop labels) or image-level classifications (e.g. presence of disease). Models like U-Net and DeepLab perform semantic segmentation of fields. CNNs learn spatial features and are state-of-the-art for visual tasks, but need many labelled images and GPU resources ^[41].
- **Recurrent Neural Networks (RNN) / LSTM:** Designed for sequential data. In agriculture, they are used with time-series (e.g. sequences of NDVI values) to predict time-dependent outcomes like yield or phenology. They model temporal dependence but are more complex to train ^[42].
- **Generative Models & Data Augmentation:** Autoencoders reduce dimensionality or detect anomalies in spectral data. Generative Adversarial Networks (GANs) can synthesize realistic crop images to augment datasets. Transfer learning (pretraining CNNs on large natural image sets then fine-tuning for crop tasks) is common to overcome data scarcity ^[43].
- **Reinforcement Learning (RL):** Used for control tasks (e.g. automated irrigation). An RL agent learns policies by trial and error (often in simulation), optimizing a reward (e.g. yield or water use). This is emerging in farm robotics and control, but less mature than vision tasks ^[44].

Table 2: AI models/algorithms in agriculture [45, 46, 47, 48, 49, 50]

Model/Algorithm	Type	Typical Inputs	Typical Outputs	Strengths	Weaknesses
Linear Regression	Supervised	Numeric features (indices, weather)	Continuous (yield, etc.)	Simple, interpretable, fast	Only linear patterns
Logistic Regression	Supervised	Numeric features	Class probabilities (e.g. healthy vs diseased)	Probabilistic, interpretable	Limited to linear boundaries
Decision Tree	Supervised	Features (e.g. NDVI, texture)	Class label or value	Easy interpretation, handles any data type	Can overfit, not smooth
Random Forest	Supervised (Ensemble)	Features	Class or regression	High accuracy, handles noise, feature importance	Less interpretable
Gradient Boosting (XGBoost)	Supervised (Ensemble)	Features	Class or regression	State-of-art in tabular data, handles missing	Parameter tuning needed
Support Vector Machine	Supervised	Features	Class or regression	Effective high-dim boundaries	Slow on large datasets, kernel choice
k-Nearest Neighbors	Supervised	Feature vectors	Class or regression	Simple, no training phase	Slow for prediction, sensitive to scale
k-Means Clustering	Unsupervised	Feature vectors or pixels	Cluster labels	Simple unsupervised grouping	Only finds spherical clusters
Gaussian Mixture	Unsupervised	Features	Probabilistic clusters	Soft clustering, density-based	Assumes Gaussian shapes

Data Sources and Preprocessing

Modern agritech relies on diverse data sources. Key public datasets include:

- **Satellite Imagery Archives:** USGS Landsat (1972present) provides global 30m multispectral data. ESA’s Sentinel-2 offers 1060m optical imagery (2015present) with 5-day revisit. MODIS (NASA) supplies daily 250m1km data. Sentinel-1 (C-band SAR) gives all-weather radar images. These archives are free and global. Preprocessing includes atmospheric correction (e.g. Sen2Cor for Sentinel-2), cloud masking and georeferencing. Data fusion (combining Landsat and Sentinel for higher frequency, or merging SAR with optical) is common [51].
- **Aerial/UAV Imagery:** The USDA NAIP program provides 1m RGB/NIR aerial images of US agricultural areas every 23 years. Research projects contribute UAV datasets: for example, Agriculture-Vision (21k drone images of US fields with anomaly masks) and various open Kaggle sets. UAV data often require orthomosaic stitching and calibration [52].
- **Ground Truth and In-situ Data:** Yield monitors on harvesters, plot harvest data and crop cutting surveys supply target values. Weather stations, soil moisture sensors and manual leaf measurements are also collected. These in-situ measurements are sparser and often interpolated or used directly in model training [53].
- **Public Crop Databases:** The USDA Cropland Data Layer (CDL) provides annual 30m crop type maps for the USA (upgraded to 10m recently). EuroCrops compiles harmonised EU field boundary and crop-type data. Tools like ESA WorldCereal and various national land-cover

maps also exist. These support model training and validation [54].

- **Agriculture Datasets** [55, 56, 57, 58, 59]:
 - a. *PlantVillage*: 54k RGB images of healthy and diseased leaves (14 crops, 38 classes).
 - b. *DeepWeeds*: 17.5k images of 8 weed species in situ (Australia).
 - c. *Cassava (Kaggle)*: ~9k images of cassava leaf diseases (Uganda). These labeled image collections fuel machine vision research (disease detection, weed classification).
 - d. *SoilGrids*: Global 250m gridded soil property maps (texture, carbon, etc).
 - e. *ERA5 Reanalysis*: Global hourly meteorology (~30km from 1979 onwards).
 - f. *SMAP/SMOS*: Satellite soil moisture (~936km).
 - g. *Global yields*: FAO and EarthStat produce country-level and some gridded yield datasets.
- **Phenotyping Repositories:** Some plant science consortia share plot-based imagery and trait values (e.g. photos of field trials). Genomic selection projects sometimes release RS phenotype data [60].

Preprocessing steps normally include georeferencing all data, radiometric normalization and construction of derived features (vegetation indices, texture metrics, time-series aggregates). Machine learning often requires data curation: splitting into training/validation, balancing classes and dealing with missing values (e.g. by interpolation or by choosing models robust to gaps) [61, 62].

Table 3: Public datasets and data sources [63, 64, 65, 66, 67]

Name	Data Type	Spatial/Temporal Resolution	Crops/Regions Covered
Landsat (USGS)	Satellite multispectral	30m pixels, 16-day revisit	Global agriculture
Sentinel-2 (ESA)	Satellite multispectral	1060m pixels, 5-day revisit	Global croplands
Sentinel-1 (ESA)	Satellite SAR (C-band)	10m pixels, 612 day revisit	Global croplands
MODIS (Terra/Aqua)	Satellite multispectral	250m1km pixels, daily	Global vegetation
PlanetScope (Planet Labs)	Satellite multispectral	3m pixels, daily potential	Global (commercial)
USDA Cropland Data Layer	Land cover (raster)	30m (10m from 2025), annual	US (row crops, etc.)
NAIP (USDA)	Aerial RGB+NIR	~1m, periodic collection	Continental USA

Applications for Crop Improvement

Remote sensing and AI techniques have been applied to a wide

range of crop improvement tasks:

Yield Prediction

Forecasting crop yield before harvest aids planning and food security. Models use features from satellite time series (vegetation indices, SAR backscatter, weather trends) and sometimes soil data. AI algorithms (e.g. random forests, neural networks) map these inputs to yield. Studies report high accuracy (e.g. R^2 often 0.60-0.9) for crops like maize, wheat and rice. Ensembles and deep nets trained on multi-year data can account for climate variability. This enables forecast maps weeks to months before harvest, allowing logistics and market decisions [68, 69].

Disease and Pest Detection

Early detection of diseases or pests saves crops. Multispectral and RGB imagery can reveal stress symptoms (color changes, defoliation) before visible damage is widespread. AI models (CNNs or classifiers on index values) identify affected areas. For instance, convolutional networks trained on UAV or ground images have detected fungal diseases in wheat, blight in potatoes and even locust damage. Performance is often reported by pixel-wise accuracy or F1-score (commonly 0.80-0.95 in research). Integration with smartphones enables field scouting [70].

High-Throughput Phenotyping

Breeding relies on phenotyping many varieties under field conditions. Manual measurement is slow, so remote sensing enables non-destructive, rapid assessment of traits. UAVs or field robots collect data on canopy height (from LiDAR or stereo images), canopy cover, biomass proxies and even flags like leaf temperature. AI processes images to extract trait values (e.g. plant height by stereo vision, biomass by spectral reflectance). High correlations ($r > 0.8$) between AI-extracted and manual measures are reported for key traits. This accelerates selection of high-yielding or stress-tolerant genotypes [71, 72, 73].

Irrigation and Fertilisation Management

Precision irrigation uses RS to track water stress: thermal imagery and vegetation indices indicate moisture deficits. For example, high canopy temperature on thermal images can signal under-watered areas. Satellite-based evapotranspiration models, combined with weather forecasts, inform when and where to water. A recent USDA case used deep learning on Landsat/Sentinel to classify fields by irrigation type (drip vs. flood), improving irrigation mapping accuracy. Variable-rate irrigation controllers can then apply water locally. Similarly, fertilisation can be guided by chlorophyll-sensitive indices (e.g. NDRE), AI models translate index changes into nitrogen needs, optimizing input use [74, 75].

Precision Spraying and Weed Control

Smart sprayers reduce pesticide use by targeting weeds. Real-time cameras detect plants, AI distinguishes weeds from crops on the fly, activating nozzles only where needed. Research systems demonstrate herbicide savings of up to 80-90%. Aerial or ground imagery can map weed infestations and RTK-GPS guides machinery to spray precise locations. Pest outbreaks (e.g. insect plagues) can also be mapped early from satellite anomalies, enabling timely intervention [76, 77].

Breeding Support

Beyond phenotyping, AI+RS supports breeding by predicting genetic values. For example, models that combine genomic markers with RS-derived traits can predict hybrid performance. In field trials, imagery and AI can rank varieties by vigor or

stress tolerance. This reduces the number of varieties needing manual evaluation. Over time, such data-driven breeding accelerates selection of improved varieties (higher yield, climate resilience) by focusing on the most promising candidates [78, 79, 80].

These applications demonstrate the broad impact of RS+AI. For instance, pilot studies in various regions show yield forecast accuracy rivaling traditional methods and disease alerts days before outbreaks. Precision irrigation systems now routinely use satellite-derived moisture data and breeding programs deploy UAVs to phenotype thousands of plots. The combination of multi-source data and AI is enabling decisions at scales from individual fields to entire watersheds [81].

Challenges and Limitations with futuristic approach

Despite progress, significant challenges remain [82, 83, 84, 85, 86, 87, 88, 89]:

- **Data Quality and Heterogeneity:** Agricultural fields vary greatly (soil, variety, management). Training data often come from one region and do not generalise elsewhere. Multi-sensor data must be harmonized (e.g. Landsat vs Sentinel differences). Missing data (due to clouds or sparse sensors) must be managed. Labelled datasets are often small, creating high-quality labels (disease vs healthy, weed vs crop) is labour-intensive. Synthetic data and transfer learning partly mitigate this, but reliable ground truth is the bottleneck for high-accuracy models.
- **Model Interpretability:** Deep learning models can be opaque. Farmers and agronomists may distrust an AI without explanations of its decisions. For example, a CNN might flag an area as diseased, but the underlying spectral cues are unclear. Explainable AI methods (visualizing important pixels or using simpler surrogate models) are active research areas. Lack of interpretability also complicates troubleshooting when models fail.
- **Deployment Practicalities:** Technical complexity can hinder adoption. Many smallholders and agronomists lack experience with AI or GIS tools. Systems need user-friendly interfaces and education. Drones and robots face regulatory hurdles (airspace rules) and require expertise to operate. Connectivity is another issue: in many rural areas, internet is limited, so edge computing (on-device inference) may be needed. Moreover, integrating new tools with existing farm machinery and workflows requires standards and interoperability.
- **Cost and Economics:** Advanced sensors and computing can be expensive. High-resolution commercial satellite data, specialized UAVs, LiDAR sensors and compute hardware represent significant investment. Farmers need clear return on investment: if yield gains or input savings outweigh costs. Sharing resources (cooperative UAV services, satellite data subscriptions) and open-source tools help, but financial barriers remain, especially for small-scale farms.
- **Ethical and Privacy Concerns:** Collecting detailed images of farmland and possibly individuals (e.g. agrarian laborers) raises privacy issues. Clear policies must govern who owns and can use RS data and derived analytics. Bias is another concern: an AI model trained only on large mechanized farms may underperform on smallholder fields. Ensuring equitable benefits is an ethical priority.
- **Environmental and Temporal Variability:** Models must cope with changing conditions (climate change, new crop varieties). A drought year or an unusual management practice can break historical patterns. Continuous model

updating and adaptive learning are needed. Deployment robustness under such non-stationarity is a challenge.

- **Explainable and Foundation AI:** There is momentum toward AI models that are transparent and can generalize widely. Large-scale pre-trained vision models may be adapted to agriculture with little fine-tuning. Integrating image data with textual or tabular data (e.g. linking satellite imagery with climate reports via vision-language models) could enable novel decision-support tools.
- **Multi-Source Integration:** Future systems will blend more data types. Examples include satellite + UAV + ground sensor fusion, combining images with IoT sensor networks, or merging remote-sensed phenotype data with genomics. Digital twin models of farms, which simulate growth under given management, will increasingly be guided by real-time remote sensing inputs.
- **Real-Time and Edge Analytics:** Advances in onboard computing will allow real-time image processing on drones or machinery. For instance, a drone might analyze crop health during flight and immediately direct treatment. Edge AI chips can run deep models without cloud connectivity. This trend supports rapid response (e.g. immediate weed spotting for spot spraying).
- **Autonomy and Robotics:** The next generation of farm robots (tractors, harvesters, drones) will be guided by AI and RS data with minimal human intervention. Fully autonomous monitoring swarms (drone fleets, sensor networks) may continuously scan fields. Robotics in greenhouses and vertical farms will exploit similar technologies on a different scale.
- **Sustainability and Policy Integration:** Remote sensing can verify sustainable farming practices (e.g. no-till adoption, nutrient runoff). Future AI tools may assist with carbon accounting and compliance. There is growing interest in linking RS data to climate resilience strategies for example, allocating water quotas based on AI-predicted crop stress.
- **Citizen Science and Platforms:** Crowdsourced ground truth (farmers uploading photos of diseased plants) can enrich datasets. Platforms that provide RS+AI as a service (cloud-based farm intelligence dashboards) will proliferate. Standards for data sharing and APIs will ease integration into farm management software.
- **Regulation and Ethics:** As AI becomes embedded in farming, guidelines will emerge (e.g. regarding data privacy on farmland). Ethical frameworks will guide fair use. Research on social acceptance, education and value distribution (ensuring smallholders benefit) will be important.

Conclusion

The combination of artificial intelligence and remote sensing creates a potent arsenal for crop development. Over the course of history, advancements in satellite and unmanned aerial vehicle imagery have made it possible to simultaneously examine areas at a variety of sizes. At the same time, advancements in artificial intelligence, particularly deep learning, make it possible to extract information from complicated data streams. A comprehensive examination of the landscape of technology, sensors, and concepts that constitute contemporary digital agriculture has been presented here. A wide range of artificial intelligence algorithms were deployed, and we provided a full explanation of how multispectral and

hyperspectral imaging, radar, LiDAR, and other sensors are included into data processing pipelines. Enhanced yield forecasting, early disease and pest warnings, quick phenotyping for breeding, precision irrigation and fertiliser application, targeted spraying, and other applications were among those that were examined. With the combination of these factors, there has been a discernible boost in efficiency: farmers have reported large input savings and yield benefits in areas where precision techniques have been used. AI-driven irrigation mapping initiatives, for instance, have resulted in significant water savings, while field testing have shown that drone-based phenotyping reduces the amount of time required by a factor of two in comparison to human scoring. In spite of this, there are still a few holes. For models to be reliable, more data and meticulous validation are required. Cost, usability, and education are three issues that need to be addressed in order to bridge the "last mile" to on-farm usage. As a result of the difficulties posed by the diverse agricultural practices throughout the world, solutions need to be flexible. In the future, it is anticipated that the synergy between artificial intelligence and remote sensing would expand. More explainable models and generic frameworks that can be applied to other locations or crops with minimum retraining are something that we foresee being available in the future. These technologies will become available to a larger variety of stakeholders as a result of the ongoing proliferation of sensors and the decrease in the cost of computing infrastructure. A road to better yields with less resources is offered by RS+AI, which is a solution to the challenges that agriculture is facing as a result of climate change and population expansion. To summarize, we are able to significantly enhance the quality of decision-making in the agricultural sector by strategically using data from the air and space. Additionally, this will contribute to the global food security and sustainable intensification of agriculture.

References

1. Khonina SN, Kazanskiy NL, Oseledets IV, Nikonorov AV, Butt MA. Synergy between artificial intelligence and hyperspectral imaging—a review. *Technologies*. 2024;12:163.
2. Chamasemani FF, Singh YP. Multi-class support vector machine (SVM) classifiers—an application in hypothyroid detection and classification. In: *Proceedings of the Sixth International Conference on Bio-Inspired Computing: Theories and Applications*; 2011 Sep 27-29; Penang, Malaysia. p. 351-356.
3. Zhang L, Zhang L. Artificial intelligence for remote sensing data analysis: a review of challenges and opportunities. *IEEE Geoscience and Remote Sensing Magazine*. 2022;10:270-294.
4. Fabbri AG, Fung KB, Yatabe SM. The usage of artificial intelligence in remote sensing: a review of applications and current research. In: Chung CF, Fabbri AG, editors. *Quantitative analysis of mineral and energy resources*. Dordrecht: Springer; 1988. p. 489-512.
5. Sharifi A, Mahdipour H. Utilizing geospatial artificial intelligence for remote sensing applications. *Environmental Earth Sciences*. 2024;183:274.
6. Zhao T, Wang S, Ouyang C, Chen M, Liu C, Zhang J, *et al*. Artificial intelligence for geoscience: progress, challenges and perspectives. *The Innovation*. 2024;5:100691.
7. Abdelmajeed AYA, Juszczak R. Challenges and limitations of remote sensing applications in northern peatlands: present and future prospects. *Remote Sensing*. 2024;16:591.

8. Aragonese E, García M, Ruiz-Benito P, Chuvieco E. Mapping forest canopy fuel parameters at European scale using spaceborne LiDAR and satellite data. *Remote Sensing of Environment*. 2024;303:114005.
9. Cremons DR. The future of LiDAR in planetary science. *Frontiers in Remote Sensing*. 2022;3:1042460.
10. Debnath S, Paul M, Debnath T. Applications of LiDAR in agriculture and future research directions. *Journal of Imaging*. 2023;9:57.
11. Disney M. Terrestrial LiDAR: a three-dimensional revolution in how we look at trees. *New Phytologist*. 2019;222:1736-1741.
12. Prajval V, Krishnamoorthi A, Thakur R, Ruchitha T, Kapoor M, Singh A, *et al.* From code to crop: how bioinformatics is transforming crop genomics in modern agriculture and bettering environment. *Journal of Advances in Biology and Biotechnology*. 2024;27(4):27-49.
13. Anushi FD, Krishnamoorthi A, Singh V. Enhancing sustainable food systems through the cultivation of nutrient-rich crops: millets.
14. Singh A, Labanya GSR. Exploring the role of hydrogen in agriculture for machinery, biomass and reducing carbon footprints. *Plant Archives*. 2025;25(1):2852-2863.
15. Debnath P, Raj R. Optimizing functional genomics and application of root wounding and immersion for enhanced virus-induced gene silencing in plants: a comprehensive review. *Plant Archives*. 2025;25(1):3115-3126.
16. Krishnamoorthi A, Chaurasia J, Baidya BK, Singh A, Kumar V, Singh A. A comprehensive review on evolution, challenges of models, opportunities in urban farming practices in the world. *Journal of Scientific Research and Reports*. 2024;30(6):136-156.
17. Raghuvanshi HR, Kalaiselvi P, Ravindra NR, Kumar V. Biotechnological breakthroughs: paving the path to cleaner and more productive agriculture through bioremediation. *Journal of Advances in Biology and Biotechnology*. 2024;27(4):119-142.
18. Bhardwaj R, Kumar M, Kaushal N, Kamboj AD, Krishnamoorthi A, Singh A, *et al.* From lab to bouquet: the biotechnological frontier in modern floriculture for sustainable and resilient flower farming. *Journal of Advances in Biology and Biotechnology*. 2024;27(2):119-137.
19. Jain S, Ranganna G, Jadhav PS, Shrivastava U, Sood A, Prasad L, Luthra S. Cultivating tomorrow: harnessing gene editing and silencing for precision horticulture. *Journal of Advances in Biology and Biotechnology*. 2024;27(1):147-160.
20. Krishnamoorthi A, Salam NK, Kalaiselvi D, KB C, Kumar S, Kumar V, Sapna D. Digital sequencing information in agricultural crops: a comprehensive review. *International Journal*. 2024;8(8):1404-1412.
21. Rimpika, Anushi, Manasa S, Anusha KN, Sharma S, Thakur A, *et al.* An overview of precision farming. *International Journal of Environment and Climate Change*. 2023;13(12):441-456.
22. Jain S, Bhujel S, Shrivastava U, Mohapatra A, Mishra G. Advancements in drone technology for fruit crop management: a comprehensive review. 2023.
23. Jaboyedoff M, Oppikofer T, Abellán A, Derron MH, Loye A, Metzger R, Pedrazzini A. Use of LiDAR in landslide investigations: a review. *Natural Hazards*. 2012;61:5-28.
24. Zhao Q, Qu Y. The retrieval of ground NDVI (normalized difference vegetation index) data consistent with remote-sensing observations. *Remote Sensing*. 2024;16:1212.
25. Mitchell AL, Rosenqvist A, Mora B. Current remote sensing approaches to monitoring forest degradation in support of countries measurement, reporting and verification (MRV) systems for REDD+. *Carbon Balance and Management*. 2017;12:9.
26. Chen Y, Morton DC, Randerson JT. Remote sensing for wildfire monitoring: insights into burned area, emissions and fire dynamics. *One Earth*. 2025;7:1022-1028.
27. Pandey P, Ramanathan A, Venkataraman G. Remote sensing of mountain glaciers and related hazards. In: Marghany M, editor. *Environmental applications of remote sensing*. Rijeka: IntechOpen; 2016.
28. Anushi BPS, Sachan K. Bioformulation: a new frontier in horticulture for eco-friendly crop management. *Journal of Plant Biota*. 2024.
29. Garg S, Dasgupta A, Motagh M, Martinis S, Selvakumaran S. Unlocking the full potential of Sentinel-1 for flood detection in arid regions. *Remote Sensing of Environment*. 2025;315:114417.
30. Nguyen-Kim S, Nguyen-The V, Nguyen DB. A systematic review of artificial intelligence in geographic information systems. In: Nghia PT, Thai VD, Thuy NT, Son LH, Huynh VN, editors. *Advances in information and communication technology. ICTA 2023. Lecture Notes in Networks and Systems*. Cham: Springer; 2023. p. 20-31.
31. Anjana NS, Amarnath A, Harindranathan Nair MV. Toxic hazards of ammonia release and population vulnerability assessment using geographical information system. *Journal of Environmental Management*. 2018;210:201-209.
32. Xia N, Cheng L, Li M. Mapping urban areas using a combination of remote sensing and geolocation data. *Remote Sensing*. 2019;11:1470.
33. Furberg D, Ban Y, Mortberg U. Monitoring urban green infrastructure changes and impact on habitat connectivity using high-resolution satellite data. *Remote Sensing*. 2020;12:3072.
34. Akhyar A, Asyraf Zulkifley M, Lee J, Song T, Han J, Cho C, *et al.* Deep artificial intelligence applications for natural disaster management systems: a methodological review. *Ecological Indicators*. 2024;163:112067.
35. Gu Z, Zeng M. The use of artificial intelligence and satellite remote sensing in land cover change detection: review and perspectives. *Sustainability*. 2024;16:274.
36. Anushi AK, Ghosh PK. From seed to succulence: mastering dragon fruit propagation techniques. *Journal of Plant Biota*. 2024.
37. Xuan X, Jianbo L, Jin Y. Research on the natural language querying for remote sensing databases. In: *Proceedings of the International Conference on Computer Science and Service System*; 2012 Aug 11-13; Nanjing, China. p. 228-231.
38. Anushi VK, Shukla P. Influence of biostimulants and organic mulch on soil microbial population in strawberry (*Fragaria × ananassa* Dutch.).
39. Anushi RM, Deshmukh RN, Sharma R. From DNA to deliciousness: a journey into molecular markers in fruits.
40. Bashmal L, Bazi Y, Melgani F, Al Rahhal MM, Al Zuair MA. Language integration in remote sensing: tasks, datasets and future directions. *IEEE Geoscience and Remote Sensing Magazine*. 2023;11:63-93.
41. Tounsi A, Temimi M. A systematic review of natural language processing applications for hydrometeorological hazards assessment. *Natural Hazards*. 2023;116:2819-2870.

42. Wu X, Hong D, Chanussot J. Convolutional neural networks for multimodal remote sensing data classification. *IEEE Transactions on Geoscience and Remote Sensing*. 2022;60:5517010.
43. Qiang W, Zhongli Z. Reinforcement learning model, algorithms and its application. In: *Proceedings of the International Conference on Mechatronic Science, Electric Engineering and Computer*; 2011 Aug 19-22; Jilin, China. p. 1143-1146.
44. Song Y, Kalacska M, Gasparovic M, Yao J, Najibi N. Advances in geocomputation and geospatial artificial intelligence (GeoAI) for mapping. *International Journal of Applied Earth Observation and Geoinformation*. 2023;120:103300.
45. Ghosh B, Garg S, Motagh M. Automatic flood detection from Sentinel-1 data using deep learning architectures. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. 2022;V-3-2022:201-208.
46. WIRED. Early detection can't stop every wildfire. 2025 Jun 24.
47. Reuters. Field to cloud: how AI is helping regenerative agriculture grow. 2024 Sep 18.
48. The Associated Press. Artificial intelligence spider monkey tracking. 2025 Jun 24.
49. Shmilovici A. Support vector machines. In: Maimon O, Rokach L, editors. *Data mining and knowledge discovery handbook*. Boston: Springer; 2009. p. 231-247.
50. Jun Z. The development and application of support vector machine. *Journal of Physics: Conference Series*. 2021;1748:052006.
51. Anushi SS, Krishnamoorthi A, Kumar S, Pareta P, Kalaiselvi P, Sinha G, *et al.* Biotech bounty on verge: GM (genetically modified) crops and the science of sustainable agriculture and horticulture.
52. Guido R, Ferrisi S, Lofaro D, Conforti D. An overview on the advancements of support vector machine models in healthcare applications: a review. *Information*. 2024;15:235.
53. Ghosh S, Dasgupta A, Swetapadma A. A study on support vector machine based linear and non-linear pattern classification. In: *Proceedings of the International Conference on Intelligent Sustainable Systems*; 2019 Feb 21-22; Palladam, India. p. 24-28.
54. Sheykhoumousa M, Mahdianpari M, Ghanbari H, Mohammadimanesh F, Ghamisi P, Homayouni S. Support vector machine versus random forest for remote sensing image classification: a meta-analysis and systematic review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*. 2020;13:6308-6325.
55. Gaye B, Zhang D, Wulamu A. Improvement of support vector machine algorithm in big data background. *Mathematical Problems in Engineering*. 2021;2021:5594899.
56. Amaya-Tejera N, Gamarra M, Velez JI, Zurek E. A distance-based kernel for classification via support vector machines. *Frontiers in Artificial Intelligence*. 2024;7:1287875.
57. Evgeniou T, Pontil M. Support vector machines: theory and applications. In: Paliouras G, Karkaletsis V, Spyropoulos CD, editors. *Machine learning and its applications: advanced lectures*. Berlin: Springer; 2001. p. 249-257.
58. Yang Q. Research on SVM remote sensing image classification based on parallelization. *Journal of Physics: Conference Series*. 2021;1852:032009.
59. Salleh SA, Khalid N, Danny N, Zaki NAM, Ustuner M, Latif ZA, Foromda V. Support vector machine (SVM) and object based classification in earth linear features extraction: a comparison. *Revue Internationale de Géomatique*. 2024;33:183-199.
60. Liu Y, Wang Y, Zhang J. New machine learning algorithm: random forest. In: Liu B, Ma M, Chang J, editors. *Information computing and applications*. Berlin: Springer; 2012. p. 246-252.
61. Sun Z, Wang G, Li P, Wang H, Zhang M, Liang X. An improved random forest based on the classification accuracy and correlation measurement of decision trees. *Expert Systems with Applications*. 2024;237:121549.
62. Sipper M, Moore JH. Conservation machine learning: a case study of random forests. *Scientific Reports*. 2021;11:3629.
63. Tang J, Henderson A, Gardner P. Exploring AdaBoost and random forests machine learning approaches for infrared pathology on unbalanced data sets. *Analyst*. 2021;146:5880-5891.
64. Vergni L, Todisco F. A random forest machine learning approach for the identification and quantification of erosive events. *Water*. 2023;15:2225.
65. Joelsson SR, Benediktsson JA, Sveinsson JR. Random forest classification of remote sensing data. In: Chen CH, editor. *Signal and image processing for remote sensing*. Boca Raton: CRC Press; 2006. p. 327-344.
66. Gislason PO, Benediktsson JA, Sveinsson JR. Random forest classification of multisource remote sensing and geographic data. In: *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*; 2004 Sep 20-24; Anchorage, AK, USA. p. 1049-1052.
67. Georganos S, Grippa T, Niang Gadiaga A, Linard C, Lennert M, Vanhuysse S, *et al.* Geographical random forests: a spatial extension of the random forest algorithm to address spatial heterogeneity in remote sensing and population modelling. *Geocarto International*. 2019;36:121-136.
68. Ezugwu AE, Ikotun AM, Oyelade OO, Abualigah L, Agushaka JO, Eke CI, Akinyelu AA. A comprehensive survey of clustering algorithms: state-of-the-art machine learning applications, taxonomy, challenges and future research prospects. *Engineering Applications of Artificial Intelligence*. 2022;110:104743.
69. Bhagwat RU, Uma Shankar B. A novel multilabel classification of remote sensing images using XGBoost. In: *Proceedings of the IEEE 5th International Conference for Convergence in Technology (I2CT)*; 2019 Mar 29-31; Bombay, India. p. 1-5.
70. Militino AF, Goyena H, Perez-Goya U, Ugarte MD. Logistic regression versus XGBoost for detecting burned areas using satellite images. *Environmental and Ecological Statistics*. 2024;31:57-77.
71. Liu Y, Wu S, Wu Z, Zhou S. Application of gradient boosting machine in satellite-derived bathymetry using Sentinel-2 data for accurate water depth estimation in coastal environments. *Journal of Sea Research*. 2024;201:102538.
72. McCarty DA, Kim HW, Lee HK. Evaluation of light gradient boosted machine learning technique in large scale land use and land cover classification. *Environments*. 2020;7:84.
73. Bui QT, Chou TY, Hoang TV, Fang YM, Mu CY, Huang PH, *et al.* Gradient boosting machine and object-based CNN for land cover classification. *Remote Sensing*. 2021;13:2709.

74. Shao Z, Ahmad MN, Javed A. Comparison of random forest and XGBoost classifiers using integrated optical and SAR features for mapping urban impervious surface. *Remote Sensing*. 2024;16:665.
75. Kumar DG, Chaudhari S. AUXG: deep feature extraction and classification of remote sensing image scene using attention UNet and XGBoost. *Journal of the Indian Society of Remote Sensing*. 2024;52:1687-1698.
76. Belgiu M, Dragut L. Random forest in remote sensing: a review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing*. 2016;114:24-31.
77. Hassine K, Erbad A, Hamila R. Important complexity reduction of random forest in multi-classification problem. In: *Proceedings of the 15th International Wireless Communications and Mobile Computing Conference (IWCMC)*; 2019 Jun 24-28; Tangier, Morocco. p. 226-231.
78. Lee WM. Supervised learning—classification using K-nearest neighbors (KNN). In: Lee WM, editor. *Python machine learning*. Hoboken: John Wiley and Sons; 2019. p. 205-220.
79. Zaky D, Gunawan PH. Computational parallel of K-nearest neighbor on page blocks classification dataset. In: *Proceedings of the 8th International Conference on Information and Communication Technology (ICoICT)*; 2020 Jun 24-26; Yogyakarta, Indonesia. p. 1-4.
80. Ray S. An analysis of computational complexity and accuracy of two supervised machine learning algorithms—K-nearest neighbor and support vector machine. In: Sharma N, Chakrabarti A, Balas V, Martinovic J, editors. *Data management, analytics and innovation*. Singapore: Springer; 2020. p. 335-347.
81. Rodriguez MZ, Comin CH, Casanova D, Bruno OM, Amancio DR, Costa LDF, Rodrigues FA. Clustering algorithms: a comparative approach. *PLoS ONE*. 2019;14:e0210236.
82. Li H, Liu X, Li T, Gan R. A novel density-based clustering algorithm using nearest neighbor graph. *Pattern Recognition*. 2020;102:107206.
83. Ahmed Soomro A, Akmar Mokhtar A, Hussin HB, Lashari N, Lekan Oladosu T, Muslim Jameel S, Inayat M. Analysis of machine learning models and data sources to forecast burst pressure of petroleum corroded pipelines: a comprehensive review. *Engineering Failure Analysis*. 2024;155:107747.
84. Sahin EK. Assessing the predictive capability of ensemble tree methods for landslide susceptibility mapping using XGBoost, gradient boosting machine and random forest. *SN Applied Sciences*. 2020;2:1308.
85. Sibindi R, Mwangi RW, Waititu AG. A boosting ensemble learning based hybrid light gradient boosting machine and extreme gradient boosting model for predicting house prices. *Engineering Reports*. 2023;5:e12599.
86. Hazeena MF, Maha L, Padma P, Anitha, Kalaiselvi. Convolutional neural network for remote sensing classification. *AIP Conference Proceedings*. 2023;2831:020002.
87. Kattenborn T, Eichel J, Fassnacht FE. Convolutional neural networks enable efficient, accurate and fine-grained segmentation of plant species and communities from high-resolution UAV imagery. *Scientific Reports*. 2019;9:17656.
88. Alam M, Wang JF, Guangpei C, Yunrong L, Chen Y. Convolutional neural network for the semantic segmentation of remote sensing images. *Mobile Networks and Applications*. 2021;26:200-215.
89. Maggiori E, Tarabalka Y, Charpiat G, Alliez P. Fully convolutional neural networks for remote sensing image classification. In: *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*; 2016 Jul 10-15; Beijing, China. p. 5071-5074.