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Remote Sensing and Machine Learning for Futuristic Horticulture: A Comprehensive Review

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***Abstract*—** *Horticultural crops—fruits, vegetables, plantation crops, flowers, spices and medicinal plants—form the nutritional and economic backbone of India's agricultural sector. However, they face persistent challenges of yield variability, water and nutrient inefficiency, pest and disease pressure and post-harvest losses. This review synthesises the transformative role of Remote Sensing (RS) and Machine Learning (ML) in enabling futuristic, sustainable and precision horticulture. The evolution of agricultural production systems from Agriculture 1.0 to Agriculture 5.0 is traced, followed by a comprehensive discussion of RS principles, elements, four fundamental resolutions (spatial, spectral, temporal, radiometric), and multi-platform architectures (satellite, aerial, UAV, ground-based). A parallel taxonomy of ML—supervised, semi-supervised, unsupervised, reinforcement and deep-learning frameworks—is presented, with emphasis on Random Forest, Support Vector Machine, XGBoost, and Convolutional Neural Network algorithms most widely applied to horticultural datasets. Five representative case studies are analysed in depth: (i) UAV multispectral + ensemble learning for leaf nitrogen monitoring in custard apple [1]; (ii) hyperspectral + ANN / RF / DT models for mango and strawberry fruit-quality parameters [2]; (iii) UAV-hyperspectral detection of citrus canker [3]; (iv) machine-learning-based crop recommendation under NPK, pH and climatic variables [4]; and (v) RS + GIS soil-site suitability for six major fruit crops in the Ganjigatti sub-watershed, Karnataka [5]. National platforms such as CHAMAN, Bhoonidhi, Bhuvan and PMFBY are reviewed as operational demonstrations of the RS + ML value chain. Finally, technical, economic and ethical challenges—ground-truth scarcity, sensor cost, model interpretability, digital divide and data privacy—are discussed, and a way forward for Indian horticulture in the Agriculture 5.0 era is proposed.*

Keywords*— *Remote sensing, machine learning, precision horticulture, UAV, hyperspectral imaging, vegetation indices, XGBoost, convolutional neural network, Agriculture 5.0, decision support system.

I. INTRODUCTION

Horticulture constitutes a vital component of the world's agricultural systems, contributing significantly to food and nutritional security, rural livelihoods, export earnings and agro-industrial development. Fruits, vegetables, spices, plantation crops and ornamental plants deliver essential vitamins, minerals, antioxidants and dietary fibre indispensable to human health and well-being. In developing economies such as India, horticulture has emerged as a high-growth sector by virtue of higher productivity per unit area, greater income potential and expanding domestic and international markets [6].

Despite its importance, horticultural production faces numerous challenges, including declining soil fertility, water scarcity, climate variability, pest and disease outbreaks, labour shortages and rising input costs. Traditional horticultural practices, largely dependent on farmer experience and visual field observations, often result in inefficient input use, yield variability and environmental degradation. These limitations have accelerated the need for advanced technologies that can support precise, timely and site-specific decision-making [7], [8].

Remote Sensing (RS) and Machine Learning (ML) together offer transformative solutions by enabling non-destructive, rapid and large-scale monitoring of crops and orchards. RS technologies provide continuous observations of crop condition across spatial and temporal scales, while ML algorithms extract meaningful patterns and predictive insights from complex, high-dimensional datasets. Their integration supports informed decision-making related to irrigation scheduling, nutrient management, disease control, harvest planning and yield forecasting [1], [2], [7], [9].

While several reviews have addressed RS and ML in agriculture broadly, this review specifically focuses on horticultural crops—a sector with unique characteristics (perennial nature, high-value produce, complex canopy structures) that pose distinct challenges and opportunities for RS + ML applications. Furthermore, this review integrates the Indian national context, covering operational platforms such as CHAMAN, Bhoonidhi, Bhuvan and PMFBY that are rarely discussed together in the international literature. The review also explicitly connects the evolution from Agriculture 1.0 to Agriculture 5.0 with the technological readiness of RS + ML systems, providing a forward-looking perspective on intelligent horticulture.

This review synthesises the state of the art of RS and ML for horticulture as of 2026. Section 2 traces the evolution of agricultural systems from Agriculture 1.0 to Agriculture 5.0. Sections 3 and 4 present the technical foundations of RS and ML respectively. Section 5 discusses the synergistic integration of RS and ML, and Section 6 presents five case studies. Section 7 reviews Indian national operational platforms (CHAMAN, Bhoonidhi, Bhuvan, PMFBY). Section 8 discusses limitations, and Section 9 concludes with a way-forward road-map.

II. EVOLUTION OF AGRICULTURE TOWARDS SMART FARMING

Agricultural systems have progressed through five clearly distinguishable phases, each characterised by transformative technological, social and economic changes. Understanding this evolution is essential for appreciating the emergence of RS and ML as core technologies of futuristic horticulture (Fig. 1) [10], [11].

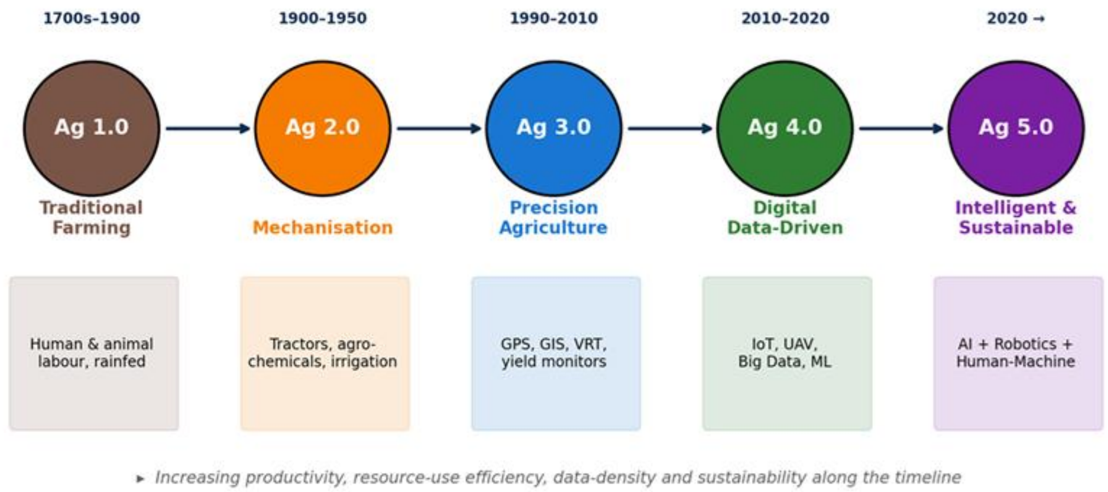

FIGURE 1: Evolution of agriculture from traditional farming (Agriculture 1.0) to intelligent, sustainable systems (Agriculture 5.0). Adapted from [10], [11].

2.1 Agriculture 1.0—Traditional Farming Systems

Agriculture 1.0 represents the era of subsistence and traditional farming (pre-1900), where crop production relied heavily on human and animal labour, indigenous knowledge and natural rainfall. Decision-making was based on farmer experience, visual crop assessment and inherited practices. In horticulture, traditional practices often resulted in non-uniform crop growth, inefficient water and nutrient use and delayed detection of pests and diseases [10].

2.2 Agriculture 2.0—Mechanisation and Input Intensification

The second agricultural revolution (1900–1950) introduced mechanisation, synthetic fertilisers, pesticides and improved irrigation infrastructure. Tractors, harvesters and chemical inputs significantly increased crop yields, but blanket application of inputs led to soil degradation, water pollution and biodiversity loss [10].

2.3 Agriculture 3.0—Precision Agriculture

Agriculture 3.0 (1990–2010) marked the transition to site-specific management using GPS, GIS, yield monitors and variable-rate applicators. RS emerged as a valuable tool, providing spatially-explicit information on crop condition and variability. In horticulture, precision approaches enabled improved irrigation scheduling, fertiliser management and yield estimation, particularly in orchards with heterogeneous soil and canopy conditions [7], [12].

2.4 Agriculture 4.0—Digital and Data-Driven Farming

Agriculture 4.0 (2010–2020) integrated the Internet of Things (IoT), cloud computing, big-data analytics and automation. Continuous data streams from sensors, weather stations, UAVs and satellites enable near-real-time monitoring of crops and environmental conditions. ML models play a central role in Agriculture 4.0 by analysing large multidimensional datasets to generate actionable insights. In horticulture, ML-driven systems support yield prediction, disease detection, fruit counting and quality assessment, significantly enhancing decision-making accuracy [13], [14].

2.5 Agriculture 5.0—Intelligent and Sustainable Systems

Agriculture 5.0 (2020 onwards) builds upon digital farming by emphasising Artificial Intelligence, robotics, human–machine collaboration and sustainability. In futuristic horticulture, Agriculture 5.0 envisions autonomous UAVs and robots integrated with RS, ML and decision-support systems to deliver precise inputs, monitor crop health continuously and adapt management strategies dynamically [10], [11], [15].

III. REMOTE SENSING—TECHNOLOGY AND PRINCIPLES

Remote Sensing is the science and technology of acquiring information about objects, areas or phenomena without direct physical contact, by measuring reflected or emitted electromagnetic radiation with instruments not physically connected to the subject. Pisharoth Rama Pisharoty is recognised as the Father of Remote Sensing in India [16].

3.1 History and Development

The term Remote Sensing was first coined in the United States in the 1950s by Ms Evelyn Pruitt of the U.S. Office of Naval Research. RS technologies in agriculture began with the launch of the Earth Resources Technology Satellite (ERTS-1, later renamed Landsat) in 1972, which carried the Return Beam Vidicon (RBV) and Multispectral Scanner (MSS) sensors. In India, the first documented use of RS was for coconut root-wilt disease detection in 1970, and the country's first RS satellite IRS-1A was launched on 17 March 1988. The most recent milestone is the NASA-ISRO Synthetic Aperture Radar (NISAR) launched on 30 July 2025 from Satish Dhawan Space Centre, Sriharikota, carrying dual-frequency L- and S-band SAR sensors with 3 m resolution for high-resolution tracking of surface moisture, biomass, crop areas, mangroves and wetlands [16], [17].

3.2 Principle of Remote Sensing and its Elements

The principle of RS rests on collecting information about a target without physical contact, using sensors to detect and record electromagnetic energy that is either reflected or emitted by the target. The seven fundamental elements of RS—Energy source, Interaction with the atmosphere, Interaction with the target, Sensor, Data transmission, Product generation and User application—form the operational chain illustrated in Fig. 2 [16].

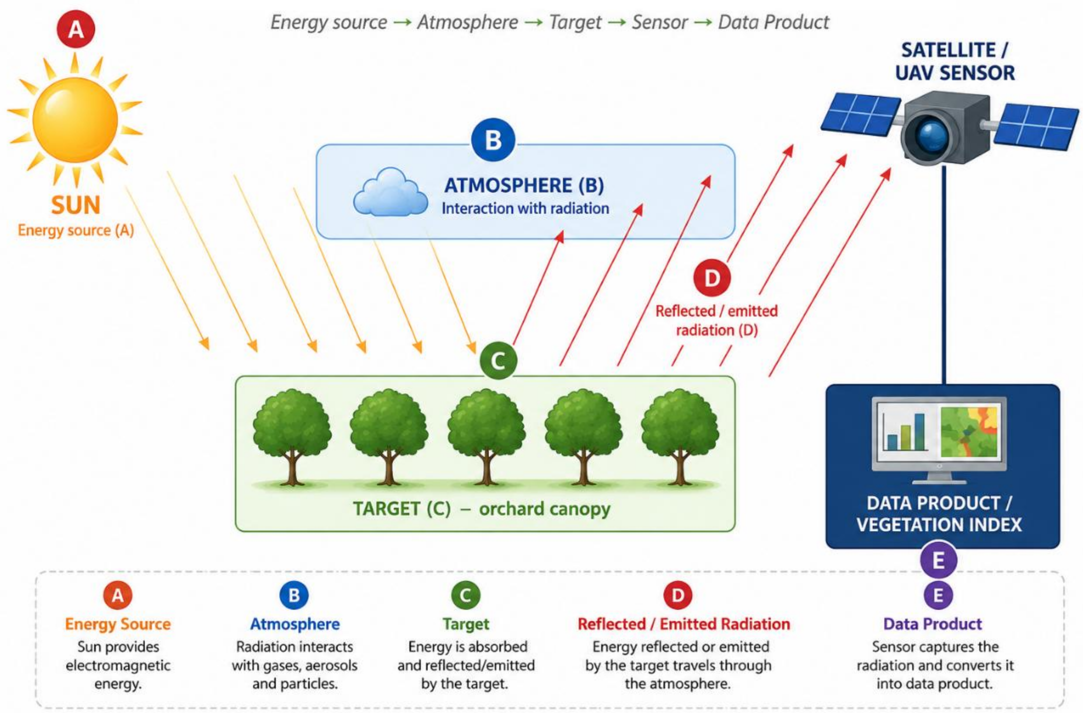

FIGURE 2: Elements and working principle of Remote Sensing—from solar energy source through atmospheric interaction, target reflectance and sensor acquisition to final data product.

3.3 Geographic Information Systems (GIS) and Global Navigation Satellite Systems (GNSS)

GIS, originating from Roger Tomlinson's 1963 work on Canada's national land-use programme, is a computer-based system designed to capture, store, manipulate, analyse and display geographically-referenced data (ESRI). Jack Dangermond and Laura Dangermond founded the Environmental Systems Research Institute (ESRI) in 1969 and developed ARC/INFO, the first commercial GIS product, in 1981. GIS-derived mapping products used in horticulture include soil classification, crop-distribution mapping, land-utilisation mapping, contour mapping and irrigation-system analysis [12].

Global Navigation Satellite Systems (GNSS) comprise localisation constellations that provide accurate location, navigation and timing information—the positioning backbone of precision agriculture. Major constellations include NAVSTAR-GPS (USA, 1972), GLONASS (Russia, 1982), BeiDou (China, 2000), Galileo (EU, 2011), QZSS (Japan, 2010) and IRNSS/NavIC (India, 2013). GNSS in horticulture supports yield monitoring, compaction profile sensing, tree-planting and site-specific fumigant application, RTK-GPS plant mapping, precise weed management and robotic operations [12].

3.4 Passive and Active Remote-Sensing Systems

RS systems are broadly classified into passive and active sensors based on the energy source. Passive sensors rely on natural energy—primarily solar radiation—and measure reflected or emitted energy from the Earth's surface. Most optical multispectral and hyperspectral sensors used in horticulture, such as Landsat, Sentinel-2 and UAV-mounted cameras, are passive systems.

Active RS systems, in contrast, emit their own energy and measure the returned signal after interaction with the target. Synthetic Aperture Radar (SAR) and Light Detection and Ranging (LiDAR) are common active systems. SAR operates in the microwave region and can acquire data under all-weather and day–night conditions, making it valuable for soil-moisture estimation and crop-structure analysis. LiDAR provides precise three-dimensional information on canopy height, volume and structure, particularly useful in orchard management and pruning assessment [18], [19].

3.5 Sensor Resolutions in Remote Sensing

The quality and applicability of RS data are determined by four fundamental resolutions—spatial, spectral, temporal and radiometric (Fig. 3) [20].

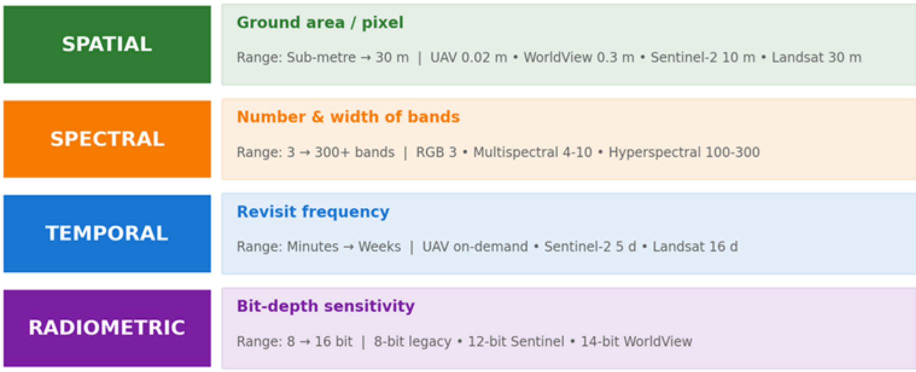

FIGURE 3: Four fundamental resolutions of Remote Sensing (spatial, spectral, temporal, radiometric) and their typical ranges across UAV, satellite and airborne platforms.

- **Spatial resolution**—the ground area represented by a single pixel. Sub-metre to a few metres (UAVs, commercial satellites) is essential for horticultural applications where individual trees, rows or fruit clusters must be resolved.
- **Spectral resolution**—the number and width of bands. Hyperspectral sensors with 100–300 narrow bands provide detailed spectral information enabling precise estimation of chlorophyll, nitrogen and water content [20].
- **Temporal resolution**—the revisit frequency. High temporal resolution is critical for monitoring crop growth dynamics, stress development and phenological changes in fast-growing horticultural crops.
- **Radiometric resolution**—the sensor's sensitivity to detect small energy differences, expressed in bits. Higher radiometric resolution improves the detection of subtle reflectance variations associated with early stress symptoms.

3.6 Remote-Sensing Platforms and Sensors for Horticulture

Modern horticulture increasingly relies on a multi-platform approach that integrates satellite, aerial, UAV and ground-based observations to capture crop variability across scales (Fig. 4).

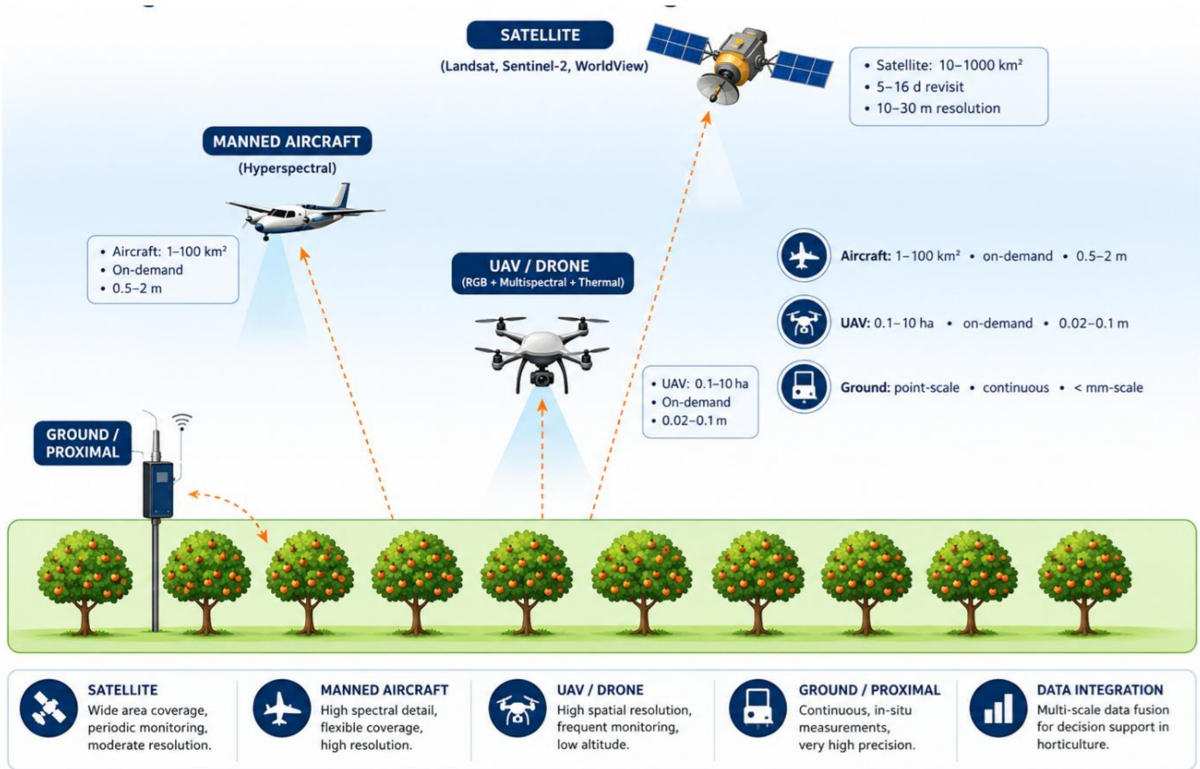

FIGURE 4: Multi-platform Remote-Sensing architecture for horticulture, spanning satellite, manned-aircraft, UAV and ground/proximal sensor levels.

3.6.1 Satellite Remote Sensing

Satellite RS remains the backbone of large-scale agricultural monitoring due to its consistent coverage, long-term data archives and standardised products. Medium-resolution satellites such as Landsat (30 m) and Sentinel-2 (10–20 m) are widely used for monitoring crop growth, phenology and stress dynamics over regional to national scales. Sentinel-2's red-edge bands offer enhanced sensitivity to canopy chlorophyll content and structure, particularly valuable for orchard and plantation-crop monitoring [7], [21], [22]. High- and very-high-resolution commercial satellites including WorldView-3/4, GeoEye-1, Pléiades and Planet Labs provide sub-metre resolution enabling detailed tree-level analysis and inventory of high-value orchards.

3.6.2 Airborne and UAV Remote Sensing

Aerial platforms include manned aircraft carrying hyperspectral or LiDAR sensors, providing high-resolution data over intermediate spatial scales. UAV platforms have revolutionised horticultural RS by delivering ultra-high spatial resolution (< 5 cm) on-demand at moderate cost. UAVs carrying RGB, multispectral, hyperspectral or thermal cameras support intensive orchard monitoring, individual-tree analysis and rapid stress detection [22], [23], [24].

IV. MACHINE LEARNING—TAXONOMY AND ALGORITHMS

Machine Learning is a subfield of Artificial Intelligence that enables computer systems to learn patterns from data and improve performance without being explicitly programmed. In horticulture, ML provides powerful tools for analysing high-dimensional RS data, integrating heterogeneous data sources and generating predictive insights that support decision-making across the crop cycle [15], [25].

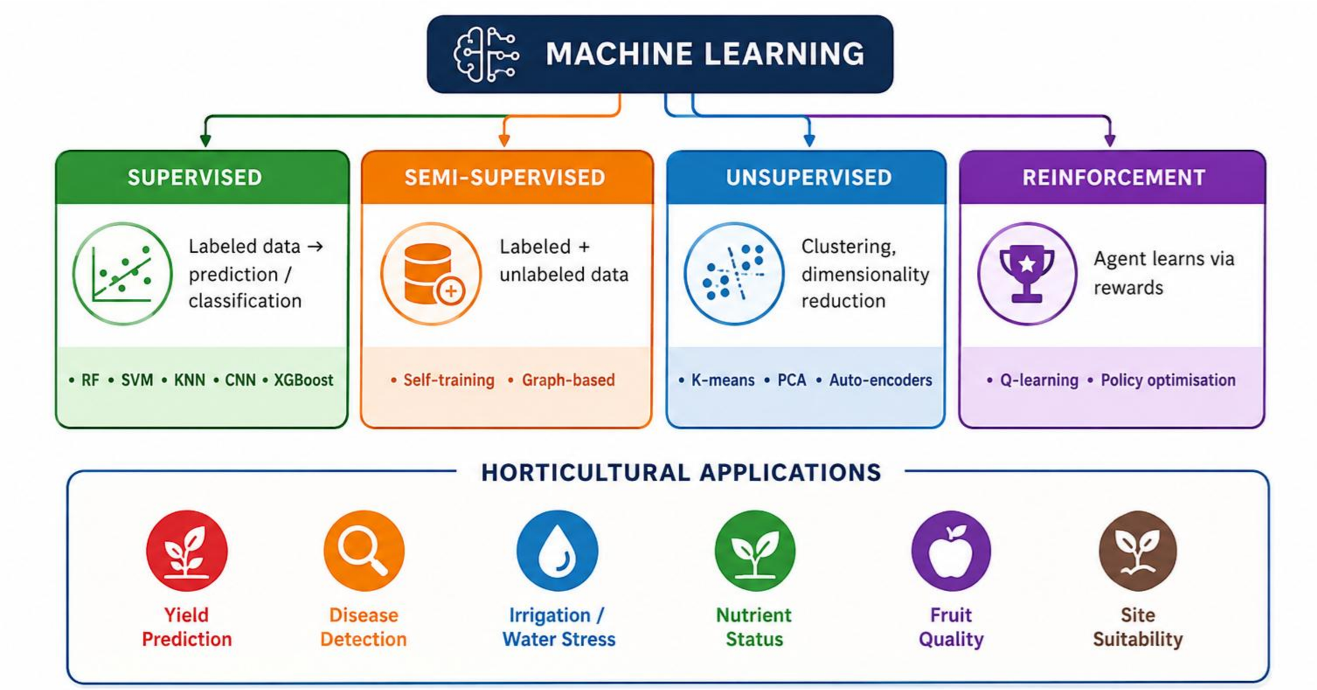

FIGURE 5: Machine-Learning taxonomy for precision horticulture—four principal learning paradigms and their key horticultural applications.

4.1 Classification of ML Models

Supervised Learning: Models learn from labelled training data to make predictions or classifications. Common families include tree-based (decision trees, random forest), Bayesian (naïve Bayes, hidden Markov models), instance-based (k-nearest neighbours, support vector machines), regularisation-based (ridge, logistic regression), neural-network based (MLP, CNN, RNN) and ensemble models (bagging, boosting, stacking).

Semi-Supervised Learning: These models use both labelled and unlabelled data—inductive (self-training, co-training, boosting) and transductive (graph-based generative, manifold, maximum-margin) methods.

Unsupervised Learning: Models analyse unlabelled data to uncover hidden patterns—cluster-based (K-means, hierarchical, DBSCAN), dimensionality-reduction (PCA, ICA) and neural-network based (autoencoders, GANs, Boltzmann networks).

Reinforcement Learning: An agent learns optimal actions in an interactive environment by maximising rewards, via model-based or model-free (policy optimisation, Q-learning) techniques.

4.2 Classical ML Algorithms Widely Applied to Horticulture

Decision Trees (DT) are intuitive models that partition data based on decision rules; easy to interpret but prone to over-fitting when used alone. Random Forests (RF), an ensemble of decision trees, improve predictive performance by reducing variance and handling non-linear relationships. RF models have been extensively used for yield prediction, disease classification and nutrient-status estimation in horticultural crops [1], [2], [25]. Support Vector Machines (SVM) are effective for high-dimensional data and have demonstrated strong performance in crop classification, disease detection and quality assessment using spectral features. K-Nearest Neighbours (KNN) is a simple, instance-based method that classifies samples based on similarity, though its performance depends on appropriate distance metrics and data normalisation.

4.3 Ensemble Learning and XGBoost

Ensemble learning combines multiple base learners to achieve better generalisation and robustness. Random Forest, Gradient Boosting Decision Trees (GBDT) and Extreme Gradient Boosting (XGBoost) are widely used in precision agriculture. XGBoost has gained particular popularity due to its high accuracy, computational efficiency and ability to handle complex non-linear interactions among variables. In horticulture, ensemble models have been applied to crop-recommendation systems using soil NPK, pH, temperature, rainfall and humidity data, as well as to yield prediction and stress assessment using RS-derived features [1], [4].

4.4 Deep Learning and Convolutional Neural Networks

Deep Learning, a subset of ML based on artificial neural networks with multiple hidden layers, has revolutionised image-based analysis in horticulture. Convolutional Neural Networks (CNNs) are particularly effective for processing RGB, multispectral and hyperspectral images. CNN-based models have been successfully applied to fruit detection, counting and sizing in orchards, enabling automated yield estimation and harvest planning. Deep-learning approaches also support disease detection by identifying subtle visual and spectral patterns associated with early infection stages [3], [14], [26].

4.5 Model Training, Validation and Performance Metrics

Robust ML model development requires careful partitioning of data into training, validation and testing sets—typically 70/15/15 or 80/20 splits. Cross-validation (5- or 10-fold) is commonly used to assess generalisation. Classification tasks are evaluated using accuracy, precision, recall and F1-score, while regression problems use coefficient of determination (R^2), root-mean-square error (RMSE) and mean absolute error (MAE). Interpretability techniques such as feature-importance analysis and SHAP (Shapley Additive Explanations) values help elucidate model behaviour and build user trust [15].

V. INTEGRATION OF REMOTE SENSING AND MACHINE LEARNING

The combination of RS and ML brings new possibilities for Precision Horticulture (PH). RS data exhibit significant complementarities in meeting PH needs, with hyperspectral RS being the most widely used and UAV RS offering the greatest per-hectare potential. Among ML algorithms, SVM is the most widely applied in horticultural literature, closely followed by Random Forest [22], [25]. The integrated workflow—from data acquisition through decision support—is illustrated in Fig. 6.

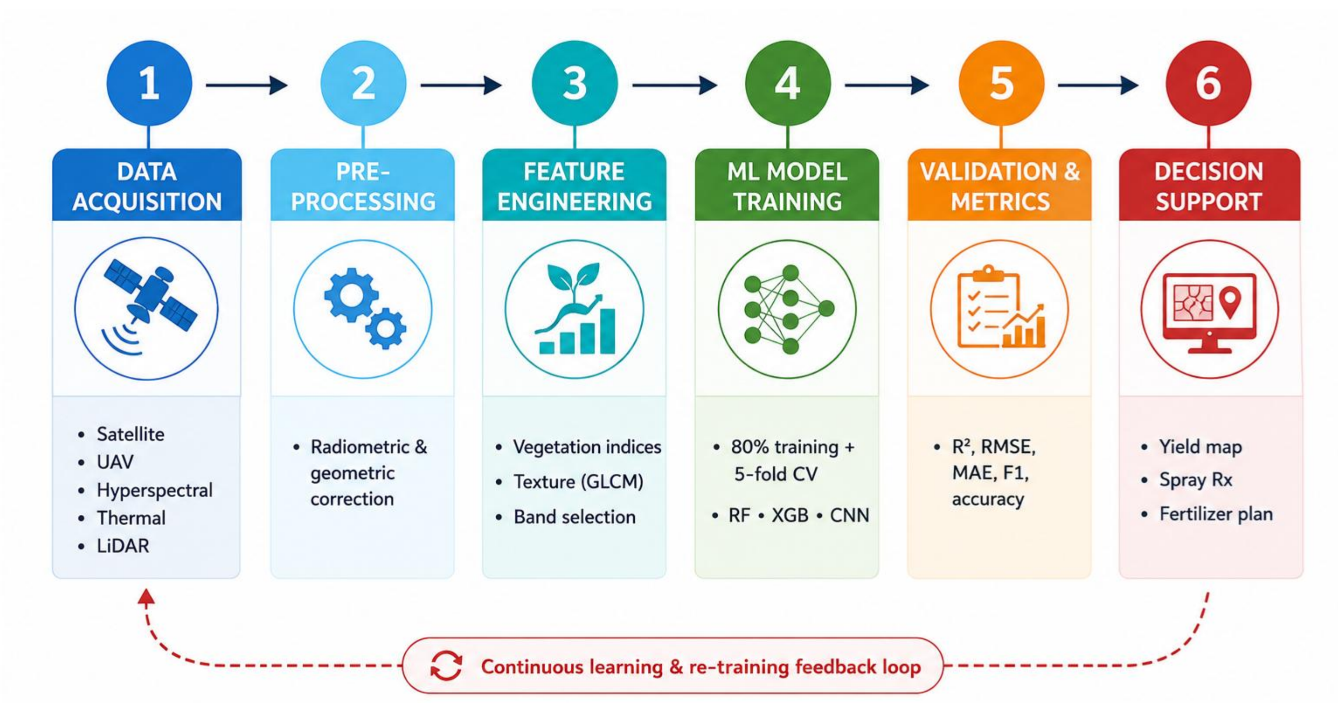

FIGURE 6: Integrated Remote-Sensing + Machine-Learning workflow for precision horticulture, showing six sequential steps and the feedback loop for continuous model improvement.

5.1 Key Application Areas of the RS + ML Combination

- **Crop-disease observation:** UAV RGB, multispectral and hyperspectral cameras coupled with CNN or SVM enable early detection of viral, fungal and bacterial diseases before visual symptoms appear [3].
- **Soil-water content estimation:** Random-Forest regression and SVR applied to UAV thermal, multispectral and hyperspectral data predict soil moisture with RMSE < 4%.
- **Weed detection:** Deep-learning models (MobileNetV2-UNet, FFB-BiseNetV2) applied to UAV imagery deliver real-time weed detection and classification.
- **Crop monitoring:** UAV multispectral and RGB cameras track crop height, phenology, chlorophyll content, flowering stages and yield potential.
- **Fruit-quality assessment:** Hyperspectral proximal sensing coupled with ANN, RF or DT accurately estimates total soluble solids, firmness, chlorophyll and colour of ripening fruits [2].

VI. RESEARCH FINDINGS AND CASE STUDIES IN PRECISION HORTICULTURE

This section synthesises five representative case studies published between 2019 and 2025 that collectively demonstrate the operational maturity of RS + ML in horticulture.

6.1 UAV Ensemble Learning for Leaf-Nitrogen Content in Custard Apple [1]

Jiang et al. (2025) [1] combined UAV multispectral imagery from a DJI Mavic 3M platform with a two-layer stacking ensemble learning framework to monitor leaf nitrogen content (LNC) in custard apple (*Annona squamosa* L.) orchards in Yuanmou County, China. Eleven vegetation indices (NDVI, MNDRE, NRI, RESR, TNDVI, WDRVI, NGI, MSR, NREI_R, RVI, NREI) were derived from green, red, red-edge and NIR bands. Eight Gray-Level Co-occurrence Matrix (GLCM) texture features were extracted per band. Five base learners—Random Forest, Gradient Boosting Decision Trees, Adaptive Boosting, Linear Regression and Extremely Randomised Trees—were stacked with Lasso regression as the meta-model. The optimised model achieved R^2 = 0.661, RMSE = 0.059 and MAE = 0.193 for LNC prediction across three growth stages, confirming the operational feasibility of UAV-based ensemble learning for site-specific nitrogen management in orchards.

Critical Evaluation: While the study demonstrates the feasibility of UAV-based ensemble learning, the R^2 value of 0.661 indicates that approximately 34% of the variance in leaf nitrogen content remains unexplained. This suggests that additional predictors (e.g., soil properties, microclimate, crop variety) may be needed for more accurate predictions. The study's reliance on a single orchard location also limits generalizability.

6.2 Hyperspectral + ML for Fruit Quality of Mango and Strawberry [2]

Elsayed et al. (2025) [2] evaluated the biochemical quality of mango cv. 'Succarri' and strawberry cv. 'Florida' at three ripening stages (unripe, ripe, overripe) using proximal hyperspectral reflectance (302–1148 nm, 2 nm spectral resolution) coupled with Artificial Neural Networks (ANN), Random Forest (RF) and Decision Trees (DT). Sixteen Spectral Reflectance Indices (SRIs)—four existing and twelve newly developed two-band indices—were used as inputs. The ANN model outperformed RF and DT for TSS, firmness and chlorophyll estimation, with R^2 values ranging 0.71–0.94 across ripening stages. This study established hyperspectral + ML as a robust non-destructive alternative to conventional laboratory-based fruit-quality analysis.

Critical Evaluation: The study's strength lies in its high R^2 values (0.71–0.94), indicating strong predictive performance. However, the laboratory-based hyperspectral measurements (handheld sensor) may not translate directly to field-based remote sensing applications. The limited sample size and single cultivar per crop also limit generalizability.

6.3 UAV Hyperspectral + ML for Citrus Canker Detection [3]

Abdulridha, Batuman and Ampatzidis (2019) [3] employed a UAV-mounted hyperspectral camera and machine-learning classifiers to detect citrus canker disease in Florida orchards. The workflow combined spectral reflectance analysis with SVM and neural-network classifiers, achieving disease-detection accuracy > 90% at symptomatic and 82% at asymptomatic stages, thereby confirming UAV-hyperspectral systems as viable precision-management tools for perennial fruit orchards.

Critical Evaluation: The high accuracy (>90% for symptomatic detection) is impressive. However, the study was conducted in a single region (Florida) with a specific citrus variety. The asymptomatic detection accuracy (82%) suggests that early detection capability, while promising, still has room for improvement.

6.4 ML-Based Crop and Fertiliser Recommendation under NPK, pH and Climate [4]

Dey, Ferdous and Ahmed (2024) [4] developed an ML-based recommendation system for agricultural and horticultural crop farming in India, integrating soil NPK, pH, temperature, rainfall and humidity variables. XGBoost achieved the highest accuracy—99.09% for agricultural crops and 99.3% for horticultural crops—outperforming previous studies that reported 95.62% accuracy for XGBoost in mixed-crop models. The output supports user-friendly precision-agriculture tools to optimise crop selection and nutrient application.

Critical Evaluation: While the high accuracy (99.3%) is notable, the recommendation system relies on static soil and climate inputs rather than dynamic, real-time data. The model's performance may vary under different soil types and climatic conditions not represented in the training data.

6.5 RS + GIS Soil-Site Suitability for Six Major Fruit Crops [5]

Narasimha Yadav et al. (2023) [5] evaluated 21 soil series of the Ganjigatti sub-watershed (5B1A4F), Dharwad district, Karnataka (15° 10′–15° 17′ N, 75° 0′–75° 4′ E, elevation 610 m MSL, annual rainfall 917 mm) using RS + GIS on ArcGIS v10.8. Suitability was assessed following FAO (1976) and Naidu et al. (2006) frameworks across three phases—landscape and soil characteristics, crop-specific requirements, and rainfed limitations (no, slight, moderate, severe, very severe). Ten soil series (BGD, BNK, KDK, KMD, KRL, MLP, MRK, SDK, SSK, YSJ) were classified as N (currently not suitable) due to severe limitations of soil depth and slope. AKT, BGH and MVD were moderately to marginally suitable for mango, guava, pomegranate, sapota, citrus and grape. This case study underscores the operational value of RS + GIS for landscape-scale horticultural land-use planning.

Critical Evaluation: The study's strength is its systematic approach to land suitability assessment. However, the classification is based on static soil and terrain parameters rather than dynamic climatic and market conditions that may affect the viability of fruit cultivation.

6.6 Comparative Summary of Case Studies

TABLE 1
COMPARATIVE SUMMARY OF CASE STUDIES

Case	Crop	Sensor / Platform	ML Model	Key Performance	Limitations
Jiang et al., 2025 [1]	Custard apple	UAV multispectral	Stacking ensemble	$R^2 = 0.661$, RMSE = 0.059	Single location; unexplained variance
Elsayed et al., 2025 [2]	Mango, Strawberry	Handheld hyperspectral	ANN, RF, DT	R^2 0.71–0.94	Lab-based; limited sample size
Abdulridha et al., 2019 [3]	Citrus	UAV hyperspectral	SVM, ANN	Accuracy > 90%	Single region; asymptomatic accuracy 82%
Dey et al., 2024 [4]	Multi-crop	Soil + climate variables	XGBoost	Accuracy 99.3%	Static inputs; limited soil diversity
Narasimha et al., 2023 [5]	6 fruit crops	Satellite + GIS	Rule-based suitability	21 series → S1-N	Static parameters; no economic assessment

VII. INDIAN NATIONAL PLATFORMS AND OPERATIONAL APPLICATIONS

FIGURE 7: Application wheel of RS + ML in futuristic horticulture—ten operationally-validated domains with representative performance metrics.

7.1 CHAMAN—Coordinated Horticulture Assessment and Management

Coordinated Horticulture Assessment and Management using Geo-informatics (CHAMAN) is a national mission project under the Mission for Integrated Development of Horticulture (MIDH), Ministry of Agriculture and Farmers Welfare, Government of India. It has extensively used satellite data for inventory of major horticultural crops (mango, banana, citrus) across 40 selected districts of the country, establishing the largest RS-based horticultural inventory in India [16].

7.2 Pradhan Mantri Fasal Bima Yojana (PMFBY)—Crop Insurance

PMFBY is the national flagship crop-insurance programme. The National Remote Sensing Centre (NRSC) conducts geomatics-based studies to improve area-yield estimates for insurance mechanisms. A Crop Insurance Decision Support System (CIDSS) is being developed as a web-enabled integrated package for States, improving efficiency, transparency and objective decision-making in sampling design and yield estimation [16].

7.3 Bhoonidhi and Bhuvan—Open RS Data Portals

Bhoonidhi (ISRO Open Data Access) is a single-window portal disseminating IRS and non-IRS satellite data products online. Under the Indian Space Policy 2023, satellite data of 5 m and coarser resolution are free and open to all users; finer data (except DEM, merged, mosaicked and customised products) are free for government entities and priced for non-government users. Available resolutions span very-high (0.1–1 m), high (1–5 m), medium (5–25 m), low (25–100 m) and coarse (100 m–1 km). Sensor types include AIS, AVHRR, AWiFS, LISS-1/2/3/4, MODIS, OCM, OLI+TIRS, PAN, SAR, SCAT, VIIRS and WiFS. Bhuvan, ISRO's Indian Geo-portal, complements Bhoonidhi by providing thematic visualisation and value-added services [16], [17].

Critical Evaluation: While these platforms provide valuable data access, challenges remain in data discovery, processing and integration for horticultural applications. The fine-resolution data (0.1–1 m) required for tree-level analysis is not freely available, limiting their use for smallholder orchard monitoring.

VIII. CHALLENGES, LIMITATIONS AND WAY FORWARD

Despite substantial advances, the widespread adoption of RS, GIS and ML in precision horticulture faces several technical, operational, economic and ethical challenges. A SWOT synthesis is presented in Fig. 8.

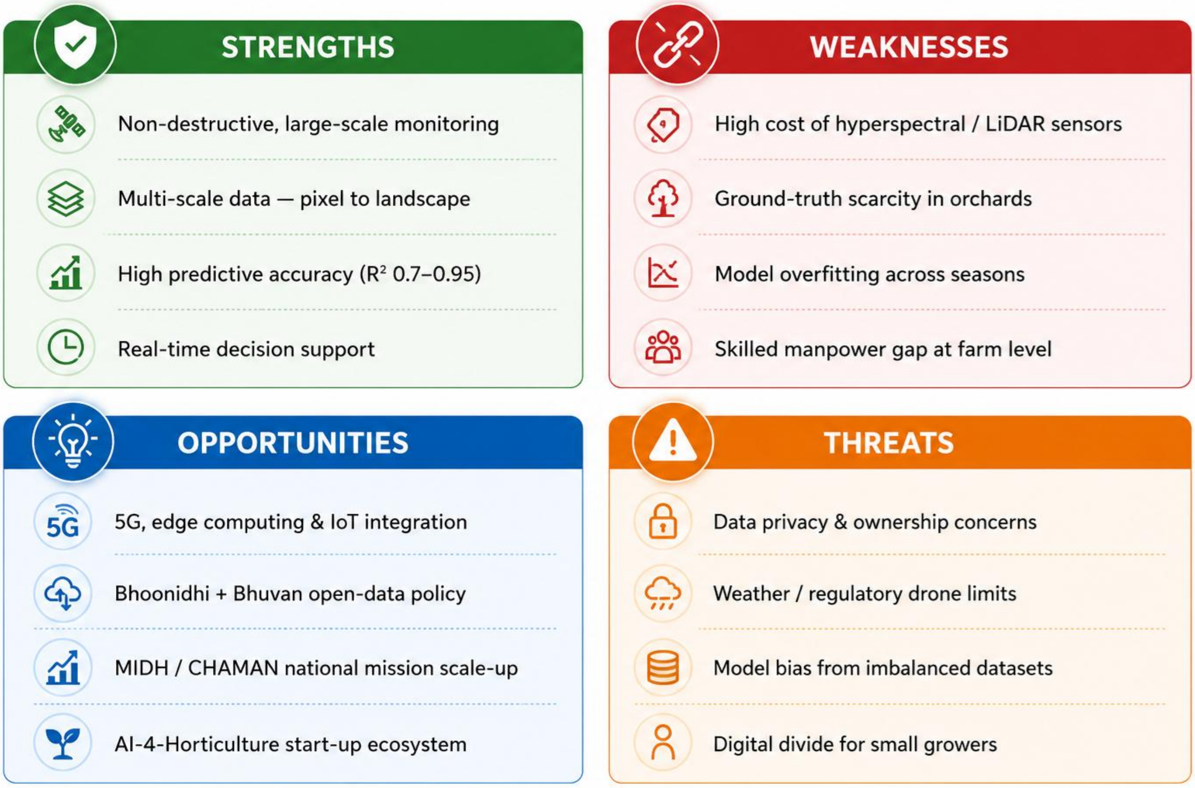

FIGURE 8: SWOT analysis of RS + ML in horticulture—strengths, weaknesses, opportunities and threats for Indian precision-horticulture ecosystems.

8.1 Data Quality, Availability and Ground-Truth Constraints

The accuracy of RS + ML systems depends heavily on the quality and representativeness of input data. Variability in sensor calibration, atmospheric conditions, illumination geometry and acquisition timing introduces noise and uncertainty into spectral measurements. Complex orchard canopies and background effects further complicate interpretation. Ground-truth data collection remains a major bottleneck for perennial orchards, and insufficient ground truth leads to model over-fitting and reduced generalisability across seasons and locations.

8.2 Sensor, Platform and Resolution Limitations

Each platform involves inherent trade-offs. Satellite data offer broad coverage but often lack the resolution required for tree-level analysis. UAVs provide high-resolution data but are constrained by limited coverage, flight regulations and weather. Hyperspectral and LiDAR sensors, though information-rich, are expensive and generate large data volumes demanding substantial computational resources [22].

8.3 Model Generalisability and Interpretability

ML models trained on one crop, region or season may not generalise well to different conditions. Deep-learning models in particular are often treated as black boxes, complicating adoption by farmers and policymakers. Explainable-AI techniques such as SHAP values are increasingly essential to build trust and regulatory acceptance [15].

8.4 Economic and Digital-Divide Barriers

High initial investment in sensors, computing infrastructure and skilled personnel limits adoption by small and marginal horticulturists. Bridging this divide requires public–private partnerships, custom-hiring service models, subsidised UAV services and integration with existing extension networks. The digital divide—access to technology, internet connectivity and digital literacy—remains a significant barrier for smallholder farmers in rural India.

8.5 Policy and Institutional Constraints

The lack of clear policies on data ownership, privacy and sharing, particularly for UAV and farmer-level data, hinders the development of scalable RS + ML solutions. Regulatory restrictions on drone operations and the absence of standardised data formats further complicate deployment.

8.6 Way Forward

1) **Establish national ground-truth data repositories** for major horticultural crops and orchard systems, with standardised protocols for data collection and sharing.
2) **Promote low-cost, MSME-fabricable UAV and sensor platforms** for last-mile deployment, reducing the cost barrier for smallholder adoption.
3) **Expand Bhoonidhi and Bhuvan** to include pre-computed vegetation-index products and ML-ready analysis-ready-data (ARD) cubes.
4) **Integrate 5G, edge computing and IoT** to enable in-field ML inference and real-time decision support.
5) **Strengthen farmer capacity** through cooperative Custom Hiring Centres (CHC) and Farmer Producer Organisations (FPOs) offering RS + ML as a service.
6) **Develop crop-specific benchmark datasets** and open-source ML libraries tailored to Indian horticulture (mango, banana, citrus, grape, guava, tomato, chilli, potato).
7) **Establish public–private partnerships** to fund infrastructure development, technology transfer and capacity building.
8) **Develop clear data policies** on ownership, privacy and sharing to facilitate collaborative research and deployment.
9) **Create regulatory frameworks** that enable safe and scalable UAV operations for agricultural monitoring.

IX. CONCLUSION

Remote Sensing and Machine Learning constitute two mutually reinforcing pillars of futuristic horticulture. RS provides multi-scale, multi-temporal, multi-spectral windows into the orchard environment, while ML converts the resulting high-dimensional data into actionable knowledge. Together, they are reshaping horticulture across every operational domain—yield forecasting, disease detection, nutrient monitoring, irrigation, fruit-quality assessment, weed detection, site-suitability planning and crop insurance. Case-study evidence from India, China, USA and Egypt demonstrates R^2 values of 0.66–0.94, accuracy > 90% and RMSE reductions of one order of magnitude against classical statistical methods.

For India, the confluence of Agriculture 5.0 principles, open-data platforms like Bhoonidhi and Bhuvan, national missions like MIDH-CHAMAN and PMFBY, and a growing agri-tech start-up ecosystem creates an unprecedented opportunity to leap-frog into intelligent, sustainable horticultural production. Addressing the current limitations of ground-truth scarcity, sensor cost, model interpretability and digital divide through coordinated policy, technology transfer and capacity building will determine how quickly this promise is realised. The next decade of Indian horticulture will be defined not merely by hectares under cultivation, but by the depth of digital intelligence guiding every hectare.

Limitations of the Review: This review is based on a narrative synthesis of published literature rather than a formal systematic review. The case studies were selected to represent diversity in crops, sensors and ML approaches, but may not be exhaustive of all relevant research. The review focuses primarily on Indian and international studies published in English, potentially overlooking research in other languages or regional contexts.

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CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

[1] Abdulridha, J., Batuman, O., & Ampatzidis, Y. (2019). UAV-based remote sensing technique to detect citrus canker disease utilizing hyperspectral imaging and machine learning. Remote Sensing, *11*(11), Article 1373.

[2] Botero-Valencia, J., García-Pineda, V., Valencia-Arias, A., Valencia, J., Reyes-Vera, E., Mejia-Herrera, M., & Hernández-García, R. (2025). Machine learning in sustainable agriculture: Systematic review and research perspectives. Agriculture, *15*(4), Article 377.

[3] Dey, B., Ferdous, J., & Ahmed, R. (2024). Machine learning based recommendation of agricultural and horticultural crop farming in India under the regime of NPK, soil pH and three climatic variables. Heliyon, *10*(3), Article e25112.

[4] Elsayed, S., Gala, H., Abd El-Baki, M. S., Maher, M., Elbeltagi, A., & Salem, A. (2025). Hyperspectral technology and machine learning models to estimate the fruit quality parameters of mango and strawberry crops. PLoS ONE, *20*(2), Article e0313397.

[5] Guebsi, R., et al. (2025). UAV-based remote sensing in olive orchards: A comprehensive case study in Sidi Bouzid, Tunisia. Precision Agriculture Journal, *8*, Article 449.

[6] ISRO. (2025a). NRSC Bhoonidhi and Bhuvan Portals-Indian Space Policy 2023 Guidelines. Indian Space Research Organisation.

[7] ISRO. (2025b). NISAR (NASA-ISRO Synthetic Aperture Radar) Reference Observation Plan (ROP)-Online Interactive Tool. Indian Space Research Organisation.

[8] Jiang, X., Gao, L., Xu, X., Wu, W., Yang, G., Meng, Y., Feng, H., Li, Y., Xue, H., & Chen, T. (2025). Combining UAV remote sensing with ensemble learning to monitor leaf nitrogen content in custard apple (Annona squamosa L.). Agronomy, *15*(1), Article 38.

[9] Kumar, N. B., et al. (2026). Use of artificial intelligence in controlled environment agriculture: A narrative review. Journal of the American Society for Horticultural Science, *151*(4), 306-318.

[10] Liu, S., Guo, X., & Chen, Y. (2020). Internet of Things and Big Data in modern agriculture: A review. Computers and Electronics in Agriculture, *175*, Article 105577.

[11] Mishra, A. R. (2017). Hyperspectral remote sensing for agricultural applications: A review. Agricultural Reviews, *38*(2), 121-129.

[12] Muhammad, A., et al. (2026). A review of remote sensing-based crop yield estimation. Frontiers in Plant Science, *17*, Article 1742689.

[13] Neisse, R. E. (2026). Remote sensing and ai-driven innovations in contemporary agriculture and horticulture: A review for crop improvement. International Journal of Environmental and Agriculture Research, *12*(4), 55-72.

[14] Neves, M. F., Casagrande, B. P., Cambaúva, V., Teixeira, G. de O., & Toledo, P. J. F. (2023). Agriculture 6.0: A new proposal for the future of agribusiness. Revista de Gestão – RGSA, *17*(9), Article e04004.

[15] Perez-Ruiz, M., & Upadhyaya, S. K. (2012). GNSS in precision agricultural operations. In New approach of indoor and outdoor localization systems (pp. 3-20). InTech.

[16] Pisharoty, P. R. (2010). Remote sensing in India-Historical perspective. ISRO Technical Bulletin.

[17] Pujar, D. U., Pujar, U. U., Shruthi, C. R., Wadagave, A., & Chulaki, M. (2017). Remote sensing in fruit crops. Journal of Pharmacognosy and Phytochemistry, *6*(5), 2479-2484.

[18] Ray, P. K. (2016). Applications of remote sensing in agriculture and horticulture. Indian Farming, *66*(4), 33-39.

[19] Saiz-Rubio, V., & Rovira-Más, F. (2020). From smart farming towards agriculture 5.0: A review on crop data management. Agronomy, *10*(2), Article 207.

[20] Steele-Dunne, S. C., McNairn, H., Monsivais-Huertero, A., Judge, J., Liu, P. W., & Papathanassiou, K. (2017). Radar remote sensing of agricultural canopies: A review. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, *10*(5), 2249-2273.

[21] Valdiviezo, J., et al. (2026). Remote sensing and artificial intelligence for crop pest and disease monitoring: A systematic review. Smart Agricultural Technology, *12*, Article 100610.

[22] Wallace, L., Lucieer, A., Watson, C., & Turner, D. (2012). Development of a UAV-LiDAR system with application to forest inventory. Remote Sensing, *4*(6), 1519-1543.

[23] Yadav, M. B. N., Patil, P. L., Hebbara, M., Angadi, S. S., & Meti, C. B. (2023). Soil-site suitability assessment for major fruit crops in Ganjigatti sub-watershed (5B1A4F), Karnataka using remote sensing and GIS techniques. The Pharma Innovation Journal, *12*(9), 994-1005.

[24] Zhai, Z., Martínez, J. F., Beltrán, V., & Martínez, N. L. (2020). Decision support systems for agriculture 4.0: Survey and challenges. Computers and Electronics in Agriculture, *170*, Article 105256.

[25] Zhang, L., Sun, C., Zheng, S., & Ni, Y. (2019). Intelligent fruit detection for apples and strawberries using convolutional networks. Computers and Electronics in Agriculture, *165*, Article 104962.

[26] Zhang, S., et al. (2025). A review of the application of UAV multispectral remote sensing in precision agriculture. Smart Agricultural Technology, *10*, Article 100641.