



Use of Drones, Satellite Imagery, and Remote Sensing in Crop Monitoring: A Comprehensive Analysis of Modern Precision Agriculture Technologies

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Abstract

Background: Precision agriculture has revolutionized crop monitoring through the integration of advanced remote sensing technologies, including unmanned aerial vehicles (UAVs), satellite imagery, and ground-based sensors. These technologies provide farmers and researchers with unprecedented capabilities for real-time crop assessment, yield prediction, and agricultural management.

Objective: This study examines the current applications, methodologies, and effectiveness of drones, satellite imagery, and remote sensing technologies in crop monitoring, analyzing their individual and combined contributions to modern agricultural practices.

Methods: A comprehensive review of recent literature was conducted, analyzing various remote sensing platforms, sensor technologies, and data processing techniques used in crop monitoring. Field studies and case analyses were examined to evaluate the practical applications and limitations of these technologies.

Results: The integration of multi-platform remote sensing approaches demonstrates significant improvements in crop monitoring accuracy, with UAVs providing high-resolution spatial data (sub-meter resolution), satellites offering large-scale temporal coverage, and ground sensors delivering continuous monitoring capabilities. Vegetation indices such as NDVI, SAVI, and EVI show strong correlations with crop health and yield parameters.

Conclusion: The synergistic use of drones, satellite imagery, and remote sensing technologies represents a paradigm shift in precision agriculture, enabling data-driven decision making, optimized resource utilization, and enhanced crop productivity. Future developments in sensor technology, artificial intelligence, and data integration platforms will further enhance the effectiveness of these monitoring systems.

Keywords: Precision agriculture, UAVs, satellite imagery, remote sensing, crop monitoring, vegetation indices, NDVI, precision farming, agricultural technology, yield prediction

1. Introduction

Agriculture faces unprecedented challenges in the 21st century, with the global population projected to reach 9.7 billion by 2050, necessitating a 70% increase in food production while simultaneously addressing climate change, resource scarcity, and environmental sustainability ^[1]. Traditional farming practices, while foundational to agricultural development, are increasingly insufficient to meet these complex demands. The emergence of precision agriculture, enabled by advanced remote sensing technologies, offers a transformative approach to crop monitoring and management.

Remote sensing in agriculture encompasses the use of sensors and platforms to collect information about crops and agricultural environments without direct physical contact. This technology has evolved from simple aerial photography in the early 20th century to sophisticated multi-spectral and hyperspectral imaging systems deployed on various platforms including satellites, aircraft, and unmanned aerial vehicles (UAVs) ^[2]. The integration of these technologies has created new opportunities for real-time crop assessment, early disease detection, yield prediction, and optimized resource management.

The three primary platforms for agricultural remote sensing – satellites, drones, and ground-based sensors – each offer unique advantages and capabilities. Satellite imagery provides large-scale, consistent temporal coverage ideal for regional crop monitoring and long-term trend analysis [3]. Drones or UAVs offer high-resolution, flexible data collection capabilities that can be deployed on-demand for specific field assessments [4]. Ground-based sensors provide continuous, localized monitoring of specific crop parameters and environmental conditions.

The technological advancement in sensor capabilities has been equally significant. Modern remote sensing systems can capture data across multiple spectral bands, from visible light to thermal infrared, enabling the detection of various crop characteristics including biomass, water stress, nutrient deficiencies, and disease symptoms [5]. The development of vegetation indices, mathematical combinations of spectral reflectance values, has provided standardized methods for quantifying crop health and vigor.

Data processing and analysis capabilities have advanced through the integration of artificial intelligence, machine learning, and cloud computing platforms. These technologies enable the processing of vast amounts of remote sensing data, automated feature extraction, and predictive modeling for agricultural applications [6]. The democratization of these technologies through user-friendly software platforms and reduced costs has made precision agriculture accessible to farmers of various scales.

This comprehensive review examines the current state of drone, satellite, and remote sensing technologies in crop monitoring, analyzing their individual capabilities, integration strategies, and practical applications in modern agriculture. The study addresses the technical aspects of these technologies, their operational advantages and limitations, and their impact on agricultural productivity and sustainability.

2. Materials and Methods

2.1 Literature Review Methodology

A systematic literature review was conducted using multiple academic databases including PubMed, Web of Science, Google Scholar, and agricultural-specific databases. The search strategy employed keywords related to "precision agriculture," "crop monitoring," "UAV agriculture," "satellite imagery agriculture," "remote sensing agriculture," and "vegetation indices" published between 2015 and 2024. Studies were selected based on relevance to crop monitoring applications, technological innovation, and practical implementation results.

2.2 Technology Platforms Analysis

The analysis encompassed three primary remote sensing platforms:

Satellite Systems: Major satellite constellations including Landsat 8/9, Sentinel-2, MODIS, WorldView, and Planet Labs constellation were analyzed for their spectral capabilities, spatial resolution, temporal resolution, and agricultural applications. Commercial and open-access satellite data sources were evaluated for accessibility and cost-effectiveness.

Unmanned Aerial Vehicles (UAVs): Various drone platforms were examined, ranging from consumer-grade multirotor systems to professional fixed-wing aircraft. Payload capacities, flight time, operational range, and sensor

compatibility were assessed. Both multispectral and hyperspectral imaging systems were analyzed for their crop monitoring capabilities.

Ground-Based Sensors: Stationary and mobile ground-based sensing systems were evaluated, including weather stations, soil sensors, plant-mounted sensors, and vehicle-mounted sensing platforms. Integration capabilities with UAV and satellite data were assessed.

2.3 Sensor Technology Assessment

Multiple sensor technologies were analyzed for their crop monitoring applications:

Multispectral Sensors: Analysis of 4-6 band sensors commonly used in agricultural applications, focusing on red, green, blue, red-edge, and near-infrared bands essential for vegetation monitoring.

Hyperspectral Sensors: Examination of sensors capable of capturing hundreds of narrow spectral bands, enabling detailed crop biochemical analysis and species identification.

Thermal Sensors: Assessment of thermal infrared sensors for crop water stress detection and irrigation management applications.

LiDAR Systems: Analysis of light detection and ranging technology for crop structure analysis, biomass estimation, and precision agriculture applications.

2.4 Data Processing and Analysis Methods

The study examined various data processing workflows including:

Preprocessing Techniques: Image calibration, atmospheric correction, geometric correction, and data fusion methods for combining multi-platform datasets.

Vegetation Index Calculation: Mathematical formulations and applications of key vegetation indices including NDVI, SAVI, EVI, GNDVI, and specialized crop-specific indices.

Machine Learning Applications: Analysis of supervised and unsupervised learning algorithms used for crop classification, yield prediction, and anomaly detection.

Statistical Analysis Methods: Examination of correlation analysis, regression modeling, and time-series analysis techniques used in crop monitoring studies.

3. Results

3.1 Satellite Remote Sensing Capabilities

Satellite-based crop monitoring has demonstrated significant capabilities across multiple agricultural applications. The analysis reveals that modern satellite systems provide varying combinations of spatial, spectral, and temporal resolution suitable for different monitoring requirements.

Spatial Resolution Performance: High-resolution commercial satellites such as WorldView-3 and WorldView-4 provide sub-meter spatial resolution (0.3-0.5m panchromatic, 1.2-1.6m multispectral) enabling individual plant identification and precision field mapping. Medium-resolution systems like Sentinel-2 (10-20m resolution) and Landsat 8/9 (15-30m resolution) are optimal for field-scale monitoring and regional agricultural assessments.

Spectral Capabilities: Modern satellite sensors capture data across 8-16 spectral bands, with some hyperspectral satellites like Hyperion capturing over 200 bands. The red-edge bands (700-750nm) available on Sentinel-2 and other modern sensors have proven particularly valuable for crop monitoring, showing strong correlations with chlorophyll content and crop health indicators.

Temporal Resolution: The combination of multiple satellite systems provides near-daily global coverage. Planet Labs constellation offers daily 3-5m resolution imagery, while

Sentinel-2 provides 5-day revisit time with free access. This temporal frequency enables monitoring of rapid crop changes during critical growth periods.

Table 1: Comparison of Major Satellite Systems for Crop Monitoring

Satellite System	Spatial Resolution	Spectral Bands	Revisit Time	Cost	Primary Applications
Landsat 8/9	15-30m	11	16 days	Free	Large-scale monitoring, historical analysis
Sentinel-2	10-20m	13	5 days	Free	Field-scale monitoring, crop classification
WorldView-3/4	0.3-1.6m	8-16	On-demand	High	Precision mapping, individual plant analysis
Planet Labs	3-5m	4-8	Daily	Moderate	Frequent monitoring, change detection
MODIS	250-1000m	36	Daily	Free	Regional analysis, phenology studies

3.2 UAV Remote Sensing Performance

Unmanned aerial vehicles have emerged as highly effective platforms for high-resolution crop monitoring, offering flexibility and precision that complements satellite-based systems.

Flight Performance: Modern agricultural UAVs demonstrate flight times ranging from 25 minutes (multirotor systems) to 120 minutes (fixed-wing systems), covering areas from 50 hectares to 1,000 hectares per flight depending on altitude and sensor requirements. Weather dependencies limit operations during high winds (>15 m/s) and precipitation.

Sensor Integration: UAVs successfully integrate various

sensor payloads including RGB cameras (providing 1-5cm resolution), multispectral sensors (4-6 bands), hyperspectral sensors (100-400 bands), thermal cameras, and LiDAR systems. Payload limitations require careful sensor selection based on monitoring objectives.

Data Quality: UAV-collected imagery provides exceptional spatial detail with ground sampling distances typically ranging from 1-10cm, enabling detection of individual plants, pest damage, and micro-variations in crop health. Multispectral UAV data shows strong correlations ($r > 0.85$) with ground-truth measurements for various crop parameters.

Table 2: UAV Platform Capabilities for Crop Monitoring

Platform Type	Flight Time	Coverage per Flight	Typical Resolution	Best Applications
Multirotor	25-45 min	50-200 ha	1-5 cm	Detailed field analysis, spot checking
Fixed-wing	60-120 min	500-1000 ha	3-10 cm	Large field surveys, mapping
VTOL Hybrid	45-90 min	300-600 ha	2-8 cm	Mixed terrain, flexible operations
Helicopter	30-60 min	100-400 ha	2-6 cm	Precision spraying integration

3.3. Vegetation Index Performance

Vegetation indices calculated from remote sensing data demonstrate strong relationships with crop health, biomass, and yield parameters across multiple studies.

NDVI Performance: The Normalized Difference Vegetation Index shows correlation coefficients ranging from 0.65-0.92 with crop yield across various crops including wheat, corn, soybeans, and rice. NDVI values typically range from 0.2-0.9 for agricultural crops, with peak values occurring during maximum canopy development.

Advanced Index Performance: Specialized vegetation indices show improved performance in specific applications.

The Soil Adjusted Vegetation Index (SAVI) performs better in early season monitoring when soil background is significant. The Enhanced Vegetation Index (EVI) shows reduced saturation effects in high biomass crops compared to NDVI.

Temporal Dynamics: Time-series analysis of vegetation indices reveals characteristic crop phenology patterns that enable crop type identification and growth stage determination. Integration of multiple indices improves crop classification accuracy by 15-25% compared to single-index approaches.

Table 3: Vegetation Index Performance in Crop Monitoring

Vegetation Index	Formula	Best Applications	Correlation with Yield	Limitations
NDVI	$(\text{NIR}-\text{Red})/(\text{NIR}+\text{Red})$	General crop health, biomass	0.65-0.92	Saturation at high biomass
SAVI	$(\text{NIR}-\text{Red})/(\text{NIR}+\text{Red}+\text{L}) \times (1+\text{L})$	Early season, sparse vegetation	0.70-0.88	Requires soil adjustment factor
EVI	$G \times (\text{NIR}-\text{Red})/(\text{NIR}+\text{C1} \times \text{Red}-\text{C2} \times \text{Blue}+\text{L})$	Dense vegetation, forest crops	0.68-0.85	Complex calculation, requires blue band
GNDVI	$(\text{NIR}-\text{Green})/(\text{NIR}+\text{Green})$	Chlorophyll assessment	0.62-0.86	Less sensitive to structural changes
Red Edge NDVI	$(\text{NIR}-\text{RedEdge})/(\text{NIR}+\text{RedEdge})$	Crop stress detection	0.72-0.90	Requires red-edge sensor

3.4. Integration and Data Fusion Results

The combination of multiple remote sensing platforms demonstrates superior performance compared to single-platform approaches in crop monitoring applications.

Multi-platform Integration: Studies combining satellite, UAV, and ground sensor data show 20-35% improvement in crop yield prediction accuracy compared to single-platform approaches. The integration leverages the large-scale coverage of satellites, high-resolution detail of UAVs, and

continuous monitoring of ground sensors.

Temporal Data Fusion: Combining high-frequency satellite data (daily Planet imagery) with periodic high-resolution UAV data enables both continuous monitoring and detailed assessment capabilities. Machine learning algorithms successfully interpolate between UAV acquisition dates using satellite data.

Scale Integration: Multi-scale approaches using satellite data for field identification and UAV data for detailed

assessment optimize data collection efficiency. This hierarchical approach reduces UAV flight requirements by 60-80% while maintaining assessment accuracy.

4. Discussion

4.1 Technological Advantages and Capabilities

The integration of drones, satellite imagery, and remote sensing technologies in crop monitoring represents a fundamental advancement in agricultural practices. Each platform contributes unique capabilities that, when combined, create a comprehensive monitoring system superior to traditional agricultural assessment methods.

Satellite remote sensing provides the foundational layer for large-scale crop monitoring, offering consistent temporal coverage essential for tracking crop development across entire growing seasons. The availability of free, high-quality satellite data from programs like Landsat and Sentinel-2 has democratized access to remote sensing technology, enabling farmers of various scales to benefit from these capabilities^[7]. The spectral diversity of modern satellite sensors, particularly the inclusion of red-edge bands, has significantly improved the sensitivity of crop health detection and stress identification.

UAV technology addresses the spatial and temporal gaps inherent in satellite-based systems. The ability to deploy drones on-demand provides farmers with rapid response capabilities for investigating anomalies detected in satellite imagery or responding to suspected crop stress events^[8]. The ultra-high spatial resolution achieved by UAV sensors enables detection of individual plant stress, pest damage, and micro-variations in crop development that are invisible to satellite sensors.

Ground-based sensors complete the monitoring ecosystem by providing continuous, localized measurements of crop and environmental parameters. The integration of Internet of Things (IoT) sensors enables real-time monitoring of soil moisture, temperature, humidity, and other critical parameters that influence crop development^[9]. This continuous data stream provides the temporal resolution necessary for precision irrigation and fertilization management.

4.2 Operational Challenges and Limitations

Despite the significant advantages, several challenges limit the operational effectiveness of remote sensing technologies in crop monitoring. Weather dependency remains a critical constraint, particularly for optical remote sensing systems that cannot penetrate cloud cover. This limitation is especially problematic in regions with frequent cloud cover during critical crop development periods^[10].

Data processing and analysis complexity presents another significant challenge. The volume of data generated by modern remote sensing systems requires sophisticated processing capabilities and expertise that may be beyond the resources of individual farmers. Cloud-based processing platforms have begun to address this challenge, but the need for technical expertise in data interpretation remains a barrier to widespread adoption^[11].

Economic considerations significantly influence the adoption of remote sensing technologies. While satellite data costs have decreased substantially, high-resolution commercial imagery and UAV operations still represent significant investments for many agricultural operations. The return on investment varies significantly based on crop value, field

size, and operational efficiency gains achieved through precision agriculture practices^[12].

Regulatory constraints, particularly for UAV operations, create additional operational challenges. Aviation regulations in many countries require pilot certification, flight planning approvals, and operational restrictions that limit the flexibility and cost-effectiveness of drone-based crop monitoring. These regulations are evolving as authorities balance safety concerns with agricultural technology advancement needs^[13].

4.3 Integration Strategies and Best Practices

Successful implementation of multi-platform remote sensing in crop monitoring requires careful consideration of integration strategies that optimize the strengths of each platform while minimizing limitations and costs.

Hierarchical monitoring approaches have proven most effective, using satellite data for broad-scale field assessment and anomaly detection, followed by targeted UAV deployments for detailed investigation of identified problem areas. This approach optimizes data collection efficiency while maintaining comprehensive coverage^[14]. The integration of machine learning algorithms enables automated anomaly detection in satellite imagery, triggering UAV missions only when necessary.

Temporal integration strategies leverage the different revisit capabilities of various platforms. Frequent satellite observations provide the temporal framework for monitoring crop development, while periodic UAV missions provide high-resolution snapshots for detailed assessment and ground-truth data collection. Ground sensors provide continuous monitoring of rapidly changing parameters like soil moisture and temperature^[15].

Data standardization and interoperability remain critical challenges in multi-platform integration. Differences in sensor spectral characteristics, spatial resolution, and data formats require sophisticated preprocessing and calibration procedures to ensure data compatibility. The development of standardized vegetation indices and processing workflows has improved interoperability, but platform-specific considerations remain important^[16].

4.4 Artificial Intelligence and Machine Learning Applications

The integration of artificial intelligence and machine learning technologies has significantly enhanced the capabilities of remote sensing systems in crop monitoring. These technologies address the challenge of processing and interpreting the vast amounts of data generated by modern remote sensing platforms.

Supervised learning algorithms have demonstrated exceptional performance in crop classification and yield prediction applications. Convolutional neural networks (CNNs) applied to high-resolution UAV imagery achieve crop classification accuracies exceeding 95% for major crop types^[17]. Random forest and support vector machine algorithms show similar performance levels while requiring less computational resources and training data.

Unsupervised learning approaches enable the discovery of patterns in remote sensing data that may not be apparent through traditional analysis methods. Clustering algorithms can identify crop stress patterns, growth anomalies, and field management zones without prior knowledge of these conditions^[18]. These approaches are particularly valuable for

identifying emerging pest and disease issues before they become widespread.

Deep learning applications in remote sensing continue to advance rapidly, with particular success in feature extraction from hyperspectral imagery and time-series analysis of satellite data. These approaches can identify subtle spectral signatures associated with specific crop stresses, diseases, or nutrient deficiencies that would be difficult to detect through traditional vegetation index approaches ^[19].

4.5 Economic Impact and Return on Investment

The economic impact of remote sensing technologies in crop monitoring extends beyond direct cost savings to include improved yield stability, resource use efficiency, and risk management capabilities.

Yield optimization through precision agriculture practices enabled by remote sensing typically achieves 5-15% yield improvements across various crop types. These improvements result from optimized fertilizer application, targeted pest control, improved irrigation management, and timely intervention for crop stress conditions ^[20]. The economic value of these improvements varies significantly based on crop prices and input costs.

Resource use efficiency improvements represent another significant economic benefit. Precision fertilizer application based on remote sensing data typically reduces fertilizer costs by 10-20% while maintaining or improving yields. Similar savings are achieved in pesticide applications through targeted treatments of affected areas rather than blanket field applications ^[21].

Risk management benefits include early detection of crop stress conditions, enabling timely intervention to prevent yield losses. Insurance applications of remote sensing technology enable more accurate crop loss assessment and potentially reduced premium costs for farmers who adopt precision agriculture practices ^[22].

The democratization of remote sensing technology through reduced costs and improved accessibility has enabled adoption by smaller agricultural operations. Cloud-based processing platforms and smartphone applications have made sophisticated remote sensing analysis accessible to farmers who previously could not justify the investment in specialized expertise and software ^[23].

4.6 Environmental Sustainability Implications

Remote sensing technologies contribute significantly to environmental sustainability in agriculture through optimized resource use, reduced chemical inputs, and improved land use efficiency.

Precision fertilizer application based on remote sensing data reduces nutrient runoff and associated water quality impacts. Variable rate application systems guided by vegetation index maps can reduce total fertilizer use by 15-30% while maintaining yields through optimized spatial distribution ^[24]. Similar reductions are achieved in pesticide applications through targeted treatments based on pest and disease detection.

Water use efficiency improvements through remote sensing-guided irrigation management are particularly significant in water-stressed regions. Thermal imaging and vegetation indices enable precise irrigation scheduling and spatial distribution, reducing water use by 20-40% in many applications ^[25]. These improvements are critical for sustainable agriculture in regions facing water scarcity.

Carbon footprint reduction results from optimized field operations, reduced fuel consumption through precision application systems, and improved soil health through precision agriculture practices. The reduction in unnecessary field passes and optimized input applications contribute to overall greenhouse gas emission reductions ^[26].

Biodiversity conservation benefits from precision agriculture include reduced pesticide impacts on non-target species, preservation of field margins and sensitive areas, and improved habitat management. Remote sensing enables identification and protection of environmentally sensitive areas within agricultural fields ^[27].

4.7 Future Technological Developments

The future of remote sensing in crop monitoring is characterized by continued technological advancement, increased automation, and improved integration capabilities. Sensor technology advancement continues at a rapid pace, with improvements in spectral resolution, spatial resolution, and sensor miniaturization. Hyperspectral sensors are becoming more accessible and affordable, enabling detailed biochemical analysis of crops. Thermal sensor improvements enable more precise water stress detection and irrigation management ^[28].

Artificial intelligence advancement will continue to improve the automation and accuracy of remote sensing data analysis. Edge computing capabilities will enable real-time processing of sensor data, reducing latency and enabling immediate response to crop stress conditions. Integration with robotic systems will enable automated crop monitoring and intervention capabilities ^[29].

Communication technology improvements, particularly 5G networks and low-earth orbit satellite internet, will enhance the connectivity and data transmission capabilities of remote sensing systems. This improved connectivity will enable real-time monitoring and response capabilities even in remote agricultural areas ^[30].

Platform integration will become more seamless through standardized data formats, improved interoperability, and cloud-based processing platforms. The development of digital agriculture ecosystems will integrate remote sensing data with farm management systems, weather data, market information, and other relevant data sources to provide comprehensive decision support capabilities.

5. Conclusion

The integration of drones, satellite imagery, and remote sensing technologies represents a transformative advancement in agricultural crop monitoring, providing farmers and researchers with unprecedented capabilities for precision agriculture implementation. This comprehensive analysis demonstrates that the synergistic use of multiple remote sensing platforms significantly outperforms single-platform approaches, achieving 20-35% improvements in crop yield prediction accuracy and enabling optimized resource management strategies.

Satellite remote sensing provides the foundational framework for large-scale, consistent crop monitoring, with modern systems offering spatial resolutions from sub-meter to regional scales and temporal frequencies enabling near-daily global coverage. The availability of free, high-quality satellite data from programs like Sentinel-2 and Landsat has democratized access to remote sensing technology, making precision agriculture accessible to farmers across various

scales of operation.

UAV technology addresses critical gaps in satellite-based monitoring through on-demand, ultra-high resolution data collection capabilities. With spatial resolutions typically ranging from 1-10cm, UAV systems enable detection of individual plant stress, pest damage, and micro-variations in crop health that are invisible to satellite sensors. The flexibility of UAV deployment provides rapid response capabilities for investigating anomalies and implementing precision agriculture interventions.

Ground-based sensors complete the monitoring ecosystem by providing continuous, real-time measurements of crop and environmental parameters. The integration of IoT sensor networks enables precision irrigation, fertilization, and pest management based on continuous monitoring of soil moisture, temperature, and other critical parameters.

The economic impact of these technologies extends beyond direct cost savings to include improved yield stability, resource use efficiency, and risk management capabilities. Typical yield improvements of 5-15% are achieved through precision agriculture practices, while resource use efficiency improvements of 10-30% in fertilizer and pesticide applications provide both economic and environmental benefits.

Environmental sustainability benefits are significant, including reduced chemical inputs, optimized water use, and decreased carbon footprints through precision agriculture practices. These technologies enable sustainable intensification of agricultural production, meeting growing food demands while minimizing environmental impacts.

Future technological developments in sensor technology, artificial intelligence, and platform integration will further enhance the capabilities and accessibility of remote sensing systems in agriculture. The continued advancement of these technologies, combined with decreasing costs and improving user interfaces, positions remote sensing as a fundamental component of sustainable, productive agricultural systems.

The successful implementation of remote sensing technologies in crop monitoring requires careful consideration of integration strategies, technical capabilities, economic factors, and operational constraints. However, the demonstrated benefits in crop productivity, resource efficiency, and environmental sustainability make these technologies essential tools for addressing the challenges of 21st-century agriculture.

As global food security challenges intensify and environmental sustainability requirements become more stringent, the role of remote sensing technologies in crop monitoring will continue to expand. The continued development and adoption of these technologies represent a critical pathway toward sustainable, productive, and resilient agricultural systems capable of feeding a growing global population while preserving environmental resources for future generations.

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