

Remote Sensing Applications in Agricultural Resource Management

Seema Mahlawat^{1*}, Naval Kishore Meena², Lucy Kumari³

¹Assistant Professor, Department of Botany, Pt NRS Govt. College, Rohtak

²Ph.D. Scholar, Department of Horticulture (Fruit Science), RCA, MPUAT, Udaipur

³Ph.D. Scholar, Department of Horticulture, Pg College of Agriculture,

Dr Rajendra Prasad Central Agriculture University Pusa Bihar

*Corresponding Author E-mail: seema.mahlawat@gmail.com

Received: 26.03.2024 | Revised: 28.04.2024 | Accepted: 24.05.2024

ABSTRACT

Remote sensing technology has emerged as a transformative tool in agricultural resource management, enabling large-scale monitoring of crops, soils, and water resources with unprecedented spatial and temporal resolution. This review paper provides a comprehensive examination of the applications of remote sensing in agriculture, encompassing satellite-based platforms such as Landsat and Sentinel, aerial systems, and unmanned aerial vehicles (UAVs). The paper discusses key vegetation indices including the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Soil-Adjusted Vegetation Index (SAVI) that are widely employed for crop health assessment, yield estimation, and stress detection. Furthermore, the role of multispectral, hyperspectral, and synthetic aperture radar (SAR) imaging in soil moisture estimation, irrigation management, nutrient stress detection, and pest and disease identification is critically analyzed. The integration of remote sensing with Geographic Information Systems (GIS) and machine learning algorithms has significantly enhanced decision-support systems for precision agriculture. Despite remarkable advancements, challenges persist in terms of data resolution trade-offs, computational requirements, high costs, and accessibility for smallholder farmers. This review synthesizes current knowledge, identifies research gaps, and proposes future directions for optimizing remote sensing applications to achieve sustainable agricultural resource management and global food security.

Keywords: Remote Sensing; Precision Agriculture; Vegetation Indices; Crop Monitoring; Agricultural Resource Management.

INTRODUCTION

Agriculture is the backbone of global food security, sustaining the livelihoods of billions of people worldwide. With the global population projected to reach 9.7 billion by 2050, the demand for food production is expected to increase by 60-70%, placing

immense pressure on agricultural systems (Foley et al., 2011). Climate variability, land degradation, water scarcity, and the depletion of natural resources pose formidable challenges to sustainable agricultural production.

Cite this article: Mahlawat, S., Meena, N.K., Kumari, L. (2024). Remote Sensing Applications in Agricultural Resource Management, *Curr. Res. Agri. Far.* 5(3), 28-38. doi: <http://dx.doi.org/10.18782/2582-7146.284>

This article is published under the terms of the [Creative Commons Attribution License 4.0](https://creativecommons.org/licenses/by/4.0/).

In this context, the adoption of advanced technologies for efficient agricultural resource management has become imperative. Remote sensing, defined as the acquisition of information about an object or phenomenon without making physical contact, has revolutionized the way agricultural resources are monitored and managed (Lillesand et al., 2015). By capturing electromagnetic radiation reflected or emitted from the Earth's surface, remote sensing provides spatially explicit and temporally consistent data that are invaluable for agricultural decision-making. The technology encompasses a wide array of platforms, from spaceborne satellites such as Landsat and Sentinel to airborne sensors and unmanned aerial vehicles (UAVs), each offering distinct advantages in terms of spatial resolution, spectral coverage, and temporal frequency (Atzberger, 2013).

Over the past five decades, remote sensing has been extensively applied in agriculture for crop identification, acreage estimation, yield prediction, crop health monitoring, soil characterization, water resource assessment, and pest and disease detection (Mulla, 2013). The integration of remote sensing data with Geographic Information Systems (GIS) and advanced analytical tools, including machine learning and artificial intelligence, has further expanded the capabilities of precision agriculture, enabling site-specific management practices that optimize input use while minimizing environmental impact (Weiss et al., 2020).

This review paper aims to provide a comprehensive synthesis of the current state of remote sensing applications in agricultural resource management. It examines the key platforms, sensors, and spectral indices employed; explores major application domains; discusses the integration of remote sensing with emerging technologies; identifies prevailing challenges; and outlines future research directions to advance sustainable agricultural practices.

2. Remote Sensing Platforms and Sensors for Agriculture

2.1 Satellite-Based Remote Sensing

Satellite remote sensing has been indispensable in understanding Earth and atmospheric dynamics over the last five decades. When compared to ground-based or aerial sensor acquisitions, satellite sensors provide data at global scales at a comparatively lower cost (Chuvieco, 2020). The Landsat series, initiated by the National Aeronautics and Space Administration (NASA) and the United States Geological Survey (USGS), has provided continuous Earth observation data since 1972, offering multispectral imagery at 30-metre spatial resolution with a 16-day revisit cycle (Roy et al., 2014). The European Space Agency's (ESA) Sentinel-2 satellites, launched as part of the Copernicus programme, provide high-resolution multispectral imagery at 10-metre spatial resolution with a 5-day revisit frequency, making them particularly suited for agricultural monitoring (Drusch et al., 2012).

Sentinel-1, equipped with Synthetic Aperture Radar (SAR), operates independently of cloud cover and daylight conditions, providing valuable data for soil moisture estimation and crop monitoring in tropical regions where optical imagery is often limited by persistent cloud cover (Torres et al., 2012). Commercial satellite constellations such as PlanetScope provide daily imagery at 3-metre resolution, enabling near-real-time field-level monitoring for precision agriculture applications (McCabe et al., 2017).

2.2 Aerial and UAV-Based Remote Sensing

Unmanned aerial vehicles have emerged as a transformative platform for agricultural remote sensing, offering advantages over both traditional field measurement techniques and satellite image analysis. UAVs provide very high spatial resolution data (sub-centimetre to centimetre level), flexible deployment schedules, and the ability to operate under cloudy conditions (Tsouros et al., 2019). Equipped with multispectral, hyperspectral, thermal, RGB, and LiDAR sensors, UAVs facilitate detailed crop health monitoring, vegetation mapping, irrigation management,

pest detection, and yield estimation at the farm level (Yang et al., 2017).

The rapid advancement of UAV technology, coupled with decreasing costs and increasing ease of operation, has made drone-based remote sensing increasingly accessible

to farmers and agronomists. However, challenges remain regarding regulatory frameworks, limited flight endurance, data processing requirements, and coverage limitations for large-scale agricultural operations (Mukherjee et al., 2019).

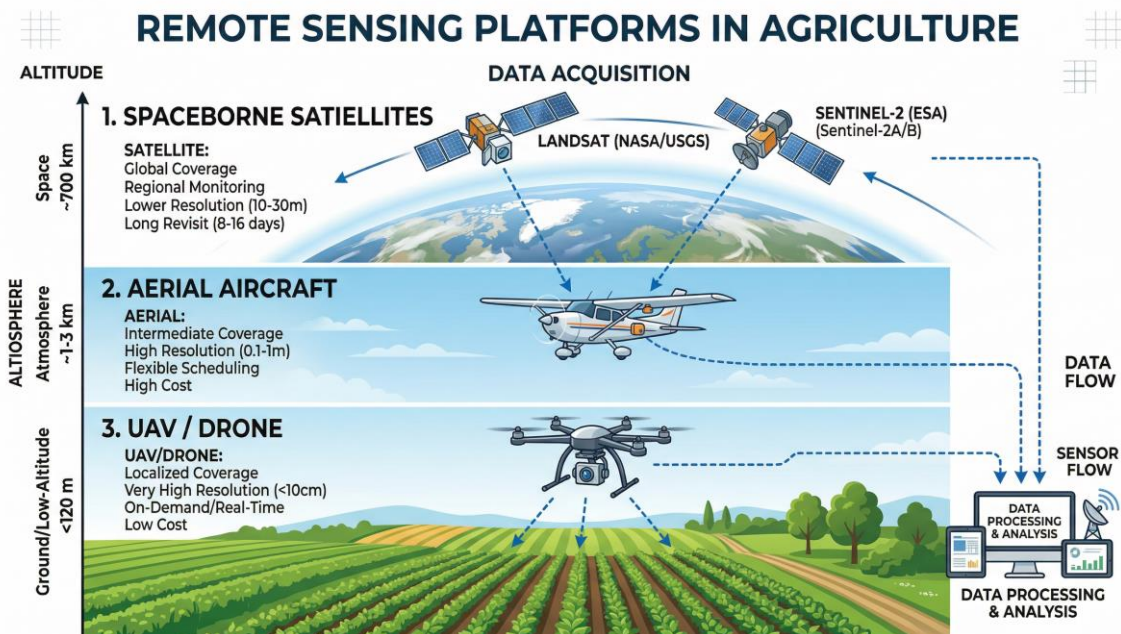


Figure1. Overview of remote sensing platforms used in agricultural resource management, including spaceborne satellites, aerial aircraft, and UAV/drone systems

2.3 Sensor Types and Spectral Imaging

The effectiveness of remote sensing in agriculture depends critically on the type of sensor and the spectral information captured. Multispectral sensors capture data in a limited number of broad spectral bands (typically 4-12 bands) and are widely used for vegetation mapping and crop classification (Thenkabail et al., 2012). Hyperspectral sensors, in contrast, capture data across hundreds of narrow, contiguous spectral bands, providing detailed spectral signatures that enable the detection of subtle physiological changes in plants, including early-stage disease, nutrient deficiencies, and water stress (Mulla, 2013). Thermal infrared sensors measure surface temperature variations, facilitating the assessment of crop water stress through indices such as the Crop Water Stress Index (CWSI) (Jackson et al., 1981). SAR sensors, operating in microwave wavelengths, are particularly valuable for soil moisture

estimation and crop structure analysis, as they penetrate cloud cover and operate day and night (Srivastava et al., 2013).

3. Vegetation Indices in Agricultural Remote Sensing

Vegetation indices (VIs) are mathematical combinations of spectral bands that enhance the vegetation signal while minimizing background noise from soil, atmosphere, and illumination conditions. They are fundamental tools for assessing crop health, biomass, and vigour from remotely sensed data (Xue and Su, 2017).

The Normalized Difference Vegetation Index (NDVI), calculated as the normalized ratio of near-infrared (NIR) and red reflectance, is the most widely used vegetation index in agricultural applications. NDVI effectively distinguishes vegetation from bare soil and provides reliable estimates of crop health, biomass, and leaf area index (Rouse et al., 1974). However, NDVI is prone

to saturation in areas of dense vegetation and is sensitive to soil background reflectance, which limits its accuracy in diverse agricultural landscapes (Huete et al., 2002).

To overcome these limitations, the Enhanced Vegetation Index (EVI) was developed, incorporating atmospheric correction coefficients and a soil adjustment factor to enhance sensitivity in high-biomass regions while reducing atmospheric and soil interference (Huete et al., 2002). The Soil-Adjusted Vegetation Index (SAVI) introduces a soil brightness correction factor to minimize

soil background effects, making it particularly useful for monitoring crops in early growth stages when canopy cover is sparse (Huete, 1988). Other important indices include the Green NDVI (GNDVI), which improves sensitivity to chlorophyll content by replacing the red band with a green band; the Normalized Difference Red Edge Index (NDRE), which is effective for nitrogen status assessment; and the Normalized Difference Moisture Index (NDMI), which monitors crop water content using shortwave infrared bands (Gitelson et al., 1996).

FIGURE 2: REMOTE SENSING VEGETATION INDEX ANALYSIS FOR CROP HEALTH

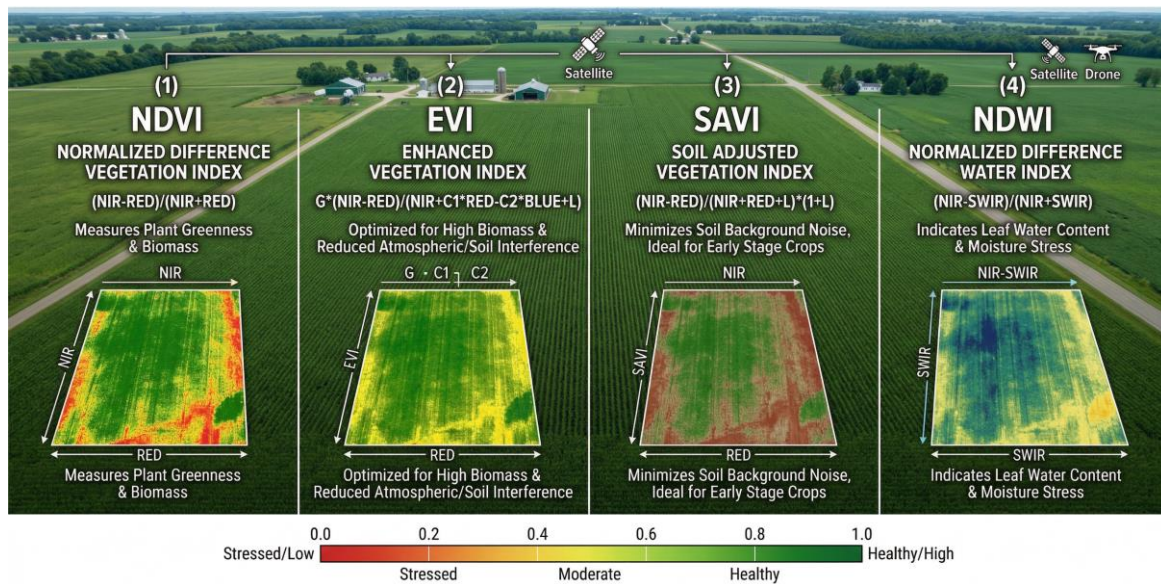


Figure2. Comparison of key vegetation indices (NDVI, EVI, SAVI, NDWI) used in remote sensing for crop health assessment and agricultural monitoring

Table1. Summary of key vegetation indices used in agricultural remote sensing

Index	Formula	Application	Reference
NDVI	$(NIR - Red) / (NIR + Red)$	Crop health, biomass estimation	Rouse et al. (1974)
EVI	$G*(NIR-Red)/(NIR+C1*Red-C2*Blue+L)$	High biomass regions, atmospheric correction	Huete et al. (2002)
SAVI	$(NIR-Red)*(1+L) / (NIR+Red+L)$	Sparse vegetation, soil adjustment	Huete (1988)
NDRE	$(NIR - RedEdge) / (NIR + RedEdge)$	Nitrogen status assessment	Gitelson et al. (1996)
NDMI	$(NIR - SWIR) / (NIR + SWIR)$	Crop water content, drought monitoring	Gao (1996)

4. Applications of Remote Sensing in Agricultural Resource Management

4.1 Crop Health Monitoring and Yield Estimation

Remote sensing has become an indispensable tool for monitoring crop health across large spatial extents. Vegetation indices derived from multispectral satellite imagery enable farmers and agronomists to assess crop vigour, identify stress conditions, and detect anomalies in plant growth throughout the growing season (Doraiswamy et al., 2004). By regularly monitoring NDVI and other spectral indices, declining crop health can be identified early, allowing targeted interventions such as adjusted fertilization, irrigation scheduling, or pesticide application. Satellite-based remote sensing provides a cost-effective alternative for crop condition and yield assessment, offering timely, accurate, and synoptic estimation of various crop parameters (Becker-Reshef et al., 2010).

Real-time satellite information, coupled with historical data, weather patterns, and crop health indicators, makes it possible to accurately forecast crop yields prior to harvest. This capability empowers farmers to plan and budget accordingly while building confidence throughout the supply chain. Machine learning models, including Random Forest, Support Vector Machines, and Convolutional Neural Networks, have been increasingly integrated with remote sensing data for improving yield prediction accuracy (Chlingaryan et al., 2018).

4.2 Soil Moisture Assessment and Irrigation Management

Timely and precise soil moisture estimation is critical for optimizing irrigation practices, enhancing crop productivity, and mitigating the impacts of droughts and floods. Traditionally, soil moisture has been measured using ground-based methods, which, although accurate, are limited in spatial coverage and labour-intensive (Robock et al., 2000). SAR-based remote sensing, particularly from Sentinel-1, offers a more efficient and comprehensive approach to soil moisture monitoring. Studies have demonstrated that machine learning models such as Random Forest and Convolutional Neural Networks achieve superior performance for soil moisture estimation from SAR-derived backscattering coefficients (Srivastava et al., 2013).

Remote sensing contributes significantly to irrigation management by identifying areas experiencing water stress through thermal infrared imagery and moisture-sensitive indices such as NDMI and MSI. In arid regions, judicious use of water is facilitated through precision technologies that combine remotely sensed canopy temperature data with drip irrigation systems, thereby increasing water use efficiency while reducing runoff and percolation losses (Jackson et al., 1981). The integration of satellite imagery with GIS platforms, as demonstrated by Esri's ArcGIS technology, enables automated water consumption assessment and real-time monitoring of irrigation systems at regional and national scales (Ibragimov, 2025).

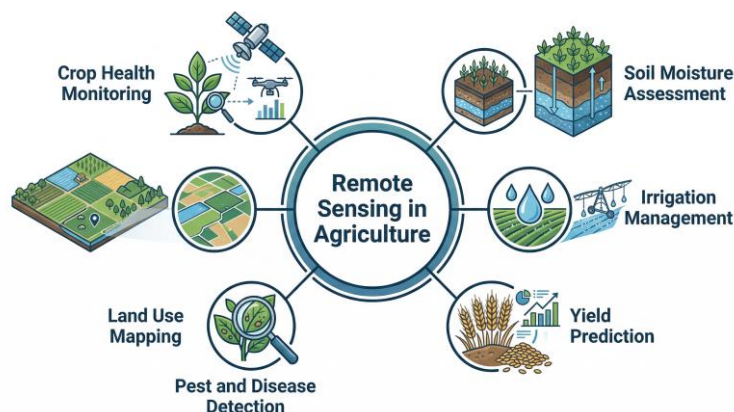


Figure3. Key applications of remote sensing technology in agricultural resource management

4.3 Nutrient Stress Detection and Management

Plants require adequate macro- and micronutrients for proper growth and vitality. Remote sensing and GIS technologies are important for site-specific nutrient management, enabling the detection of nutrient deficiencies and optimizing fertilizer application, thereby reducing cultivation costs while increasing fertilizer use efficiency (Mulla, 2013). Hyperspectral imaging has emerged as a powerful tool for detecting subtle changes in crop biochemistry associated with nitrogen, phosphorus, and potassium deficiencies. By analyzing spectral reflectance at specific wavelengths sensitive to chlorophyll content and cellular structure, nutrient deficiency maps can be generated to guide variable-rate fertilizer application (Thenkabail et al., 2012).

Modern precision agriculture platforms integrate high-resolution satellite imagery with variable rate application (VRA) technology, allowing farmers to generate nitrogen maps tailored to specific field zones. This targeted approach to fertilization has been shown to improve crop uniformity, reduce excess chemical inputs, and enhance environmental sustainability (Zhang et al., 2019).

4.4 Pest and Disease Detection

Early detection of pest infestations and disease outbreaks is critical for minimizing crop losses and reducing the need for widespread pesticide application. Remote sensing technologies, particularly hyperspectral imaging and UAV-based multispectral sensors, have demonstrated significant potential for identifying disease symptoms at pre-symptomatic stages by detecting physiological and biochemical changes in plant tissue (Yang et al., 2017). Different diseases cause specific alterations in plant pigments, cell structure, and water content, leading to unique spectral fingerprints that can be differentiated using advanced machine learning algorithms.

UAV remote sensing technology, when integrated with deep learning models, enables rapid, accurate, and scalable

monitoring of crop health, providing real-time identification of pest-infested areas and enabling targeted pesticide application. This precision approach reduces chemical usage, lowers costs, and minimizes environmental impact while maintaining crop quality and yield (Ahmad et al., 2022).

4.5 Land Use and Land Cover Mapping

Remote sensing and GIS are extensively used for land use and land cover (LULC) mapping, which is essential for agricultural planning, resource allocation, and environmental management. By analyzing satellite images, different land use types including forests, agricultural fields, urban areas, and water bodies can be identified and mapped over time (Weiss et al., 2020). LULC change detection enables monitoring of agricultural expansion, deforestation, land degradation, and urbanization, providing critical information for policy-makers and land managers. Multi-temporal remote sensing data, combined with machine learning classification algorithms, facilitate accurate crop type mapping and acreage estimation at regional and national scales, supporting food security assessments and agricultural policy formulation (Atzberger, 2013).

5. Integration of Remote Sensing with Emerging Technologies

5.1 GIS and Decision Support Systems

Geographic Information Systems provide a powerful framework for integrating, analyzing, and visualizing spatially referenced remote sensing data. GIS enables the creation of detailed and interactive maps that facilitate watershed delineation, land suitability analysis, flood risk assessment, and water resource management (Malczewski, 2004). The integration of remote sensing with GIS allows for comprehensive spatial analysis considering multiple factors such as topography, land use, vegetation cover, and hydrological conditions, supporting evidence-based agricultural decision-making.

5.2 Machine Learning and Artificial Intelligence

The convergence of remote sensing with machine learning and artificial intelligence has

ushered in a new era of precision agriculture. Machine learning algorithms including Random Forest, Support Vector Machine, Artificial Neural Networks, and deep learning architectures such as Convolutional Neural Networks have demonstrated superior performance in processing large volumes of remote sensing data for crop classification, yield prediction, disease detection, and soil property estimation (Kamilaris & Prenafeta-Boldu, 2018). Edge AI, which enables spectral data processing directly on drones and sensors, is emerging as a key trend that promises instant field-level decision-making without requiring cloud connectivity (Zhang et al., 2019).

5.3 Internet of Things and Smart Agriculture

The Internet of Things (IoT) complements remote sensing by providing ground-level, real-time data from in-situ sensors deployed across agricultural fields. Wireless sensor networks monitor soil moisture, temperature, humidity, and nutrient levels, which, when integrated with satellite and UAV imagery, create comprehensive farm management systems. The fusion of IoT data with remote sensing analytics enables predictive modelling for irrigation scheduling, pest forecasting, and crop growth monitoring, forming the backbone of smart agriculture initiatives (Wolfert et al., 2017).

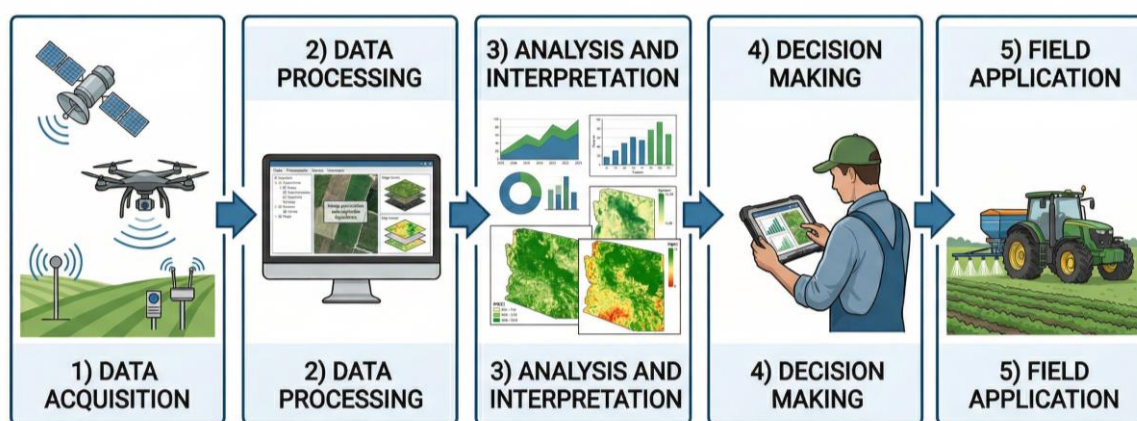


Figure4. Workflow of remote sensing in precision agriculture: from data acquisition to field application

6. Challenges and Limitations

Despite the significant advancements in remote sensing applications for agriculture, several challenges and limitations persist that hinder the widespread adoption and effective implementation of these technologies. A critical challenge is the trade-off between spatial, spectral, and temporal resolution. Satellite sensors often provide either high spatial resolution with limited spectral detail or broad spectral coverage at coarser spatial scales, making it difficult to obtain imagery with the optimal combination of resolutions for effective stress detection (Mulla, 2013).

The high cost of advanced sensors, particularly hyperspectral systems, and the computational demands of processing large volumes of remote sensing data present

significant barriers to adoption, especially for smallholder farmers in developing countries (Tsouros et al., 2019). Cloud cover, atmospheric interference, and varying illumination conditions can compromise the quality and availability of optical satellite imagery, particularly in tropical regions. While SAR sensors overcome some of these limitations, the complexity of radar data interpretation requires specialized expertise and processing capabilities.

Network connectivity issues in remote agricultural areas pose challenges for the effective implementation of precision farming technologies. Poor communication infrastructure limits real-time data transmission and cloud-based processing, which are essential for timely decision-making

(Wolfert et al., 2017). Additionally, the lack of standardized protocols for data collection, calibration, and validation across different

sensor platforms creates interoperability challenges that hinder the integration of multi-source remote sensing data.

Table2. Key challenges and potential solutions in remote sensing for agriculture

Challenge	Impact	Potential Solution
Resolution trade-offs	Limits detection accuracy	Multi-sensor data fusion
High costs of sensors	Restricts smallholder access	Open-source satellite data
Cloud cover interference	Reduces data availability	SAR and radar integration
Data processing complexity	Requires technical expertise	AI-automated processing
Poor rural connectivity	Limits real-time analysis	Edge computing solutions

7. Future Perspectives

The future of remote sensing in agricultural resource management is poised for transformative advances driven by technological innovation, data integration, and expanded accessibility. The development of next-generation satellite constellations with higher spatial, spectral, and temporal resolutions will enable more precise and frequent monitoring of agricultural systems. The fusion of satellite, aerial, and drone data with ground-based IoT sensor networks will create comprehensive, multi-scale monitoring systems capable of capturing field-level variability while maintaining regional and global coverage (Weiss et al., 2020).

Advances in artificial intelligence and deep learning will enable more sophisticated analysis of remote sensing data, including automated crop mapping, real-time anomaly detection, and predictive analytics for yield forecasting and risk assessment. The integration of genomics with spectral analysis, linking plant genetics with hyperspectral profiles, holds promise for predicting crop performance and breeding more resilient varieties (Zhang et al., 2019). The increasing availability of open-access satellite data, cloud computing platforms such as Google Earth Engine, and user-friendly analytical tools will democratize access to remote sensing technology, particularly for smallholder farmers in developing countries who stand to benefit most from precision agriculture

approaches (Kamilaris & Prenafeta-Boldu, 2018).

CONCLUSION

Remote sensing technology has fundamentally transformed agricultural resource management by providing spatially explicit, temporally consistent, and cost-effective monitoring capabilities that were previously unattainable through conventional methods. This review has comprehensively examined the diverse applications of remote sensing across multiple domains of agriculture, including crop health monitoring, yield estimation, soil moisture assessment, irrigation management, nutrient stress detection, pest and disease identification, and land use mapping.

The evolution from traditional satellite platforms to advanced UAV-based systems, combined with the development of sophisticated vegetation indices such as NDVI, EVI, SAVI, and NDRE, has significantly enhanced our ability to characterize crop conditions with increasing precision and accuracy. The integration of remote sensing with Geographic Information Systems, machine learning algorithms, and Internet of Things technologies has created powerful decision-support frameworks that enable site-specific management practices, optimize resource utilization, and minimize environmental impacts.

However, persistent challenges including resolution trade-offs, high sensor

costs, data processing complexity, cloud cover interference, and limited accessibility for smallholder farmers continue to constrain the full realization of remote sensing's potential in agriculture. Addressing these challenges through technological innovation, open data policies, capacity building, and interdisciplinary collaboration will be essential for advancing sustainable agricultural resource management.

As the global community confronts the dual imperatives of feeding a growing population while preserving natural resources, remote sensing will undoubtedly play an increasingly pivotal role in guiding evidence-based agricultural decision-making, promoting climate-smart farming practices, and achieving global food security and environmental sustainability.

Acknowledgements:

The authors extend their sincere thanks to all co-authors for their valuable contributions and timely support.

Funding:

The authors received no financial assistance for this work.

Conflict of Interest:

No conflict of interest exists.

Author Contributions:

All authors participated in critical revision and approved the final manuscript.

REFERENCES

Ahmad, A., Saraswat, D., & El Gamal, A. (2022). A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools. *Smart Agricultural Technology*, 3, 100083. <https://doi.org/10.1016/j.atech.2022.100083>

Atzberger, C. (2013). Advances in remote sensing of agriculture: Context description, existing operational monitoring systems and major information needs. *Remote Sensing*,

5(2), 949-981. <https://doi.org/10.3390/rs5020949>

Becker-Reshef, I., Justice, C., Sullivan, M., Vermote, E., Tucker, C., Anyamba, A., & Doorn, B. (2010). Monitoring global croplands with coarse resolution Earth observations: The Global Agriculture Monitoring (GLAM) project. *Remote Sensing*, 2(6), 1589-1609. <https://doi.org/10.3390/rs2061589>

Chlingaryan, A., Sukkarieh, S., & Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Computers and Electronics in Agriculture*, 151, 61-69. <https://doi.org/10.1016/j.compag.2018.05.012>

Chuvieco, E. (2020). Fundamentals of satellite remote sensing: An environmental approach (3rd ed.). CRC Press. <https://doi.org/10.1201/9780429506482>

Doraiswamy, P. C., Hatfield, J. L., Jackson, T. J., Akhmedov, B., Prueger, J., & Stern, A. (2004). Crop condition and yield simulations using Landsat and MODIS. *Remote Sensing of Environment*, 92(4), 548-559. <https://doi.org/10.1016/j.rse.2004.05.017>

Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., & Meygret, A. (2012). Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote Sensing of Environment*, 120, 25-36. <https://doi.org/10.1016/j.rse.2011.11.026>

Foley, J. A., Ramankutty, N., Brauman, K. A., Cassidy, E. S., Gerber, J. S., Johnston, M., & Zaks, D. P. (2011). Solutions for a cultivated planet. *Nature*, 478(7369), 337-342. <https://doi.org/10.1038/nature10452>

Gao, B. C. (1996). NDWI: A normalized difference water index for remote sensing of vegetation liquid water

- from space. *Remote Sensing of Environment*, 58(3), 257-266. [https://doi.org/10.1016/S0034-4257\(96\)00067-3](https://doi.org/10.1016/S0034-4257(96)00067-3)
- Gitelson, A. A., Kaufman, Y. J., & Merzlyak, M. N. (1996). Use of a green channel in remote sensing of global vegetation from EOS-MODIS. *Remote Sensing of Environment*, 58(3), 289-298. [https://doi.org/10.1016/S0034-4257\(96\)00072-7](https://doi.org/10.1016/S0034-4257(96)00072-7)
- Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment*, 83(1-2), 195-213. [https://doi.org/10.1016/S0034-4257\(02\)00096-2](https://doi.org/10.1016/S0034-4257(02)00096-2)
- Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, 25(3), 295-309. [https://doi.org/10.1016/0034-4257\(88\)90106-X](https://doi.org/10.1016/0034-4257(88)90106-X)
- Jackson, R. D., Idso, S. B., Reginato, R. J., & Pinter, P. J. (1981). Canopy temperature as a crop water stress indicator. *Water Resources Research*, 17(4), 1133-1138. <https://doi.org/10.1029/WR017i004p01133>
- Kamilaris, A., & Prenafeta-Boldu, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70-90. <https://doi.org/10.1016/j.compag.2018.02.016>
- Lillesand, T. M., Kiefer, R. W., & Chipman, J. W. (2015). *Remote sensing and image interpretation* (7th ed.). John Wiley & Sons.
- Malczewski, J. (2004). GIS-based land-use suitability analysis: A critical overview. *Progress in Planning*, 62(1), 3-65. <https://doi.org/10.1016/j.progress.2003.09.002>
- McCabe, M. F., Rodell, M., Alsdorf, D. E., Miralles, D. G., Uijlenhoet, R., Wagner, W., & Wood, E. F. (2017). The future of Earth observation in hydrology. *Hydrology and Earth System Sciences*, 21(7), 3879-3914. <https://doi.org/10.5194/hess-21-3879-2017>
- Mukherjee, A., Misra, S., & Raghuwanshi, N. S. (2019). A survey of unmanned aerial sensing solutions in precision agriculture. *Journal of Network and Computer Applications*, 148, 102461. <https://doi.org/10.1016/j.jnca.2019.10.2461>
- Mulla, D. J. (2013). Twenty-five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems Engineering*, 114(4), 358-371. <https://doi.org/10.1016/j.biosystemseng.2012.08.009>
- Robock, A., Vinnikov, K. Y., Srinivasan, G., Entin, J. K., Hollinger, S. E., Speranskaya, N. A., & Namkhay, A. (2000). The global soil moisture data bank. *Bulletin of the American Meteorological Society*, 81(6), 1281-1299. [https://doi.org/10.1175/1520-0477\(2000\)081<1281:TGSMDB>2.3.CO;2](https://doi.org/10.1175/1520-0477(2000)081<1281:TGSMDB>2.3.CO;2)
- Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. *NASA Special Publication*, 351, 309-317.
- Roy, D. P., Wulder, M. A., Loveland, T. R., Woodcock, C. E., Allen, R. G., Anderson, M. C., & Zhu, Z. (2014). Landsat-8: Science and product vision for terrestrial global change research. *Remote Sensing of Environment*, 145, 154-172. <https://doi.org/10.1016/j.rse.2014.02.01>
- Srivastava, P. K., Han, D., Ramirez, M. R., & Islam, T. (2013). Machine learning techniques for downscaling SMOS satellite soil moisture using MODIS land surface temperature for

- hydrological application. *Water Resources Management*, 27(8), 3127-3144. <https://doi.org/10.1007/s11269-013-0337-9>
- Thenkabail, P. S., Lyon, J. G., & Huete, A. (2012). Hyperspectral remote sensing of vegetation. CRC Press. <https://doi.org/10.1201/b11222>
- Torres, R., Snoeij, P., Geudtner, D., Bibby, D., Davidson, M., Attema, E., & Rostan, F. (2012). GMES Sentinel-1 mission. *Remote Sensing of Environment*, 120, 9-24. <https://doi.org/10.1016/j.rse.2011.05.028>
- Tsouros, D. C., Bibi, S., & Sarigiannidis, P. G. (2019). A review on UAV-based applications for precision agriculture. *Information*, 10(11), 349. <https://doi.org/10.3390/info10110349>
- Weiss, M., Jacob, F., & Duveiller, G. (2020). Remote sensing for agricultural applications: A meta-review. *Remote Sensing of Environment*, 236, 111402. <https://doi.org/10.1016/j.rse.2019.111402>
- Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big data in smart farming: A review. *Agricultural Systems*, 153, 69-80. <https://doi.org/10.1016/j.agry.2017.01.023>
- Xue, J., & Su, B. (2017). Significant remote sensing vegetation indices: A review of developments and applications. *Journal of Sensors*, 2017, 1353691. <https://doi.org/10.1155/2017/1353691>
- Yang, G., Liu, J., Zhao, C., Li, Z., Huang, Y., Yu, H., & Yang, H. (2017). Unmanned aerial vehicle remote sensing for field-based crop phenotyping: Current status and perspectives. *Frontiers in Plant Science*, 8, 1111. <https://doi.org/10.3389/fpls.2017.01111>
- Zhang, N., Wang, M., & Wang, N. (2019). Precision agriculture: A worldwide overview. *Computers and Electronics in Agriculture*, 36(2-3), 113-132. [https://doi.org/10.1016/S0168-1699\(02\)00096-0](https://doi.org/10.1016/S0168-1699(02)00096-0)