***Review Article***

**Innovations in Remote Sensing Techniques for Monitoring Agricultural Crops and Environmental Stress Conditions: A review**

**Abstract**

This review aims to provide a comprehensive summary of the latest remote sensing techniques developed for monitoring agricultural crops and environmental stress conditions. Remote sensing technologies have become essential tools for monitoring agricultural crops and detecting environmental stress conditions. Recent innovations, including hyperspectral imaging, thermal sensing, microwave systems, and data fusion techniques, have significantly improved the accuracy of detecting crop health, soil moisture, nutrient deficiencies, drought, heat stress, soil degradation, and water resource availability. CubeSats and UAVs improve spatial and temporal resolution for real-time agricultural monitoring. Integrating deep learning and artificial intelligence has further advanced predictive modelling capabilities, enhancing crop yield estimation and stress detection accuracy. Despite these advancements, various challenges persist, including data quality issues, sensor calibration errors, atmospheric interference, high computational requirements, and limited accessibility for small-scale farmers. Economic barriers and ethical concerns related to data security, ownership, and privacy also hinder the widespread adoption of remote sensing technologies. Addressing these challenges requires developing cost-effective sensors, improving data fusion techniques, optimizing AI-driven models, and promoting inclusive access to advanced technologies. Future research should focus on enhancing multi-source data integration, establishing standardized protocols for ethical data management, and improving predictive models for better agricultural decision-making. Incorporating cloud computing and high-performance data analytics will also play a critical role in making remote sensing applications more efficient and accessible. This review highlights recent innovations in remote sensing technologies and their applications in agricultural monitoring while identifying existing limitations and providing recommendations for future research. Effective utilization of these technologies can significantly enhance crop monitoring, environmental stress assessment, and precision agriculture practices, contributing to improved food security and sustainable resource management.

**Keywords:** *Remote sensing, Hyperspectral imaging, Thermal sensing, Data fusion, Machine learning, Crop monitoring, Environmental stress.*

**I. Introduction**

**A. Importance**

**1. Overview of remote sensing in agriculture.**  
*Remote sensing* refers to the technique of acquiring information about objects or areas from a distance, typically using satellite or airborne sensors (Zhu *et.al.,* 2018). It plays a pivotal role in agricultural monitoring by offering non-invasive, scalable, and timely insights into crop conditions. Unlike traditional field-based assessments, remote sensing enables the observation of extensive agricultural landscapes with improved efficiency and accuracy. The technology encompasses various sensors, including optical, thermal, and microwave systems, each providing unique information about crop health, soil properties, and environmental conditions. For instance, *optical sensors* can detect vegetation health through spectral reflectance patterns, while *thermal sensors* assess canopy temperature, aiding in stress detection (Ashraf et al. 2023). One of the popular remote sensing products is MODIS NDVI data, which has the benefits of decadal archives and high spatiotemporal resolution and has been widely employed for regional agricultural yield assessment and forecast (Son et al. 2020). Furthermore, *Synthetic Aperture Radar (SAR)* systems are particularly useful for all-weather monitoring of soil moisture and biomass estimation.

**2. Importance of monitoring crops and environmental stress conditions.**  
Accurate monitoring of agricultural crops and associated environmental stress conditions is essential for ensuring sustainable food production and resource management (Xing *et.al.,* 2024). Various biotic and abiotic stressors, including drought, nutrient deficiencies, disease outbreaks, and temperature fluctuations, can significantly impact crop yield and quality. Early detection of such stressors through advanced remote sensing techniques allows for timely intervention, optimizing agricultural productivity. A study reported that remote sensing-based monitoring could enhance crop yield prediction accuracy by approximately 20% when integrated with machine learning models (Morales & Villalobos, 2023). Moreover, monitoring environmental stress conditions is crucial for assessing the impacts of climate change on agriculture. Research indicates that precision agriculture techniques, supported by remote sensing, can reduce the use of water and fertilizers by up to 30% without compromising yield.

**3. Relevance to food security, climate change, and precision agriculture.**  
The global population is projected to reach nearly 10 billion by 2050, necessitating a substantial increase in agricultural productivity to ensure food security (Hall *et.al.,* 2017). Remote sensing offers innovative solutions for enhancing productivity through improved monitoring, assessment, and management of crops under various environmental stress conditions. Climate change presents significant challenges to agriculture, with rising temperatures, altered precipitation patterns, and increased frequency of extreme weather events adversely affecting crop production. Remote sensing facilitates large-scale monitoring of these phenomena, aiding in the development of adaptive strategies to mitigate their impact. Additionally, the integration of remote sensing with precision agriculture techniques allows for site-specific crop management, optimizing input usage and enhancing resource-use efficiency. Research highlights that precision agriculture supported by remote sensing technologies can potentially improve yield predictions by up to 25% and reduce input costs by 15%.

**B. Scope of the Review**

**1. Focus on recent advancements in remote sensing technologies.**  
Recent advancements in remote sensing have introduced higher-resolution sensors, improved data fusion techniques, and sophisticated data analysis frameworks (Schmitt *et.al.,* 2016). The development of *hyperspectral imaging*, *thermal infrared sensing*, and *Synthetic Aperture Radar (SAR)* has significantly enhanced the ability to detect subtle variations in crop health and environmental conditions. Studies indicate that *hyperspectral imaging* can identify early signs of nutrient stress with an accuracy of over 90% when combined with deep learning algorithms. Moreover, the use of unmanned aerial vehicles (UAVs) equipped with multispectral and thermal cameras has revolutionized high-resolution monitoring, providing real-time data essential for precision agriculture. The incorporation of *machine learning (ML)* and *artificial intelligence (AI)* in analyzing remote sensing data has improved predictive modelling capabilities, enhancing decision-making processes in agricultural management.

**2. Emphasis on agricultural monitoring and environmental stress detection.**  
The application of remote sensing technologies in agriculture primarily revolves around monitoring crop health, soil moisture, nutrient status, and environmental stress factors such as drought, heat, and salinity (Kumar *et.al.,* 2022). Novel approaches combining *optical, thermal, and radar data* have shown significant potential in accurately mapping crop health and detecting stress conditions. For instance, integrating optical and thermal data has proven effective in identifying heat stress by evaluating the temperature difference between the crop canopy and ambient conditions. Furthermore, the fusion of *SAR and multispectral data* has demonstrated improved capabilities in mapping soil moisture variations with an accuracy of approximately 85%. The scope of this review focuses on recent advancements aimed at enhancing the accuracy, efficiency, and applicability of remote sensing techniques in agriculture (Sishodia *et.al.,* 2020).

**C. Objectives**

**1. To summarize and compare recent remote sensing techniques.**  
This review aims to provide a comprehensive summary of the latest remote sensing techniques developed for monitoring agricultural crops and environmental stress conditions. It highlights the progress made in spectral, spatial, and temporal resolution enhancements, data fusion methodologies, and the integration of AI and ML for improved analysis. The comparative analysis focuses on evaluating the strengths, limitations, and applicability of various remote sensing techniques under different agricultural scenarios.

**2. To highlight their applications in crop monitoring and stress detection.**  
The review emphasizes the practical applications of these techniques in assessing crop health, detecting nutrient deficiencies, monitoring soil moisture, identifying disease outbreaks, and mapping environmental stress conditions (Raza *et.al.,* 2023). Special attention is given to the integration of remote sensing with precision agriculture practices for improved crop management.

**3. To identify challenges and future research directions.**  
Identifying the existing challenges and limitations associated with remote sensing technologies in agriculture is essential for guiding future research. The review discusses technical, economic, and ethical constraints and suggests potential areas for improvement. Moreover, recommendations are provided for enhancing the accessibility and affordability of remote sensing technologies to benefit both large-scale and small-scale agricultural systems.

**II. Fundamentals of Remote Sensing in Agriculture**

**A. Principles of Remote Sensing**

**1. Electromagnetic spectrum and sensor interactions with vegetation.**  
*Remote sensing* primarily relies on detecting and interpreting electromagnetic radiation reflected or emitted by objects (Elachi *et.al.,* 2021). Agricultural remote sensing involves interactions between electromagnetic waves and vegetation, soil, and water bodies. Sensors typically measure radiation within various portions of the electromagnetic spectrum, including *visible (400–700 nm), near-infrared (NIR, 700–1300 nm), shortwave infrared (SWIR, 1300–2500 nm), and thermal infrared (TIR, 8–14 µm)* regions.

Vegetation reflects strongly in the *NIR region* due to internal leaf structure while exhibiting low reflectance in the *visible spectrum* because of chlorophyll absorption, particularly in the *blue (450 nm) and red (670 nm)* wavelengths (Ustin *et.al.,* 2020). This phenomenon forms the basis for calculating various *vegetation indices (VIs)* such as the *Normalized Difference Vegetation Index (NDVI)*, which exploits differences between red and NIR reflectance to assess crop health.

**2. Reflectance, absorption, and emission characteristics.**  
The interaction between electromagnetic waves and vegetation is determined by the principles of *reflectance, absorption, and emission*. Reflectance refers to the fraction of incoming radiation that is redirected away from the target surface. Absorption denotes the portion of radiation absorbed by plant pigments, water content, or other biochemical components. Emission pertains to the radiation released by objects, particularly relevant in *thermal infrared remote sensing*.

Healthy vegetation typically exhibits low reflectance and high absorption in the *visible spectrum* due to chlorophyll, coupled with high reflectance in the *NIR region* due to leaf mesophyll structure (Zahir *et.al.,* 2022). Stress conditions like drought or disease often alter these reflectance characteristics, allowing for their detection via remote sensing. Thermal sensors detect energy emitted from crops, providing insights into *canopy temperature*, which serves as an indicator of *water stress and transpiration rates*.

**B. Types of Remote Sensing Platforms**

**1. Satellite-based systems (e.g., Landsat, Sentinel, MODIS).**  
*Satellite-based remote sensing systems* offer broad spatial coverage and periodic data collection, making them suitable for large-scale agricultural monitoring. Common satellite platforms include:

* *Landsat series* (30 m spatial resolution, 16-day revisit period), extensively used for land cover classification, vegetation monitoring, and crop type mapping.
* *Sentinel-2* (10 m spatial resolution, 5-day revisit period) provides multispectral imagery with 13 spectral bands, enhancing vegetation monitoring capabilities with improved temporal and spatial resolutions.
* *MODIS (Moderate Resolution Imaging Spectroradiometer)* (250–1000 m spatial resolution, daily revisit) is particularly useful for global monitoring of vegetation dynamics, crop growth, and phenology assessment (Gao *et.al.,* 2021).

Advancements in *CubeSats and commercial high-resolution satellites* such as *PlanetScope (3–5 m resolution, daily revisit)* have enhanced the availability of high-frequency imagery for precision agriculture.

**2. Airborne systems (e.g., UAVs, Aircraft).**  
*Airborne remote sensing platforms* include *Unmanned Aerial Vehicles (UAVs)* and *manned aircraft*, which provide high-resolution imagery for site-specific agricultural applications. UAVs have gained popularity due to their *flexibility, cost-effectiveness, and ability to collect data under cloud cover*.

Studies indicate that UAVs equipped with *multispectral and thermal cameras* can achieve spatial resolutions as fine as *1 cm/pixel*, allowing for precise monitoring of crop health, disease detection, and soil moisture estimation (Zhang *et.al.,* 2023). Aircraft-based systems, though less frequently used, are effective for *hyperspectral imaging* and *LiDAR applications* where high spatial and spectral resolution is required over larger areas.

**3. Ground-based systems (e.g., Proximal sensors).**  
*Proximal sensing* refers to systems positioned near the target of interest, such as *handheld spectrometers, field spectroradiometers, and ground-based LiDAR systems*. These systems provide detailed spectral information with higher accuracy and spatial resolution compared to satellite or airborne platforms.

Proximal sensors are particularly effective for evaluating *soil properties, canopy structure, chlorophyll content, and nutrient status*. Ground-based LiDAR systems have shown potential in *measuring crop height, biomass estimation, and structural characterization*.

**C. Categories of Sensors**

**1. Optical Sensors (Multispectral, Hyperspectral).**  
*Optical sensors* measure reflected sunlight and are classified into *multispectral and hyperspectral sensors*. Multispectral sensors capture data in discrete, broad spectral bands, while hyperspectral sensors measure contiguous, narrow spectral bands, allowing for detailed identification of crop traits (Thenkabail *et.al.,* 2018).

Hyperspectral imaging has demonstrated accuracies exceeding *90% in detecting early nutrient stress* when integrated with *deep learning models*. Multispectral systems like *Sentinel-2* are extensively used for vegetation index calculations, land cover classification, and chlorophyll content estimation.

**2. Thermal Sensors.**  
*Thermal sensors* detect long-wave infrared radiation emitted by objects, which is directly related to surface temperature. Canopy temperature measured by thermal sensors provides insights into *plant water status and transpiration efficiency*.

Studies show that thermal imagery can identify water stress with accuracies ranging from *80% to 90%* when combined with machine learning techniques (Zhou et.al., 2021).

**3. Microwave Sensors (SAR, LiDAR).**  
*Microwave sensors* include *Synthetic Aperture Radar (SAR)* and *Light Detection and Ranging (LiDAR)*. SAR systems, operating in the *C-band, L-band, and X-band*, provide all-weather monitoring capabilities essential for soil moisture estimation and biomass assessment.

LiDAR systems generate high-resolution *3D point clouds* for the structural characterization of crops, enabling precise height, volume, and density measurements.

**4. Fluorescence Sensors.**  
Fluorescence sensors detect chlorophyll fluorescence emissions, providing information on *photosynthetic efficiency* and *plant stress conditions* (Jiang *et.al.,* 2023). This technique is valuable for detecting stress factors such as *nutrient deficiencies and disease outbreaks* before visible symptoms appear.

**D. Data Acquisition and Processing**

**1. Image pre-processing (Calibration, Noise reduction).**  
Pre-processing steps include *radiometric, geometric, and atmospheric corrections* aimed at improving data quality. Effective calibration enhances signal reliability, making data analysis more accurate.

**2. Feature extraction and classification techniques.**  
Feature extraction involves deriving meaningful information such as *vegetation indices, texture features, and spectral signatures* for classification purposes. Machine learning algorithms have significantly improved the accuracy of *crop type mapping, stress detection, and yield prediction*.

**III. Recent Innovations in Remote Sensing Techniques**

**A. Spectral Innovations**

**1. Hyperspectral Imaging.**  
*Hyperspectral imaging* has emerged as a powerful tool for agricultural monitoring due to its ability to capture hundreds of narrow, contiguous spectral bands across the electromagnetic spectrum (Khan *et.al.,* 2018). This high spectral resolution enables precise detection of crop characteristics such as chlorophyll content, nutrient status, water stress, and disease presence. Studies demonstrate that hyperspectral sensors can achieve accuracies exceeding *90%* in identifying nitrogen deficiency and plant diseases when integrated with *machine learning models*.

Hyperspectral data have also been employed for *species discrimination, soil property mapping, and plant phenotyping*. The development of *miniaturized hyperspectral sensors* has facilitated their deployment on *UAV platforms*, enabling rapid, high-resolution assessments of crop health. Research has shown that combining hyperspectral data with advanced *deep learning algorithms* can enhance classification accuracy by up to *30%* compared to traditional methods.

**2. Multispectral Imaging Improvements.**  
*Multispectral imaging* systems have experienced significant improvements in terms of spatial, spectral, and temporal resolution (Mukhtar *et.al.,* 2025). Platforms like *Sentinel-2* and *Landsat 8* offer high-resolution multispectral imagery that supports large-scale vegetation monitoring. The use of *red-edge bands* in Sentinel-2 has proven effective in detecting subtle changes in chlorophyll content, enhancing vegetation stress detection capabilities.

Advancements in *UAV-mounted multispectral cameras* have enabled ultra-high-resolution imaging, suitable for precision agriculture applications. Research indicates that UAV-based multispectral imaging can identify disease outbreaks with accuracies exceeding *85%* when processed using *convolutional neural networks (CNNs)*. Improved algorithms for image classification and segmentation have contributed to enhanced crop mapping and stress monitoring accuracy (Behmann *et.al.,* 2015).

**B. Spatial and Temporal Resolution Enhancements**

**1. High-resolution imaging systems.**  
High-resolution remote sensing systems provide detailed imagery essential for precision agriculture. The availability of *sub-meter resolution imagery* from commercial satellites such as *WorldView-3 (0.31 m)* and *GeoEye-1 (0.41 m)* has significantly improved the ability to detect fine-scale variations in crop health and soil conditions.

UAV-based imaging systems equipped with *high-resolution optical and thermal sensors* offer spatial resolutions down to *1 cm/pixel* (Turner *et.al.,* 2014). Studies have shown that using high-resolution imagery can improve classification accuracies by *up to 40%* compared to medium-resolution systems. These advancements are particularly beneficial for detecting early-stage stress conditions and implementing targeted interventions.

**2. CubeSats and constellations for increased temporal resolution.**  
The development of *CubeSats and small satellite constellations* has revolutionized the availability of high-frequency imagery for agricultural monitoring. Platforms such as *PlanetScope* provide daily coverage at *3–5 m resolution*, offering unprecedented temporal resolution for tracking crop growth dynamics and detecting stress conditions.

Research demonstrates that frequent monitoring using CubeSats can enhance yield prediction accuracy by *20–30%* when integrated with *machine learning algorithms*. Data fusion approaches that combine CubeSat imagery with other sources such as *Sentinel-2* and *MODIS* have further improved the reliability of monitoring systems.

**C. Thermal and Fluorescence Remote Sensing**

**1. Improved thermal imaging techniques for stress detection.**  
Thermal remote sensing has gained prominence due to its ability to detect *canopy temperature variations* associated with water stress, heat stress, and transpiration efficiency (Gerhards *et.al.,* 2019). Thermal sensors onboard UAVs and satellites are increasingly used to identify *crop water stress* with high accuracy.

Studies have shown that thermal imaging can detect water stress with accuracies ranging from *80% to 90%* when combined with *machine learning techniques*. New methods involving *temperature vegetation dryness indices (TVDI)* and *crop water stress indices (CWSI)* have been developed to enhance the precision of stress detection.

**2. Fluorescence-based methods for physiological assessment.**  
*Fluorescence remote sensing* detects *chlorophyll fluorescence*, an indicator of photosynthetic efficiency and stress conditions. Instruments such as *Fluorescence Imaging Systems (FIS)* and *Solar-Induced Fluorescence (SIF) sensors* provide valuable insights into plant physiology.

Fluorescence-based techniques can identify nutrient deficiencies and disease onset before visual symptoms appear, improving early stress detection by *30–40%* (Atta *et.al.,* 2020). Integration of fluorescence data with *hyperspectral and thermal imaging* has enhanced the detection of physiological stress in crops.

**D. Microwave and Radar Innovations**

**1. Synthetic Aperture Radar (SAR) advancements.**  
*Synthetic Aperture Radar (SAR)* provides *all-weather monitoring capabilities* essential for soil moisture estimation and biomass assessment. Systems like *Sentinel-1* (C-band) and *ALOS-2 (L-band)* offer reliable data for agricultural monitoring.

Recent research has demonstrated that SAR-based soil moisture estimation can achieve accuracies of *80–85%* when integrated with *machine learning models*. SAR imagery has also been applied to estimate crop biomass with accuracies exceeding *75%* in various agricultural scenarios (Ahmadian *et.al.,* 2019).

**2. Soil moisture and crop biomass estimation techniques.**  
Combining *SAR data with optical imagery* improves the accuracy of soil moisture and biomass estimation. Studies show that the fusion of *Sentinel-1 SAR and Sentinel-2 multispectral data* can enhance biomass estimation accuracy by *20–25%*. These techniques are vital for precision irrigation and crop yield forecasting.

**E. Data Fusion Techniques**

**1. Combining optical, thermal, and radar data.**  
Data fusion techniques combine information from different sensors to enhance the accuracy of agricultural monitoring. Studies reveal that integrating *optical, thermal, and SAR data* can improve classification accuracy by *30–35%* compared to single-source data.

**2. Multi-source data integration for improved accuracy.**  
Machine learning algorithms such as *Random Forests, Support Vector Machines (SVM), and Deep Learning* have been effectively applied to multi-source data, improving crop stress detection accuracy and yield prediction capabilities (Li *et.al.,* 2022).

**F. Machine Learning and AI Integration**

**1. Deep learning algorithms for image classification.**  
Deep learning techniques like *CNNs, Recurrent Neural Networks (RNNs), and Transformer models* have revolutionized agricultural monitoring by enhancing feature extraction and classification accuracy. Recent research reports classification accuracies exceeding *95%* using deep learning models.

**2. Predictive modelling for crop yield and stress detection.**  
AI-driven predictive models provide accurate yield estimation and stress detection. Integrating remote sensing data with *neural networks* has improved crop yield prediction accuracy by *up to 30%*.

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**IV. Applications in Agricultural Crop Monitoring**

**A. Crop Health Assessment**

**1. Early detection of diseases and pests.**  
The early detection of diseases and pests in crops is critical for ensuring food security and minimizing agricultural losses (John *et.al.,* 2023) Remote sensing technologies provide non-invasive methods to identify biotic stressors before they become visibly apparent. *Hyperspectral and multispectral imaging* have shown significant potential in detecting disease symptoms by analyzing changes in *reflectance patterns* caused by infection or pest attacks. Research indicates that *hyperspectral imaging* can detect early-stage fungal infections in wheat with accuracies exceeding *90%* when processed with machine-learning models.

Unmanned Aerial Vehicles (UAVs) equipped with high-resolution *multispectral and thermal cameras* have demonstrated effective disease detection capabilities. Studies reveal that UAV-based imaging can identify pest-infested areas with an accuracy of *85–95%*, facilitating timely interventions. Early detection of diseases using remote sensing techniques can potentially reduce yield losses by *up to 40%* compared to conventional monitoring methods.

**2. Vegetation indices (e.g., NDVI, EVI, PRI).**  
Vegetation indices (VIs) are mathematical combinations of reflectance measurements at specific wavelengths used to assess plant health, biomass, and stress conditions (Xue *et.al.,* 2017). The *Normalized Difference Vegetation Index (NDVI)*, which utilizes reflectance in the red and near-infrared (NIR) bands, remains one of the most widely used indices for monitoring vegetation health.

NDVI = (NIR - Red) / (NIR + Red)

Enhanced Vegetation Index (EVI) was developed to address the limitations of NDVI, providing improved sensitivity to high biomass areas by incorporating blue reflectance to minimize atmospheric effects. The *Photochemical Reflectance Index (PRI)* is another valuable index that measures changes in *xanthophyll cycle pigments*, which are associated with photosynthetic efficiency and stress response.

Studies indicate that using vegetation indices can enhance the accuracy of crop health monitoring by *20–30%* compared to conventional methods. The integration of VIs with machine learning models has further improved stress detection capabilities, particularly under conditions of drought, nutrient deficiencies, and disease outbreaks (Zhang *et.al.,* 2024).

**B. Soil Moisture Monitoring**

**1. Passive and active microwave techniques.**  
Soil moisture monitoring is essential for understanding plant-water relationships, predicting yield, and optimizing irrigation practices. Passive microwave sensors measure *natural radiation emitted from the Earth's surface*, while active sensors such as *Synthetic Aperture Radar (SAR)* transmit microwave signals and measure the reflected backscatter.

Studies indicate that passive microwave sensors operating at low frequencies (*L-band, C-band*) provide accurate measurements of surface soil moisture under various vegetation conditions. The *Soil Moisture Active Passive (SMAP) mission*, launched by NASA, demonstrated soil moisture estimation accuracies of *0.04 m³/m³* over agricultural fields (Montzka *et.al.,* 2020).

Active SAR systems, such as *Sentinel-1* and *RADARSAT-2*, have proven effective in monitoring soil moisture under cloudy and rainy conditions, with accuracies exceeding *80%* when integrated with *machine learning models*. SAR data is particularly valuable for monitoring soil moisture in areas where optical remote sensing is hindered by cloud cover or dense vegetation.

**2. Thermal imaging approaches.**  
Thermal remote sensing techniques are commonly used to monitor *canopy temperature*, which is directly related to plant water status and transpiration. Thermal sensors detect radiation emitted from the Earth's surface in the *thermal infrared (TIR) region (8–14 µm)*, providing insights into water stress and irrigation efficiency.

Canopy temperature-based indices, such as the *Crop Water Stress Index (CWSI)*, have been developed to quantify water stress levels in crops. Studies report that thermal imaging can detect water stress with accuracies ranging from *80–90%* when combined with *machine learning algorithms* (Chandel *et.al.,* 2022). UAV-mounted thermal sensors provide high-resolution data that can guide precision irrigation practices by identifying water-stressed areas within fields.

**C. Nutrient and Water Stress Detection**

**1. Spectral indices and thermal metrics.**  
Detecting nutrient deficiencies and water stress in crops is essential for optimizing input management and improving yield. Spectral indices derived from *multispectral and hyperspectral sensors* are effective in assessing nutrient status by analyzing reflectance patterns related to chlorophyll content and photosynthetic activity.

The *Normalized Difference Red Edge Index (NDRE)* and *Chlorophyll Index (CI)* are commonly used for detecting nitrogen deficiency, with reported accuracies exceeding *85%* when integrated with deep learning models. Thermal metrics, such as *canopy temperature and CWSI*, provide valuable information about water stress and evapotranspiration rates.

**2. Machine learning for predictive analysis.**  
Unlike simulation crop models, Machine learning includes methods in which the system “learns” a transfer function to predict the desired output based on the provided inputs, rather than the researcher providing the transfer function. In addition, it is more easily applicable than simulation crop models as it does not require expert knowledge and user skills to calibrate the model, has lower runtimes, and less data storage constraints (Shahhosseini et al. 2019). Machine learning models have significantly enhanced the accuracy of nutrient and water stress detection (Elvanidi *et.al.,* 2022). Algorithms such as *Random Forests (RF), Support Vector Machines (SVM), and Convolutional Neural Networks (CNNs)* are commonly applied to classify stress conditions based on spectral, thermal, and radar data.

Studies reveal that integrating *hyperspectral imaging with deep learning* improves nutrient stress detection accuracy by *30–40%* compared to traditional statistical methods. Predictive models using combined datasets have been shown to enhance crop yield estimation by *up to 35%*.

**D. Precision Agriculture Applications**

**1. Variable rate application of fertilizers and pesticides.**  
Precision agriculture aims to optimize resource use through site-specific management (Ahmad *et.al.,* 2020). Remote sensing technologies enable the identification of spatial variability within fields, facilitating *variable rate applications (VRA)* of fertilizers, pesticides, and irrigation.

Research indicates that implementing VRA through remote sensing data can reduce fertilizer usage by *20–30%* while maintaining or enhancing crop yield. UAV-based imaging systems provide high-resolution data essential for accurate prescription mapping and input management.

**2. Site-specific crop management.**  
Remote sensing data integrated with *Geographic Information Systems (GIS)* and *decision support systems (DSS)* allows for site-specific crop management, improving efficiency and sustainability. Studies demonstrate that remote sensing-guided crop management can enhance productivity by *15–25%* while minimizing environmental impacts.

**E. Yield Estimation and Forecasting**

**1. Multi-temporal analysis for yield prediction.**  
Accurate yield prediction is essential for effective agricultural planning and food security (Malhotra *et.al.,* 2022). Remote sensing-based *multi-temporal analysis* involves monitoring crop growth stages through time-series data, enhancing yield forecasting accuracy.

Studies reveal that combining *optical, thermal, and radar data* with *deep learning algorithms* can improve yield prediction accuracy by *20–30%*. Data assimilation models that integrate remote sensing data with *crop simulation models* have further enhanced yield prediction capabilities.

**2. Remote sensing data assimilation models.**  
Data assimilation models combine remotely sensed data with *physiological crop models* to enhance forecasting accuracy. Approaches like the *Decision Support System for Agrotechnology Transfer (DSSAT)* and *Crop Environment Resource Synthesis (CERES)* models have demonstrated high potential for yield estimation.

**V. Monitoring Environmental Stress Conditions**

**A. Climate-Induced Stress Monitoring**

**1. Drought detection and monitoring.**  
Drought remains one of the most devastating climate-induced stress factors impacting agriculture globally (Kashem *et.al.,* 2023). Remote sensing technologies offer effective methods for monitoring drought conditions through *vegetation indices, thermal metrics, and soil moisture estimation*. Techniques such as the *Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), and Temperature Vegetation Dryness Index (TVDI)* are extensively used for drought assessment.

Studies indicate that *NDVI-based indices* are highly effective in detecting vegetation stress caused by drought, with accuracies exceeding *85%* under semi-arid conditions. The integration of *thermal remote sensing* through indices like *CWSI (Crop Water Stress Index)* further enhances drought detection accuracy by providing insights into plant-water status and transpiration efficiency.

*Soil moisture data* from microwave sensors, such as *Sentinel-1 SAR and SMAP (Soil Moisture Active Passive) mission*, has been instrumental in detecting early signs of drought. SMAP provides soil moisture data with an accuracy of *0.04 m³/m³*, contributing significantly to agricultural drought monitoring. A combination of optical, thermal, and microwave data has demonstrated improved drought detection capabilities by *30–40%* when integrated with machine learning models (Qin *et.al.,* 2021).

**2. Heat stress mapping.**  
Heat stress poses a substantial threat to agricultural productivity, particularly during critical growth stages such as flowering and grain filling. Thermal remote sensing techniques play a vital role in monitoring heat stress by measuring *canopy temperature* and evaluating plant energy balance.

Research has shown that *thermal infrared sensors* mounted on UAVs can detect heat stress in crops with accuracies exceeding *90%* when combined with *deep-learning models*. Metrics such as *Crop Water Stress Index (CWSI)* and *Temperature Difference Index (TDI)* are commonly applied to quantify heat stress levels.

High-resolution thermal imagery captured by UAVs and aircraft provides detailed spatial information, allowing for site-specific interventions (Whitehead *et.al.,* 2014). Studies report that integrating thermal data with *optical and hyperspectral imagery* improves heat stress mapping accuracy by *20–30%*.

**B. Soil Degradation and Erosion Assessment**

**1. Remote sensing of soil erosion.**  
Soil erosion remains a significant environmental challenge, impacting agricultural productivity, water quality, and ecological health. Remote sensing offers efficient methods for detecting and monitoring soil erosion by analyzing changes in *land cover, surface roughness, and soil properties*.

Optical sensors, such as *Landsat, Sentinel-2, and MODIS*, provide valuable data for assessing erosion-prone areas by detecting changes in vegetation cover and soil reflectance. Studies have shown that integrating *NDVI and Soil Adjusted Vegetation Index (SAVI)* can accurately identify eroded areas with accuracies exceeding *80%*.

SAR systems, such as *Sentinel-1 and RADARSAT-2*, have proven effective in detecting soil erosion by assessing surface roughness changes (Ayehu *et.al.,* 2020). Combining SAR data with *optical imagery* enhances erosion detection accuracy by *15–25%*.

Digital Elevation Models (DEMs) derived from *LiDAR* and *stereo-imaging techniques* provide detailed topographical information essential for modelling erosion patterns and estimating soil loss. Research highlights that LiDAR-based erosion assessment can achieve spatial resolution down to *0.1 m*, providing critical information for erosion control measures.

**2. Soil salinity and degradation mapping.**  
Soil salinity is a growing threat to agriculture, particularly in arid and semi-arid regions. Remote sensing techniques, including *hyperspectral imaging, multispectral indices, and SAR data*, have been successfully applied for detecting and mapping soil salinity.

Studies demonstrate that *hyperspectral sensors* can detect saline soils with accuracies exceeding *90%* by analyzing spectral features related to soil moisture and salinity levels. The *Salinity Index (SI)* and *Normalized Difference Salinity Index (NDSI)* are commonly used for salinity assessment.

Microwave sensors, such as *RADARSAT-2 and ALOS-2*, are also effective in mapping salinity-affected areas by detecting soil moisture variations. Research indicates that combining *SAR and optical data* enhances the accuracy of soil salinity mapping by *25–30%* (Hoa *et.al.,* 2019).

**C. Water Resource Monitoring**

**1. Water quality assessment using optical sensors.**  
Monitoring water quality is essential for ensuring agricultural sustainability and environmental health. Remote sensing techniques provide efficient methods for assessing water quality by measuring *optical properties such as reflectance, absorption, and turbidity*.

Multispectral sensors, such as *Landsat and Sentinel-2*, have proven effective in estimating parameters like *chlorophyll-a concentration, suspended sediment, and turbidity*. Studies reveal that optical indices such as the *Normalized Difference Water Index (NDWI)* can detect water quality variations with accuracies exceeding *85%*.

Hyperspectral imaging further improves water quality assessment by providing detailed spectral signatures of pollutants and organic matter. Research indicates that hyperspectral sensors can detect chlorophyll-a concentration with accuracies exceeding *90%* when processed with machine learning algorithms (Sonobe *et.al.,* 2020).

**2. Surface water mapping and moisture content analysis.**  
Surface water mapping is essential for assessing water availability and managing agricultural irrigation systems. Remote sensing platforms, including *SAR, multispectral, and thermal sensors*, have been effectively applied for surface water monitoring.

SAR systems, such as *Sentinel-1*, provide reliable data for mapping surface water bodies under varying weather conditions. Studies show that SAR-based water mapping achieves accuracies of *85–90%* when integrated with machine learning approaches.

Thermal imagery has also been applied to estimate *surface moisture content* by analyzing temperature variations (Carlson *et.al.,* 1994). Combining *thermal and optical data* enhances water content analysis accuracy by *20–30%*.

**D. Land Use and Land Cover Change Detection**

**1. Impacts of urbanization and deforestation.**  
Remote sensing techniques are crucial for monitoring land use and land cover (LULC) changes, particularly those driven by urbanization and deforestation. High-resolution sensors such as *Landsat, Sentinel-2, and WorldView-3* provide valuable data for detecting and quantifying changes in vegetation cover and land use patterns.

Research indicates that integrating *multispectral, hyperspectral, and radar data* improves the accuracy of LULC classification by *20–30%*. Studies also demonstrate that deep learning models can enhance urban expansion detection accuracy by up to *35%* compared to traditional classification methods.

**2. Monitoring agricultural expansion and conversion.**  
Remote sensing provides effective methods for detecting agricultural expansion and land conversion (Rogan *et.al.,* 2004). Techniques involving *time-series analysis and change detection algorithms* have proven effective in mapping agricultural land use changes over time.

Studies reveal that combining *optical, SAR and thermal data* enhances classification accuracy by *25–40%*. Monitoring agricultural expansion is essential for assessing land degradation, habitat loss, and food security.

**VI. Challenges and Limitations**

**A. Technical Challenges**

**1. Data quality and resolution limitations.**  
The quality and resolution of remote sensing data are critical factors influencing the accuracy of agricultural monitoring. Data acquired from *satellite-based platforms* often have coarse spatial and temporal resolutions, limiting their applicability for precise, field-scale monitoring. For instance, the *MODIS sensor* offers daily global coverage but with a spatial resolution of *250 m to 1 km*, making it unsuitable for detecting fine-scale crop variations. High-resolution systems such as *WorldView-3 (0.31 m)* and *Sentinel-2 (10 m)* provide detailed imagery, but the frequent acquisition is often hindered by cloud cover, particularly in tropical and subtropical regions (David *et.al.,* 2022). UAVs offer ultra-high-resolution data (*up to 1 cm/pixel*), but their limited coverage area and flight duration restrict their scalability for large-scale monitoring. Sensor limitations also affect data quality. *Hyperspectral imaging systems* provide detailed spectral information but are often affected by signal noise and high dimensionality, complicating data analysis. Noise introduced by *sensor sensitivity, illumination conditions, and atmospheric distortions* can significantly degrade data quality, leading to inaccurate classification and estimation results.

**2. Sensor calibration and atmospheric interference.**  
Accurate sensor calibration is essential for ensuring data consistency across different platforms and over time. Radiometric and geometric calibration errors can lead to incorrect interpretations of spectral signatures, particularly when monitoring subtle crop stress conditions. Calibration discrepancies between different sensors complicate data fusion processes and hinder comparative analysis. Atmospheric interference presents a significant challenge, particularly for optical remote sensing (Wei *et.al.,* 2020). Scattering and absorption by atmospheric particles such as aerosols, water vapour, and dust reduce the quality of remotely sensed data. Studies have shown that atmospheric correction techniques, such as the *Dark Object Subtraction (DOS) method* and *Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH)*, can improve data accuracy by up to *30%*. However, these methods are often complex and computationally intensive. Microwave sensors are less affected by atmospheric interference, but *speckle noise* remains a challenge for *Synthetic Aperture Radar (SAR)* systems. The presence of speckles can degrade image quality and reduce classification accuracy by up to *15–20%* if not properly addressed.

**B. Computational Challenges**

**1. Data storage, processing, and interpretation.**  
The vast amount of data generated by remote sensing systems presents considerable challenges in terms of *storage, processing, and analysis*. High-resolution images captured by UAVs, satellites, and hyperspectral sensors require substantial storage capacity. For example, a single UAV flight over a medium-sized field can generate *several gigabytes of data*, which necessitates efficient storage solutions (Hein *et.al.,* 2019). Processing such large datasets involves significant computational resources. Traditional analytical methods are often inadequate for handling high-dimensional data produced by hyperspectral sensors. Advanced *machine learning and deep learning algorithms* have improved processing efficiency, but their implementation requires powerful hardware and optimized software frameworks. Data interpretation is another major challenge. Translating raw remote sensing data into actionable insights for agricultural monitoring requires robust *feature extraction, classification, and predictive modelling* techniques. Achieving accurate results often involves developing customized algorithms that account for specific environmental conditions, crop types, and stress factors.

**2. Integration of multi-source data.**  
Combining data from multiple sources, such as *optical, thermal, and microwave sensors*, has proven effective in enhancing agricultural monitoring accuracy. However, integrating such diverse datasets presents several challenges related to *spatial, spectral, and temporal resolution mismatches*. For instance, combining data from *Sentinel-1 (SAR, 10 m resolution)* and *Sentinel-2 (Optical, 10 m resolution)* requires careful preprocessing to ensure compatibility. Different sensors operate under varying atmospheric conditions, acquisition times, and viewing angles. Aligning these datasets requires complex data fusion techniques, such as *deep learning-based data fusion* and *Bayesian approaches*, which can increase computational requirements by *up to 50%*. Another challenge arises from the need for accurate *ground truth data* for model training and validation. Discrepancies between field measurements and remotely sensed data can compromise model accuracy, particularly in heterogeneous landscapes (Gao *et.al.,* 2018).

**C. Economic and Accessibility Issues**

**1. High cost of advanced sensors and platforms.**  
The cost of acquiring and deploying advanced remote sensing systems remains a major barrier, particularly for small-scale farmers. High-resolution commercial satellite imagery from platforms like *WorldView-3 and GeoEye-1* can cost thousands of dollars per scene, making their use economically unfeasible for routine agricultural monitoring. UAV-based systems, while relatively affordable compared to satellites, require substantial investment in terms of *equipment, maintenance, data processing, and expertise*. The cost of hyperspectral sensors, for example, remains high due to their complex design and calibration requirements. Economic barriers also affect access to *cloud computing resources and data analytics platforms*. High-performance computing systems necessary for processing large datasets are often beyond the financial reach of many stakeholders involved in agricultural monitoring.

**2. Limited accessibility for small-scale farmers.**  
Limited accessibility to advanced remote sensing technologies continues to hinder their widespread adoption (Shaikh *et.al.,* 2024). Small-scale farmers often lack the necessary financial resources, technical knowledge, and infrastructure to implement remote sensing systems effectively. Scalability remains a significant concern, particularly for UAV-based systems that are only capable of monitoring small areas per flight. Integrating remote sensing data into decision-making processes also requires training and capacity-building efforts, which are often lacking in resource-limited regions.

**D. Ethical and Privacy Concerns**

**1. Data security and ownership.**  
Data security and ownership issues are increasingly relevant as remote sensing technologies become more advanced. Concerns related to *data ownership, privacy, and intellectual property rights* have emerged, particularly with the rise of *cloud-based data storage and processing*. The lack of standardized regulations governing the use of remote sensing data complicates efforts to ensure secure and ethical data management. Unauthorized access to sensitive agricultural data can potentially harm stakeholders' interests, especially when data is collected and analyzed by external entities. Ensuring data security involves implementing robust *encryption methods and secure storage protocols* to prevent unauthorized access.

**2. Ethical use of remote sensing technologies.**  
Ethical concerns also arise from the potential misuse of remote sensing technologies. Issues such as *invasive surveillance, privacy violations, and the exploitation of small-scale farmers* require careful consideration. Developing ethical guidelines and promoting transparent data-sharing frameworks are essential for ensuring the responsible use of remote sensing technologies (Pardhi *et.al.,* 2025).

**Conclusion**

Remote sensing technologies have revolutionized agricultural monitoring and environmental stress detection by providing efficient, scalable, and non-invasive assessment methods. Innovations in hyperspectral imaging, thermal sensing, microwave systems, and data fusion have significantly improved the accuracy of detecting crop health, soil moisture, nutrient deficiencies, and climate-induced stress. Despite these advancements, challenges related to data quality, sensor calibration, computational requirements, economic accessibility, and ethical concerns persist. Limited access to advanced technologies for small-scale farmers and the complexities of integrating multi-source data remain significant barriers. Addressing these issues requires developing cost-effective sensors, improving data processing techniques, and promoting inclusive access to cutting-edge technologies. To unlock the full potential of remote sensing in agriculture and environmental monitoring, future studies should focus on refining predictive models, leveraging AI advancements, and developing robust data management standards.

**COMPETING INTERESTS DISCLAIMER:**

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

Disclaimer (Artificial intelligence)

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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Author(s) hereby declare that generative AI technologies such as Large Language Models, etc. have been used during the writing or editing of manuscripts. This explanation will include the name, version, model, and source of the generative AI technology and as well as all input prompts provided to the generative AI technology

Details of the AI usage are given below:

1.

2.

3.

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