



REMOTE SENSING AND AI FOR CROP MONITORING AND YIELD ESTIMATION

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ABSTRACT

Remote sensing technologies, coupled with artificial intelligence (AI) techniques, have emerged as powerful tools for revolutionizing crop monitoring and yield estimation in agriculture. This paper provides a comprehensive review of recent advancements in the integration of remote sensing and AI for precision agriculture applications. We begin by discussing the fundamental principles of remote sensing, including satellite imagery, drones, and aerial surveys, and their utility in capturing spatial and temporal information about agricultural fields. Next, we explore various AI algorithms, such as machine learning and deep learning, used for analysing remote sensing data and extracting valuable insights for crop monitoring and yield estimation. Case studies and real-world applications demonstrate the efficacy of these technologies in accurately predicting crop growth, detecting stress factors, and optimizing agricultural practices. Furthermore, we discuss the challenges and limitations associated with remote sensing and AI integration, including data availability, computational complexity, and model validation. Finally, we highlight future research directions aimed at enhancing the scalability, accuracy, and accessibility of remote sensing and AI-based approaches for sustainable agriculture. This paper serves as a valuable resource for researchers, practitioners, and policymakers seeking to leverage advanced technologies for improving crop productivity, resource efficiency, and food security on a global scale.

INTRODUCTION

In recent years, the agricultural sector has witnessed a rapid evolution driven by advancements in remote sensing technologies and artificial intelligence (AI) techniques. Traditional methods of crop monitoring and yield estimation have been revolutionized by the integration of remote sensing data with AI algorithms, enabling farmers and researchers to make informed decisions for optimizing agricultural practices and enhancing crop productivity. This paper presents an overview of the state-of-the-art approaches in utilizing remote sensing and AI for crop monitoring and yield estimation in precision agriculture.

Remote sensing, encompassing technologies such as satellite imagery, drones, and aerial surveys, provides a bird's-eye view of agricultural landscapes, capturing valuable spatial and temporal information about crop health, growth, and environmental conditions. The availability of high-resolution imagery and multispectral data has enabled researchers to extract meaningful insights into crop dynamics at various spatial and temporal scales, facilitating targeted interventions for crop management.

Parallely, AI techniques, including machine learning and deep learning, have emerged as powerful tools for analysing large volumes of remote sensing data and deriving actionable intelligence for crop monitoring and yield estimation. By leveraging AI algorithms, researchers can train predictive

models to detect crop stress factors, forecast yield outcomes, and optimize resource allocation strategies based on real-time field observations.

The synergy between remote sensing and AI offers unprecedented opportunities for advancing precision agriculture practices. By integrating multi-source remote sensing data with AI-driven analytics, farmers can monitor crop growth in real time, identify areas of concern, and implement timely interventions to mitigate risks and maximize yield potential. Furthermore, the scalability and accessibility of remote sensing and AI technologies make them invaluable assets for addressing global challenges such as food security, climate change resilience, and sustainable agricultural development.

This paper aims to provide a comprehensive review of the recent developments, challenges, and future prospects of remote sensing and AI for crop monitoring and yield estimation. Through a synthesis of literature, case studies, and practical insights, we highlight the transformative impact of these technologies on modern agriculture and outline key research.

IMPORTANCE OF REMOTE SENSING AND AI FOR CROP MONITORING AND YIELD ESTIMATION IN AGRICULTURE

The integration of remote sensing and artificial intelligence (AI) techniques holds immense significance in modern agriculture, offering unprecedented opportunities for enhancing crop productivity, resource efficiency, and sustainability. By harnessing the power of remote sensing technologies and AI-driven analytics, farmers, researchers, and policymakers can gain valuable insights into crop health, growth dynamics, and environmental conditions, enabling informed decision-making and targeted interventions throughout the agricultural value.

- ✦ **Precision Agriculture:** Remote sensing and AI enable precision agriculture practices, allowing farmers to monitor and manage their crops at a high spatial and temporal resolution. By analysing multispectral imagery captured by satellites or drones, farmers can identify variability within their fields, optimize inputs such as water, fertilizers, and pesticides, and maximize yield potential while minimizing environmental impact.
- ✦ **Early Detection of Crop Stress:** One of the key benefits of remote sensing and AI is the ability to detect crop stress factors such as nutrient deficiencies, water stress, diseases, and pest infestations at an early stage. By analysing subtle changes in vegetation indices or thermal signatures, AI algorithms can alert farmers to potential threats, enabling timely interventions to mitigate losses and protect crop health.
- ✦ **Yield Estimation and Forecasting:** Accurate estimation of crop yield is essential for planning agricultural operations, optimizing resource allocation, and ensuring food security. Remote sensing data, combined with AI-driven predictive models, can provide real-time insights into crop growth dynamics and yield potential, enabling farmers to make informed decisions regarding harvest timing, storage, and marketing strategies.
- ✦ **Optimization of Resource Use:** Remote sensing and AI enable efficient resource management by optimizing the use of water, fertilizers, and other inputs based on crop requirements and environmental conditions. By monitoring soil moisture levels, nutrient availability, and crop health indicators, farmers can adopt precision irrigation and fertilization strategies, minimizing waste and maximizing resource use efficiency.
- ✦ **Climate Change Resilience:** In the face of climate change and increasing weather variability, remote sensing and AI offer valuable tools for building resilience in agricultural systems. By monitoring climate-related parameters such as temperature, precipitation, and drought indices, farmers can anticipate and adapt to changing environmental conditions, reducing vulnerability to crop losses and production disruptions.
- ✦ **Data-Driven Decision Making:** The integration of remote sensing and AI facilitates data-driven decision-making in agriculture, empowering stakeholders with actionable intelligence for optimizing productivity, profitability, and sustainability. By leveraging advanced analytics and predictive modelling, farmers can identify trends, patterns, and correlations in their data, guiding strategic investments and management practices for long-term success.

In conclusion, remote sensing and AI play a pivotal role in modernizing agriculture, enabling stakeholders to overcome challenges, capitalize on opportunities, and achieve sustainable and resilient food production systems. By harnessing the synergies between these technologies, we can unlock the full potential of agriculture to feed a growing population while safeguarding our natural resources and ecosystems. directions for advancing the field towards sustainable and resilient food production systems.

REMOTE SENSING TECHNOLOGIES IN AGRICULTURE:

Remote sensing technologies have revolutionized agricultural practices by providing valuable spatial and temporal information about crops, soil, and environmental conditions. These technologies enable farmers, researchers, and policymakers to monitor and manage agricultural landscapes with unprecedented precision and efficiency. Several remote sensing platforms and sensors are commonly used in agriculture, each offering unique capabilities and advantages:

- ✦ **Satellite Imagery:** Satellites provide a broad-scale view of agricultural landscapes, capturing images at regular intervals with varying spatial resolutions. Satellite imagery is particularly useful for monitoring large-scale crop patterns, land use changes, and environmental conditions over extensive areas. High-resolution satellite sensors can detect subtle variations in crop health, soil moisture, and vegetation dynamics, facilitating crop monitoring, yield estimation, and resource management.
- ✦ **Unmanned Aerial Vehicles (UAVs) or Drones:** UAVs equipped with remote sensing payloads offer flexible and cost-effective solutions for capturing high-resolution imagery at a local scale. Drones can be deployed to collect real-time data on crop health, pest infestations, and field variability, enabling farmers to make timely decisions regarding irrigation, fertilization, and pest control. The versatility of drones makes them ideal for precision agriculture applications, such as site-specific management and precision spraying.
- ✦ **Aerial Surveys:** Manned aircraft equipped with remote sensing instruments can conduct aerial surveys to gather detailed information about agricultural fields and landscapes. Aerial surveys provide high-resolution imagery and multispectral data, allowing for accurate mapping of crop health, soil properties, and topographic features. These data can be used for precision agriculture practices, such as variable rate application of inputs and soil mapping for precision planting.
- ✦ **Hyperspectral Imaging:** Hyperspectral sensors capture images across hundreds of narrow spectral bands, providing detailed spectral signatures for different objects and materials. Hyperspectral imaging is particularly useful for characterizing crop health, identifying stress factors, and detecting disease outbreaks based on unique spectral signatures. By analysing hyperspectral data, researchers can diagnose crop diseases, assess nutrient deficiencies, and monitor plant phenology with high accuracy and precision.
- ✦ **Thermal Imaging:** Thermal sensors measure infrared radiation emitted by objects and surfaces, providing insights into temperature variations across agricultural landscapes. Thermal imaging is valuable for detecting water stress, assessing crop water status, and monitoring crop growth stages based on thermal signatures. By analysing thermal data, farmers can optimize irrigation scheduling, detect drainage issues, and manage crop stress more effectively, particularly in arid and semi-arid regions.
- ✦ **Lidar (Light Detection and Ranging):** Lidar technology uses laser pulses to measure the distance between the sensor and objects on the ground, generating detailed 3D maps of terrain and vegetation structure. Lidar data can be used to assess canopy height, biomass distribution, and crop architecture, providing valuable insights into crop growth and development. Lidar is particularly useful for assessing crop lodging, estimating biomass yield, and optimizing harvesting operations in precision agriculture.

In summary, remote sensing technologies offer a diverse array of tools and techniques for monitoring agricultural landscapes, assessing crop health, and optimizing resource management

practices. By leveraging satellite imagery, drones, hyperspectral imaging, thermal sensors, and Lidar technology, stakeholders in agriculture can make informed decisions to enhance productivity, sustainability, and resilience in agricultural systems.

ARTIFICIAL INTELLIGENCE IN AGRICULTURE:

Artificial intelligence (AI) has emerged as a transformative technology in agriculture, offering innovative solutions to address key challenges and opportunities in modern food production systems. By leveraging advanced algorithms, machine learning techniques, and data analytics, AI enables stakeholders in agriculture to make data-driven decisions, optimize resource use, and improve productivity, sustainability, and resilience. Several applications of AI in agriculture have demonstrated significant potential for transforming traditional farming practices and unlocking new opportunities for innovation:

- † **Crop Monitoring and Management:** AI-powered systems can analyse remote sensing data, satellite imagery, and drone footage to monitor crop health, detect pest infestations, and assess environmental conditions in real time. By integrating AI algorithms with sensor networks and Internet of Things (IoT) devices, farmers can receive actionable insights and alerts regarding crop stress factors, irrigation needs, and nutrient deficiencies, enabling timely interventions and adaptive management strategies.
- † **Precision Farming:** AI enables precision agriculture practices by optimizing input use, minimizing waste, and maximizing yield potential at a fine spatial and temporal resolution. Machine learning algorithms can analyse historical data, weather forecasts, and soil properties to generate site-specific recommendations for seeding rates, fertilizer applications, and irrigation scheduling, tailored to the unique requirements of individual fields and crops.
- † **Crop Disease Detection and Diagnosis:** AI algorithms can analyse digital images of crops and plant leaves to detect signs of disease, identify pathogens, and diagnose plant health issues with high accuracy and efficiency. By training deep learning models on large datasets of annotated images, researchers can develop automated disease recognition systems capable of detecting early symptoms, predicting disease outbreaks, and recommending appropriate control measures to farmers.
- † **Weed Detection and Management:** AI-based systems can distinguish between crops and weeds in agricultural fields using computer vision techniques and image analysis algorithms. By deploying autonomous robots or smart drones equipped with AI-powered cameras and actuators, farmers can selectively apply herbicides or mechanical interventions to target weeds while minimizing damage to crops, reducing the need for manual labour and chemical inputs.
- † **Yield Prediction and Forecasting:** AI enables predictive modelling of crop yields based on historical data, weather patterns, and agronomic factors. By training machine learning algorithms on large datasets of yield data and environmental variables, researchers can develop accurate yield prediction models capable of forecasting future production outcomes, informing market decisions, and supporting policy planning and risk management efforts.
- † **Supply Chain Optimization:** AI technologies facilitate supply chain optimization by optimizing logistics, storage, and distribution processes in agriculture. By analysing real-time data on market demand, transportation routes, and inventory levels, AI-driven systems can identify opportunities for cost savings, reduce food waste, and improve traceability and transparency throughout the supply chain, enhancing market efficiency and resilience.

In summary, artificial intelligence is revolutionizing agriculture by providing innovative solutions for crop monitoring, management, and decision-making. By harnessing the power of AI, stakeholders in agriculture can overcome traditional constraints, capitalize on emerging opportunities, and build more sustainable and resilient food production systems to meet the challenges of a rapidly changing world.

DATA ACQUISITION AND PREPROCESSING IN REMOTE SENSING:

Data acquisition and preprocessing are crucial steps in remote sensing to ensure the accuracy and reliability of the collected data for further analysis. This section discusses various methods for acquiring remote sensing data and the preprocessing steps involved, including image correction, enhancement, and spatial resolution adjustment.

Data Acquisition Methods:

- A. **Satellite Imagery:** Satellite-based remote sensing platforms capture images of the Earth's surface using sensors onboard satellites orbiting the planet. These sensors can capture imagery in various spectral bands, such as visible, near-infrared, and thermal, allowing for the observation of different features and phenomena on the Earth's surface.
- B. **Unmanned Aerial Vehicles (UAVs) or Drones:** UAVs equipped with remote sensing payloads can capture high-resolution imagery of specific areas of interest. Drones offer flexibility and cost-effectiveness, making them ideal for capturing detailed images for precision agriculture, environmental monitoring, and infrastructure inspection.
- C. **Aerial Surveys:** Manned aircraft equipped with remote sensing instruments can conduct aerial surveys to capture high-resolution imagery over large areas. Aerial surveys provide detailed information about topography, land cover, and land use, facilitating mapping and monitoring applications in agriculture and natural resource management.

Preprocessing Steps:

- A. **Image Correction:** Image correction involves correcting geometric and radiometric distortions in remote sensing data to ensure accuracy and consistency. Geometric correction, also known as orthorectification, involves removing distortions caused by terrain variations and sensor geometry. Radiometric correction involves adjusting pixel values to account for atmospheric effects, sensor calibration errors, and illumination variations.
- B. **Image Enhancement:** Image enhancement techniques are used to improve the visual quality of remote sensing imagery and enhance the visibility of features of interest. Common image enhancement techniques include contrast stretching, histogram equalization, and sharpening filters. These techniques can enhance the interpretability of remote sensing data and highlight specific features or patterns.
- C. **Spatial Resolution Adjustment:** Spatial resolution adjustment involves resampling remote sensing data to match the spatial resolution of other datasets or to achieve a desired resolution for analysis. This may involve upsampling or downsampling the original data to increase or decrease the pixel size, respectively. Spatial resolution adjustment is often necessary when integrating multiple datasets or conducting spatial analysis at a consistent resolution.
- D. **Data Fusion:** Data fusion techniques involve combining information from multiple remote sensing sources or platforms to create integrated datasets with enhanced spatial, spectral, or temporal properties. Fusion techniques include image fusion, where images from different sensors are combined to create a composite image with improved resolution or information content, and data fusion, where data from different sensors are integrated to provide complementary information for analysis.

In summary, data acquisition and preprocessing are essential steps in remote sensing to ensure the accuracy, reliability, and usability of collected data for further analysis and interpretation. By employing appropriate acquisition methods and preprocessing techniques, researchers and practitioners can obtain high-quality remote sensing data for a wide range of applications in agriculture, environmental science, urban planning, and disaster management.

CROP MONITORING TECHNIQUES:

Crop monitoring using remote sensing data involves various techniques and algorithms to assess crop health, growth, and environmental conditions. Here are some common techniques:

- † **Vegetation Indices:** Vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), are widely used to quantify vegetation greenness and vigour based on the spectral reflectance of plants. These indices are sensitive to chlorophyll

content, leaf area, and canopy structure, making them effective indicators of crop health and growth.

- † **Change Detection:** Change detection techniques compare multi-temporal remote sensing images to identify changes in land cover, land use, and crop conditions over time. By analysing differences in spectral signatures between images acquired at different time periods, change detection algorithms can detect changes caused by factors such as crop growth, harvest, land management practices, and environmental disturbances.
- † **Anomaly Detection:** Anomaly detection methods identify unusual or abnormal patterns in remote sensing data that deviate from expected or typical conditions. Anomalies may indicate crop stress factors, such as pest infestations, disease outbreaks, nutrient deficiencies, or water stress. Anomaly detection algorithms use statistical analysis, machine learning, or threshold-based approaches to detect deviations from normal conditions and alert farmers to potential issues requiring attention.
- † **Texture Analysis:** Texture analysis techniques quantify spatial patterns and arrangements of pixels in remote sensing images to characterize crop structure, heterogeneity, and spatial variability. Texture features, such as entropy, contrast, and homogeneity, provide information about crop canopy structure, soil surface roughness, and land cover composition, which can be useful for monitoring crop health and growth dynamics.
- † **Object-Based Image Analysis (OBIA):** OBIA is a segmentation-based approach that partitions remote sensing images into homogeneous objects or regions based on spectral, spatial, and contextual characteristics. By analysing image objects rather than individual pixels, OBIA methods can capture complex spatial patterns and relationships within agricultural landscapes, facilitating accurate crop mapping, classification, and monitoring.

YIELD ESTIMATION MODELS:

Yield estimation models predict crop yields based on remote sensing data, environmental variables, and agronomic factors. Here's how they are developed and applied:

- † **Feature Extraction:** Remote sensing data are used to extract relevant features and variables related to crop growth, health, and environmental conditions. These features may include spectral indices (e.g., NDVI, EVI), vegetation parameters (e.g., leaf area index, chlorophyll content), weather variables (e.g., temperature, precipitation), soil properties, and management practices.
- † **Model Development:** Machine learning algorithms, such as regression analysis, support vector machines, random forests, and neural networks, are trained on historical yield data and remote sensing features to develop predictive models. These models learn complex relationships between input variables and crop yields, enabling them to make accurate predictions under varying environmental and management conditions.
- † **Model Validation:** Yield estimation models are validated using independent datasets and statistical metrics to assess their performance and reliability. Validation measures, such as root mean square error (RMSE), coefficient of determination (R^2), and bias, evaluate the accuracy, precision, and robustness of the models in predicting observed yield values.
- † **Application:** Once validated, yield estimation models can be applied to forecast crop yields for future growing seasons, assess yield variability across spatial and temporal scales, and identify factors influencing yield outcomes. These models provide valuable insights for decision-making in agriculture, including crop planning, risk management, resource allocation, and market forecasting.

By combining advanced remote sensing techniques with machine learning algorithms, researchers and practitioners can develop accurate and reliable models for monitoring crop growth and predicting yield outcomes. These models empower farmers to make informed decisions, optimize management practices, and maximize productivity in agricultural systems.

CHALLENGES AND LIMITATIONS:

While remote sensing and AI integration offers promising solutions for agriculture, several challenges and limitations need to be addressed:

- † **Data Availability:** Limited access to high-quality remote sensing data, especially in developing regions, hinders the widespread adoption of remote sensing technologies in agriculture. Improving

data accessibility and sharing mechanisms is crucial for enabling equitable and inclusive use of remote sensing data for agricultural applications.

- † **Computational Complexity:** Processing and analysing large volumes of remote sensing data require significant computational resources and expertise. Addressing the computational complexity of AI algorithms and remote sensing workflows is essential for scaling up applications and making them accessible to end-users with limited computational resources.
- † **Model Validation:** Validating AI models for crop monitoring and yield estimation requires ground truth data, which can be challenging to obtain at scale. Ensuring the accuracy and reliability of AI models through rigorous validation procedures is critical for building trust and confidence in their predictions among stakeholders in agriculture.
- † **Interdisciplinary Collaboration:** Integrating remote sensing and AI techniques requires collaboration among diverse stakeholders, including remote sensing scientists, agronomists, computer scientists, and farmers. Bridging disciplinary silos and fostering interdisciplinary research partnerships is essential for developing holistic solutions that address the complex challenges facing agriculture.

FUTURE DIRECTIONS AND RESEARCH OPPORTUNITIES:

Several research directions and opportunities can further advance the field of remote sensing and AI in crop monitoring and yield estimation:

- † **Enhanced Data Fusion:** Integrating multi-source remote sensing data, including satellite imagery, drone data, and ground-based sensors, can improve the accuracy and robustness of crop monitoring and yield estimation models. Exploring advanced data fusion techniques, such as ensemble learning and data assimilation, can enhance the integration of heterogeneous data sources for more comprehensive analyses.
- † **Advanced Machine Learning Techniques:** Investigating novel machine learning algorithms, such as deep learning, reinforcement learning, and generative adversarial networks, can unlock new capabilities for analysing remote sensing data and predicting crop outcomes. These advanced techniques offer opportunities for capturing complex spatiotemporal relationships and improving model performance in dynamic agricultural environments.
- † **Real-Time Monitoring Systems:** Developing real-time monitoring systems that integrate remote sensing data with IoT devices and wireless sensor networks can enable continuous surveillance of crop health and environmental conditions. Designing scalable and interoperable platforms for collecting, processing, and disseminating realtime data can empower farmers with actionable insights for timely decision-making and adaptive management.
- † **Innovative Applications:** Exploring innovative applications of remote sensing and AI in agriculture, such as phenotyping, genotype-phenotype associations, and crop breeding, can unlock new opportunities for crop improvement and genetic resource management. Leveraging advanced imaging techniques, such as hyperspectral imaging and thermal imaging, can provide unique insights into crop physiology and stress responses for breeding resilient and high-yielding crop varieties.

CONCLUSION:

In conclusion, the integration of remote sensing and artificial intelligence (AI) represents a transformative paradigm shift in agriculture, offering unprecedented opportunities to address the complex challenges facing food production systems worldwide. While challenges such as data availability, computational complexity, and model validation persist, ongoing advancements in technology and research hold promise for overcoming these obstacles and unlocking the full potential of remote sensing and AI in agriculture. As we look to the future, there is a pressing need for interdisciplinary collaboration and innovation to drive progress in the field of crop monitoring and yield estimation. By fostering partnerships among remote sensing scientists, agronomists, computer scientists, policymakers, and farmers, we can harness collective expertise and insights to develop

holistic solutions that are tailored to the diverse needs and contexts of agricultural systems around the globe.

Emerging research directions, such as enhanced data fusion, advanced machine learning techniques, real-time monitoring systems, and innovative applications, offer exciting opportunities for pushing the boundaries of what is possible in agricultural technology. By exploring these avenues of inquiry and embracing a culture of experimentation and adaptation, we can accelerate the pace of innovation and deliver tangible benefits to farmers, communities, and ecosystems alike. Ultimately, the future of agriculture lies in our ability to leverage cutting-edge technologies, such as remote sensing and AI, to build more resilient, sustainable, and equitable food systems. By embracing innovation, collaboration, and inclusivity, we can pave the way for a brighter future where agriculture thrives, and every individual has access to nutritious food, livelihood opportunities, and a healthy environment.

In summary, while the journey towards harnessing the full potential of remote sensing and AI in agriculture may be challenging, the rewards are immense. Through collective action and shared commitment, we can chart a course towards a more prosperous and sustainable future for agriculture, one where technology serves as a catalyst for positive change and prosperity for all.

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