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Application of Remote Sensing in Crop Monitoring

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Abstract

Remote sensing has become an important technology for monitoring agricultural crops and forecasting crop productivity over field, regional and national scales. Conventional crop monitoring depends heavily on field surveys, which are often time-consuming, labour-intensive and difficult to implement over large geographical areas. Remote sensing provides repeated, spatially explicit observations of crop condition through satellite, unmanned aerial vehicle (UAV) and airborne sensors. Multispectral, hyperspectral, thermal and synthetic aperture radar (SAR) observations can provide information on crop area, phenology, biomass, vegetation vigour, water status, nutrient stress, disease symptoms and other biophysical characteristics. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI) and red-edge indices have been widely used for crop monitoring. Recent developments in Sentinel-1, Sentinel-2, Landsat and other Earth-observation missions, together with machine learning and deep learning, have expanded the potential for near-real-time crop monitoring and yield forecasting. Recent reviews indicate a methodological shift from simple statistical relationships toward machine learning, deep learning, data assimilation and multi-sensor data-fusion approaches. However, remote-sensing-based forecasting remains affected by cloud cover, mixed pixels, limited ground observations, model transferability, crop diversity and uncertainty in yield measurements. This review discusses the principles, sensors, applications, forecasting methods, advantages, limitations and future prospects of remote sensing for agricultural crop monitoring and forecasting. Integration of remotely sensed observations with weather, soil, management and crop-growth information is likely to be particularly important for developing reliable operational agricultural decision-support systems.

Keyword: Remote Sensing; Crop Monitoring; Crop Forecasting; Yield Prediction; Satellite Imagery; NDVI; Sentinel-2; Machine Learning; Precision Agriculture; Agricultural Intelligence

Introduction

Agriculture is strongly influenced by weather, soil properties, water availability, crop management and biological stresses. Timely information about crop condition and expected production is therefore essential for farm management, food-security planning, agricultural markets and resource allocation.

Traditional crop monitoring generally involves field visits, crop-cutting experiments, farmer surveys and statistical agricultural records. Although these approaches remain important, they may be expensive and difficult to conduct frequently over large areas. Remote sensing provides an alternative source of spatially continuous information by measuring electromagnetic radiation reflected or emitted from the Earth's surface.

The increasing availability of freely accessible satellite imagery has substantially expanded the use of remote

sensing in agriculture. Sentinel-2, Landsat and MODIS are among the major data sources used for crop monitoring and yield estimation. Recent research indicates that Sentinel-2 has become particularly important because of its relatively high spatial resolution, frequent observations and red-edge spectral bands. Sentinel-1 radar data provide complementary information and can be acquired despite cloud cover.

Remote sensing can support crop monitoring from the early stages of crop establishment through maturity and harvest. It can also provide information for estimating crop area, identifying crop types, monitoring crop development and forecasting yield before harvest.

The rapid development of machine learning and deep learning has further expanded these applications. Current approaches increasingly combine satellite imagery with weather, soil and other ancillary information rather than relying on a single vegetation index.

Objectives

The major objectives of this review are:

1. To describe the principles of remote sensing for agricultural monitoring.
2. To examine satellite, UAV and other sensors used for crop assessment.
3. To discuss applications of remote sensing in crop monitoring.
4. To examine methods for crop yield forecasting.
5. To evaluate the role of machine learning and artificial intelligence.
6. To identify major advantages and limitations of remote-sensing-based agricultural forecasting.
7. To discuss future research directions and operational applications.

3. Principles of Remote Sensing in Agriculture

Remote sensing involves obtaining information about objects or surfaces without direct physical contact. In agricultural applications, sensors measure electromagnetic radiation reflected or emitted by crops and soil.

Plants interact with radiation differently across wavelengths. Healthy green vegetation generally absorbs substantial amounts of visible red radiation because of chlorophyll while reflecting strongly in the near-infrared region. Changes in plant structure, chlorophyll concentration, water content and stress can alter these spectral responses.

This relationship allows remote sensing to estimate or monitor characteristics such as:

- Vegetation vigour;
- Canopy cover;
- Biomass;
- Leaf area;
- Crop phenology;
- Chlorophyll status;
- Water stress;
- Crop damage; and
- Crop productivity.

The interpretation of remote-sensing observations is generally strengthened when imagery is combined with field measurements and environmental information.

Major Remote-Sensing Platforms

Satellite Remote Sensing

Satellites provide repeated observations over large areas and are particularly suitable for regional and national crop monitoring.

Important satellite data sources include:

Landsat

The Landsat programme provides a long historical record of multispectral observations. Its long-term archive is valuable for examining agricultural land-use change and historical crop dynamics.

Sentinel-2

Sentinel-2 provides multispectral observations at spatial resolutions of approximately 10–60 m depending on the spectral band and has red-edge bands particularly useful for vegetation studies. Its temporal frequency and spatial resolution have made it an important source for field-scale crop monitoring.

Sentinel-1

Sentinel-1 uses synthetic aperture radar. Unlike optical sensors, radar observations can be collected through clouds and during both day and night. Radar backscatter can provide information related to crop structure, surface conditions and moisture.

MODIS

MODIS provides frequent observations at comparatively coarser spatial resolution. Its long temporal record makes it useful for regional and continental vegetation monitoring.

UAV-Based Remote Sensing

Unmanned aerial vehicles have become increasingly useful for field-level agricultural monitoring.

UAV platforms can carry:

- RGB cameras;
- multispectral cameras;
- hyperspectral sensors;
- thermal cameras; and
- LiDAR systems.

Compared with satellites, UAVs can provide very high spatial resolution and flexible acquisition timing. They are particularly useful for experimental plots, orchards and precision agriculture.

Potential applications include:

- Plant counting;
- Crop stand assessment;
- Disease detection;
- Weed mapping;
- Nutrient-stress assessment;
- Canopy-temperature monitoring;
- Biomass estimation; and
- Site-specific management.

However, UAV surveys generally cover smaller areas and require flight planning, image processing and compliance with applicable aviation regulations.

Important Spectral Indices for Crop Monitoring

Vegetation indices transform spectral measurements into numerical indicators related to vegetation characteristics.

Normalized Difference Vegetation Index

The NDVI is one of the most widely used vegetation indices:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

where **NIR** represents near-infrared reflectance and **Red** represents red reflectance.

NDVI can be used to monitor vegetation development, crop vigour and seasonal dynamics.

However, NDVI may become less sensitive when vegetation is very dense. Consequently, alternative indices may be more appropriate under some conditions.

Enhanced Vegetation Index

The Enhanced Vegetation Index (EVI) was developed to improve vegetation monitoring under conditions involving atmospheric effects and dense vegetation.

It can provide useful information about canopy characteristics and is frequently used in crop monitoring and yield modelling.

Red-Edge Indices

Red-edge wavelengths are sensitive to changes in chlorophyll and canopy characteristics.

Sentinel-2's red-edge bands have therefore become valuable for crop monitoring and yield estimation. Recent research identifies red-edge information as an important advantage of Sentinel-2 for agricultural applications.

Water-Related Indices

Spectral indices using near-infrared and shortwave-infrared wavelengths can provide information related to vegetation water content.

These indices can assist in identifying drought stress and assessing crop water status.

Crop Identification and Acreage Estimation

One of the fundamental applications of remote sensing is determining where crops are grown and estimating their spatial extent.

Different crops can exhibit distinct spectral and temporal signatures. Time-series satellite imagery can therefore be used to classify agricultural land into crop categories.

Crop-area information is important for:

- Agricultural statistics;
- Food-security planning;
- Irrigation management;
- Crop insurance;
- Disaster assessment;
- Market analysis; and
- Government agricultural programmes.

Machine-learning classification methods can improve crop-type identification when adequate training data are available.

Monitoring Crop Phenology

Crop phenology describes the timing of important developmental stages, such as:

1. Emergence;
2. Vegetative growth;
3. Flowering;
4. Grain or fruit development;
5. Maturity; and
6. Senescence.

Time-series remote sensing can detect changes in vegetation indices associated with these stages.

Phenological information is valuable because crop development is strongly related to final productivity and the timing of environmental stresses.

Satellite time series can therefore provide information considerably earlier than harvest-based measurements.

Monitoring Crop Health

Remote sensing can identify changes in crop spectral characteristics associated with stress.

Potential stress factors include:

- Drought;
- Waterlogging;
- Nutrient deficiency;
- Pest infestation;

- Disease;
- Heat stress;
- Salinity; and
- Physical damage.

Healthy and stressed vegetation may differ in chlorophyll content, canopy structure, water content and thermal properties.

However, an important limitation is that similar spectral changes may result from different stress factors. Therefore, remote sensing alone may identify the presence of abnormal crop conditions without always being able to determine the exact cause.

Field observations remain important for diagnosis.

Detection of Water Stress

Water availability is a major determinant of crop productivity.

Thermal remote sensing can provide information about canopy temperature. Water-stressed plants may close their stomata and reduce transpiration, potentially increasing canopy temperature.

Combining thermal observations with multispectral information can therefore support drought monitoring and irrigation management.

Remote sensing can help identify areas with relatively greater crop water stress and support variable-rate irrigation where suitable irrigation infrastructure exists.

Nutrient Monitoring

Nitrogen is essential for crop growth and productivity.

Changes in chlorophyll concentration can influence crop reflectance, particularly in visible and red-edge wavelengths. Consequently, spectral data can be used to develop indicators associated with crop nitrogen status.

Red-edge-based measurements are particularly relevant for this application.

However, nutrient estimation is influenced by crop species, growth stage, soil background, canopy structure and environmental conditions. Field calibration is therefore important before applying a model across different regions.

Crop Disease and Pest Monitoring

Remote sensing can contribute to early detection of crop stress associated with diseases and pests.

Disease infection can alter:

- Chlorophyll;
- Leaf structure;
- Canopy temperature;
- Water status; and
- Spectral reflectance.

High-resolution UAV imagery is particularly useful for detecting spatial patterns of stress within individual fields.

Hyperspectral imaging may provide additional spectral information, although high data volumes and processing complexity can limit operational adoption.

Remote sensing should generally be regarded as a screening and monitoring tool rather than a replacement for field-based diagnosis.

Biomass Estimation

Crop biomass is closely related to plant growth and can be used as an intermediate variable in productivity assessment.

Remote-sensing approaches for biomass estimation may use:

- Vegetation indices;
- Canopy reflectance;
- Red-edge bands;
- Sar backscatter;
- Lidar measurements; and
- Machine-learning models.

Biomass estimates can support crop-growth modelling and yield prediction.

14. Crop Yield Forecasting

Crop yield forecasting involves estimating expected production before harvest.

A simplified relationship can be represented as:

Remote sensing data + weather + soil + crop information + management data → Yield model → Forecast yield

Remote-sensing variables can provide information about crop growth and development, while weather and soil data provide information about environmental conditions.

Recent reviews classify remotely sensed yield-estimation methods into empirical/statistical models, light-use-efficiency models, data-assimilation approaches and machine-learning approaches.

Statistical Approaches

Early remote-sensing-based yield models frequently used relationships between vegetation indices and observed crop yields.

For example:

$$\text{Yield} = a + b(\text{NDVI})$$

where:

- **Yield** = predicted crop yield;
- **a** = intercept;
- **b** = regression coefficient; and
- **NDVI** = vegetation index.

More sophisticated models may incorporate multiple observations from different growth stages.

Advantages

- Relatively simple;
- Easy to interpret;
- Low computational requirements.

Limitations

- Relationships may vary between years;
- Crop growth stages must be considered;
- Environmental variables may be omitted;
- Models may have poor transferability to other regions.

Crop Growth Models and Data Assimilation

Process-based crop models simulate physiological processes such as:

- Photosynthesis;
- Biomass accumulation;
- Phenological development;
- Water use;
- Nutrient uptake; and
- Yield formation.

Remote sensing can provide observations of variables such as leaf area index or canopy condition to update model states.

This process is known as data assimilation.

Combining process-based crop models with satellite observations can potentially provide a more mechanistic representation of crop development than purely empirical models. Recent reviews identify data assimilation as one of the major approaches in contemporary remote-sensing-based yield estimation.

Machine Learning in Crop Forecasting

Machine learning can identify complex relationships between remote-sensing observations and crop yield.

Frequently used algorithms include:

- Random Forest;
- Support Vector Machine;
- Gradient Boosting;
- Artificial Neural Networks;
- XGBoost;
- Convolutional Neural Networks; and
- Long Short-Term Memory networks.

A systematic review of crop-yield prediction research found increasing use of machine learning and deep learning, with variables such as temperature, rainfall, soil and vegetation information frequently used as predictors.

Random Forest models are particularly useful when relationships are nonlinear and predictor variables are numerous.

Deep Learning and Time-Series Forecasting

Deep-learning approaches can process large volumes of spatial and temporal information.

Convolutional Neural Networks

CNNs are particularly suitable for image-based analysis because they can identify spatial patterns.

Potential applications include:

- Crop classification;
- Disease detection;
- Biomass estimation; and
- Yield prediction.

Long Short-Term Memory Networks

LSTM networks are designed to capture temporal dependencies and can therefore be useful for analysing satellite time series.

Recent systematic reviews identify CNN and LSTM approaches among the important deep-learning methods used for crop-yield prediction.

Multi-Sensor Data Fusion

No single sensor provides all information needed for reliable crop monitoring.

Multispectral optical sensors provide valuable information about vegetation reflectance, while SAR provides complementary structural and moisture-related information. Combining Sentinel-1 and Sentinel-2 can improve temporal coverage because radar observations are less affected by cloud cover.

Current research increasingly emphasizes multi-sensor data fusion as a means of improving crop-yield estimation and operational monitoring.

Other useful data sources include:

- Weather stations;
- Numerical weather products;

- Soil maps;
- Irrigation records;
- Crop calendars;
- Field surveys;
- Yield-monitoring data; and
- Farm-management information.

Applications in Precision Agriculture

Remote sensing supports precision agriculture by identifying spatial variability within agricultural fields.

Potential applications include:

Variable-rate fertilizer

Satellite or UAV observations can identify areas with differences in crop vigour and potentially support variable fertilizer application.

Variable-rate irrigation

Thermal and multispectral observations can identify areas experiencing greater water stress.

Pest and disease management

High-resolution imagery can identify abnormal crop patches requiring field inspection.

Field zoning

Fields can be divided into management zones according to soil, vegetation and productivity variability.

Yield mapping

Remote-sensing information can complement harvest data to identify spatial differences in productivity.

Applications in Agricultural Early-Warning Systems

Remote sensing can support early-warning systems by providing repeated information about crop condition before harvest.

This can be particularly valuable for:

- Drought monitoring;
- Food-security assessments;
- Crop-failure detection;
- Agricultural disaster assessment;
- Regional yield forecasting; and
- Humanitarian planning.

Recent work has demonstrated the use of satellite-derived vegetation and biophysical variables for crop-yield forecasting in climate-vulnerable regions.

Early estimates can help institutions identify potential production shortfalls before official harvest statistics become available.

Advantages of Remote Sensing in Crop Monitoring

Major advantages include:

Large-area coverage

Satellites can monitor agricultural landscapes extending from individual fields to entire countries.

Repeated observations

Regular satellite revisits permit crop development to be monitored throughout the season.

Spatial information

Remote sensing provides information about the geographic distribution of crop conditions.

Reduced field-survey burden

Remote sensing can reduce the amount of field sampling required for some monitoring activities, although ground observations remain necessary.

Historical data

Long satellite archives permit analysis of historical crop and land-use trends.

Near-real-time monitoring

Frequent satellite observations can support timely detection of changing crop conditions.

Limitations and Challenges

Despite major advances, several challenges remain.

Cloud Cover

Optical satellite observations can be obscured by clouds, particularly during rainy seasons. SAR can help overcome this limitation.

Mixed Pixels

At moderate spatial resolution, individual pixels may contain crops, soil, roads or other land-cover components. This can reduce classification accuracy.

Ground-Truth Requirements

Reliable forecasting models require high-quality field observations for calibration and validation. Recent research continues to identify limited ground-truth data as an important constraint on Sentinel-2 yield-estimation systems.

Model Transferability

A model developed in one region may not perform equally well elsewhere because of differences in:

- Climate;
- Varieties;
- Soil;
- Management;
- Crop calendars;
- Irrigation; and
- Agricultural practices.

Computational Requirements

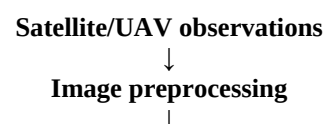
Large satellite archives and deep-learning approaches can require substantial computational resources.

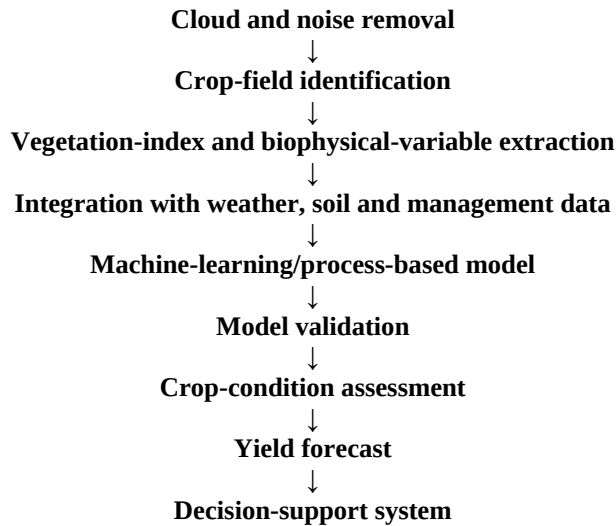
Yield Data Quality

Observed yield data may contain measurement errors, inconsistent sampling and differences in reporting methods. These errors can affect model development and validation.

Proposed Framework for Operational Crop Forecasting

A practical operational system can follow the following workflow:





This framework can be implemented at field, district, state or national scales depending on data availability and modelling requirements.

Future Prospects

The future of agricultural remote sensing is likely to involve increasing integration of multiple data sources and modelling techniques.

Artificial Intelligence

AI models can process large and complex datasets and identify nonlinear relationships between crop observations and productivity.

Foundation and Self-Supervised Models

Emerging research is exploring pre-trained models capable of learning general representations from large Earth-observation datasets before being adapted to specific agricultural tasks.

Multi-Source Data Integration

Combining optical, radar, thermal, weather, soil and management data can provide a more complete representation of crop growth.

Digital Agriculture

Remote sensing can become an important component of digital farm-management platforms, providing farmers and agricultural institutions with spatial information for decision-making.

High-Resolution Monitoring

Increasing availability of high-resolution satellite and UAV imagery will make monitoring at individual-field and potentially sub-field scales increasingly practical. Recent reviews emphasize multi-sensor fusion, knowledge-guided modelling, improved ground observations and computationally efficient workflows as important directions for future operational yield-estimation systems.

Implications for Developing Countries

Remote sensing can be particularly valuable in developing countries where agricultural statistics and field monitoring may be spatially incomplete. Open satellite datasets such as Sentinel and Landsat provide opportunities for developing relatively low-cost agricultural monitoring systems.

However, technical infrastructure, internet connectivity, computational resources, field validation and local expertise remain important constraints.

For successful adoption, remote-sensing systems should therefore be designed around local agricultural calendars, crop varieties, farming practices and institutional requirements rather than simply transferring models developed in other regions.

Conclusion

Remote sensing has transformed the capacity to monitor agricultural crops over large geographical areas. Satellite, UAV, multispectral, hyperspectral, thermal and radar observations can provide valuable information about crop area, crop type, phenology, biomass, water status, vegetation health and environmental stress.

The development of Sentinel-1, Sentinel-2, Landsat and other Earth-observation platforms has significantly increased the availability of agricultural observations. At the same time, machine learning, deep learning, crop-growth modelling and data assimilation have expanded the possibilities for crop-yield forecasting. Recent literature shows a clear movement toward multi-sensor and multi-source approaches rather than dependence on individual vegetation indices.

Nevertheless, remote sensing is not a substitute for field observations. Cloud contamination, mixed pixels, limited ground-truth data, uncertain yield measurements and poor model transferability can reduce forecasting reliability. The most robust systems are therefore likely to integrate remote sensing with weather, soil, crop-management and field information.

Overall, remote sensing represents an important component of modern agricultural intelligence. Its integration with artificial intelligence, crop-growth models and multi-source environmental information has considerable potential to improve crop monitoring, early warning, precision agriculture and pre-harvest yield forecasting. Future progress will depend not only on increasingly sophisticated algorithms but also on high-quality ground observations, transparent validation, locally adapted models and systems that can be practically deployed by farmers and agricultural institutions.

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