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Spectral Remote Sensing and AI-Powered Decision Systems in Modern Crop Management

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Satellites, drones and proximal sensors now measure crop condition at a scale and frequency no scouting programme can match, and machine learning turns those measurements into predictions. This article explains how spectral signals relate to crop physiology, reviews the evidence for AI-based disease detection and yield prediction, and sets out how sensing, models and agronomic action fit together in a decision system. It also highlights where the evidence is weak: models that score above 99% in the laboratory can fall below 32% on field images. Reliable decision systems therefore depend as much on data quality and validation as on algorithms.

Introduction

Crop management has always depended on information: when to irrigate, where disease is starting, what yield to plan for. Weiss et al. (2020) describe remote sensing as a way to provide repetitive information on crop status throughout the season, at different scales and for different users. They identify applications in crop breeding, land-use monitoring, yield forecasting and ecosystem services. The new element is not the sensor alone but the pairing of sensors with learning algorithms that extract decisions from large image archives. This article follows that chain, from the physics of the signal to the field operation it informs, and keeps a critical eye on the evidence at each step.

What Spectral Sensing Measures

Healthy leaves absorb strongly in the red part of the spectrum, where chlorophyll captures light, and reflect strongly in the near-infrared (NIR), where leaf structure scatters it. Vegetation indices exploit this contrast. The most widely used, the Normalised Difference Vegetation Index (NDVI), is computed as (NIR − Red) / (NIR + Red) and was developed from early work on red and infrared band combinations for monitoring vegetation (Tucker, 1979). Stress, disease or low biomass changes the ratio, which is why index maps reveal within-field variability that is invisible from the roadside. Modern multispectral satellites go beyond red and NIR. The European Space Agency's Sentinel-2 mission carries an instrument with 13 spectral bands between 443 and 2190 nm and a 290 km swath. Two satellites together revisit a location every five days at the equator [European Space Agency (ESA)]. ESA lists leaf chlorophyll content, leaf water content and leaf area index among the biophysical variables the mission is used to map. Its red-edge and shortwave-infrared (SWIR) bands add sensitivity to chlorophyll and to vegetation moisture stress.

Table 1. Sentinel-2 spectral bands and their agronomic use

Spatial resolution	Bands	Typical agronomic use	Source
10 m	4: blue, green, red, NIR	Greenness and vigour indices such as NDVI	ESA (n.d.); Tucker (1979)
20 m	6: four red-edge/narrow NIR bands (about 704, 740, 783, 865 nm) and two SWIR bands (about 1610, 2190 nm)	Chlorophyll status; moisture stress assessment	ESA (n.d.)
60 m	3: coastal aerosol, water vapour, cirrus	Atmospheric correction	ESA (n.d.)

Spectral measurements are only proxies. Weiss *et al.* (2020) distinguish empirical approaches, which relate reflectance to measured traits statistically, from deterministic approaches based on radiative transfer models. Empirical relationships are simple but tend to be specific to a site, crop and season; physical models transfer better but require careful parameterization. Machine learning sits between the two, learning the relationship from data.

AI Models for Crop Monitoring

Disease and stress detection

Image classification is the best-documented use of deep learning in agriculture. Mohanty *et al.* (2016) trained a convolutional neural network on 54,306 leaf images covering 14 crop species and 26 diseases (or healthy leaves) and reached 99.35% accuracy on a held-out test set. The same study, however, tested the model on images collected from other sources under different conditions and found accuracy fell to 31.4%. That is far above random selection (2.6%) but far below what a farmer would trust. The authors concluded that more diverse training data are needed.

Yield prediction

Van Klompenburg *et al.* (2020) screened 567 studies on machine-learning yield prediction and analysed 50 in detail. Temperature, rainfall and soil type were the most commonly used features, and artificial neural networks were the most applied algorithm. In a further search of 30 deep-learning studies, convolutional neural networks were the most widely used, followed by long short-term memory networks and deep neural networks. Their review frames yield prediction as decision support for both what to grow and what to do during the season.

Overall performance

A survey of 40 deep-learning studies in agriculture by Kamilaris and Prenafeta-Boldú (2018) found that deep learning gave high accuracy and outperformed commonly used image-processing techniques. These are encouraging results, but they describe published studies, which tend to report successful experiments.

Table 2. Evidence base for AI in crop monitoring

Study	Task	Data	Main finding
Mohanty *et al.* (2016)	Leaf disease classification	54,306 images; 14 species; 26 diseases	99.35% on held-out test set; 31.4% on images from other sources
Van Klompenburg *et al.* (2020)	Yield prediction	50 ML studies (567 screened); 30 DL studies	ANNs most used ML model; CNNs most used DL model
Kamilaris & Prenafeta-Boldú (2018)	Agricultural tasks in general	40 DL studies	High accuracy; outperformed common image-processing methods
Bégué *et al.* (2018)	Mapping cropping practices	Literature review	Most studies exploratory, local, ground-data dependent, single sensor

From Prediction to Decision

A prediction is not yet a decision. A decision system links sensing, modelling and action in a loop, and each link has its own requirements. The sequence in Figure 1 is the author's synthesis of the literature cited, not a standard published architecture.

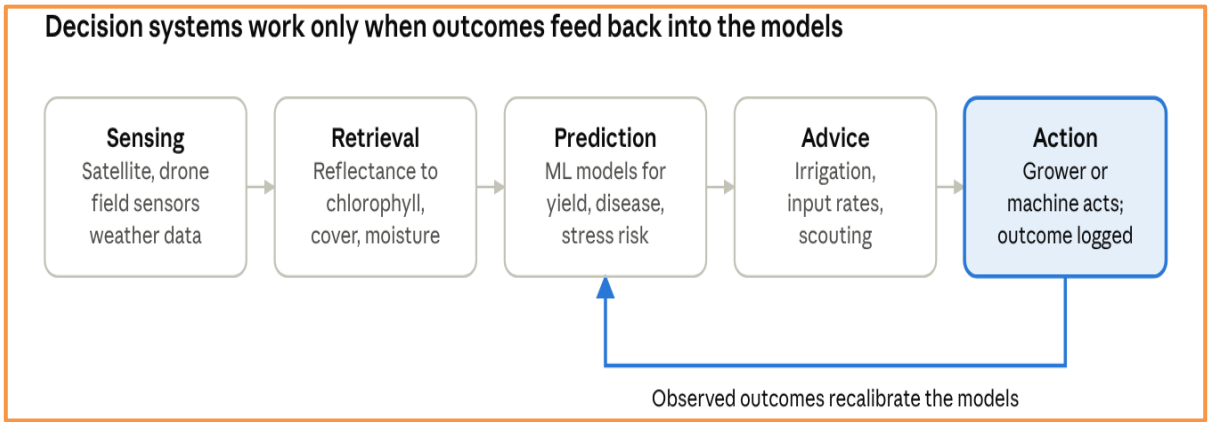


Figure 1. decision system work model

The last step is often missing. Weiss *et al*. (2020) argue that remote sensing must deliver operational, efficient and long-term services matched to different stakeholders, which implies sustained validation against ground data rather than one-off demonstrations.

Limits and Risks

The gap between 99.35% and 31.4% in Mohanty *et al*. (2016) is the clearest warning that a model is only as good as the diversity of its training data. Bégué *et al*. (2018) reached a compatible conclusion for mapping cropping practices: most methods were exploratory, tested locally, dependent on ground data and on one sensor type, and relied heavily on local knowledge of management, environment and plant material.

Data gaps. Optical sensors cannot see through cloud, so revisit frequency on paper is not the same as usable observations. Combining optical data with radar and weather information is one response, but each added source brings calibration and integration costs.

Interpretability and trust. A farmer who cannot see why a model flags a field is unlikely to change an input plan on its advice. Reporting uncertainty alongside predictions, and validating against local ground data, are prerequisites for adoption.

Equity. Smallholders may lack connectivity, devices and training. Smartphone-based diagnosis, as proposed by Mohanty *et al*. (2016), only helps where models work on the images people can actually capture.

Conclusion

Spectral remote sensing supplies frequent, field-scale information on crop condition, and machine learning converts it into predictions of disease, stress and yield. The published evidence shows high accuracy in controlled settings, but it also shows a consistent weakness: results often do not transfer across sites, sensors and seasons. Effective decision systems will therefore combine physically grounded retrieval, diverse and locally validated training data, and a feedback loop with the grower. Research priorities are broader benchmark datasets, transparent uncertainty reporting and trials that measure agronomic and economic outcomes, not only model accuracy.

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