

Integrating Smart Digital Technologies and Artificial Intelligence in Crop Protection

Prof. Dimitrios Tsitsigiannis

1. Introduction

Agricultural production is facing a combination of challenges that increasingly threaten the sustainability, resilience and profitability of crop production systems. Global demand for food continues to increase, while agricultural production is simultaneously expected to reduce its environmental footprint, use fewer chemical inputs and adapt to increasingly variable climatic conditions. At the same time, the emergence, introduction and geographical expansion of plant pests and pathogens are creating new and sometimes unpredictable risks for agricultural production. Climate change, international trade, the movement of plant material and changing cropping systems can alter the distribution, epidemiology and severity of important pests and diseases, making timely surveillance and early intervention increasingly important. Emerging plant disease pandemics have consequently become a significant concern for global food security (Ristaino et al., 2021).

Within this context, crop protection is undergoing a gradual transition from predominantly reactive approaches towards more proactive, predictive and data-driven strategies. Conventional plant disease diagnosis remains fundamental to plant pathology and will continue to play an essential role in confirming disease identity and establishing causal relationships. However, conventional approaches frequently depend on expert visual assessment, pathogen isolation, laboratory-based molecular analyses and specialized personnel. These procedures can be time-consuming and may not provide the spatial coverage or temporal resolution required for modern crop protection. In particular, latent infections and early stages of disease development may remain difficult to detect before visible symptoms become apparent. Sampling, transport and laboratory analysis can further delay decision-making, while the quality of diagnostic results can depend strongly on sampling procedures and laboratory infrastructure (Buja et al., 2021; Pereira et al., 2025).

Smart digital technologies offer an opportunity to address several of these limitations. Precision agriculture combines spatially explicit information with sensing, positioning, communication, data analytics and automated machinery to understand and manage variability within agricultural systems. In plant protection, this technological framework includes satellite and unmanned aerial vehicle (UAV) imagery, proximal and environmental sensors, Internet of Things (IoT) networks, smart insect traps, automated application platforms, geographic information systems (GIS), global navigation satellite systems (GNSS), artificial intelligence (AI), machine learning (ML), predictive modelling and decision-support systems (DSS). These technologies do not replace conventional plant pathology; rather, they provide complementary sources of information that can extend diagnosis from individual samples to plants, fields, landscapes and regions.

The central opportunity is therefore not simply to digitize existing crop protection practices, but to connect previously separate components into integrated plant health management systems. Molecular diagnostics can provide highly specific information about pathogen identity; optical, spectral and thermal sensors can provide rapid information about plant physiological responses; IoT networks can continuously monitor environmental conditions; AI can identify patterns in complex datasets; predictive models can estimate future pest and disease risks; and DSS can translate these observations into actionable recommendations. The convergence of these technologies has the potential to move crop protection from a system that mainly responds to visible symptoms towards one that anticipates risks and supports interventions before substantial damage occurs.

2. From Conventional Diagnosis to Digital Plant Health Monitoring

Traditional plant disease diagnosis is based on a combination of symptom observation, pathogen signs, microscopy, isolation, serological tests and molecular methods. Visual diagnosis remains the first and often most accessible step in field investigations. However, visual symptoms are not always specific to a particular pathogen, because similar symptoms can result from different pathogens or from abiotic stresses such as drought, nutrient deficiencies or temperature extremes. Moreover, symptom severity is often influenced by cultivar, environmental conditions, pathogen strain and stage of disease development. Consequently, accurate diagnosis frequently requires laboratory confirmation.

Molecular and immunological techniques have considerably improved diagnostic sensitivity and specificity. Polymerase chain reaction (PCR), quantitative PCR (qPCR), loop-mediated isothermal amplification (LAMP), lateral-flow immunoassays and other molecular approaches can detect pathogens at low concentrations and, in some cases, provide results directly from plant tissues. Recent developments are extending these capabilities further through recombinase polymerase amplification (RPA), CRISPR-based diagnostics, nanopore sequencing and metagenomic approaches (Marcolungo et al., 2022; Paul et al., 2025).

Nevertheless, even highly sensitive laboratory methods have limitations when they are expected to support large-scale surveillance. Sample collection, preparation, transportation, processing and high cost can introduce delays, while laboratory-based methods generally require trained personnel and appropriate infrastructure. These constraints are particularly important in rural and remote production areas where access to diagnostic laboratories may be limited. The future of digital crop protection should therefore not be understood as a choice between laboratory diagnostics and digital sensing. Instead, the two should become increasingly interconnected.

A promising approach is the development of **layered diagnostic systems**. Remote sensing can identify areas exhibiting abnormal crop responses; UAVs can subsequently provide high-resolution imagery of those areas; proximal sensors can characterize plant physiological responses; and molecular and classical diagnostics can be used to confirm the presence of the suspected pathogen. In such a system, molecular diagnostics provide biological specificity, while digital sensing provides spatial and temporal scalability. This combination can make surveillance more efficient because laboratory analyses can be directed towards strategically selected samples rather than relying exclusively on extensive random sampling.

Recent developments in portable diagnostics strengthen this possibility. LAMP, RPA and CRISPR-based assays can potentially bring molecular detection closer to the point of need, while portable sequencing platforms such as Oxford Nanopore technologies can provide rapid genomic information outside conventional laboratories (Aman et al., 2020). Metagenomic sequencing is also increasingly useful when the pathogen is unknown or when several microorganisms may be associated with disease symptoms. Abdelrazek et al. (2025), for example, demonstrated the potential of metagenomic sequencing for strain-level pathogen identification in tomato plants exhibiting wilt symptoms.

The future challenge is to connect these diagnostic outputs to digital spatial information. A confirmed molecular diagnosis becomes considerably more valuable when it can be georeferenced, associated with environmental conditions and incorporated into a temporal surveillance database. Such integration can help identify disease hotspots, follow pathogen spread and improve subsequent predictive models.

3. Smart Sensing and Remote Observation

Remote sensing is one of the most important technological foundations of precision crop protection. Satellite platforms provide repeated observations over large geographical areas, while UAVs provide much higher spatial resolution and flexibility. Ground-based and proximal sensing systems provide detailed measurements at plant, canopy or plot scale. Each platform therefore has different strengths, and their combination can create a multi-scale monitoring system (Trippa et al., 2024).

Conventional RGB cameras remain highly useful because they are relatively inexpensive and widely available, including through smartphones, fixed cameras and UAV platforms. RGB imagery can capture visible symptoms such as chlorosis, necrosis, lesions, discoloration and defoliation as well as different pests. However, visible symptoms frequently represent a relatively advanced stage of disease development. Digital plant health monitoring is therefore increasingly incorporating multispectral, hyperspectral, thermal and fluorescence sensing. The biological basis for this approach is important. Pathogen infection can alter photosynthesis, stomatal regulation, water relations, pigment composition, respiration and plant metabolism before obvious symptoms develop. These physiological changes modify the way plants interact with electromagnetic radiation. Changes in reflectance, canopy temperature and chlorophyll fluorescence can therefore provide indirect indicators of plant stress. This creates a bridge between plant physiology and digital sensing: physiological processes that are invisible to the human eye may nevertheless generate measurable signals that can be detected by sensors (Pérez-Bueno et al., 2019; Cheaib and Killiny, 2025).

Multispectral and hyperspectral imaging are particularly promising because they provide information beyond the visible spectrum. Hyperspectral systems measure reflectance across numerous narrow spectral bands and can identify subtle changes associated with biochemical and physiological alterations. For example, ground-based hyperspectral imaging has been used to distinguish grapevine plants affected by leafroll disease from healthy plants under field conditions. Hyperspectral measurements have also been investigated for the detection of *Verticillium* wilt and other disease-related stresses (Bendel et al., 2020; Zhang et al., 2023).

Thermal imaging provides a complementary perspective. Because disease can alter stomatal conductance and transpiration, infected plants may exhibit changes in canopy temperature. Thermal sensing can therefore provide information about physiological stress that may precede visible symptom development. Such measurements are particularly relevant to vascular diseases and diseases that interfere with water transport. Thermal imaging has also been investigated for *Fusarium* head blight and other disease-related stress responses (Mahlein et al., 2019).

LiDAR introduces another dimension by measuring plant structure. Disease and pest infestation can alter canopy density, height, volume and architecture. When LiDAR-derived structural information is combined with hyperspectral or multispectral information, it can improve the discrimination of disease-related changes.

Franceschini et al. (2024), for example, demonstrated the value of combining LiDAR point-cloud characteristics with hyperspectral vegetation indices for detecting blackleg in potatoes.

The most promising direction is consequently the **multi-platform sensing**. Satellites can identify broad spatial anomalies, UAVs can map affected areas in detail, and proximal sensors can provide continuous ground observations. Rather than treating these platforms as competing technologies, they should be regarded as different layers of the same plant health monitoring system. This hierarchical approach allows surveillance resources to be directed progressively towards areas where the probability of pest or disease presence is highest (Alexopoulos et al., 2023).

4. Internet of Things and Continuous Field Monitoring

The IoT provides the communication infrastructure required to connect sensors, traps, machinery and digital platforms. In crop protection, IoT systems can continuously monitor temperature, relative humidity, rainfall, leaf wetness, soil moisture, canopy conditions and other environmental variables that influence pest and disease development. Wireless sensor networks can transmit these measurements to centralized or cloud-based platforms, allowing information to be analysed in near real time. This continuous monitoring capability is particularly valuable because many pests and pathogens respond rapidly to environmental conditions. Short periods of high humidity, leaf wetness or favourable temperature can create conditions suitable for infection or pest development that may not be captured by conventional scouting. IoT systems can therefore provide temporal resolution that is difficult to achieve through periodic field visits (Tao et al., 2021).

Smart traps represent an important application. Conventional traps usually require manual inspection and counting. In contrast, camera-equipped traps can automatically photograph insects and use machine learning algorithms to identify and count target species. When connected through IoT networks, trap observations can be transmitted automatically to a central platform, allowing pest populations to be monitored continuously across multiple fields. Such systems can provide alerts when pest abundance exceeds predefined thresholds, helping farmers or advisors determine when intervention is justified (Ahmed et al., 2024).

Electronic spore traps provide a comparable approach for fungal pathogens. Automated systems can sample airborne particles and use optical, imaging or molecular methods to characterize fungal propagules. The ability to monitor airborne inoculum continuously could improve disease forecasting because pathogen presence can be detected before symptoms become widespread. Recent work has explored automated spore detection and UAV-based sampling, creating opportunities for spatially explicit monitoring of pathogen dispersal (Tummon et al., 2024;).

IoT therefore, transforms crop protection from periodic observation into continuous monitoring. Its value, however, depends on the quality and relevance of the information collected. More sensors do not necessarily produce better decisions. The objective should be to identify the smallest and most appropriate set of measurements capable of improving a specific management decision.

5. Artificial Intelligence for Pest and Disease Detection

The rapid development of AI, particularly machine learning and deep learning, has fundamentally changed the analysis of agricultural imagery. Traditional image-analysis systems often required experts to manually define characteristics such as colour, texture, shape or spectral indices. Machine learning algorithms can use these features to classify healthy and diseased plants. Deep learning, and particularly convolutional neural networks (CNNs), can go a step further by learning relevant features directly from images. CNN-based approaches have become dominant in image-based plant disease recognition because they can detect complex spatial patterns associated with lesions, discoloration and other symptoms. Recent studies report high classification performance for many crop disease datasets, sometimes exceeding 95% under controlled or semi-controlled conditions. However, such performance should be interpreted cautiously because accuracy obtained from laboratory or publicly available datasets does not necessarily translate into equivalent performance under field conditions (Kouadio et al., 2023; Majdalawieh et al., 2025).

The field environment is much more complicated than a typical training dataset. Leaves may overlap, lighting can change rapidly, symptoms may be partially obscured, weeds and soil can create background noise, and disease symptoms may vary considerably between cultivars, developmental stages and geographical regions. Furthermore, images of different diseases may share similar visual characteristics. These factors can lead to false positives and false negatives when AI systems are deployed outside the conditions in which they were trained. Data augmentation can partially address the problem by increasing the apparent diversity of training datasets through rotation, reflection, cropping, scaling and changes in brightness or color. Synthetic image generation can also supplement limited datasets. Nevertheless, artificial augmentation cannot replace genuinely diverse field observations. Real-world datasets should include different cultivars, disease stages, environmental conditions, geographic regions and management systems (Ouhami et al. 2021; Shorten and Khoshgoftaar, 2019).

An important development is **the use of AI for pest detection and counting**, rather than simply disease classification. Object-detection architectures such as YOLO can identify and localize individual insects in trap images or field imagery. This makes it possible to quantify pest pressure, monitor population trends and establish threshold-based interventions. Tian et al. (2023), for example, developed a multi-scale YOLO model for detecting small pest targets, while recent IoT systems have combined cameras, smart traps and deep learning for automated pest monitoring.

6. Predictive Modelling and Decision-Support Systems

Detection is only one part of crop protection. From the perspective of sustainable agriculture, the most important question is often what should be done after a risk has been detected. Predictive modelling and decision-support systems provide this link. Process-based epidemiological models have traditionally been used to describe relationships between temperature, humidity, rainfall, crop phenology and pathogen development. Degree-day models can estimate pest emergence based on accumulated temperature. Their major advantage is biological interpretability. However, they require appropriate calibration and may perform poorly when environmental conditions differ substantially from those under which the model was developed.

Machine learning provides an alternative approach by learning statistical relationships from historical observations and real-time data. Such models can capture nonlinear relationships between weather, crop conditions, pest pressure and disease outcomes. Their major limitation is that high predictive performance in one dataset does not guarantee reliable performance in another environment. Models can therefore become highly accurate within their training domain but fail to generalize across regions, cultivars or seasons (Cammarano et al., 2023). Hybrid modelling is consequently becoming increasingly attractive. Combining biological models with machine learning can incorporate established plant pathology knowledge while exploiting the predictive capacity of data-driven methods. Such approaches may improve robustness, reduce dependence on very large datasets and provide greater interpretability.

DSSs are the operational component of this process. A DSS can integrate weather data, sensor observations, pest monitoring, crop phenology, disease and pest models, economic thresholds and management objectives to produce recommendations. Importantly, a DSS should not simply state that disease risk is high. It should help answer practical questions: Where is the risk? When is intervention required? What type of intervention is appropriate? What area should be treated? And what is the expected benefit relative to the environmental and economic cost? Spatial DSS platforms are particularly important in precision crop protection. GIS can integrate georeferenced satellite imagery, UAV maps, proximal observations and smart-trap data to produce maps of pest pressure or disease severity. GNSS ensures that observations and interventions can be accurately located and repeated over time. These maps can then guide targeted scouting, localized pesticide application, biological control or variable-rate treatments.

8. From Detection to Precision Intervention

The ultimate objective of smart crop protection is not simply better diagnosis but better intervention. The combination of sensing, AI, DSS and automated machinery makes it possible to move towards site-specific management. Traditional pesticide application generally treats an entire field uniformly, even when pests or diseases are unevenly distributed. Precision spraying aims to apply products only where they are required and, where possible, at an intensity proportional to pest or disease pressure. This approach can reduce unnecessary pesticide applications, lower costs and minimize environmental exposure. Smart spraying systems can integrate machine vision, GNSS, AI and variable-rate application technologies. A camera mounted on a tractor, robot or UAV can detect weeds, pest damage or disease symptoms, while the control system determines whether a nozzle should be activated. The spatial information generated by UAVs or other sensors can also be transformed into prescription maps that guide subsequent applications. Autonomous and semi-autonomous platforms are extending this concept further. Agricultural robots can move through fields while collecting observations and performing targeted interventions. AI-assisted unmanned ground vehicles have already been investigated for crop disease identification and spraying, demonstrating how detection and treatment can be integrated into a single operational platform (Sujatha et al., 2023). This is particularly relevant to the objectives of zero-pesticide and low-input agriculture. Digital technologies cannot eliminate the need for pesticides in all production systems, nor should technology be viewed as a substitute for integrated pest management. Their value lies in helping farmers avoid interventions that are unnecessary, poorly timed or spatially excessive.

A mature **holistic digital IPM system** could therefore operate according to a sequence such as:

Monitor → Detect → Identify → Predict → Assess Risk → Decide → Intervene → Evaluate.

The evaluation step is particularly important. After an intervention, new sensor observations can determine whether pest or disease pressure has declined. This creates a feedback loop through which the system can continuously

improve management decisions. Such feedback-based systems represent a significant step beyond static DSS platforms.

9. Integrated Digital Crop Protection Ecosystems

The greatest potential of these technologies lies in their convergence. Sensors, AI algorithms and autonomous machinery are individually useful, but their value increases substantially when they operate as components of an integrated system. An integrated digital crop protection ecosystem may begin with continuous environmental monitoring and remote sensing. Anomalies identified from satellite imagery can trigger UAV surveys. UAV imagery can identify specific areas of concern, while proximal sensors provide detailed measurements. Smart traps can provide direct information on pest abundance, while molecular diagnostics can confirm the pathogen responsible for suspected disease outbreaks. All these data streams can be transferred through IoT communication networks into a common digital platform. AI algorithms can analyse the information, while predictive models estimate disease or pest risk. A DSS can then translate these predictions into management options. Finally, precision machinery can implement the recommended intervention and provide feedback on the outcome.

The STELLA Pest Surveillance System (PSS) represents an example of this integrated approach (<https://stella-pss.eu/>). The STELLA PSS is a digital platform designed for the early detection, warning (in-field and remote sensing), and management of regulated plant pests and quarantine diseases using AI, modern sensing technology and decision-support framework. It incorporates information from optical imaging, environmental sensors, smart traps and predictive models with the objective of enabling early detection and forecasting of pest and disease outbreaks and supporting targeted management.

The integration of digital technologies can also support cross-border and regional plant health surveillance. Standardized data formats, shared databases and interoperable platforms can allow observations from different farms, regions and countries to contribute to common surveillance networks. This is particularly important in the context of invasive pests and pathogens whose movement is not restricted by administrative boundaries.

10. Challenges to Real-World Deployment

Despite rapid technological progress, the transition from experimental demonstrations to operational crop protection systems remains challenging. One of the most important limitations is data quality. Many AI models have been trained using relatively small datasets or images acquired under controlled conditions. Real agricultural environments are considerably more variable. Models must therefore be validated using independent, geographically diverse field datasets that include different cultivars, disease stages, weather conditions and management practices. Model generalization is closely related to this issue. A model developed for one crop or region may not perform reliably in another. Biological variability is particularly important in plant pathology because pathogen populations, host susceptibility and environmental conditions can change over space and time. Future AI systems should therefore incorporate continuous validation and, where appropriate, adaptive learning.

Explainability and interpretability are also important. A farmer or crop adviser may be reluctant to act on an AI-generated recommendation if the reasoning behind it is unclear. This is especially relevant when the recommendation involves pesticide application or the removal of infected plants. AI systems should therefore increasingly provide interpretable information, confidence estimates and links to the underlying observations. Another challenge is data interoperability. Different sensors and platforms often generate data in different formats, spatial resolutions and temporal frequencies. Satellite imagery, UAV imagery, IoT sensors, molecular diagnostics and farm-management systems may operate as isolated systems. Without standardized data structures and interoperable platforms, the potential benefits of data fusion cannot be fully realized.

Economic feasibility is equally important. Sophisticated hyperspectral sensors, UAVs, autonomous robots and high-performance computing systems may be beyond the financial capacity of many small farms. The digital divide is therefore a significant concern. If digital crop protection is designed primarily for large commercial farms, it could unintentionally increase inequalities between large and small producers. For smallholders, shared technology-service models may offer an alternative. Rather than purchasing expensive equipment, farmers could access UAV surveys, smart spraying, digital diagnostics or AI-based advisory services through cooperatives, farmer organizations, extension services or private providers. This model could be particularly relevant in fragmented agricultural landscapes. Connectivity is another constraint. IoT-based systems depend on reliable communication networks, while cloud-based AI platforms may require continuous internet access. Edge computing and offline-capable systems can partially address this problem, allowing data to be processed locally and synchronized when connectivity becomes available. Finally, farmer adoption depends on trust, usability and perceived economic value. Farmers are unlikely to adopt complex technologies simply because they are technologically impressive. Digital solutions must demonstrate a clear advantage in terms of reduced costs, reduced pesticide use, improved yields, lower risk or labour savings. Evidence from European farming systems indicates that farm size, income, confidence in economic returns and access to information and training influence the adoption of precision technologies. Therefore, technological development must be accompanied by training, advisory support and participatory design.

11. Future Research Priorities

The next generation of digital crop protection systems should focus on integration rather than the development of isolated technologies. Several priorities are particularly important. First, research should move towards **multi-source and multi-scale datasets** that combine satellite, UAV, proximal, environmental, molecular and management information. Such datasets should be collected under real field conditions and made available through standardized and interoperable infrastructures. Second, greater attention should be given to **early and pre-symptomatic detection**. The most valuable digital signal is not necessarily the most visible symptom but the earliest reliable indication that a plant is undergoing a biologically meaningful change. Combining spectral, thermal, fluorescence, physiological and molecular information could provide more sensitive indicators of early infection. Third, AI research should increasingly move beyond classification towards **prediction (prognosis) and decision-making**. A system that correctly identifies a disease/pest is useful, but a system that can determine disease/pest risk several days in advance and recommend an economically and environmentally appropriate intervention is considerably more valuable. Fourth, **hybrid AI and biological modelling** should be further developed. Crop protection is a biological system, and purely data-driven models may not always capture the mechanisms governing pathogen development or pest population dynamics. Integrating biological knowledge into AI models can improve interpretability and robustness. Fifth, research should address **human-AI interaction**. Farmers and agronomists should remain active participants in the decision process. AI should support expert judgment rather than attempt to eliminate it. The most effective systems are likely to be those in which the farmer can inspect the evidence behind a recommendation, provide feedback and override an automated decision when local knowledge indicates that the recommendation is inappropriate. Sixth, digital systems should increasingly incorporate **environmental and economic objectives**. The optimal intervention is not necessarily the one that maximizes disease suppression. It may instead be the intervention that achieves an acceptable level of disease control while minimizing pesticide use, cost, environmental impact and resistance-selection pressure. Finally, digital crop protection should be evaluated under **real agricultural conditions**. Proof-of-concept demonstrations and high laboratory classification accuracies are not sufficient. Technologies need to be tested across multiple seasons, farms, cultivars, climates and management systems. Long-term validation will determine whether digital crop protection can genuinely deliver the promised improvements in sustainability and resilience.

12. Conclusions

The convergence of smart sensing, precision agriculture, molecular diagnostics, IoT, AI, predictive modelling and DSS is creating a new technological foundation for crop protection. The emerging paradigm is fundamentally different from conventional reactive management because it seeks to detect risks earlier, understand their spatial and temporal dynamics, predict their development and intervene only where and when intervention is justified. Molecular diagnostics provide the specificity required to identify pathogens, while remote and proximal sensing provide scalable observations of plant health. IoT networks add continuous environmental and pest monitoring, while AI provides the analytical capacity required to interpret large and heterogeneous datasets. Predictive models transform observations into estimates of future risk, and DSS translate those estimates into actionable recommendations. Precision spraying, robotics and other automated platforms can then implement interventions at the required spatial scale. The most important shift is therefore not the replacement of one technology by another, but the **integration of complementary technologies into a coherent plant health management ecosystem**. Satellite imagery alone cannot diagnose a pathogen; molecular diagnostics alone cannot provide landscape-scale surveillance; AI alone cannot compensate for poor-quality data; and automated machinery cannot determine whether an intervention is biologically justified. Their real value emerges when they are connected.

For the objectives of the **T0P-AGRI-Network**, this convergence provides a pathway towards more sustainable and potentially zero-pesticide-oriented crop protection. By improving early detection, strengthening disease forecasting, supporting biological and non-chemical interventions, and enabling highly targeted pesticide applications when they remain necessary, digital technologies can contribute to reducing unnecessary agrochemical use while maintaining crop productivity.

At the same time, technological innovation should not be confused with sustainability. The successful digital transformation of crop protection will depend on data quality, biological knowledge, interoperability, affordability, farmer participation and appropriate governance. Technologies must be developed around real agricultural problems and validated under real field conditions. Future systems should therefore be accurate but also explainable, sophisticated but affordable, automated but farmer-centred, and data-driven but grounded in biological knowledge. Ultimately, the integration of molecular diagnostics, smart sensing, precision agriculture and AI represents a transition from reactive disease control towards proactive, predictive and adaptive plant health management. This transition has the potential to strengthen the resilience of agricultural systems, reduce dependence on chemical inputs and support the development of more sustainable crop protection strategies consistent with the goals of the T0P-AGRI-Network.

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