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Integrating digital technologies and artificial intelligence in plant protection: diagnosis, prognosis, surveillance, and management of plant pests and diseases

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Summary. As world population continues to grow, sustainable food production has become an increasingly urgent priority. At the same time, emergence and spread of invasive plant pests and diseases is causing new outbreaks that threaten plant health, reduce agricultural productivity, and undermine environmental sustainability. Conventional diagnostic approaches, based primarily on visual inspections and laboratory analyses, remain fundamental in plant pathology; however, these are often time-consuming, rely heavily on expert knowledge, have limited sensitivity at early stages, and are constrained by low scalability and throughput. In addition, their inherent subjectivity makes them prone to error, frequently leading to delayed plant protection interventions and suboptimal disease management. Precision agriculture has emerged as a transformative paradigm that integrates advanced sensing, data analytics, automation technologies, and artificial intelligence, to support early detection, continuous monitoring, and site-specific management of plant biotic and abiotic stressors. The present review synthesizes recent advances in plant pest and disease monitoring, covering current biochemical and molecular diagnostic methods and precision agriculture technologies that are organized into two complementary domains: hardware technologies, including sensing systems, positioning and communication networks, application platforms; and software technologies, including data management, machine and deep learning, modelling, and decision-support systems. Current evidence indicates that integration of spectral imaging, environmental sensing, and artificial intelligence can substantially improve accuracy, timeliness, and scalability of pest and disease detection, while supporting targeted use and reduction of agrochemical inputs. Despite rapid technological progress, however, major challenges remain, including data interoperability, model robustness under heterogeneous field conditions, economic feasibility, regulatory alignment, and farmer adoption. This review highlights current molecular and digital diagnostic capabilities, identifies key research gaps, and outlines future directions for developing resilient, cost-effective, and sustainable precision agriculture systems for plant pest and disease management. Convergence of molecular diagnostics, smart sensing technolo-

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gies, and artificial intelligence, is redefining plant pathology, enabling transition from reactive disease control toward proactive, data-driven disease management.

Keywords. Plant health, digital plant pathology, decision support systems, AI-driven disease detection, remote sensing.

INTRODUCTION

Effective management of plant diseases is a critical challenge for international agriculture in the 21st century, that is intensified by rapid population growth and the escalating demand for safe, secure and sustainably produced food. With the world human population projected to reach 9.7 billion by 2050 (United Nations Department of Economic and Social Affairs, 2019), food production systems must become resilient, resource-efficient, and aligned with sustainability principles (Dhankher and Foyer, 2018). Plant diseases caused by fungi, bacteria, viruses, parasitic plants, or nematodes, remain major constraints for world agricultural productivity, reducing yields and product quality, while threatening food security and plant health. Under favourable weather conditions and inadequate phytosanitary management, the impacts of crop pests and diseases are intensified, leading to annual yield reductions of 20 to 40% in major food crops, and contributing to losses estimated at approx. $US 220 billion (Savary *et al*., 2019; Buja *et al*., 2021). Increasing incidence of crop pests and diseases also poses risks to biodiversity and land ecosystem services (Singh *et al*., 2023).

Plant disease control has traditionally relied heavily on chemical pesticides; however their extensive use has contributed to ecological degradation, contamination of agroecosystems, emergence of pesticide-resistant pathogen populations, and adverse human health effects (Carvalho, 2017). In response, the European Union's Farm to Fork strategy targets a 50% reduction in pesticide use and risks by 2030, and expansion of organic farming to 25% of agricultural land, thereby promoting integrated pest management and sustainable alternatives (European Commission, 2020). Achieving these goals depends on development of low-impact technological innovations and comprehensive phytosanitary surveillance frameworks.

Climate change, which is driven largely by rising atmospheric carbon dioxide concentrations and is expressed through increased frequency of extreme weather events, including increased temperatures, prolonged and unexpected heatwaves, and altered rainfall patterns, profoundly affects plant disease dynamics. These effects modify geographic distribution, lifecycles, epidemiology, and seasonal activity of many plant pathogens, while also altering host plant susceptibility and physiological response dynamics (Velásquez *et al*., 2018; Lahlali *et al*., 2024).

Rising temperatures may expand the geographic ranges of plant pathogens, that are currently constrained by their inability to overwinter in cold regions, as exemplified by wheat stem rust caused by *Puccinia graminis* f. sp. *tritici* (Singh *et al*., 2023). Increased precipitation, particularly when associated with flooding and waterlogging, can create anaerobic soil conditions that favour development and spread of water-associated pathogens, including *Pythium* spp. and *Phytophthora* spp. (Martínez-Arias *et al*., 2022). Conversely, reduced precipitation may limit the incidence and transmission of diseases, such as downy mildew and powdery mildew, while simultaneously increasing plant susceptibility to drought stress and potentially enhancing vulnerability to other pathogens, including *Fusarium* and *Verticillium* spp. (Maurya *et al*., 2022). Elevated CO_2 can also increase wheat susceptibility and virulence of *Fusarium graminearum*, resulting in increased disease severity (Velásquez *et al*., 2018).

Climate change can intensify disease pressure in both annual and perennial cropping systems by enhancing pathogen fitness and virulence and aligning pathogen life cycles with prolonged growing seasons. Climate-driven environmental shifts also affect plant development, the durability of host resistance, and structure and function of plant-associated microbiomes, thereby indirectly modulating disease outcomes (Chen *et al.,* 2023). Climate change can also reshape rhizosphere, phyllosphere, and endophytic microbial communities, reducing beneficial microbial functions such as competition, antibiosis, nutrient acquisition, and induction of host resistance. These disruptions may weaken natural disease suppression and create ecological opportunities for opportunistic, invasive, or thermotolerant pathogens to establish and spread with increased efficiency, such as mycotoxigenic *Aspergillus* spp. (Casu *et al.,* 2024).

In addition, disruption of indigenous microbial communities and changes in resource availability can further generate vacant ecological niches, that facilitate establishment of invasive or emerging pathogens (Pautasso *et al*., 2012; Singh *et al*., 2023). Collectively, the combined effects of temperature fluctuations, altered water availability, and increased frequencies of extreme weather events are reshaping disease emergence, progression, and

spatial distribution, increasing the international frequency and unpredictability of pest outbreaks (Singh *et al*., 2023; Bradshaw *et al*., 2024; Kirk *et al*., 2025).

The Mediterranean Basin is consistently recognized as a climate-change hotspot, primarily due to convergence of rapid temperature increases, reduced and more variable precipitation, and increased frequency of extreme weather events such as droughts and heatwaves. These factors intensify water stress, disrupt crop phenology, and create favourable conditions for establishment, survival, and spread of plant pests, with significant implications for agroecosystem resilience, agricultural productivity, and plant health (Battilani *et al*., 2016; Pinheiro *et al*., 2022; Lazoglou *et al*., 2024).

Human-driven land-use change, including urbanization, deforestation, and agricultural expansion, disrupt and fragment natural habitats, and create novel interfaces among wild and cultivated plant hosts, thereby increasing opportunities for cross-species pathogen transmission (McDonald and Stukenbrock, 2016; Pope *et al*., 2023; Khusnitdinova *et al*., 2026). In parallel, world trade of living plants and plant products has emerged as a dominant pathway for the transboundary movement of plant pests and pathogens, frequently enabling their introduction into regions where they have little or no prior ecological history (Liebhold *et al*., 2012; Santini *et al*., 2013; Eschen *et al*., 2015). Over recent decades, human activities have substantially intensified intercontinental dissemination of crop pathogens, increasing the likelihood of transmissions from regions with established disease presence to previously pathogen-free areas, with consequent major economic and ecological impacts (Sikes *et al*., 2018).

Natural dispersal mechanisms such as wind, water, and biological vectors generally constrain the spatial spread of microorganisms to distances within the limits of their inherent dispersal capacities, and prevailing environmental conditions. However, globalization now facilitates long-distance pathogen movements, and the emergence of novel disease complexes that far exceed what would occur through natural processes (McDonald and Stukenbrock, 2016; Miedaner and Garbelotto, 2024). By bypassing geographic and ecological barriers, human-mediated introductions substantially increase the complexity of disease surveillance, risk assessment, and predictive modelling, while facilitating rapid pathogen establishment and severe disease outbreaks (Singh *et al*., 2023).

Although biosecurity and phytosanitary measures have expanded in many regions (Black and Bartlett, 2020), international trade in plants and plant products remains a major biosecurity pathway for introduction and spread of plant pests and pathogens, underscoring the need for strengthened border inspections, risk-based phytosanitary controls, climate-informed trade-based modelling, early detection, and rapid response systems (Bebber *et al*., 2014). Accurate and highly sensitive identification of phytopathogens is a critical prerequisite for effective disease management, as diagnostic errors can compromise control decisions and exacerbate yield and economic losses (Bock *et al*., 2010). Conventional diagnostic workflows typically combine field-based symptom assessments with laboratory-based phenotypic (e.g., pathogen isolation and microscopy), serological (e.g., ELISA), and molecular analyses (e.g., PCR, qPCR and LAMP) (Khaled *et al*., 2018). However, these approaches remain limited by their subjectivity of visual evaluations, substantial resource and time requirements, and reduced capacity to detect early-stage or latent infections.

Precision agriculture offers a change in thinking in pest and disease management, by enabling site-specific, timely, and data-driven interventions. At its core, precision agriculture integrates technologies such as global navigation satellite system (GNSS), geographic information systems (GIS), remote and proximal sensing technologies, Internet of Things (IoT) systems, and advanced data analytics, to capture spatial and temporal variability within agricultural fields (Anghelache *et al*., 2021; Barbosa Júnior *et al*., 2024; Getahun *et al*., 2024; Godavari *et al*., 2024; Surendran *et al*., 2024). By exploiting this variability, precision agriculture systems can support early detection of pest and disease outbreaks, optimize input use, and reduce unnecessary applications of chemical plant protection products, thereby improving both crop productivity and environmental sustainability.

Remote sensing technologies have played foundational roles in the evolution of precision pest and disease monitoring. Satellite, unmanned aerial vehicle (UAV), and ground-based imaging systems enable large-scale and high-spatial resolution observation of crop health indicators, facilitating early identification of stress patterns associated with pest infestation or disease development (Gebbers and Adamchuk, 2010; Huang *et al*., 2018; Chattopadhyay *et al*., 2024). Advances in multispectral, hyperspectral, and thermal imaging have further enhanced capacity to detect morphological and physiological alterations associated with plant stress, often before visual symptoms become apparent (Castrignanò *et al*., 2021).

Complementing remote sensing, proximal sensing and IoT-based systems provides continuous, real-time monitoring of crop and environmental conditions directly in the field (Tao *et al*., 2021). Smart insect traps, environmental sensors, and wireless sensor networks (IoT) have been developed to capture pest population

dynamics, and the microclimatic variables relevant to disease development, enabling responsive, targeted, and site-specific pest and disease management strategies (Zhang and Kovacs, 2012; Singh *et al*., 2016; Psirofonia *et al*., 2017; Sharma *et al*., 2018; Huang *et al*., 2018; Tsouros *et al*., 2019; Singh *et al*., 2025).

The rapid adoption of machine learning and deep learning techniques has further accelerated progress in pest and disease monitoring, for example, in the recognition of cotton diseases caused by *Cercospora* and *Alternaria* spp. (Nagasubramanian *et al.,* 2021). Convolutional neural networks and other data-driven models have demonstrated high accuracy for detecting and classifying crop diseases and insect pests using image-based data, often outperforming traditional rule-based approaches (Pan and Wang, 2021; Coulibaly *et al*., 2022; Liu *et al*., 2025). Recent studies have also emphasized the value of multimodal data fusion, integrating visual, thermal, and environmental sensor data to enhance model robustness under heterogeneous and dynamic field conditions (Chen *et al*., 2025; Liu *et al*., 2025).

Beyond monitoring, precision agriculture technologies are increasingly supporting decision-making and interventions. Integration of decision support systems, variable-rate spray application technologies, and autonomous or semi-autonomous platforms (Han *et al*., 2023; Kethineni and Pradeepini, 2024; Rovira-Más *et al*., 2024), enables site-specific pest and disease control, thereby reducing chemical inputs and improving operational efficiency (Campos *et al*., 2020; Rai *et al*., 2025). Collectively, these developments reflect a transition from reactive control toward proactive, predictive, adaptive disease and pest management strategies.

Despite these advances, challenges remain. Issues related to data interoperability, scalability, model generalization across crops and regions (Shahid *et al*., 2012; Johnson *et al*., 2020), economic constraints (White *et al*., 2021), and user adoption (Genius *et al*., 2014) continue to hinder the widespread implementation of precision pest and disease management systems (Lal, 2015; Godavari *et al*., 2024). Addressing these barriers is essential to fully realize the potential of precision agriculture for sustainable crop protection. The present review consolidates current knowledge on precision agriculture technologies used for pest and disease detection, surveillance, and management. The review also critically evaluates the capabilities and limitations of these technologies, and identifies future research directions required to advance sustainable, resilient, and farmer-centric crop protection systems.

Early and accurate pathogen detection, coupled with timely intervention, is critical for minimizing economic crop losses and ecological impacts of crop production systems. Accordingly, this review provides an integrated perspective on pathogen-induced symptoms, their underlying physiological mechanisms, and application of emerging digital and sensor-enabled technologies in data-driven, quantitative phytopathometry and precision disease management. To provide a structured overview of precision agriculture tools relevant to plant health, the review is organized around two complementary technological domains. First, hardware technologies are discussed, covering sensing systems, GNSS-based positioning, communication networks, and application platforms, for site-specific interventions such as variable-rate and autonomous spraying (Jiang *et al*., 2022; Hussain *et al*., 2025). Second, software technologies are examined, including data organization and management, analytical methods leveraging machine learning and deep learning, modelling frameworks, and decision-support systems for pest and disease monitoring and management (Oerke *et al*., 2010; Krishna *et al*., 2025). Together, these technologies complement established biochemical and molecular diagnostic methods, such as ELISA and PCR, by supporting scalable monitoring, targeted sampling, and integration of laboratory-confirmed diagnoses with spatial and temporal data, for increased and effective disease surveillance and management.

PLANT DISEASE SYMPTOMS AND SIGNS

Disease symptoms and visual inspection

Visual inspection for a plant disease involves identification of affected plants based on the presence and patterns of pathological symptoms. In plant pathology, a disease symptom is defined as any visible alteration in appearance, structure, or function of plant tissue resulting from biotic (pathogen infection) or abiotic (environmental factor) stress (Ray, 2024). Symptoms are external manifestations of internal physiological disruptions, and therefore serve as primary diagnostic indicators during field inspections.

In traditional field diagnoses, practitioners systematically observe symptom patterns and associate them with potential etiological agents. Assessments typically focus on characteristic disease symptoms, and, where present, visible signs of pathogens, such as spores, mycelium, or fruiting structures. Common disease symptoms include chloroses, necroses, tissue wilting, leaf deformations, mosaic patterns, and abnormal growth, all of which provide important clues about identity and progression of causal agents (Ray, 2024). Structured inspections, progressing from detailed organ-level observations to broad

plant-, canopy-, plot-, and field-level assessments, can further aid in distinguishing between biotic and abiotic causes, and can refine hypotheses regarding the probable causal agents (Vollenweider and Günthardt-Goerg, 2005).

These labour-intensive methods require expertise of highly trained practitioners with advanced diagnostic and disease-detection skills, and are therefore vulnerable to observer bias and subjective interpretation (Mahlein, 2016). Although accuracy and reproducibility of visual assessments have improved over time through adoption of standardized assessment protocols and formal rater training (Bock *et al*., 2010), visual diagnoses remain inherently constrained by the non-specific nature of many disease symptoms. Symptom overlap between pathogen infections and abiotic stress responses, such as mineral nutrient imbalances, water limitation, heat stress, and herbicide-induced phytotoxicity, complicate accurate causal attribution. Disease complexes present additional challenges, as multiple pathogens or pest-pathogen interactions may occur simultaneously on the same host, generating overlapping or atypical symptom patterns that are difficult to assign to a single cause (Boixel *et al*., 2024). Additionally, latent or early-stage infections often lack visible manifestations, increasing the risk of misdiagnoses and delaying timely interventions (Vollenweider and Günthardt-Goerg, 2005). Thus, while visual assessments remain essential for rapid field diagnoses, their integration with digital and sensor-based technologies is becoming increasingly important. These technologies transform visual symptoms into quantitative features, enabling standardized, objective disease assessment and facilitating early detection of plant diseases.

Types of symptoms induced by pathogens

Plants are susceptible to a wide spectrum of pathogens, including fungi, oomycetes, bacteria, phytoplasmas, viruses, and viroids. These pathogens have diverse lifestyles ranging from biotrophs that obtain nutrients from living host cells to necrotrophs that colonize and exploit dead plant tissue, as well as hemibiotrophs that transition between these two modes. Pathogens also differ in infection strategies (intracellular or extracellular), and in the plant tissues they target, such as xylem, phloem, roots, or leaves (Singh *et al*., 2023). During the initial stages of infection, plant tissues are often phenotypically indistinguishable from healthy tissues, and are therefore described as asymptomatic, pre-symptomatic, or non-symptomatic. As disease progresses, macroscopic symptoms develop, and affected tissues exhibit visible alterations that distinguish them from healthy counterparts, entering the symptomatic phase (Pereira *et al*., 2025). Although specific pathogen groups and species often induce characteristic symptom patterns, considerable overlap among symptoms can frequently complicate accurate diagnoses (Cubero *et al*., 2024).

Phytopathogenic fungi are one of the most destructive groups affecting crops across all developmental stages of crop production, from seed germination to post-harvest storage. Their widespread impacts reflect diverse infection strategies, prolific reproductive capacity, and adaptability to fluctuating environmental conditions. Disease symptoms vary considerably depending on specific pathogen, host species, and environmental contexts. These symptoms commonly include wilting associated with vascular dysfunction, such as symptoms caused by *Fusarium oxysporum* or *Verticillium dahliae*; necrotic lesions and leaf spots resulting from localized host cell death, as caused by *Alternaria solani*; and visible mould formation resulting from surface mycelium growth and sporulation, as observed in *Botrytis cinerea* infections (Nazarov *et al*., 2020). Additional disease manifestations include pustule formation associated with spore aggregation, abnormal tissue proliferation and organ malformation caused by hormonal imbalance, fruit mummification, and soft or dry rots resulting from tissue maceration (Dean *et al*., 2012; Nazarov *et al*., 2020; Ray, 2024).

Bacterium pathogens typically cause infections classified as systemic and localized. Systemic infections, such as those caused by *Ralstonia solanacearum* and *Xylella fastidiosa*, invade and proliferate within host vascular systems, particularly in xylem vessels. Infection spread, coupled with biofilm formation, disrupt water transport and nutrient flow, leading to plant wilting, chloroses, and eventual plant decline (Anguita-Maeso *et al*., 2022; Chachar *et al*., 2025). In contrast, localized bacterial infections primarily affect host parenchymal tissues, producing necrotic lesions, scab-like symptoms, and soft rots. Tumour-like overgrowths (galls) are also characteristic symptoms induced by pathogens such as *Agrobacterium tumefaciens* and *Pseudomonas savastanoi* pv. *savastanoi* (Lee *et al*., 2009; Ramos *et al*., 2012).

Phytoplasmas, such as the quarantine pest Flavescence dorée phytoplasma of grapevine, are obligate, phloem-restricted pathogens that interfere with plant developmental pathways and reproductive processes and organs. Typical symptoms include virescence (green pigmentation of floral tissues), phyllody (conversion of floral organs into leaf-like structures), and floral proliferation (MacLean *et al*., 2011). Additionally, vegetative abnormalities such as witches' broom, dwarfism, and leaf deformation are associated with phytoplasma effector proteins, such as Zaofeng6 and SAP11, that inter-

fere with host transcriptional regulation and hormone signalling pathways, as occurs in jujube witches' broom (JWB) associated with Candidatus *Phytoplasma ziziphi* (Chen *et al.,* 2022).

Viruses induce a wide range of predominantly systemic symptoms on host plants, that can be broadly categorized into growth suppression, foliar discolouration, morphological distortion, necroses, and impairment of reproductive processes (Nazarov *et al*., 2020). Developmental abnormalities can include: stunted growth (e.g., caused by Tomato spotted wilt virus - TSWV), reduced biomass and leaf and shoot curling or rolling, as induced by Tomato yellow leaf curl virus (TYLCV), enations (e.g. caused by Tomato leaf curl New Delhi virus - ToLCNDV), and floral abortion (e.g. caused by Zucchini yellow mosaic virus - ZYMV). Foliar symptoms frequently involve chloroses, mosaic patterns such as those associated with Tobacco mosaic virus (TMV), leaf vein clearing or banding, and localized or systemic necroses. Less common symptoms can include shoestring syndrome, leaf blistering or pitting, tumour-like growths, and excessive lateral root proliferation (rhizomania) (Gao and Lozano-Durán, 2026). These symptoms arise from virus-mediated disruptions of chloroplast function, hormone signalling, changes in gene expression, accumulation of reactive oxygen species (ROS), or modifications to cell cycle regulation (Jiang and Zhou, 2023).

Viroids, the smallest known infectious plant agents, cause disease symptoms ranging from latent infections to severe disorders, that often resemble diseases caused by viruses. Infected plants may exhibit leaf epinasty and chloroses, distortion of flowers, fruits, and storage organs, stem and bark cracking, reduced growth, and dwarfism. These effects are associated with structural distortions to cell walls and chloroplasts, and accumulations of cytoplasmic and plastid inclusions (Ortolá and Daròs, 2023).

EFFECTS OF PATHOGENS ON HOST PLANT PHYSIOLOGY

Pathogens disrupt plant physiology both locally and systemically, inducing multi-scale physiological responses that are shaped by pathogen lifestyle, the colonized tissues, invasion strategies, and infection stage, frequently manifesting prior to appearance of visible host symptoms (Cheaib and Killiny, 2025). Initial host–pathogen interactions occur at external plant interfaces or through root exudate-mediated signalling prior to tissue penetration (Fernandez and Burch-Smith, 2019). Following establishment, pathogen infections impair fundamental host physiological processes, leading to reduced photosynthetic performance, chloroses, lowered chlorophyll fluorescence, stomatal and vascular dysfunctions, altered canopy temperatures, and changes in nutrient translocation. Pathogen-induced disturbances are accompanied by reprogramming of hormonal signalling networks involving salicylic acid (SA), jasmonic acid (JA) and ethylene (ET), which coordinate immune signalling and defense activation (Ma and Ma, 2016). Infections also alter host metabolism and promote degradation or redistribution of key pigments including chlorophylls, carotenoids, and anthocyanins, leading to measurable changes in leaf light absorption and reflectance properties (Zhao *et al*., 2016).

These physiological alterations modify plant light reflectance, thermal behaviour, fluorescence, and volatile organic compound (VOC) emissions, forming the mechanistic links between biological stress responses and sensor-detectable signals. These changes provide critical targets for early disease detection using hyperspectral, thermal, fluorescence, and VOC-based sensing systems. Understanding these responses is therefore key for translating sensor observations into biologically meaningful interpretations, and for identifying pre-symptomatic indicators of disease progression (Buja *et al*., 2021) (Figure 1).

Photosynthesis

Photosynthetic inhibition is among the earliest plant responses to pathogen infections, resulting from coordinated structural, physiological, and molecular disruptions of host tissues and metabolic pathways. Many plant pathogens target photosynthetically active host tissues, inducing symptoms such as leaf spots, blights, chloroses, and defoliation, that reduce chlorophyll content and the photosynthetically active surface areas and constrain carbon assimilation (Cheaib and Killiny, 2025). In many pathosystems, plants restrict carbon availability to pathogens by downregulating photosynthesis as a defense strategy through stomatal closure (e.g. against *Pseudomonas syringae* pv. *tomato*, or *Botrytis cinerea*), impairment of photosystems I and II (e.g. against *Zymoseptoria tritici*), reduced Calvin–Benson cycle activity, and transcriptional repression of photosynthesis-associated genes (e.g. against Cucumber mosaic virus – CMV), while vascular occlusions impair water and assimilate transport (e.g. induced by *Xylella fastidiosa*) (Berger *et al.* 2007; Cheaib and Killiny, 2025). At subcellular scales, pathogens target chloroplasts, the central hubs of energy production and immune signalling, deploying effectors that alter thylakoid structure, interfere with PSII, and suppress defense-related signals such as ROS, salicylic acid (SA), and nitric

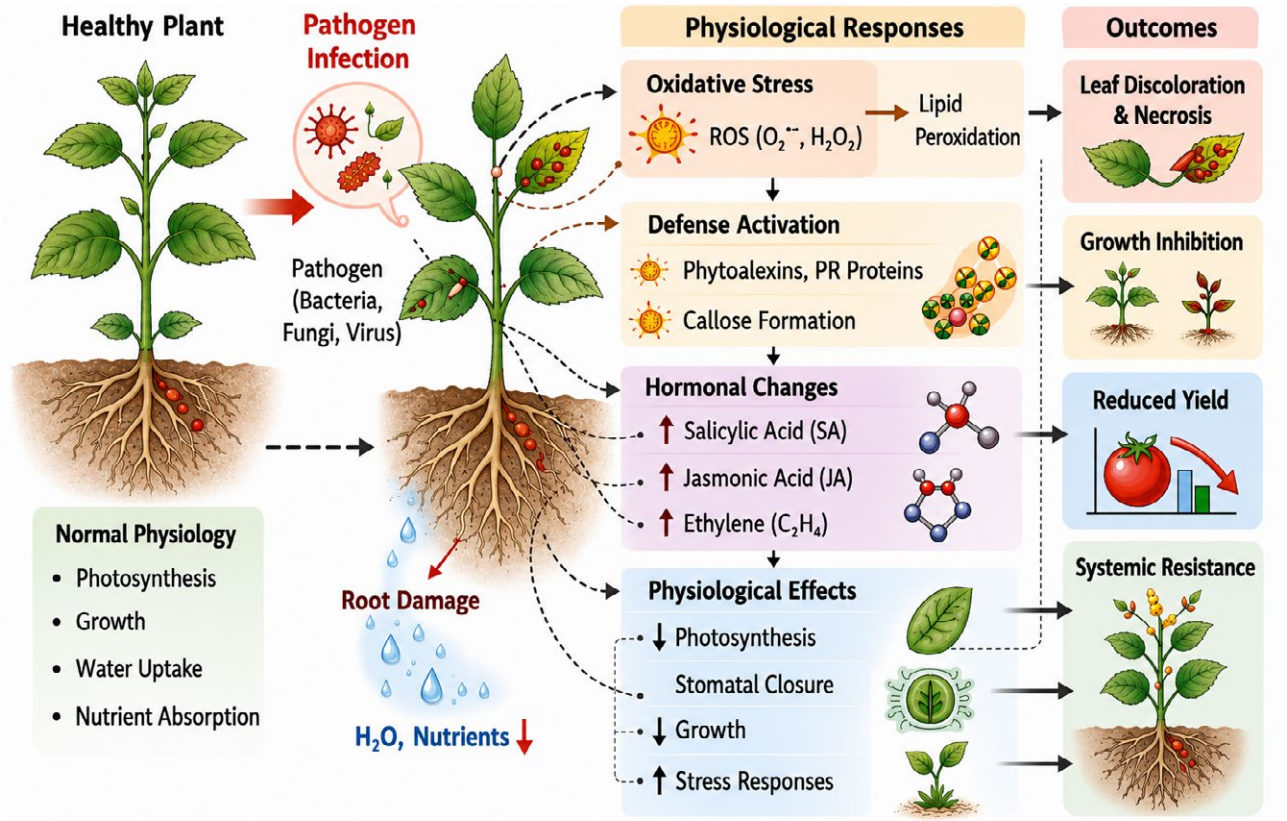


Figure 1. Physiological changes in plants after pathogen infections.

oxide (NO), thereby facilitating disease progression (Zabala *et al*., 2015; Xu *et al*., 2019).

Photorespiration and respiration

In photosynthetically plant active tissues, photorespiration functions as a central metabolic hub linking carbon fixation with nitrogen and sulfur metabolism, thereby contributing to photosynthetic stability, immune responses, and energy balance (Timm and Hagemann, 2020; Ciereszko and Kuźniak, 2024). Pathogen-induced stomatal closure decreases internal CO_2 concentrations and increases O_2 levels, reducing CO_2 to O_2 ratios and favouring RuBisCO-mediated oxygenation, thereby stimulating photorespiration activity (Grimmer *et al*., 2012; Ciereszko and Kuźniak, 2024). This metabolic shift is often associated with increased production of reactive oxygen species (ROS) as part of the plant defense responses, elevated leaf temperatures, and reduced transpiration rates (Zavala *et al*., 2013; Qi *et al*., 2018). Concurrently, pathogen infection typically stimulates respiratory activity, often preceding visible symptom development, as plants mobilize carbohydrate reserves to meet the increased defense-associated energy demands (Major *et al*., 2010). Enhanced respiratory enzyme activity promotes glucose catabolism and can lead to localized temperature increases in infected host tissues (Kalariya *et al*., 2024). In rapidly necrotizing tissues, respiration may initially peak and then decline following pathogen sporulation, whereas in slowly senescing tissues respiration can remain elevated for extended periods. These increases are primarily host-driven rather than pathogen-mediated, and may result from wound-induced respiration, elevated ATP demand, accumulation of soluble sugars due to impaired translocation, and hormone-mediated regulation of growth and metabolism that further stimulate respiration (Ray, 2024).

Membrane integrity, transpiration and water regulation

Alterations in host plant cell membrane permeability and integrity are among the earliest responses to pathogen infection, leading to electrolyte leakage, disrupted osmotic balance, and enhanced nutrient availability in apoplasts that can facilitate pathogen colonization, thereby accelerating tissue damage and necroses (Ray, 2024).

Pathogen-derived toxins, hydrolytic enzymes, and oxidative stress destabilize membrane integrity, while pathogen invasion further disrupts transpiration and water relations by altering stomatal function and xylem integrity, compromising water use efficiency (WUE) (Kalariya *et al*., 2024; Ray, 2024).

Foliar pathogens often cause direct damage to the host cuticle and stomatal complexes, inhibiting normal stomatal closure in the dark, and compromising water regulation (Grimmer *et al*., 2012). The pathogens may enter through stomata or directly penetrate host cuticles, with pathogen reproductive structures emerging through stomatal openings or epidermis ruptures. Localized substomatal infections impair stomatal regulation, reducing CO_2 assimilation and photosynthetic efficiency during daylight, and compromising water retention in the dark (Grimmer *et al*., 2012).

Disruption of xylem integrity is a central mechanism by which vascular pathogens impair transpiration and plant water status, leading to wilting through loss of turgour pressure. Pathogens such as *Fusarium oxysporum, Verticillium dahliae,* and *Ralstonia solanacearum* reduce hydraulic conductivity primarily through host-induced occlusions, including host responses such as tyloses and gels, which restrict water and nutrient flows (Yadeta and Thomma, 2013). While these host responses restrict pathogen spread, they also induce drought-like stress, reduce transpiration, and shift plant resource allocation toward water conservation at the expense of growth, primary metabolism and defense. (Beattie, 2011; Gorshkov and Tsers, 2022). Wilting typically progresses acropetally, starting with epinasty and flaccidity, followed by chloroses and vascular browning, whereas canker- and gall-forming pathogens such as *Agrobacterium tumefaciens* and *Meloidogyne* spp. impair water transport, predominantly through direct xylem destruction (Ray, 2024).

Growth and reproduction

Pathogen infections directly impair plant growth and reproductive fitness by altering host resource allocation, metabolism, developmental processes, and physiology. Following invasion, pathogen-derived elicitors disrupt primary metabolism and reduce photosynthetic capacity (Rojas *et al*., 2014). Beyond these direct effects, pathogens also manipulate host hormonal pathways and networks, through effectors and phytotoxins that disturb hormone homeostasis. These interactions affect defense-related hormones such as salicylic acid (SA), jasmonic acid (JA), and ethylene (ET), as well as growth regulators including auxin, cytokinins (CKs), gibberellins (GAs), abscisic acid (ABA), and brassinosteroids (BRs) (Kazan and Lyons, 2014; Zhao *et al*., 2021). Overall, hormonal "hijacking" by pathogens suppresses defense responses and also reshapes developmental processes, resulting in stunted vegetative growth, abnormal organ formation, altered flowering phenology, and reduced seed production. These changes can enhance pathogen fitness by extending periods for pathogen colonization, proliferation, and dispersal (Ma and Ma, 2016).

Biomass accumulation and yield reductions

Plant pathogens adversely affect host plant biomass accumulation and crop yields through integrated effects on photosynthesis, respiration, transpiration, nutrient uptake, metabolism, biochemical processes, gene expression, and host defense mechanisms (Peck and Mittler, 2020; Kalariya *et al*., 2024). Under optimal conditions, biomass production depends on radiation interception (RI) and radiation use efficiency (RUE), both of which are compromised by disease development (Bingham and Topp, 2009). Foliar pathogens diminish functional canopies of photosynthetically active tissues through lesion formation, chloroses, necroses, and premature leaf senescence, which collectively reduce plant radiation interception (Robert *et al*., 2006; Serrago *et al*., 2019). In crops such as wheat, foliar pathogens reduce green leaf area indices (GLAI), lowering radiation interception and biomass production, while lesion development and accelerated senescence impair canopy photosynthesis and RUE (Carretero *et al*., 2010; Newton, 2016; Serrago *et al*., 2019).

When infections occur during critical plant developmental stages such as grain filling, reduced assimilate availability leads to low grain weight and overall yields (Dimmock and Gooding, 2002; Serrago *et al*., 2019). The impacts of reductions in radiation interception and RUE on biomass accumulation and crop yields strongly depend on infection timing, and reflect disruptions in assimilate allocation, reserve remobilization, and source-sink balance of affected crops (Reynolds *et al*., 2007). Root and vascular pathogens exacerbate reductions in yield by impairing water uptake, altering root architecture, and reducing hydraulic conductivity, thereby reducing water-use efficiency, increasing susceptibility to drought stress, and further constraining crop productivity (Yadeta and Thomma, 2013).

DISEASE ASSESSMENTS: FROM TRADITIONAL SCORING TO BIOCHEMICAL AND DIGITAL METRICS

Visual estimation remains the most widely used approach for assessing plant disease severity, relying

on observer abilities to distinguish symptomatic from asymptomatic plant tissues and assign disease severity scores. Accurate disease assessment is important for evaluating control efficacy, estimating yield losses, informing forecasting models and economic thresholds, and ensuring reliable germplasm evaluations. Errors in assessment can compromise research experiment outcomes and disease management decisions, resulting in wasted resource use and economic losses (Bock *et al*., 2010; Chiang *et al*., 2014; Chiang *et al*., 2017). Beyond visual assessments, a range of molecular and biochemical techniques are available for plant pathogen detection, each relying on different detection mechanisms, as summarized in Table 1.

Quantitative disease assessments include key metrics such as prevalence, incidence, severity, and intensity, that describe disease occurrence across spatial and biological scales. Prevalence refers to the proportions of large spatial units affected, incidence includes the proportions of infected plants or organs, severity quantifies the extent of tissue damage within each sampling unit, and intensity refers to the overall disease level within a defined population or experimental system (Madden *et al*., 2007; Bock *et al*., 2022). Plant disease severity is typically evaluated using measurement scales that may be general or pathogen-specific (Nutter and Esker, 2006; Madden *et al*., 2007). These most commonly include nominal, ordinal, or ratio scales, with each differing in precision and applicability.

Nominal scales rely on descriptive categories, and are simple to apply but inherently subjective (Nutter and Esker, 2006), whereas ordinal scales assign ranked numerical categories based on symptom descriptions or proportional (percentage) ranges (Bock *et al*., 2020a). The Horsfall-Barratt scale exemplifies this approach, by dividing 0 to 100% severity into 12 logarithmic intervals to improve standardization, although this still reflects perceptual bias (Nutter and Esker, 2006; Bock *et al*., 2010; Chiang *et al*., 2014). Ratio scales quantify severity directly as percent affected tissue, enabling clear statistical interpretation though still influenced by observer variability (Bock *et al*., 2010; Bock and Chiang, 2019).

Visual estimation of plant disease severity is prone to multiple error sources arising from rater bias and method variability across pathosystems. Accuracy and precision are influenced by factors such as scale selection, assessment method, rater expertise, symptom heterogeneity, plant structural complexity, and observation timing (Bock *et al*., 2022), with quantitative ordinal scales potentially increasing type II errors (false negatives), and low-severity infections often overestimated (Chiang *et al*., 2020; Chiang and Bock, 2022). Strategies to improve assessment reliability include computer-assisted tools and targeted training, which enhance reliability but may be temporary or context-dependent (Bock *et al*., 2020b), as well as standard area diagrams (SADs), which reduce error and improve inter-rater consistency by standardizing severity estimates across crops and pathosystems (González-Domínguez *et al*., 2014; Del Ponte *et al*., 2017).

Despite their utility, visual symptoms often require confirmation through laboratory-based diagnostics for accurate pathogen identification. Conventional methods include microscopy, isolation of pathogens in nutrient media, molecular, serological, or microbiological methods. Microscopy-based diagnostics characterize pathogen morphology following culture on selective media or direct observation when cultivation is not feasible, relying on features such as hyphae, spores, and reproductive structures (Ward *et al*., 2004). Although taxonomic keys assist identifications, isolation requirements prolong workflows and morphological similarity among closely related organisms can limit discrimination (Ward *et al*., 2004; Martinelli *et al*., 2015). While simple and low-cost, these approaches often lack reproducibility or suitability for non-culturable pathogens, prompting the use of molecular and serological assays for rapid and scalable disease detection (Martinelli *et al*., 2015; Buja *et al*., 2021; Pereira *et al*., 2025).

Over recent decades, DNA-based and serological/immunological assays, including polymerase chain reaction (PCR), loop-mediated isothermal amplification (LAMP), fluorescence *in situ* hybridization (FISH), and enzyme-linked immunosorbent assay (ELISA), have provided high specificity and sensitivity for pathogen detection (Fang and Ramasamy, 2015; Yang *et al.* 2025). These techniques have advanced pathogen diagnostics, enabling rapid and precise identification across field, greenhouse, and supply chain contexts (Bock *et al*., 2010; Mahlein, 2016; Pereira *et al*., 2025). Despite their sensitivity, these methods remain constrained by sample preparation requirements, lengthy workflows, dependence on skilled well-trained personnel, and reliance on specialized laboratory infrastructure, all of which can delay diagnostic outputs (Buja *et al*., 2021). Accurate disease diagnoses also depend on appropriate sampling procedures. Tissue collection, transport, and storage conditions can affect the integrity of nucleic acids, proteins, and pathogen structures, potentially leading to false-negative or false-positive results (Pereira *et al*., 2025). Therefore, the selection of suitable plant tissues and diagnostic methods must be aligned with specific objectives of analyses, and be supported by adequate technical expertise and laboratory capacity (Trippa *et al*., 2024).

Table 1. Overview of plant pathogen detection techniques, classified by detection mechanism, target organisms, and diagnostic performance indicators.

Category	Method/Platform	Target pathogen	Limit of detection (LOD)/ Feature	Reference
Immunological and molecular diagnostics	ELISA (standard / variants)	Viral, bacterial and fungal pathogens (various species)	Varies significantly based on the pathogen type (e.g. *Xylella fastidiosa*: 10^5 CFU mL^{-1})	Waliullah *et al*., 2019
	Lateral flow immunoassay (LFIA)	Viral and bacterial pathogens (e.g., *Erwinia amylovora*)	~0.25 ng mL^{-1}	Razo-Regino *et al*., 2021
	Conventional PCR	Viral, bacterial and fungal pathogens (various species)	Varies significantly based on the pathogen type (*Magnaporthe oryzae:* 10^6 copies/reaction)	Karan *et al*., 2026
	Real-time PCR (qPCR)	Viral, bacterial and fungal pathogens (e.g. Candidatus *Liberibacter* spp.)	6 copies μL^{-1}	de Chaves *et al*., 2023
	Droplet digital PCR (ddPCR)	Fungal pathogens (e.g., *Tilletia caries*)	0.24 fg μL^{-1}	Ren *et al*., 2022
Isothermal Amplification Techniques	LAMP (including digital LAMP variants)	Bacterial, phytoplasmas, fungal, viral pathogens (e. g., *Magnaporthe oryzae, Fusarium oxysporum* f. sp. *Cicero*, *Xylella fastidiosa*, *Ralstonia solanacearum*)	~10 fg to 100 ng nucleic acid per µl	Muthukumar *et al*., 2025
	Recombinase polymerase amplification (RPA)	Sugarcane mosaic virus (SCMV) + Maize chlorotic mottle virus (MCMV)	10^2 copies μL^{-1}	Gao *et al*., 2021
	RPA-LFA	*Ralstonia solanacearum*	1 pg DNA; 10^3 CFU/g stems; 10^4 CFU/g soil	Li *et al*., 2021
CRISPR-based Diagnostics	CRISPR-Cas12a platforms (LAMP/RPA-DETECTR)	*Xylella fastidiosa*, *Setophoma terrestris*, Chili leaf curl virus (ChiLCV)	Femtomolar to fg-level detection (~7 fg μL^{-1} ChiLCV)	Farrall *et al*., 2024; Zhao *et al*., 2024; Paul *et al*., 2025
	SHERLOCK (Cas13a)	RNA viruses (e. g., ToBRFV)	Sub-femtomolar RNA detection	Zhang *et al*., 2022b
	One-pot LAMP–Cas12b	*Fusarium oxysporum* f. sp. *Lycopersici*	88.9 copies $reaction^{-1}$	Dai *et al*., 2024
	iSCAN-one-pot (iSCAN-OP)	RNA viruses (e.g. PVX, PVY)	down to picomolar range	Aman *et al*., 2020
	Portable Cas12a diagnostic platform	*Leptosphaeria maculans*	4.7 genomic copies	Lei *et al*., 2022
	RT-RAA–Cas12a lateral flow assay	Maize chlorotic mottle virus (MCMV)	2.5 RNA copies	Lei *et al*., 2023
Genomic Approaches	DNA microarrays	Multiple plant pathogens	Simultaneous detection of many pathogens	Lievens *et al*., 2005
	Metagenomic Sequencing	Tomato wilt pathogens (*Ralstonia solanacearum, Pseudomonas corrugata*)	Strain-level detection	Abdelrazek *et al*., 2025
	Nanopore sequencing (ONT MinION)	*Xylella fastidiosa, Phytophthora infestans*	10^1 copies μL^{-1}, early detection	Marcolungo *et al*., 2022; Fratini *et al*., 2026

(Continued)

Table 1. (Continued).

Category	Method/Platform	Target pathogen	Limit of detection (LOD)/ Feature	Reference
Electrochemical Biosensors	Electrochemical impedance spectroscopy (EIS)	*Pseudomonas syringae* pv. *Lachrymans*	337 CFU mL^{-1}	Cebula *et al*., 2019
	DNA-based nanobiosensor	*Phytophthora palmivora*	0.3 ng mL^{-1}	Franco *et al*., 2019
	Amperometric microfluidic biosensor	Citrus tristeza virus (CTV)	0.3 fg mL^{-1}	Freitas *et al*., 2019
	EGOFET-based biosensor	Plum pox virus (PPV)	180 pg mL^{-1}	Berto *et al*., 2019
	Graphene-based electrochemical biosensors	*Ustilaginoidea virens*	10 fmol L^{-1}	Rana *et al*., 2021
Optical Biosensors	Gold nanoparticle (AuNP) colorimetric assay	*Xanthomonas campestris*	~100 bacterial cells (10^2 CFU mL^{-1}).	Peng and Chen, 2019
	Surface plasmon resonance (SPR) biosensor	*Xylella fastidiosa*	10^5 CFU mL^{-1}	Sarcina *et al*., 2021
	AuNP-based lateral flow biosensor	*Phytophthora infestans*	0.1 pg μL^{-1}	Zhan *et al*., 2018
	Quantum-dot FRET biosensor	*Ganoderma boninense*	3.55×10^{-9} M	Mohd Bakhori *et al*., 2013
Piezoelectric (Mass-Sensing) Biosensors	Quartz crystal microbalance (QCM) based biosensor	Maize chlorotic mottle virus (MCMV)	~ 250 ng mL^{-1}	Huang *et al*., 2014
	Surface acoustic wave (SAW) biosensor	Grapevine leafroll-associated virus 3 (GLRaV-3)	0.3 ng	Rizzato *et al*., 2023

Despite their high sensitivity and specificity, these laboratory-based diagnostic approaches are often constrained by time, cost, and infrastructure requirements, reinforcing the need for complementary sensor-based and AI-driven approaches that enable rapid, scalable, and in-field disease detection (Table 1).

SENSING TECHNOLOGIES FOR PEST AND DISEASE MONITORING IN PRECISION AGRICULTURE

Sensing technologies based on imaging or punctual measurements, provide the foundations of precision agriculture systems for pest and disease monitoring, as they enable the acquisition of spatially and temporally resolved information on crop condition, pest presence, and disease development (Kanwal *et al*., 2022). By capturing variations in plant reflectance, canopy structure, and microclimatic conditions, sensing systems facilitate early detection of different forms of biotic stress, and provide essential inputs for site-specific crop protection strategies (Dhau *et al*., 2017, 2018; Rothe and Rothe, 2019; Samreen *et al*., 2022). Advances in sensing technologies have expanded the scope of precision agriculture from descriptive monitoring toward predictive and proactive plant health management, determined from real-time, data-rich observations (Way and Van Emden, 2000; Thomson *et al*., 2012; Huang *et al*., 2013, 2015).

The main detection/sensing methods for pest and disease monitoring in precision agriculture include optical sensing (RGB, multispectral, hyperspectral, LiDAR, thermal, and sun induced fluorescence imaging), synthetic aperture radar (SAR), and in-field electronic sensing systems (IoT sensors, smart traps, VOC detection). Among the available sensing technologies, optical image data has a central role, due to its non-destructive, non-invasive nature and its capacity to observe subtle host plant physiological and structural changes associated with pest infestation and disease onset. Optical data acquired across multiple spatial scales, ranging from

leaf-level measurements to canopy and field-scale observations, form the bases of many contemporary pest and disease monitoring systems (Moran *et al*., 1997; Bastiaanssen *et al*., 2000; Pinter *et al*., 2003; Mulla, 2013; Huang *et al*., 2018; Kanwal *et al*., 2022). Figure 2 illustrates a conceptual framework of digital and remote sensing-based pest and disease detection methods in agriculture, integrating multi-source data acquisition, feature engineering, machine and deep learning modelling, and decision support components.

These sensing modalities capture complementary signals linked to plant physiological status. For example, multispectral and hyperspectral sensors detect changes in plant pigment composition, water content, and cellular structure; thermal sensors capture alterations in canopy temperature associated with transpiration and stomatal regulation; fluorescence sensing provides direct insight into photosynthetic efficiency; and VOC sensors detect stress-induced metabolic emissions. SAR contributes additional value through its ability to operate independently of illumination and cloud cover, enabling all-weather monitoring of canopy structure and moisture dynamics. IoT-based in-field sensors further enhance system resolution by continuously recording environmental variables such as temperature, humidity, and leaf wetness, which are drivers of disease development.

Optical and complementary sensing approaches for plant health assessments

Optical sensing approaches are widely employed in precision agriculture to assess plant health, by analysing reflected or emitted radiation from plants across the visible and non-visible regions of the electromagnetic spectrum. These approaches include passive (RGB imaging, multispectral and hyperspectral sensing, and thermal and fluorescence-based sensing), and active (LiDAR and SAR) sensing methods, each offering complementary information on crop condition, canopy structure, and physiological stress responses to existing field conditions. This section of the review also incorporates SAR, as it is weather-independent and provides complementary information on canopy structure, surface roughness, and structural and moisture dynamics. When integrated with optical data, SAR can improve robustness of plant health assessment, particularly under cloudy conditions or in regions where optical image acquisition is frequently constrained. Table 2 summarizes the main sensing technologies used for plant health monitoring, highlighting their principal applications, strengths, and limitations, while Figure 3 illustrates their integration with different platforms and applications for plant health monitoring in precision agriculture.

RGB imaging

Despite its limited production of spectral information, RGB imaging is a widely used technique for plant health monitoring, due to its affordability and ease of deployment across ground-based systems, unmanned aerial vehicles (UAVs), and fixed monitoring installations (Kouadio *et al*., 2023). Changes in colour, texture, leaf shape, canopy appearance, and leaf morphology captured in RGB imagery can be associated with pest damage and disease symptoms, enabling their automated detection when combined with image analysis, machine learning, pattern recognition techniques, and deep learning algorithms.

In practice, RGB imagery has supported plant disease diagnoses and pest detection, with strong reported performance. For disease monitoring, the Automated Agricultural Crop Disease Identification System (AACDIS) used RGB leaf images to classify four apple leaf diseases, and gave a best test performance (Model 3) of 99.49% accuracy, with an F1-score of 0.99, precision of 0.98, and recall of 1.00 (Krishna *et al*., 2025). For pest monitoring, RGB images captured from automated pheromone traps in orchard conditions were used to detect fruit flies (Ahmed *et al*., 2024). The study reported 97.50% overall accuracy, 92.82%precision, 98.92% recall, an F1-score of 95.00%, and also had strong discrimination performance with AUC = 0.97 on the Receiver Operating Characteristic (ROC) curve, indicating excellent predictive capability. Beyond image classification, RGB imagery has also been applied to field-scale multiclass detection and counting, where small target sizes and dense pest distributions make monitoring challenging. Using RGB pest-trap images in the Pest24 dataset, the Pest-PVT detector achieved mean average precision (mAP) of 77.2%, precision of 78.42%, recall of 81.27%, and an F1-score of 0.80, highlighting the feasibility of robust pest detection under complex field-scale conditions (Chen *et al.,* 2025). These results demonstrate that RGB imaging in combination with deep learning architectures can achieve satisfactory detection performances, while maintaining practical advantages of cost and deployment flexibility.

Multispectral and hyperspectral imaging

Multispectral and hyperspectral imaging extend RGB-based analyses by capturing plant reflectance beyond the visible spectrum. While RGB imaging is lim-

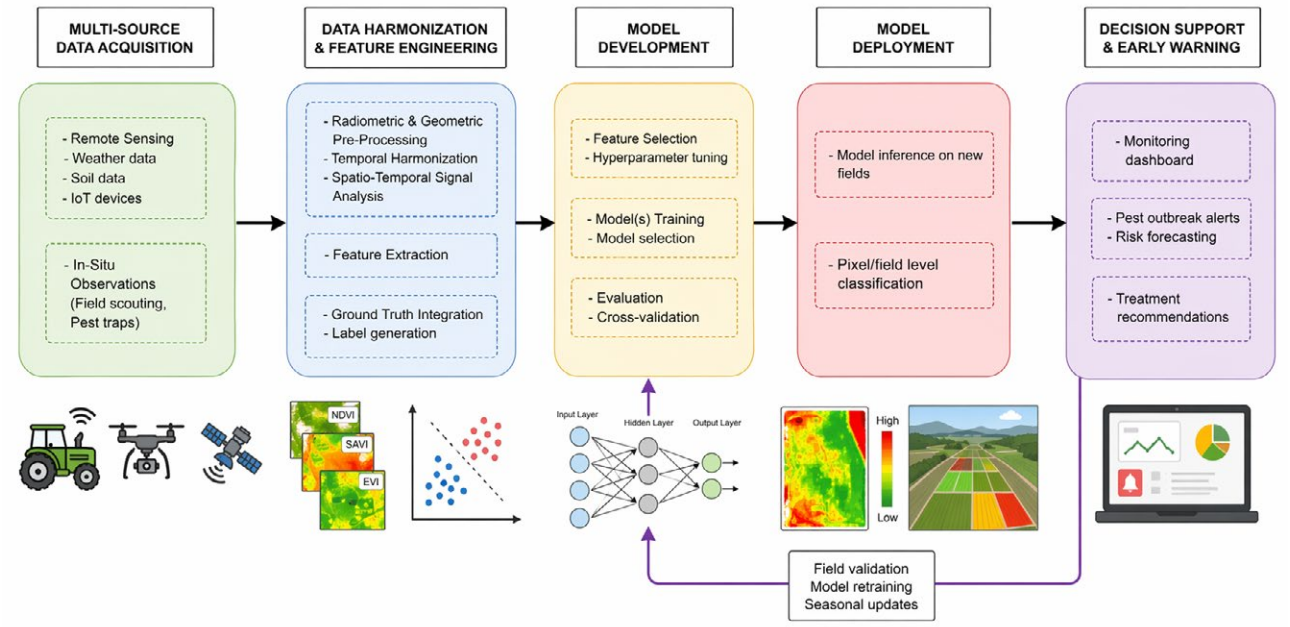


Figure 2. Conceptual framework for digital and remote sensing-based pest and disease detection methods in agriculture, integrating multi-source data acquisition, feature extraction, machine learning–based modelling, and decision-support systems for precision crop protection.

ited to the 400 to 700 nm wavelength range, multispectral and hyperspectral sensors operate across the visible, near-infrared (NIR), and shortwave infrared (SWIR) wavelengths, enabling detection of physiological and biochemical stress responses associated with pest infestation and disease development that may not be visually apparent to human observers (Lowe *et al.*, 2017). Multispectral sensors acquire reflectance in a limited number of discrete and often broad spectral bands, whereas hyperspectral sensors measure in more narrow bands of the electromagnetic spectrum, providing high resolution spectral information for detailed characterization of plant biochemical composition and leaf structural traits. These technologies are valuable for early stress detection, disease severity assessments, and spatial mapping of pest- and disease-affected areas (Lowe *et al.*, 2017), which can be applied across multiple spatial levels, such as leaf, canopy, field, and regional scales. Compared to multispectral imaging, hyperspectral sensors offer greater spectral richness that improve sensitivity to subtle physiological changes, enhancing ability to detect early or pre-symptomatic plant stress. However, hyperspectral systems are typically expensive, and generate large and complex datasets with coarse spatial resolution. In contrast, multispectral imaging is a more cost-effective and operationally practical solution, although with reduced spectral specificity.

The diagnostic value of multispectral and hyperspectral imaging lies in the mechanistic relationship between spectral regions and plant physiological processes. Reflectance in the visible spectrum is primarily governed by pigment composition, making blue, green, and red wavelengths sensitive to chlorophyll degradation, carotenoid shifts, anthocyanin accumulation, chloroses, and necroses. The red-edge region is particularly informative for detecting early changes in chlorophyll status and photosynthetic activity, before symptoms become visually apparent. Near-infrared reflectance is mainly influenced by leaf internal structure and canopy architecture, allowing detection of tissue disruption, cell collapse, and biomass changes. Shortwave-infrared wavelengths are strongly associated with water content and biochemical constituents such as cellulose, lignin, proteins, and starch, providing indicators of dehydration, membrane damage, and pathogen-induced metabolic reprogramming. Spectral sensing therefore links pathogen-driven physiological disruption to measurable optical signatures or unique “fingerprints”, enabling disease assessment to move beyond visual symptom recognition toward quantitative and mechanistic plant health monitoring. Stress responses like drought or pathogens alter these signatures. An example is the Photochemical Reflectance Index (PRI) in narrow green-yellow bands, which tracks photoprotection and light-use efficiency, often before visible disease symptoms appear. This non-destructive approach bridges optical data to processes such as photosynthesis, stress acclimation, and nutri-

Table 2. Overview of optical and complementary sensing technologies for plant health assessments.

Sensing technology	Applications for plant health monitoring	Main advantages	Main limitations
RGB imaging	Visual symptom detection (colour changes, texture, pest damage identification, pattern recognition)	Low cost, high spatial resolution, easy deployment (from smartphones to UAVs), intuitive interpretation	Limited spectral information, low sensitivity to early/latent stress, high sensitivity to illumination and shadows
Multispectral imaging	Vegetation indices (NDVI, NDRE), crop vigour monitoring, stress detection, nutrient and water deficiency mapping	Targeted bands (e.g. red-edge, NIR) sensitive to physiology, moderate data volume, operational sensors on drones and satellites	Subtle biochemical signals can be missed, sensor cost greater than RGB, band choices may not generalize across crops and diseases
Hyperspectral imaging	Early disease detection, biochemical trait estimation (chlorophyll, water content), pest stress detection.	High spectral resolution, strong potential for early, non-destructive disease diagnostics	High cost, large data volume, computational complexity, data redundancy, calibration challenges
LiDAR (active laser sensing)	3D canopy structure, plant height, biomass estimation, structural damage assessment	Independent of solar illumination, accurate structural metrics, penetrates canopy, addition to spectral data	Affected by atmospheric conditions, processing complexity. Limited for disease-specific diagnoses
Thermal infrared imaging	Stress detection *via* canopy temperature anomalies, physiological stress monitoring linked to transpiration disruption	Direct proxy of transpiration and water stress, useful for drought monitoring	Affected by atmospheric conditions, canopy structure, background effects. Limited for disease-specific diagnosis
Fluorescence-based sensing	Detection of pest and disease stress via monitoring of photosynthetic efficiency and physiological disruption	Sensitive to presymptomatic stress, provides direct functional insights into plant physiological status	Acquisition geometry and ambient light strongly affect measurements, more common in proximal than large-scale field deployments. Specialized and often costly
Synthetic Aperture Radar (SAR)	Monitoring soil and canopy moisture, flood detection	Weather and daylight independent, sensitive to structure, frequent coverage from satellites, complement to optical indices	Not linked to plant physiology, speckle noise and complex backscatter mechanisms, interpretation requires ground data

ent uptake, for precision monitoring in phytopathology (Mahlein *et al*., 2016), as schematized in Figure 4.

Applications of multispectral imaging for pest and disease monitoring have demonstrated that a limited number of discrete spectral bands, particularly in the visible and near-infrared regions, can be sufficient for reliable disease detection, especially when combined with machine and deep learning techniques (Saleem *et al*., 2019). A field-based study using near-infrared (NIR) multispectral imagery, collected leaf images of ten agricultural crop species under natural environmental conditions, and demonstrated effective discrimination between healthy and diseased plants. The multispectral dataset was evaluated using multiple convolutional neural network architectures under different train-test splits, and the best-performing model (Xception) achieved a training accuracy of 100% and a test accuracy of 87.17% under a 10:90 train-test split. Saleem *et al.* (2019) also reported class-dependent precision and recall values, and highlighted the influence of training data availability on model performance. These results demonstrate that multispectral NIR data collected outside controlled laboratory settings can support automated disease identification, indicating its potential suitability for practical field deployment in precision agriculture systems (De Silva and Brown, 2023).

Applications of hyperspectral imaging in pest and disease monitoring have demonstrated ability to detect infestations through canopy-level spectral changes. Fitzgerald *et al*., 2004, using airborne hyperspectral sensing, showed that changes in canopy colour and reflectance patterns were associated with early mite infestations in cotton, indicating that pest-induced stress could be detected prior to severe visual damage. Their study used AVIRIS hyperspectral imagery (224 contiguous bands spanning 400–2500 nm) to accurately map spider mite damage across commercial cotton fields. Spectral analysis successfully discriminated between infested and control plots, with no false positives detected in control fields during key observation periods. Quantitative analyses revealed a statistically significant correlation between shade-normalized mite abundance fractions and yield-based damage severity ($r^2 = 0.60$), with substantial yield loss differences between infested and protected fields (1338 *vs.* 3310 kg ha^{-1}; $P < 0.0001$), confirming the agronomic relevance of hyperspectral stress detection.

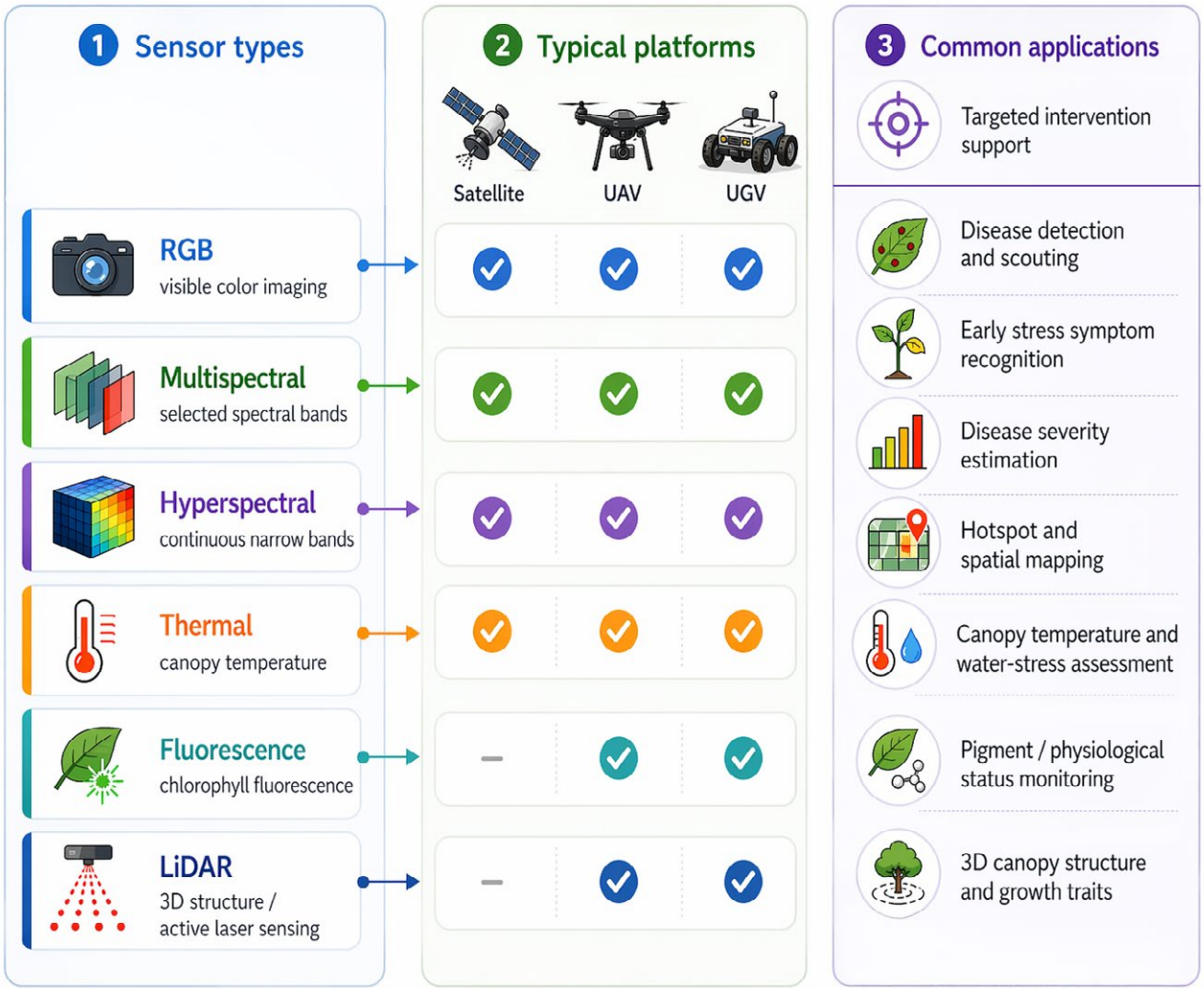


Figure 3. Integration of sensing technologies, platforms, and applications, for plant health monitoring in precision agriculture.

The potential of hyperspectral satellite imagery (PRISMA) has also been demonstrated using PRISMA data for monitoring maize ear damage caused by cotton bollworm larvae in Hungary. In comparison analyses, PRISMA outperformed Sentinel-2 for sweet maize pest monitoring, while Sentinel-2 showed better performance for sweet maize, highlighting the importance of crop type and sensor characteristics for detection performance (Sári-Barnácz *et al.*, 2023). Hyperspectral approaches have also been explored for proximal grapevine disease detection. Spectral measurements across the 350–2500 nm range revealed disease-associated reflectance changes in grapevines affected by grapevine leaf stripe disease, demonstrating the potential of proximal hyperspectral sensing for non-destructive symptom detection (Junges *et al.*, 2018). Similarly, ground-based hyperspectral imaging (400–2500 nm) has been used to detect grapevine leafroll disease (GLD) caused by GLRaV-1 and GLRaV-3 in white and red grapevine cultivars, enabling discrimination between symptomatic, asymptomatic, and healthy plants, under greenhouse and field conditions (Bendel *et al.*, 2020).

Light Detection and Ranging (LiDAR)

The active remote sensing technology LiDAR uses laser pulses to measure distances in an environment, which can generate high-resolution three-dimensional representations of vegetation structures. Detailed information such as canopy height, density, volume, and architecture can be calculated, enabling precise characterization of plant structural traits that are often affected by pest infestations and disease development. Structural changes such

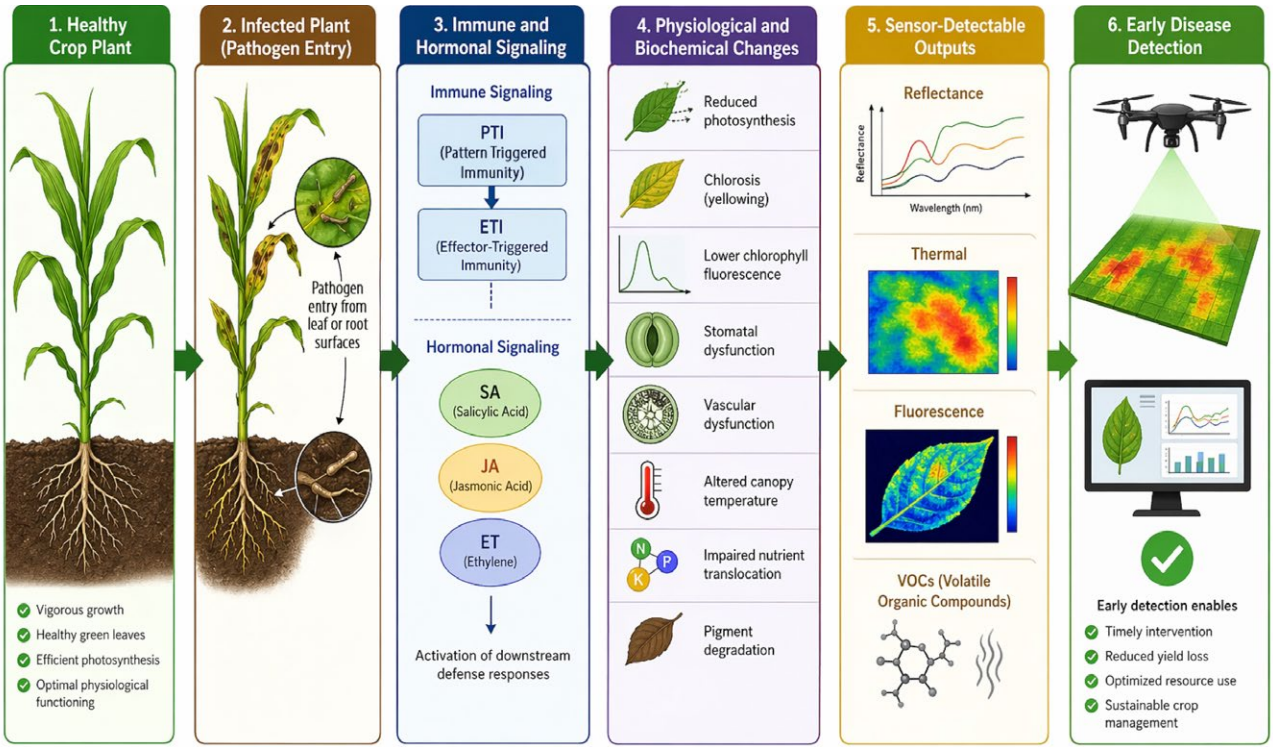


Figure 4. Conceptual framework linking plant-pathogen interactions with physiological responses and sensor-based disease detection in precision agriculture.

as reduced canopy density, defoliation, altered plant architecture, and growth suppression can therefore be detected through LiDAR-derived metrics. LiDAR data can be integrated with other remote sensing modalities, particularly multispectral and hyperspectral imagery, to improve plant health assessments and disease detection (Farhan *et al.*, 2024). For example, Franceschini *et al.* (2024) combined LiDAR-derived point cloud features with hyperspectral vegetation indices to detect blackleg in potatoes. Integration of structural and spectral information improved classification accuracy by up to 18% compared to models based solely on spectral data, highlighting the complementary value of LiDAR for capturing disease-induced morphological changes in plants. Overall, LiDAR provides a unique structural perspective that complements spectral and thermal sensing, by linking pathogen-induced physiological stress to measurable alterations in plant architecture, making it particularly valuable in multi-sensor data fusion frameworks for precision disease monitoring.

Thermal imaging

Thermal imaging can exploit differences in canopy temperature to detect plant stress associated with pest infestations and disease development (Jackson *et al.*, 1981; Chattopadhyay *et al.*, 2024). Because biotic stress often disrupts transpiration and stomatal regulation, affected plants typically exhibit elevated leaf or canopy temperatures relative to healthy vegetation (Idso *et al.*, 1981). Thermal sensors measure emitted longwave infrared radiation, enabling non-contact assessment of plant physiological responses that frequently precede visible symptoms of plant stress (Leinonen and Jones, 2004; Oerke *et al.*, 2014). Thermal imaging is directly linked to plant water status and stomatal conductance: pathogen-induced stomatal closure reduces evaporative cooling, leading to increased canopy temperatures. This makes thermal sensing particularly effective for detecting early physiological stress associated with vascular dysfunction, impaired transpiration, and altered water-use efficiency.

Applications of thermal imaging for disease detection have demonstrated its effectiveness in identifying stress-related temperature anomalies at leaf and canopy scales. Ground-based thermal imaging has been used to detect Fusarium head blight in wheat, where infected plants exhibited higher canopy temperatures due to reduced transpiration (Mahlein *et al.*, 2019; Chattopadhyay *et al.*, 2024). When combined with machine learning techniques, thermal features enabled accurate dis-

crimination between healthy and infected plants, demonstrating the sensitivity of thermal signals to disease-induced physiological disruption.

Thermal imaging has also been successfully applied for field-scale disease monitoring using aerial platforms. For example, in citrus orchards, UAV-based thermal imaging was used to map Huanglongbing (HLB, citrus greening disease), where temperature-derived features were integrated into object-based image analysis frameworks for spatial disease mapping (Garcia-Ruiz *et al*., 2013; Sankaran *et al*., 2013). In olive trees, integration of thermal imaging with airborne hyperspectral images enabled differentiation between *Verticillium dahliae* and *Xylella fastidiosa* infections, combining temperature-based stress indicators with spectral traits related to plant pigments and photosynthetic activity (Poblete *et al*., 2021). Key spectral traits, such as the blue index, structural parameter, and carotenoid pigment content, were effective for differentiating *Verticillium dahliae* infections, while traits of the normalized PRI index, blue index, fluorescence curvature reflectance-based index, and chlorophyll index were effective for identifying *Xylella fastidiosa* infections. Strong agreement between thermally detected stress patterns and expert field assessments demonstrated the potential for canopy temperature anomalies to be used for operational disease mapping.

Despite these advantages, thermal imaging is sensitive to environmental conditions, including solar radiation, wind speed, humidity, and background soil temperature, which can confound biotic stress signals if not adequately controlled. Therefore, consistent acquisition conditions, relative temperature analysis, and normalization against reference healthy vegetation to reduce environmental effects on thermal measurements are essential to improve assessment reliability. Therefore, thermal sensing is most effective when integrated with complementary optical and environmental data, rather than used as a stand-alone diagnostic tool for pest and disease detection (Grisso *et al*., 2005; Kuenzer and Dech, 2013; Chattopadhyay *et al*., 2024).

Fluorescence-based optical sensing

Fluorescence-based optical sensing, particularly chlorophyll fluorescence imaging (Chl-FI), exploits changes in chlorophyll α fluorescence emission to assess alterations in photosynthetic activity induced by biotic stresses. Because photosynthesis is linked with plant defense and metabolic regulation, pest infestations and pathogen infections often cause measurable disruptions in photosystem II (PSII) efficiency before visible symptoms appear. Chlorophyll fluorescence imaging enables spatially and temporally resolved assessments of these functional changes at cellular, leaf, and whole-plant scales, making it a sensitive tool for plant stress phenotyping (Pérez-Bueno *et al*., 2019).

Applications of fluorescence-based sensing for pest and disease monitoring have demonstrated potential for presymptomatic detection of biotic stresses. Experimental studies have shown that viral, bacterial, and fungal infections, as well as insect herbivory, alter key fluorescence parameters, including maximum quantum efficiency of PSII (Fv/Fm), effective quantum yield (ΦPSII), and non-photochemical quenching (NPQ). These alterations frequently exhibit spatially heterogeneous patterns that correspond to pathogen infection sites or pest feeding zones, and can be detected prior to visible symptom development, highlighting the sensitivity of fluorescence signals to early physiological disruption (Cséfalvay *et al*., 2009; Honorato Júnior *et al*., 2015).

Fluorescence imaging has been applied under controlled and semi-controlled conditions, using active illumination systems, such as pulse-amplitude-modulated (PAM) fluorometers, to characterize host-pathogen and host-pest interactions. The reviewed studies demonstrate that Chl-FI can differentiate between compatible and incompatible plant-pathogen interactions, can track disease progression over time, and quantify stress severity through spatial analysis of fluorescence parameter distributions. In several crop-pathogen systems, fluorescence-based indicators have shown correlations with infection severity and pathogen spread, providing functional insights that complement reflectance-based imaging approaches (Pineda *et al*., 2011; Rousseau *et al*., 2013; Barón *et al*., 2016).

Despite its high sensitivity, the operational deployment of fluorescence-based sensing in precision agriculture remains constrained by technical and environmental limitations. Active fluorescence measurements require controlled excitation and are sensitive to ambient light conditions, which complicates large-scale deployment under natural field environments. However, emerging approaches, including laser-induced fluorescence (LIF) and sun-induced fluorescence (SIF), are expanding the potential for fluorescence-based monitoring at plant canopy and regional scales. Overall, fluorescence sensing is currently most effective as a complementary modality, integrated with spectral, thermal, and environmental data sources, to enhance early disease detection and physiological interpretation rather than for use as a standalone solution for pest and disease monitoring (Pérez-Bueno *et al*., 2019). Looking ahead, the future European Space Agency (ESA) FLEX satellite mission, planned for September 2026, will provide multi-band SIF observations in synergy with Sentinel-3, and will be capable of directly measuring the small amount of fluorescence emitted by plant chloroplasts from

space (Verrelst *et al*., 2026), thereby enabling global monitoring of plant photosynthetic activity and stress.

Synthetic Aperture Radar (SAR)

Synthetic Aperture Radar (SAR) is an active microwave sensing technology that enables all-weather, day-night monitoring of agricultural fields, as it is largely insensitive to cloud cover and illumination conditions. Unlike optical sensors, SAR measures backscattered microwave signals, which are influenced by canopy structure, surface roughness, and moisture content, rather than spectral reflectance. These characteristics make SAR particularly valuable in environments where optical data acquisition is constrained by atmospheric conditions (Alexopoulos *et al*., 2023).

For pest and disease monitoring, SAR is primarily used to capture indirect indicators of crop stress, including changes in canopy structure and moisture dynamics resulting from pest damage or disease progression. Time-series analysis of SAR backscatter can reveal deviations in crop growth patterns and canopy development, supporting broad-scale assessment of vegetation anomalies. Although SAR signals are not specific to particular pests or pathogens, they can effectively highlight areas of potential stress and abnormal structural or moisture changes that warrant closer inspection using increased resolution optical or in-field sensing (Muhammad *et al*., 2025). The greatest value of SAR for plant health monitoring lies in its integration with optical and in-field sensing data within multi-sensor frameworks. For example, the combined use of Sentinel-2 optical bands and Sentinel-1 C-band SAR has been successfully applied to map soil moisture and irrigation demand, demonstrating the complementary nature of microwave and optical observations (Bousbih *et al*., 2018).

SAR's robustness under variable atmospheric conditions makes it a reliable source of contextual information for filling temporal gaps in optical datasets, and for supporting continuous crop monitoring in regions with frequent cloud cover. As such, SAR sensing is increasingly recognized as a complementary data source that enhances the resilience, temporal resolution, and reliability of precision agriculture systems for plant health monitoring (Zhao *et al*., 2020; Berger *et al*., 2022).

SENSING PLATFORMS AND SCALES OF OBSERVATION

While optical sensing technologies can determine what type of plant health information can be captured, their practical application in pest and disease monitoring depends on the platforms used for data acquisition, and the spatial and temporal scales of observations. Different sensing platforms involve distinct trade-offs in coverage, spatial resolution, revisit frequency, operational complexity, and costs. Remote sensing, which relies on data collected at a distance from target plants, provides wide-area coverage at variable spatial resolutions and revisit intervals, enabling detection of crop health changes that may indicate pest infestations or disease development. In contrast, proximal and ground-based sensing systems use instruments positioned close to crop canopies, such as handheld, fixed tractor-mounted, robotic sensors, offering high spatial detail and flexible acquisition timing, although over limited spatial extent. Recent reviews have emphasized that no single platform is sufficient for robust crop health monitoring. Instead, satellite, UAV-based, and ground-based or proximal sensing systems should be used in complementary multi-scale frameworks, to improve detection accuracy, temporal continuity, and operational relevance in integrated precision agriculture frameworks (Huang *et al*., 2018; Alexopoulos *et al*., 2023).

Satellite-based platforms

Satellite platforms provide repeated, large-area observations that support regional- to field-scale monitoring of crop health. Optical satellite sensors are widely used to track vegetation conditions and identify spatial patterns associated with crop stress across extensive agricultural landscapes. Their strengths include wide spatial coverage, systematic data availability, and long-term temporal consistency, making them suitable for broad surveillance, early warning, and prioritization of areas requiring closer inspection. However, satellite-based observations and platforms are constrained by spatial resolution, revisit intervals, and atmospheric conditions such as cloud cover, which can limit detection of localized pest infestations or early-stage disease symptoms in individual fields. Consequently, satellite data are often used as first-tier monitoring tools within hierarchical and multi-scale sensing strategies (Huang *et al*., 2018).

Among publicly available satellite missions, Sentinel-2 is extensively used in agricultural applications due to its rich spectral configuration and moderate spatial resolution. The Sentinel-2 MultiSpectral Instrument (MSI) provides 13 spectral bands at 10 to 60 m spatial resolution. With its twin satellites, MSI covers the Earth every 5 d (Vuolo *et al*., 2016), providing data that can be utilized in pest detection. These characteristics enable development of disease-specific indices. An example

is the Red Edge Disease Stress Index (REDSI), which has been successfully applied for detecting yellow rust in winter wheat, achieving classification accuracies of 84.1% at crop canopy scale, and 85.2% at regional scale. Zheng *et al.* (2018) concluded that Sentinel-2 MSI and the REDSI index can support effective disease detection.

High spatial resolution satellite imagery data provides potential for precise identification of individual infested plants, and mapping of affected areas. For example, ZY-3 imagery has been used to map wheat rust, with classification accuracies ranging from 90.8% to 95.1%, using machine learning approaches such as support vector machines (SVM) and random forests (RF) (Chen *et al*., 2018a). Similarly, high-resolution PlanetScope imagery (~3 m) combined with RF classification has been applied to detect sudden death syndrome in soybean fields in Iowa, United States of America, achieving detection accuracies exceeding 75% even before the appearance of visible disease symptoms (Raza *et al*., 2020).

Unmanned aerial vehicle (UAV)-based platforms

Unmanned aerial vehicle (UAV) platforms offer high-resolution, flexible, and on-demand data acquisition at field scale, bridging the gap between satellite observations and ground-based sensing. UAVs can be equipped with a wide range of sensors, including RGB, multispectral, hyperspectral, thermal, and fluorescence sensors, enabling targeted monitoring of pest and disease dynamics under specific phenological and environmental conditions. Published literature highlights the effectiveness of UAV-based sensing for capturing spatial heterogeneity in crop health, identifying infestation hotspots, and supporting site-specific pest or disease management decisions. For example, UAV-acquired hyperspectral imagery has demonstrated strong potential for tree crop disease detection. Navrozidis *et al.* (2023) applied Random Forest (RF) and XGBoost classifiers to UAV-derived spectral signatures to discriminate healthy from infected olive trees, optimizing model performance through Recursive Feature Elimination and Mutual Information techniques for spectral feature selection. Both classifiers achieved high discrimination accuracy, with RF and XGBoost reaching ROC-AUC scores, respectively, of 0.977 and 0.955, trained on a dataset of 1,507 features derived from 11 statistical descriptors across 137 spectral bands. Despite these advantages, UAV deployment is constrained by regulatory requirements, limited flight endurance, sensitivity to weather conditions, and requirement for substantial data processing and management (Huang *et al*., 2018). In addition, the transferability of UAV-based models between fields and acquisition periods remains challenging, as models often learn field-specific or season-specific patterns rather than disease-specific signals.

Ground-based and proximal sensing platforms

Ground-based and proximal sensing platforms provide detailed observations at the plant, canopy or plot scales, and enable high-frequency monitoring of pest and disease processes. These platforms include handheld instruments and sensors, fixed imaging systems, vehicle-mounted systems, automated monitoring stations, and smart traps designed specifically for pest surveillance. Several studies have reported integration of proximal sensing with IoT architectures and wireless communication systems, enabling near-real-time data acquisition, transmission, and decision support. While proximal sensing offers high temporal resolution and detailed and precise local measurements, its spatial coverage is inherently limited, necessitating strategic sensor deployment or integration with aerial and satellite observations (Alexopoulos *et al*., 2023).

Proximal measurements serve as ground-truth data for calibrating and validating remote sensing observations. For example, hyperspectral reflectance data collected using handheld instruments provide detailed insight into plant–pathogen interactions, and are essential for interpreting satellite and UAV-derived signals (Prabhakar *et al*., 2022). In a representative application, ground-based hyperspectral imaging (400–2500 nm) has been successfully applied to detect grapevine leafroll disease (GLD) in white and red grapevine cultivars, caused by GLRaV-1 and GLRaV-3, enabling discrimination between symptomatic, asymptomatic, and healthy plants under greenhouse and field conditions (Bendel *et al*., 2020). Similarly, an ASD FieldSpec HandHeld 2 hyperspectral radiometer (350–1075 nm) was used under field conditions to discriminate five Verticillium wilt severity levels in cotton, with the best-performing model achieving 91.2% overall accuracy (Zhang *et al*., 2023). In vineyards, portable Hamamatsu C12880MA (340–850 nm) and DLP NIRScan Nano (900–1700 nm) spectrometers were evaluated for discriminating asymptomatic Flavescence dorée-positive and healthy grapevine leaves, with the Hamamatsu sensor achieving up to 96% classification accuracy when combined with feature selection and logistic regression (Imran *et al*., 2023).

Multi-platform integration

An increasing number of precision agriculture systems adopt multi-platform sensing strategies that inte-

Table 3. Overview of recently developed remote sensing-based methods and technologies that have been used across different platforms and sensors for pest and disease detection in crops.

Platform/Sensor	Method	Crop	Pest/Disease	Reference
UAV (hyperspectral and thermal)	Correlation analysis	Olive	Verticillium wilt	Calderón *et al*., 2013
UAV (multispectral)	Multilayer perceptron, CNN, RF, SVR	Potato	*Phytophthora infestans*	Duarte-Carvajalino *et al*., 2018
ZY-3 satellite	SVM and RF	Wheat	Wheat rust	Chen *et al*., 2018b
Sentinel-2	Optimal threshold method	Wheat	Wheat Yellow Rust	Zheng *et al*., 2018
Ground-based hyperspectral sensor	Various ML models	Grapevine	Grapevine Leafroll-Associated Virus 1 and 3	Bendel *et al*., 2020
PlanetScope satellite	RF	Soybean	Sudden death syndrome	Raza *et al*., 2020
UAV and IoT	Image-based pest recognition	Rice	Multiple pests	Bhoi *et al*., 2021
Multisource UAV	Back-propagation NN and SVM	Arecanut	Yellow leaf disease	Lei *et al*., 2021
Sentinel-2	UNet++	Forest	Bark beetle, aspen leaf miner	Zhang *et al*., 2022a
Sentinel-1 and Sentinel-2	K-means clustering and fuzzy deep neural networks (FDNN)	Rice	Multiple diseases	Safari and Malian, 2024
UAV	RF and XGBoost	Olive	*Verticillium wilt,* and other olive diseases	Navrozidis *et al*., 2023
UAV	Karhunen-Loeve Expansion (KLE)	Sugar Belle mandarin, avocado	Citrus canker, Laurel wilt disease	Hariharan *et al*., 2023
UAV	Domain adaptation model - DATS-ASSFormer	Wheat	Wheat rust, wheat yellow dwarf, wheat scab	Zhang *et al*., 2025
UAV	CNN-ViT-based deep learning algorithm	Blueberry	Blueberry scorch virus (BIScV)	Jamali *et al*., 2025
Hyperspectral satellite imagery (PRISMA)	PLSR and linear regression	Maize	*Helicoverpa armigera*	Sári-Barnácz *et al*., 2024

grate satellite, UAV, and ground-based observations to leverage the strengths of each scale. Research literature consistently emphasizes that multi-scale integration enhances detection robustness, reduces uncertainty, and improves the operational relevance of pest and disease monitoring under field conditions (Alexopoulos *et al*., 2023). Recent advances in pest and disease detection integrate multi-source sensing data with machine learning (ML) and deep learning (DL) techniques, to improve detection accuracy and decision-making (Table 3). For example, Calderón *et al.* (2013) used multi-source data imagery (thermal, multispectral, and hyperspectral) to detect early-stage water stress associated with Verticillium wilt in olive trees. In their study, thermal indices including canopy temperature minus air temperature, Crop Water Stress Index, and the plant physiological indices of chlorophyll fluorescence, blue/green/red ratios, and the Photochemical Reflectance Index, were effective for identifying Verticillium wilt infections, and assessing disease severity in olive orchards. The study of Lei *et al.* (2021) used multispectral data and UAV high-resolution imagery to calculate five vegetation indices, including NDVI and OSAVI, and applied the machine learning algorithms of back-propagation neural networks (BPNN) and SVM to quantify disease severity, based on the yellowing area of areca crowns. These authors proposed integration of hyperspectral sensors with 3D laser radar and employing deep learning algorithms, highlighting the growing trend toward fully integrated, data-driven plant health monitoring systems.

IN-FIELD AND ENVIRONMENTAL SENSING TECHNOLOGIES FOR PEST AND DISEASE MONITORING

In-field and environmental sensing technologies provide continuous, localized measurements that capture microclimatic and ecological conditions that affect pest population dynamics and disease development. Unlike remote imaging approaches, these sensing systems operate directly within crop environments, offering high temporal

Table 4. Overview of recent IoT based methods for pest and disease detection in agriculture.

Method	Tools	Crops	Pests/Diseases	References
YOLOv8	Smartphones, cloud computing, and DSS	Tomato	*Tuta absoluta*	Christakakis *et al.* 2024
Optimized Yolov3 ResNet50	IoT sensors for capturing images	Multiple crops	102 insect pests (IP102 dataset)	Prasath and Akila, 2024
Multi-scale Dense YOLO	Insect traps, optical sensor	Orchards	Lepidoptera	Tian *et al.* 2023
SVM (IoT for activating spraying of pesticides)	Camera and NodeMCU	Multiple crops	Multiple diseases	Krishna *et al.* 2019
R-CNN and YOLOv5	Traps, cameras and mobile apps	Multiple crops	Whitefly pests	Cardoso *et al.* 2022
UNet and Deep batch normalized AlexNet	Web cameras and base station	14 species	38 diseases	Mishra *et al.* 2024
Tiny-LiteNet CNN (lightweight DL model on edge device)	AI-IoT edge device and onboard camera	Multiple cereals and vegetables	Multiple pests and foliar diseases	Nyakuri *et al.* 2025
DMF-ResNet	Acoustic sensors	-	32 types of insects	Dhanaraj *et al*., 2024

resolution and enabling early detection of conditions conducive to pest outbreaks and pathogen infections (Ahmed *et al*., 2024). By monitoring temperature, relative humidity, leaf wetness, soil moisture, rainfall, and wind speed variables, and pest activity, in-field sensors provide actionable information for disease forecasting, risk assessments, and timely interventions. When integrated with IoT architectures and decision-support systems, these technologies support responsive, site-specific, and preventive Integrated Pest Management (IPM) strategies (Table 4).

IoT-based environmental sensing

IoT-based environmental and soil sensing systems are widely used in precision agriculture, to monitor key abiotic variables that influence pest and disease epidemiology, including air and soil temperatures, relative humidity, leaf wetness duration, rainfall, and soil moisture (Khajuria *et al*., 2018). These variables are key factors affecting pathogen infection cycles, pest emergence, lifecycle completion, and population growth, making them essential inputs for pest and disease risk assessments. Environmental sensors are widely used to identify conditions favourable to pathogen infection and pest activity. Temperature and humidity affect fungal and bacterial disease cycles, while leaf wetness duration influences infection success for many foliar pathogens.

Continuous in-field measurements of these variables enable detection of short-duration favourable conditions that are often missed by periodic scouting or from monitoring of coarse-resolution weather data (Brunelli *et al*., 2019; Kumar *et al*., 2024). For example, an IoT-based weather station integrating measurements of air and soil temperatures and moisture, relative humidity, leaf wetness, rainfall, wind, and solar radiation measurements, was used to forecast early blight, late blight, and powdery mildew in potato and tomato (Khattab *et al*., 2019). The resulting disease-warning models enabled timely fungicide applications, and reduced spray frequency by 75 to 86% relative to fixed schedule programmes. Similarly, in-field IoT nodes deployed across four Spanish vineyards continuously recorded temperature, air and soil humidity, rainfall, wind speed, and wind direction, to run near-real-time warning models for downy mildew, powdery mildew, black rot, and disease caused by *Botrytis*. The system generated disease-specific alerts as environmental conditions approached defined infection thresholds, thereby supporting timely risk-based interventions (Trilles *et al*., 2019).

Soil sensors further extend environmental monitoring by capturing root zone conditions that directly affect soil-borne pathogens, plant stress, and pest habitat suitability (Bogena *et al*., 2009). Soil moisture and soil temperature sensors, in particular, can provide valuable information for monitoring environmental conditions conducive to specific root and crown diseases, as incidence and severity of diseases caused by *Fusarium* spp., *Rhizoctonia solani*, *Pythium* spp., *Phytophthora* root/crown pathogens are strongly influenced by interactions between soil moisture, temperature, and host susceptibility. For example, continuous soil moisture monitoring has been applied to identify conditions conducive to soil-borne disease development, and to support irrigation management strategies that reduce disease pressure. Recent advances in low-power, networked soil sensor systems have enabled long-term, *in-situ* monitoring and real-time data transmission, allowing soil-driven stress to be detected before above-ground symptoms become visible, thus improving reliability of pest and disease risk

assessments when combined with environmental sensing within precision IPM frameworks (Bogena *et al*., 2009; Yin *et al*., 2021). Continuous in-field monitoring therefore enables accurate disease forecasting and supports timely, risk-based interventions.

Smart traps and automated pest monitoring

Smart traps are an increasingly important in-field sensing approach for direct pest monitoring, combining conventional trapping mechanisms with sensors, imaging devices, and wireless communication. These systems are designed to automatically detect, identify, and quantify insect pests in near real time, reducing reliance on manual trap inspection and improving temporal resolution of pest population data. Recent studies report the use of image-based smart traps equipped with RGB cameras and embedded processing, to automatically identify target insect species using machine learning and deep learning models. For example, automated pheromone traps deployed under field conditions have been used to detect and classify fruit fly species with high accuracy, demonstrating high detection accuracy and reliable discrimination between target pests and non-target insects. These systems enable continuous monitoring of pest population dynamics, and can generate timely alerts when pest abundance exceeds predefined thresholds (Ahmed *et al*., 2024).

Beyond species identification, smart traps also support pest counting, population trend analyses, and spatial mapping of pest pressure. When connected through IoT architecture, trap data can be transmitted to centralized platforms where pest abundance is spatially and temporally visualized across multiple crop fields. This improves responsiveness of IPM interventions, and reduces labour requirements compared with conventional scouting-based methods (Chen *et al*. 2025). Smart traps are most effective when integrated with environmental sensing and decision-support systems. Environmental data provides context for interpreting pest activity, while automated trap observations provide direct evidence of pest presence and pressure. Together, these data streams support accurate, timely and threshold-based pest management decisions under field conditions, making smart traps key components of modern precision agriculture monitoring systems (Samreen *et al*., 2022).

Electronic spore traps

Electronic spore traps (e-spore traps) for fungal propagules are a rapidly advancing class of in-field sensing technologies for automated monitoring of airborne inoculum. These enable high-resolution, and real-time assessments of disease risk in precision agriculture. These systems integrate active air sampling with optical, imaging, or molecular detection modules, to capture and characterize fungal spores in the field. Recent advances include automated microscopy combined with machine learning for spore classification, laser-based optical detection systems for continuous bioaerosol monitoring, and portable molecular platforms (e.g., qPCR and LAMP) for species-specific identifications, with automated systems also developed for detection of airborne *Sclerotinia sclerotiorum* conidia (West and Kimber, 2015). Recent studies have provided a paradigm shift toward real-time, automated monitoring networks, which can provide high temporal resolution data and support operational decision-making across agricultural and environmental domains (Tummon *et al*., 2024). Technological developments now include field-deployable optical systems capable of real-time airborne propagule detection and integration with image-processing algorithms for pathogen surveillance, with applications demonstrated for powdery mildew and grey mould in protected crops (Bouquet *et al*., 2024), as well as UAV-based spore sampling devices that enable spatially explicit monitoring of pathogen dispersal in cropping systems (Guo *et al*., 2024). In parallel, recent reviews on biosensors have emphasized the growing roles of advanced sensing platforms for detecting airborne fungal pathogens, with improved sensitivity and selectivity, supporting agricultural and environmental applications (Memon *et al*., 2024). The key advantage of these systems is their ability to link inoculum presence with environmental conditions, thereby improving forecasting accuracy and enabling precise timing of interventions within IPM frameworks. However, challenges remain, related to species-level discrimination, environmental interference, system cost, and the need for standardization and validation under diverse field conditions (West and Kimber, 2015; West *et al*., 2017).

Volatile Organic Compounds analysis for pathogen detection

Volatile organic compound (VOC) profiling is increasingly recognized as a rapid, non-destructive, and highly sensitive approach for plant pathogen detection, requiring no chemical reagents during sensing. As an indirect diagnostic method, VOC profiling exploits the fact that plants synthesize and emit diverse compounds as part of their defense responses against pathogen attack (Scala *et al*., 2013). Pathogen infections often

modify VOC emission patterns, generating distinct chemical signatures that reflect plant health status, and these can be exploited for non-invasive disease surveillance (Ficke *et al*., 2022; MacDougall *et al*., 2022).

Conventionally, VOC analyses have relied on gas chromatography-mass spectrometry (GC-MS), which provides high analytical sensitivity and compound-level identifications (Vallarino *et al*., 2018; Vermeeren *et al*., 2025). However, GC-MS is constrained by high cost, complex sample preparation, long analysis times, bulky instrumentation, and the need for skilled operators (Sharma *et al*., 2019). Electronic nose (E-nose) systems have gained attention as practical alternatives, for rapid, non-invasive, and cost-effective VOC detection (Laothawornkitkul *et al*., 2008; Cellini *et al*., 2016; Loulier *et al*., 2020; Sun and Zheng, 2024). An E-nose system consists of a multisensory array, an information-processing unit, and digital pattern-recognition software supported by reference-library databases. Upon exposure to VOC mixtures, sensor elements undergo reversible chemical or physical changes that alter their electrical properties, generating distinct response patterns. These patterns are then processed using computational algorithms to classify VOC profiles to individual compounds, and associate them with specific plant health states, pathogen infections, or stress conditions. This has been demonstrated by the successful discrimination of fire blight caused by *Erwinia amylovora* and blossom blight caused by *Pseudomonas syringae* pv. *syringae* in apple trees, under laboratory and field conditions (Cui *et al*., 2018).

DATA PROCESSING, FEATURE EXTRACTION, AND MODELLING FOR PEST AND DISEASE MONITORING

Data preprocessing and feature extraction

Raw data acquired from optical, environmental, and in-field sensing systems require pre-processing and feature extraction before they can be used for pest and disease detection or modelling. Pre-processing aims to improve data quality, consistency, and comparability, while feature extraction transforms sensor measurements into informative variables that capture biologically relevant patterns associated with pest activity or disease development. In image-based workflows, acquisition is typically followed by pre-processing, segmentation, feature extraction, and classification. Common pre-processing operations include radiometric or colour normalization, noise reduction, geometric correction, background removal, and segmentation to isolate plant tissue, disease symptoms, or pest targets from surrounding scenes (Singh *et al*., 2020). In RGB and multispectral imagery, accurate segmentation of leaves, canopies, or trap contents is particularly important, because complex backgrounds, variable illumination, and uncontrolled acquisition conditions can introduce irrelevant image features and complicate disease identification (Barbedo, 2016).

Background interference is especially challenging in field images containing soil, overlapping foliage, shadows, and surrounding vegetation. In contrast, many published methods have been developed using detached leaves, or images acquired against homogeneous backgrounds. Studies further demonstrate that the impacts of background removal on classification performance vary substantially across crops and datasets, with the greatest effects observed in relatively small datasets acquired under realistic conditions (Barbedo, 2016, 2018).

A frequent limitation in development of pest and disease detection models, particularly deep learning-based approaches, is the scarcity of large, diverse, and accurately annotated image datasets. Deep convolutional networks generally require substantial numbers of samples representing a wide range of symptom appearances, disease stages, environmental conditions, backgrounds, and acquisition devices. Constructing these datasets is difficult, because symptoms vary during disease development, field conditions are highly heterogeneous, and reliable annotation is labour-intensive and may require specialist expertise (Barbedo, 2018). Limited or homogeneous datasets can therefore encourage models to learn dataset-specific backgrounds or acquisition characteristics, rather than biologically meaningful disease features, increasing overfitting and reducing generalization to independent field imagery.

This limitation was illustrated by Mohanty *et al*. (2016), who trained convolutional neural networks using 54,306 images representing 14 crop species and 26 diseases or healthy classes. Although the best model achieved 99.35% accuracy and a mean F1-score of 0.9934 on a held-out subset of the controlled PlantVillage dataset, its performance declined markedly when evaluated on images obtained under different, more realistic conditions. The authors consequently emphasized that models trained on single leaves positioned against homogeneous backgrounds required further evaluation using images acquired directly from plants under field conditions. To address limited training data, data augmentation is widely used to increase sample diversity, reduce overfitting, and mitigate class imbalance. Conventional image augmentation approaches include rotation, reflection, translation, cropping, scaling, colour-space transformations, filtering, and random erasing, while more advanced methods include image mixing, feature-space augmentation, neural style transfer, and synthetic-image

generation using generative adversarial networks (Shorten and Khoshgoftaar, 2019). Augmentation can expand the range of image appearances represented during training, and improve robustness to variation in viewpoint, illumination, scale, and background. Augmented samples, however, remain derived from the original dataset and cannot fully replace collection of genuinely diverse, independently acquired field images (Shorten and Khoshgoftaar, 2019).

To address this issue, data augmentation is widely used in plant disease detection to increase sample diversity and mitigate class imbalance, particularly when real diseased images are scarce (Shorten and Khoshgoftaar, 2019; Sambana *et al*., 2025). Data augmentation artificially increases the diversity and size of training datasets, through geometric transformations such as rotation, flipping, and cropping, colour and brightness adjustments, and synthetic image generation *via* generative adversarial networks (GANs), which can produce visually realistic disease symptom imagery to supplement limited real-world observations (Shorten and Khoshgoftaar, 2019; Antwi *et al*., 2024).

Several studies have demonstrated that robust preprocessing pipelines enhance classification accuracy under variable illumination and heterogeneous field conditions (Ahmed *et al*., 2024; Chen *et al*., 2025). Feature extraction from optical imagery can be achieved using either handcrafted descriptors or learned representations. Handcrafted features include colour indices, texture descriptors, shape metrics, and vegetation indices derived from multispectral and hyperspectral data, which have been widely used to characterize stress-related changes in plant appearance and canopy structure. Hyperspectral features and spectral indices are especially valuable for capturing subtle physiological changes in plants, that are associated with early pest infestations or disease onset (Fitzgerald *et al*., 2004). In contrast, environmental and soil sensor data typically undergo temporal aggregation, normalization, and smoothing to extract features such as degree-day accumulations, temperature and humidity thresholds, leaf wetness duration, and soil moisture dynamics (Yin *et al*., 2021). These features represent biologically meaningful indicators for pest emergence, infection risk, and disease progression, and are commonly used as inputs to risk prediction models and decision-support systems (Samreen *et al*., 2022). Increasingly, feature extraction is performed implicitly through machine learning and deep learning models, which learn hierarchical representations directly from raw or minimally processed data. While these approaches can improve detection performance, research literature consistently emphasizes that data quality, appropriate preprocessing, and domain-informed feature design remain critical for ensuring robust and generalizable pest and disease monitoring under real field conditions (Chen *et al*., 2025).

Machine and deep learning approaches for pest and disease detection

Machine learning (ML) and deep learning (DL) techniques have central roles in transforming heterogeneous sensing data into actionable information for pest and disease monitoring in precision agriculture. ML and DL models are used to analyse relationships between diverse data sources (images, meteorological variables, spectral reflectance), and disease incidence and severity (Lei *et al*., 2021; Zheng *et al*., 2021), as well as pest population dynamics across multiple crops and sensing modalities. Recent advances have confirmed that artificial intelligence approaches have become the dominant paradigm for image-based plant health monitoring (Pantazi *et al*., 2019; Majdalawieh *et al*., 2025). Classical machine learning methods, including support vector machines (SVM), k-nearest neighbours (k-NN), and random forests (RF), have been widely applied, using handcrafted features derived from RGB, multispectral, and hyperspectral imagery, including colour descriptors, texture metrics, and spectral indices (Karthickmanoj *et al*., 2021). These approaches remain effective in scenarios with limited training data and where model interpretability and computational efficiency are important. However, their reliance on manually engineered features restricts their ability to capture complex, multi-scale visual patterns associated with diverse pest damage and disease symptoms, particularly under variable field conditions (Nandhini *et al*., 2023; Saleki and Tahmoresnezhad, 2024) (Table 4).

Deep learning models, especially convolutional neural networks (CNNs), have emerged as the most widely adopted and practical approaches for image-based pest and disease detection, due to their ability to process large, complex datasets, and automatically learn discriminative features. Unlike conventional machine learning methods, which often depend on manually engineered descriptors, CNNs extract hierarchical spatial features directly from image data, enabling superior performance in many classification and detection tasks. Recent systematic reviews have indicated that CNN-based architectures dominate the relevant literature, and consistently achieve high classification accuracy across multiple crops and disease types, with reported accuracies frequently exceeding 95%, and, in some cases, surpassing 99%, under controlled or semi-controlled conditions (Sujatha *et al*., 2023; Hemalatha and Jayachandran, 2024; Kunduracioglu, 2024). The popularity of CNNs is largely attrib-

uted to their strong feature extraction capability, compatibility with RGB imagery, and relatively favourable balance between accuracy and computational cost (Rezk *et al*., 2022; Perveen *et al*., 2023; Rajpoot *et al*., 2023; Majdalawieh *et al*., 2025).

YOLOv8, the latest iteration of the Ultralytics YOLO (You Only Look Once) family, offers innovative real-time object detection and instance segmentation capabilities, making this system suitable for plant disease diagnoses in precision agriculture. Trained on images of leaves or crops, it can automatically detect symptoms of diseases caused by pathogens such as *Alternaria*, *Phytophthora*, or mycotoxigenic fungi, leveraging spectral imaging, thermal sensors, or drone imagery to generate precise bounding boxes and segmentation masks for affected areas. This approach enhances integrated disease management by reducing reliance on chemical residues, improving epidemic forecasting through Decision Support Systems, and aligning seamlessly with research expertise in smart diagnostics and precision agriculture applications (Ghafar *et al*., 2024) (Table 4).

Vision Transformer (ViT) architectures have also been explored for plant disease detection and pest-related image analyses. ViT-based models have demonstrated superior classification accuracy in several studies, in some cases approaching near-perfect performance. However, the reviewed literature highlights that these gains are often accompanied by substantially increased computational requirements, increased training complexity, and having reduced suitability for real-time or resource-constrained agricultural deployments. As a result, CNN-based models are currently the most cost-effective and scalable options for operational pest and disease monitoring systems (Mishra *et al.* 2020; Yu *et al.* 2023; Bhowmik *et al.* 2024; Hemalatha and Jayachandran, 2024; Prashanthi *et al.* 2025).

Beyond classification, deep learning approaches have been increasingly applied to object detection, segmentation, and counting tasks, which are particularly relevant for automated pest monitoring using smart traps and field imagery. Detection-based architecture enables localization and enumeration of insects, supporting population trend analyses and threshold-based decision-making for integrated pest management. These capabilities extend AI-based monitoring beyond presence-absence detection toward operationally meaningful assessments of pest pressure (Hadipour-Rokni *et al*., 2023; Ariza-Sentís *et al*., 2024; Dhaliwal *et al*., 2024).

Despite substantial progress, significant challenges remain. Model performance is strongly influenced by dataset characteristics, including image quality, annotation standards, crop diversity, and geographic representation. Systematic reviews consistently report heavy reliance on publicly available RGB datasets collected under controlled conditions, raising concerns regarding model generalization to diverse field environments. In addition, deep learning models are often computationally demanding, which can limit their deployment in low-resource settings. Consequently, current research increasingly focuses on lightweight architectures, transfer learning, hybrid modelling strategies, and improved dataset diversity, to enhance robustness, scalability, and real-world applicability of AI-based pest and disease monitoring systems (Singh and Yogi, 2023; Deeba *et al.,* 2024; Rajpal *et al.,* 2024; Sood and Singh, 2024).

Multi-source data fusion and integrated modelling

Multi-source data fusion aims to combine heterogeneous information streams from optical imagery, in-field environmental and soil sensors, smart traps, and, where available, radar observations, to improve the robustness and reliability of pest and disease monitoring. Because individual sensing modalities capture different components of crop-pest-pathogen interactions, their integration can mitigate the limitations of single-source approaches, and enhance situational awareness under variable field conditions (Zheng *et al*., 2021; Huang *et al*., 2022; Li *et al*., 2023). Recent reviews have emphasized that data fusion is becoming increasingly central to operational precision agriculture systems, particularly for addressing noise, missing data, and environmental confounding factors (Alvarez-Vanhard *et al*., 2021; Ouhami *et al*., 2021; Majdalawieh *et al*., 2025).

Fusion strategies are commonly categorized by the levels at which integration occurs. Feature-level fusion combines engineered or learned features derived from multiple data sources (e.g., vegetation indices, texture features, degree-day metrics, soil moisture dynamics) into unified input for machine learning models (Huang *et al.,* 2018; Kanwal *et al.,* 2022). This approach enables models to exploit complementary signals, such as coupling canopy stress indicators from imagery with microclimatic drivers of infection captured by IoT sensors. Decision-level fusion, in contrast, integrates the outputs of independently trained models (e.g., image-based disease classifiers and environment-based risk predictors), allowing flexible combination of heterogeneous predictions and improved interpretability (Huang *et al*., 2018; Kanwal *et al*., 2022). Integrated modelling frameworks increasingly incorporate temporal information, recognizing that pest populations and disease development are dynamic processes. Time-series fusion of satellite or UAV imagery with continuous in-field sensor measurements supports tracking of stress

evolution, pest emergence, and infection risk throughout a growing season. Incorporating temporal context improves early warning capability and reduces false positives, compared with static, single date analyses (Alexopoulos *et al*., 2023; Majdalawieh *et al*., 2025).

Data fusion also has a key role in operational deployment, where practical constraints often limit data availability. For example, optical imagery may be unavailable due to cloud cover, while in-field sensors can provide continuous context that maintains monitoring continuity. Conversely, high-resolution imagery can spatially contextualize localized sensor observations. Research literature consistently reports that such complementary use of data sources enhances system resilience, and supports increased reliability of pest and disease monitoring under agricultural conditions (Alexopoulos *et al*., 2023). Despite its advantages, multi-source data fusion introduces challenges related to data alignment, scale mismatch, sensor reliability, and model complexity. Differences in spatial resolution, temporal frequency, measurement uncertainty, and data format across sensing streams require careful preprocessing and model design. Recent studies have emphasized modular architectures, standardized data pipelines, and scalable fusion strategies, that balance performance gains with computational and operational feasibility (Alexopoulos *et al*., 2023; Majdalawieh *et al*., 2025).

Predictive modelling and forecasting approaches in precision agriculture

Predictive modelling provides formal frameworks for anticipating pest and disease dynamics by representing interactions among crops, pests or pathogens, soil conditions, weather, and management practices. In precision agriculture, modelling shifts pest and disease management from reactive detection toward forecasting risk, timing, and potential impacts, thereby supporting early warning and optimized intervention strategies. Modelling approaches have long been central to crop protection, and remain foundational components of decision support systems in precision agriculture (Cammarano, 2023).

Process-based models are widely used to represent pest and disease development through mechanistic descriptions of biological and environmental processes. These models simulate key drivers, including temperature, humidity, rainfall, soil moisture, and crop phenology, to estimate pest emergence, infection risks, and disease progression. Epidemiological disease models and pest phenology models based on degree-day accumulation are common examples. Their main strengths are biological interpretability and potential transferability across regions, although their accuracy depends on appropriate parameterization validation, and local calibration (Baumgärtner and Gilioli, 2008; Rossi *et al*., 2010; Cammarano *et al*., 2023; Fedele *et al*., 2024). In precision agriculture, process-based models are increasingly applied at field and sub-field scales, supported by high-resolution weather, soil, and crop data. Integration with sensing technologies enables spatially explicit simulation of pest and disease risks, allowing models to account for within-field variabilities in environmental conditions and crop development. This capability is particularly valuable for site-specific management, targeted interventions, and variable-rate crop protection strategies (Been *et al*., 2005; van Evert *et al*., 2012; Kessel *et al*., 2018; Fedele *et al*., 2024).

Alongside mechanistic approaches, data-driven predictive models based on statistical and machine learning techniques are increasingly used to forecast pest and disease risks from historical observations and real-time sensor data. These models capture complex, nonlinear relationships among environmental variables, crop status indicators, pest pressure, and disease outcomes. However, while they may achieve strong predictive performance when sufficient representative data are available, they often lack explicit biological interpretability, and may generalize poorly beyond the conditions represented in the training datasets (Cammarano *et al.,* 2023).

Recent literature highlights the growing importance of hybrid modelling approaches, which combine process-based crop, pest, and disease models with data-driven learning. By integrating biological knowledge with observational data, hybrid models can improve robustness, reduce data requirements, and enhance adaptability across variable environments. These approaches are increasingly regarded as promising pathways for scalable and reliable pest and disease forecasting within precision agriculture systems (Cammarano *et al.,* 2023). Overall, predictive modelling complements sensing and detection technologies, by enabling anticipatory pest and disease management. When coupled with multi-source data streams, and embedded within decision support systems, predictive models provide critical links between environmental monitoring, risk assessment, and timely, site-specific crop protection decisions (Cammarano *et al.,* 2023).

DECISION SUPPORT SYSTEMS FOR PEST AND DISEASE MONITORING AND MANAGEMENT IN AGRICULTURE

Decision support systems (DSS) play critical roles in precision agriculture by transforming heterogeneous data

Table 5. Overview of examples of commercial platforms and digital systems for pest and disease monitoring in agriculture.

System	Technology used	Data inputs	Plant type/pests	Reference/link
Agrigenius®	DSS, AI forecasts, mobile app	Weather stations, sensors, satellite	Various crops/pests	https://www.agro.basf.gr/el/Products/Applications/Agrigenius/
Agrio	Mobile app, AI-based alert system	User-uploaded photos, hyper-local weather, and Sentinel-2/PlanetScope satellite imagery	Various crops/pests	https://agrio.app/
CropDiagnosis app	Mobile app – user inputs	Questionnaire for symptoms	Various crops/pests	https://www.cropdiagnosis.com/portal/crops/en/home
Croptimus™	Scouting system, cameras	Image based recognition	Horticultural *and* Greenhouse crops/pests	https://www.fermata.tech/
FarmSense	AI/ML, patented FlightSensor (optical sensors)	Real-time insect flight captures from deployed sensors, cloud analytics	Multiple row crops (e.g., fruits) /pests	https://www.farmsense.io/
FieldClimate	Cloud-based IoT platform, AI (for insect counting), mobile app (iOS/Android)	iMETOS weather stations, soil probes, iSCOUT insect traps, CropVIEW cameras, and Sentinel-2 satellite imagery	Over 80 different disease models for more than 45 crops/pests	https://metos.global/en/fieldclimate/
Plantix	Mobile app, AI image recognition	User-uploaded photos	30+ crops, 120+ diseases	https://plantix.net/en/
Semios	IoT sensors, automated insect traps, wireless networks, AI/ML, DSS	Weather data, soil moisture, pest images *and* counts, historical *and* real-time farm data	Apples, almonds, pistachios, grapes, citrus, cherries, pears, walnuts, stone fruits	https://semios.com/
Xarvio®	AI/ML, Image Recognition, DSS, mobile apps	Satellite biomass imagery, hyper-local weather, user-uploaded field photos and historical field data	Corn, soybeans, wheat, canola, wine/table grapes, rice, cotton, and various vegetables	https://ag.xarvio.com/

streams into actionable information for pest and disease management (Rossi *et al*., 2012). Agriculture 4.0 provides digital transformation of agriculture through integration of interconnected sensors, artificial intelligence, robotics, remote sensing, big data, and automated decision-support systems, to enable precise, efficient and sustainable agricultural production. In the context of Agriculture 4.0, a DSS integrates data from remote sensing platforms, in-field environment and soil sensors, pest monitoring devices, and predictive models, to support evidence-based decision-making under spatially and temporally variable field conditions (Caffi and Rossi, 2018)

Rather than issuing rigid prescriptive commands, agricultural DSSs are designed to assist farmers, advisors, and crop protection specialists, by providing risk assessments, alerts, scenario analyses, and management options, while leaving final decisions to end users (Rossi *et al*., 2012; Alsalam *et al*., 2017; López-Riquelme *et al*., 2017; Zhai *et al*., 2020). In pest and disease management, these systems can integrate predictive models and disease-risk assessments to support decisions on whether, when, and how control measures should be applied, thereby improving the timing and targeting of crop protection interventions (Caffi and Rossi, 2018). Several platforms and mobile applications are now available for pest prediction and detection and crop health management, some of which combine artificial intelligence, remote sensing, in-field monitoring, and data integration to help farmers and other users to detect, monitor, respond and control pest and disease outbreaks, including grape and tomato downy and powdery mildews, olive anthracnose, tomato leafminer (*Tuta absoluta*) and others diseases and pests (Table 5).

Risk assessment and early warning

Primary functions of DSSs in pest and disease management are risk assessment and early warning. Environmental variables including temperature, relative humidity, rainfall, leaf wetness, and soil moisture, strongly influence pathogen infection cycles, pest emergence, and population dynamics. DSSs integrate these inputs, often in combination with crop phenology, pest

monitoring data, process-based models, and data-driven algorithms, to identify periods and locations of elevated disease or pest risk. Continuous monitoring enables detection of short-duration favourable conditions for infection or pest activity, that may not be captured by conventional scouting or coarse-resolution weather data. By providing timely alerts, DSS can support preventive or threshold-based interventions, improve the timing of scouting and applications of control measures, and reduce reliance on reactive pesticide applications (Chougule *et al*., 2016; Navarro-Hellín *et al*., 2016; Alexopoulos *et al*., 2023). Modern DSSs increasingly combine mechanistic models describing crop, pest, and pathogen processes with machine-learning methods capable of identifying patterns in large sensor datasets, thereby improving predictive adaptability under variable field conditions (Chlingaryan *et al.,* 2018; Liakos *et al*., 2018; Zhai *et al.,* 2020). Nevertheless, DSS practical adoption depends on overcoming data-integration and interoperability problems, model uncertainty, limited responsiveness to unexpected field conditions, and usability barriers. Consequently, operational systems should provide transparent, reliable, and actionable recommendations that can be aligned with farmers' management practices (Rose *et al.,* 2016; Tyrychtr and Vostrovsky, 2017; Zhai *et al.,* 2020).

Spatial decision support and site-specific management

Spatial decision support is a defining feature of precision pest and disease management. DSSs commonly operate within GIS-based environments, integrating georeferenced outputs from satellite imagery, UAV surveys, proximal sensing, smart traps, and ground-based sensors, to generate spatially explicit maps of pest pressures, disease severities, or infection risks. GNSS-enabled georeferencing ensures spatial consistency across datasets, and supports repeatable monitoring over time. These spatial products enable site-specific pest/disease management by identifying disease or pest hotspots, and guiding targeted scouting, localized pesticide applications, biological control deployment, or variable spray rate treatments (Peña-Barragán *et al.,* 2013; Kadiyala *et al.,* 2015; Alexopoulos *et al.,* 2023).

CHALLENGES, LIMITATIONS, AND FUTURE RESEARCH DIRECTIONS

Despite significant advances in precision agriculture technologies for pest and disease monitoring, several challenges continue to limit their widespread and reliable adoption in agricultural conditions. These challenges span data acquisition, sensing, modelling, model robustness, system integration, decision-support implementation, and practical deployment, highlighting important directions for future research and development. Addressing these challenges is essential for translating digital and AI-enabled monitoring tools from experimental proof-of-concept studies into scalable, reliable, and farmer-oriented crop protection systems. The future of plant disease management will probably depend on integrating digital technologies with traditional plant pathology expertise, through continuous validation and implementation within IPM frameworks.

Data quality, availability, and representativeness

A major limitation across sensing and modelling approaches is availability of high-quality, representative data, and well-annotated datasets. Many image-based and data-driven models are trained on datasets collected under controlled or semi-controlled conditions, often covering limited numbers of crops, pests, diseases, cultivars, disease stages, or environmental contexts. This restricts model generalization when systems are applied across different agroecological zones, crop varieties, management practices, imaging conditions, and seasonal conditions. Several studies and reviews have highlighted the need for large, more balanced, and open-access datasets, that can support development of models capable of detecting multiple pests and diseases under realistic field conditions.

Transfer learning and data augmentation have been proposed as useful strategies to partially overcome data scarcity and improve model robustness (Barbedo, 2018; Patel and Bhatt, 2021; Ye *et al*., 2022; Li *et al*., 2023). However, these approaches cannot fully replace extensive field-based data collection. The rescue and digitization of historical pest and disease records can provide additional sources of valuable long-term data, for modelling pest population dynamics and support of management decisions (O'Donnell *et al*., 2025). These findings demonstrate that sustained, multi-year surveillance enhances early detection of pest species prior to their establishment, and reduces the likelihood of incorrectly classifying invasive species as absent. Therefore, the development of diverse, multi-season, multi-year, multi-location, and multi-crop datasets remains essential for capturing real-field variability, and enabling reliable model evaluation, benchmarking, and deployment (Wu *et al*., 2019; Zhang *et al*., 2023).

Model uncertainty, interpretability, and trust

While machine learning and deep learning models have demonstrated strong performance in pest and disease detection, uncertainty quantification and interpretability remain insufficiently developed. Most current systems provide deterministic predictions without explicit confidence estimates, which can limit their usefulness in risk-sensitive agricultural contexts where false positives may lead to unnecessary interventions, and false negatives may allow disease or pest outbreaks to progress. Incorporating uncertainty-aware modelling, probabilistic forecasting, and explainable AI approaches is therefore important for improving user trust and supporting risk-based decision making. Explainable outputs, such as feature importance rankings (Mohan *et al*., 2025), saliency maps (Alhammad *et al.,* 2025), confidence intervals, or risk probabilities (Hernández and López, 2020), can help farmers, advisors, and crop protection specialists understand why particular recommendations are generated and how reliable they are. This transparency is critical for moving beyond simple binary outputs toward interpretable, trustworthy, and operational decision-support systems.

Integration and scalability of multi-sensor systems

Multi-source data integration has increasingly been proposed as a strategy to overcome the limitations of individual sensing modalities. Advances in deep learning, large datasets, improved computational capacity, and increasing affordability of sensors, have accelerated research on multi-source data fusion for pest and disease detection. Different data sources provide complementary information across spatial and temporal scales (O'Donnell *et al*., 2025). For example, satellites offer frequent and wide-area observations, whereas UAVs provide high-resolution imagery over smaller areas, and proximal sensors deliver continuous local measurements (Alexopoulos *et al.,* 2023).

However, integrating heterogeneous data streams, including optical imagery, environmental and soil sensors, smart traps, and radar data, introduces challenges related to data alignment, scale mismatch, sensor reliability, and system complexity. Differences in spatial resolution, temporal frequency, data format, sensor types, and measurement uncertainty can complicate fusion and modelling efforts. Future research should therefore prioritize scalable architectures, standardized data pipelines, interoperable data formats, and modular system designs, that enable flexible integration of sensing components while maintaining operational robustness under real field conditions (Figure 5).

Cost, infrastructure, and adoption barriers

Economic, infrastructural, and human-capacity constraints continue to shape the adoption of precision pest and disease monitoring technologies, particularly for small farms and systems requiring specialised sensors, connectivity, software, and analytical support. A 2024 survey of 1,444 farms across nine EU Member States, including Greece, Spain, Italy, and France, found that although 93% of farms used at least one general IT or software tool, adoption of individual crop- or livestock-specific technologies was much less, generally ranging from 3% to 23%. Fifteen percent of surveyed farms reported poor internet connectivity, and econometric estimates indicated that poor or insufficient connectivity was associated with the adoption of 4 to 35% fewer digital technologies. Farm size and training were also strongly associated with uptake: large farms adopted 10 to 84% more technologies than small farms, while farmers who had received specialised digital training adopted 14 to 71% more technologies than those without such training. At least half of the crop- and livestock-specific technologies examined were perceived as expensive, with financial constraints and lack of knowledge or skills among the most frequently reported barriers (Tur Cardona *et al.,* 2025).

Earlier cross-regional evidence from 971 arable farmers in Belgium, Germany, Greece, the Netherlands, and the United Kingdom, similarly showed that adoption of machine guidance and variable-rate nitrogen technologies were associated with large farm size, high income, confidence in economic returns, and information-seeking behaviour. The study also highlighted the greater knowledge, software, and analytical-service requirements of information-intensive technologies, as well as the need for demonstration and advisory support to reduce uncertainty about returns on investment (Barnes *et al.,* 2019).

Mediterranean evidence (Kakkavou *et al*., 2024) has further indicated that adoption is influenced by affordability, whether technologies fit existing practices, and whether farmers feel capable of operating them. Among 82 olive and cotton farmers in Messenia and Thessaly (Greece), intention to adopt precision irrigation technologies was associated with perceived behavioural control, economic benefits, compatibility, and environmental awareness, whereas risk aversion showed a weak negative association. Kakkavou *et al.* (2024) noted that these constraints may be particularly important in Greek farming systems dominated by small holdings, where the perceived risks of investing in unfamiliar technologies are greater. Wider adoption will therefore require afford-

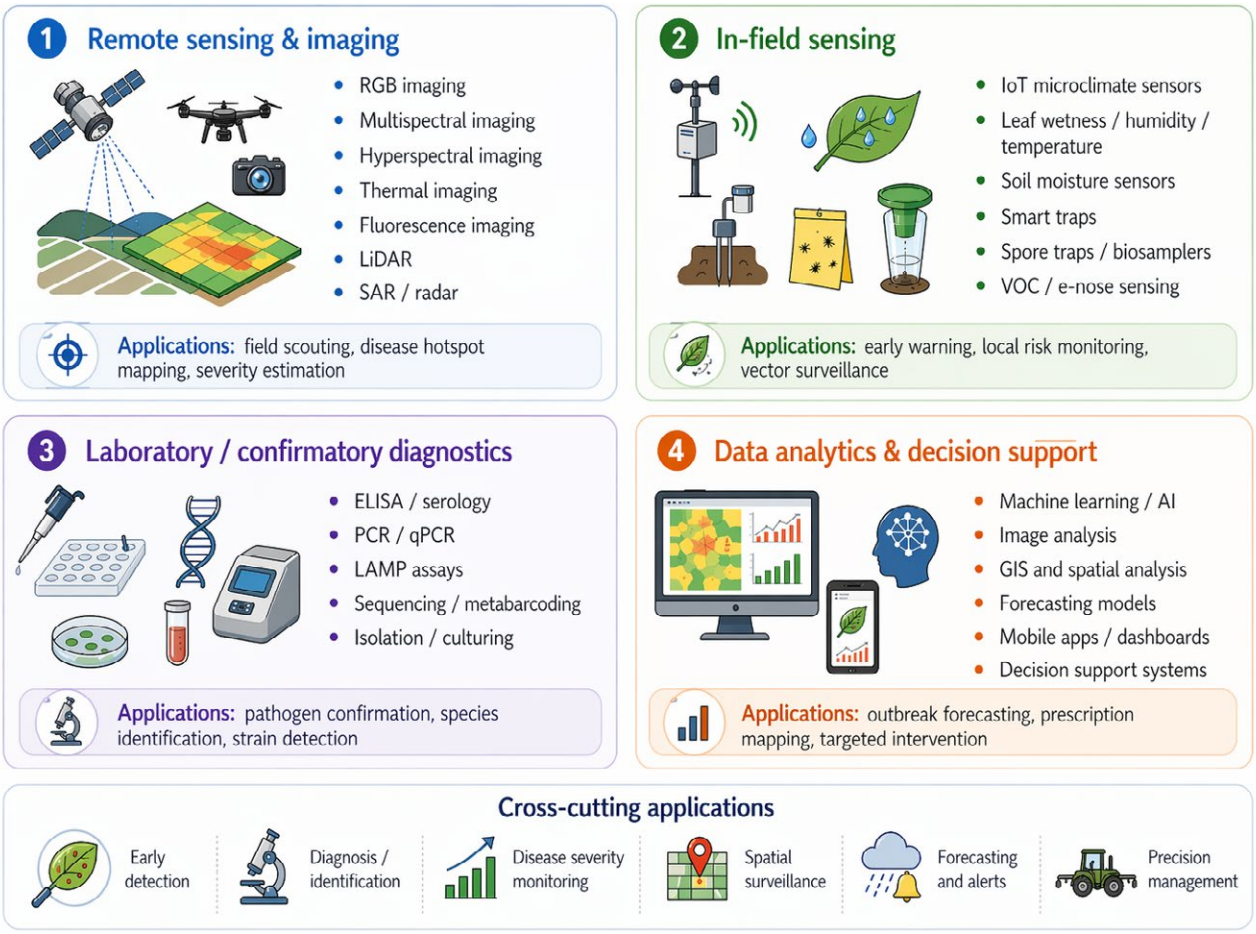


Figure 5. Integrated framework for pest and disease monitoring and management in precision agriculture.

able technologies, strong training and advisory support, and systems that can operate under the connectivity and resource constraints faced on small farms.

From detection to management

Although considerable progress has been made in pest and pathogen detection, fewer systems effectively support anticipatory management through reliable forecasting and adaptive decision-making. Increased emphasis is required to integrate predictive models with decision support systems that account for uncertainty, management objectives, economic thresholds, environmental risks, and farmer preferences. Hybrid modelling that combines biological knowledge with data-driven learning are promising pathways for improving robustness, interpretability, and scalability across diverse agricultural contexts. In addition, disease incidence, environmental conditions, management practices, and control outcomes, generated through ongoing projects, monitoring networks, and international collaborations, would substantially improve accuracy, transferability, and practical applicability of pest and disease detection systems, under real agricultural conditions.

The STELLA project (https://stella-pss.eu/), is an example of transition toward integrated, digital plant protection ecosystems, as it brings together advanced molecular diagnostics, in-field sensing, remote sensing, and artificial intelligence, within a unified decision-support framework. By developing a platform that integrates multi-source data, including optical imaging, environmental sensors, smart traps, and predictive models, STELLA aims to enable early detection and forecasting of pest and disease outbreaks, supporting targeted and sustainable pest/disease management strategies. This approach is closely aligned with principles of precision agriculture and IPM, shifting crop protection from reactive responses toward proactive, data-driven decision-making. Overall, the STELLA project illustrates how

convergence of interdisciplinary knowledge and digital technologies can transform plant pathology into predictive, scalable, and operational system that can address current and future challenges in agricultural production.

CONCLUSIONS

Increasing pressures of plant pests and diseases on global agriculture, exacerbated by climate change and region-specific vulnerabilities such as those in the Mediterranean basin, underscore the urgent need for rapid, scalable, and proactive disease management strategies (Singh *et al*., 2023). In an era of intensified world trade, diagnostic systems must deliver rapid, reliable, and quantitative outputs. Concurrently, globalization and climate warming are accelerating the emergence and spread of pests and pathogens, increasing demands for early detection and precise identification to prevent their introductions into new regions, and limit further dispersal (Ristaino *et al.,* 2021). Although conventional diagnostic approaches remain foundational to plant pathology and entomology, they are often constrained by their reliance on specialized expertise, time-consuming procedures, and delayed response times, which can hinder timely interventions and reduce effectiveness of pest and disease control, under rapidly evolving epidemiological conditions.

Transition toward digital plant protection represents a change in thinking. Advances in imaging technologies, sensor systems, artificial intelligence, and data integration frameworks have enabled development of precise, rapid, non-invasive, and scalable diagnostic tools (Figure 5). These range from leaf-level symptom detection using deep learning to landscape-scale pest and disease surveillance through remote sensing, with monitoring of *Xylella fastidiosa* outbreaks as a good example (Ferentinos, 2018; Zarco-Tejada *et al.,* 2018; Velasco-Amo *et al*., 2022). Integrating plant physiological indicators, such as stomatal conductance and chlorophyll content, with digital measurements can provide multi-scale insights into plant health and pest and disease dynamics, enhancing early detection and enabling intervention prior to the onset of severe symptoms (Calderón *et al.,* 2013; Zarco-Tejada *et al*., 2018). Despite these advances, significant challenges remain. Limitations related to data quality and representativeness, model generalization across diverse environments, biological variability of pathogens, and the need for robust ground-truth validations, continue to constrain operational deployment (O'Donnell *et al*., 2025). Furthermore, economic barriers, infrastructure gaps, issues related to data ownership and accessibility, as well as user adoption, must be addressed to ensure equitable adoption, particularly by smallholder farmers and in resource-limited regions.

Future precision agriculture systems for pest and disease management are expected to evolve toward integrated, multi-scale, and farmer-centric platforms, in which sensing, modelling, and decision support components operate synergistically rather than in isolation. Advances in sensor technology, multi-source data fusion, predictive modelling, and human-AI interaction will be important for delivering timely, interpretable, and actionable information. Progress in this field will also depend on inclusive cross-sector collaboration, ensuring that innovations are technically robust and are also socially acceptable, economically viable, and environmentally sustainable.

Pest and disease surveillance must move beyond isolated diagnostic activities toward coordinated, multi-stakeholder systems that integrate monitoring, forecasting, and decision-making. Addressing current limitations through interdisciplinary research, open data sharing, and user-centered design, will be essential for translating technological innovation into sustainable and resilient crop protection practices (Majdalawieh *et al*., 2025; Zhai *et al*., 2020). Furthermore, integrating epidemiological and economic models, while accounting for landscape connectivity, climate variability, trade dynamics, and socioeconomic conditions, can enhance surveillance design, optimize resource allocation, and improve response capacity during pest or disease outbreaks. Convergence of digital monitoring tools, robust diagnostics, predictive analytics, and collaborative networks, will be key for building resilient agricultural systems that safeguard crop productivity and ensuring international food security under conditions of environmental change.

Integrating multi-platform sensing such as satellites for broad-scale surveillance, UAVs for high-resolution field mapping, and proximal sensors for continuous *in situ* measurements, can create hierarchical decision-making frameworks tailored to IPM. Satellites detect anomalies to guide targeted scouting; UAVs map infestation hotspots and assess severity, and ground sensors verify diagnoses while tracking disease progression in real time (Gao *et al*., 2025). When combined with decision-support systems and predictive models, these data streams enable precise, threshold-triggered actions. These include targeted spraying, biological control releases, or canopy adjustments, that optimize inputs, minimize chemical use, and advance IPM from reactive to proactive, site-specific strategies for enhanced agronomic and environmental outcomes.

In conclusion, convergence of molecular diagnostics, smart sensing technologies, and artificial intelligence is redefining pest research and plant pathology, enabling a transition from reactive pest and disease control toward proactive, data-driven management. Molecular tools provide highly specific and sensitive pest and pathogen identification, while digital sensing systems and AI-driven analytics extend detection across spatial and temporal scales, supporting continuous surveillance and early warnings. When integrated within decision-support frameworks, these technologies create powerful, multi-layered systems can link detection with prediction and targeted intervention. Realizing their full potential, however, requires overcoming challenges related to data quality and interoperability, model robustness and interpretability, infrastructure and cost barriers, and alignment with real-world agricultural practices. Future progress will depend on interdisciplinary collaboration, open and standardized data ecosystems, and development of user-centered, scalable solutions that embed biological knowledge within digital workflows. Ultimately, these integrated approaches will be essential for advancing resilient, sustainable, and globally coordinated plant health management systems in the face of increasing biotic threats and environmental change.

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REVIEW STRUCTURE

This review was carried out using a keyword-based search to identify current trends and the recent state-of-the-art in agricultural pest and disease monitoring. The literature review was accomplished in Google Scholar, ScienceDirect, and Scopus, utilizing the following keywords: "pest OR disease detection", "pest OR disease prediction", "remote sensing", "machine learning", "deep learning", "proximal AND in-field sensors"', and "IoT". In addition, Google's search engine Perplexity AI and AI search engine Scopus AI were used to collect information on the recent progress in pest monitoring systems, and to identify platforms and apps used for pest monitoring in agriculture.

Publications available from 2015 to 2026 were selected for analyses, with certain additional relevant studies published before 2015. The focus was on peer-reviewed publications in English, that addressed plant pest/disease detection or prediction, and their enabling technologies (remote/proximal sensing, ML/DL, IoT).

All figures presented in this paper were generated using ChatGPT (OpenAI) based on prompts and scientific content provided by the authors.

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