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REVIEW

Opportunities and Challenges in Combining Optical Sensing and Epidemiological Modeling

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Abstract

Plant diseases impair the yield and quality of crops and threaten the health of natural plant communities. Epidemiological models can predict disease and inform management. However, data are scarce, because traditional methods to measure plant diseases are resource intensive, which often limits model performance. Optical sensing offers a methodology to acquire detailed data on plant diseases across various spatial and temporal scales. Key technologies include multispectral, hyperspectral, and thermal imaging, as well as light detection and ranging; the associated sensors can be installed on ground-based platforms, uncrewed aerial vehicles, airplanes, and satellites. However, despite enormous potential for synergy, optical sensing and epidemiological modeling have rarely been integrated. To address this gap, we first review the state of the art to develop a common language accessible to both research communities. We then explore the opportunities and challenges in combining optical sensing with epidemiological modeling. We discuss how optical sensing can inform epidemiological modeling by improving model selection and parameterization and providing accurate maps of host plants. Epidemiological modeling can inform optical sensing by boosting measurement accuracy, improving data interpretation, and optimizing sensor deployment. We consider outstanding challenges in (A) identifying particular diseases; (B) data availability, quality, and resolution; (C) linking optical sensing and epidemiological modeling; and (D) emerging diseases. We conclude with recommendations to motivate and shape research and practice in both fields. Among other suggestions, we propose standardizing methods and protocols for optical sensing of plant health and developing open access databases including both optical sensing data and epidemiological models to foster cross-disciplinary work.

Keywords: artificial intelligence, data capture standards, data fusion, disease identifiability, disease surveillance, error propagation, machine learning, model parametrization, remote sensing, spectral signature

Plant diseases affect the yield, quality, and profitability of crops and forestry products. Estimated impacts vary, making it difficult to unambiguously quantify losses (Acuña et al. 2023; Oerke 2006; Savary et al. 2019). However, the consequences of disease can be substantial and can even impact food security (Strange and Scott 2005). Analogous impacts on ecosystem services are caused by pathogens of natural vegetation (Boyd et al. 2013). Some pathogens are endemic, routinely causing disease in locations within which they are well established, at least in the absence of management. Other pathogens are emerging, that is, increasing in incidence, geographic range, or host range (Ristaino et al. 2021). Outbreaks of emerging pathogens are increasingly well documented (Fielder et al. 2024; Jeger et al. 2023; Rosace et al. 2023), and rates of invasion are escalating (Ristaino et al. 2021).

Plant disease epidemics develop across multiple spatial and temporal scales. Models tracking the dynamics of disease in time and space, as well as the epidemiological mechanisms causing these dynamics, have been improved and have become increasingly popular over the past few decades (Gilligan 2008; Madden et al. 2007). The current state of the art (see below) often involves complex spatiotemporal epidemic models fitted using advanced Bayesian techniques (Godding et al. 2023; Pleydell et al. 2018; Soubeyrand et al. 2009). Modeling provides a rational basis for integrating what is known with what is unknown, but can reasonably be inferred, to predict the future epidemic dynamics. Predictions from such models can then be used to design surveillance and control strategies (Cunniffe and Gilligan 2020; Parnell et al. 2017). However, to make concrete predictions for a specific pathosystem, models must be fitted to and validated using experimental or observational data, and a lack of suitable data is often a significant limiting factor.

In part, this data limitation is because traditional methods for the detection and quantification of plant diseases are time and resource intensive, largely because they involve human observers (Bock et al. 2020). Proximal and remote sensing—which can be distinguished from each other in terms of the distance separating sensor and target (Oerke 2020)—have great potential in this context. Many pathogens cause changes in plant health that can be detected not only in the visible spectral range but also beyond that range (Mahlein et al. 2024). Among many examples are tan spot on wheat leaves (caused by the fungus *Drechslera tritici-repentis*) that results in a characteristic reduction in reflectance in the near-infrared plateau (Bohnenkamp et al. 2021) and latent infections by *Venturia inaequalis* (apple scab) that were detected as spots of lower temperature by capturing light in the thermal infrared range (Oerke et al. 2011). Use of optical sensing to measure these signals is thus particularly attractive. Here, we use "optical sensing" as a common term to describe a range of proximal and remote sensing techniques making use of electromagnetic radiation across a potentially wide spectral domain, including ultraviolet (UV; a list of acronyms used is given in Table 1, and a glossary is provided in the Supplementary Material), visible, and infrared (IR).

Optical sensing technologies and platforms have advanced in the past decades, meaning that cheap uncrewed aerial vehicles (UAVs), standard piloted aircraft carrying affordable imaging sensors, and spaceborne systems collecting ever higher-resolution (spatial and spectral) imagery have become available (X. Jin et al. 2021). As a result, a portfolio of digital systems can now deliver optical sensing data at unprecedented spatial, spectral, and temporal resolutions and scales. Optical sensing of vegetation is now a leading focus in remote sensing science, allowing us to use nested data that span a wide range of spatial scales (Gamon et al. 2019). Further developments, including hyperspectral satellite imagery at high temporal and spatial resolutions, will accelerate the use of remote sensing data to detect and map disease and inform epidemiological modeling.

In plant disease research, there is a significant focus on epidemiology and modeling. However, it is hitherto uncommon for modelers to use optical sensing-derived measurements of plant diseases. Although there are some exceptions in which optical sensing is used to inform summaries such as logistic or Gompertz disease progress curves (Gongora-Canul et al. 2020; Zhang et al. 2023), only few papers make meaningful links between optical sensing and the state-of-the-art approaches in epidemiological modeling (Camino et al. 2021; Leclerc et al. 2023). Indeed, in part due to deficiencies in current training programs and a lack of training focusing on applied data science, most individuals interested in sensing technologies for plant disease do not have a background in epidemiological modeling. On the other hand, disease modelers, who can often be skilled data scientists, generally lack understanding of the opportunities and challenges involved in processing and interpreting remotely sensed information. Significant links between the optical sensing community and disease modelers remain absent, despite the logical benefits of such collaboration (Heim et al. 2019).

Excited by the possibilities of building such links, a subset of the authors of this paper organized a Satellite Meeting of the 2023 International Congress of Plant Pathology in Lyon: "How to combine remote sensing with epidemiological modelling to improve plant disease management?" By assigning all attendees preparatory work focusing on identifying challenges in linking the fields, and by making time for didactic talks in the meeting's program (archive: https://reseau-modstatsap.mathnum.inrae.fr/episense), attendees from backgrounds predominantly in remote sensing or epidemiological modeling were able to engage and discuss. By working collaboratively, we came to a consensus view on the opportunities—and challenges—in linking the two fields and allowing epidemiological modeling to inform work in optical sensing, and vice versa.

This paper is the output of this work. We review the opportunities and challenges in combining optical sensing with epidemiological modeling. We start by describing the state of the art in each field. Although thorough reviews of both fields are available (Bock et al. 2020; Cunniffe and Gilligan 2020; Fabre et al. 2021; Gilligan and van den Bosch 2008; Mahlein et al. 2024; Oerke 2020), in part, we wanted to use this paper to develop a common language accessible to both research communities. This requires a more detailed explanation. To illustrate what might be possible, we highlight opportunities for optical sensing to contribute to epidemiological modeling, and vice versa. We then review the outstanding challenges and categorize them into those associated with (A) identifying particular diseases; (B) data availability, quality, and resolution; (C) linking optical sensing and epidemiological models; and (D) emerging diseases. We conclude with a set of recommendations to provide a road map to motivate and shape future research and practice in both fields.

TABLE 1
List of acronyms

Acronym	Full form
UV	Ultraviolet
IR	Infrared
UAVs	Uncrewed aerial vehicles
RGB	Red-green-blue
CIR	Color-infrared
HSI	Hyperspectral imaging
NIR	Near-infrared
SWIR	Shortwave infrared
TIR	Thermal infrared
LiDAR	Light detection and ranging
VNIR	Visible and near-infrared
MSI	Multispectral imaging
BRDF	Bidirectional reflectance distribution function
RTM	Radiative transfer models
ML	Machine learning
OQDS	Olive quick decline syndrome
CLS	Cercospora leaf spot
CNN	Convolutional neural networks
PLSR	Partial least squares regression
SSL	Self-supervised learning
DA	Data assimilation
PPV	Positive predictive value

Current State of the Art

Optical sensing of plant diseases

Sensors. The most commonly used sensors are standard red-green-blue (RGB) and color-infrared (CIR) cameras. These are affordable, portable, and capable of millimeter-scale spatial resolution when used in proximal sensing settings (Anderegg et al. 2024; Barbedo 2016; Bock et al. 2020). However, such sensors only capture images in three spectral bands, reducing the number of spectral characteristics that can be monitored. Despite their fine spatial resolution and low prices, RGB and CIR cameras are optimized to reflect human vision and thus do not provide quantitative measurements of light reflection and absorption.

Multispectral imaging systems, in contrast, operate across multiple discrete spectral bands and are often designed to quantitatively measure the intensity of electromagnetic radiation. Because the spectral bands tend to be narrower than those used in RGB and CIR sensors, this enables more precise estimation of changes in specific absorption features. They also often cover spectral regions beyond the visible, enabling characterization of pigments or structural plant traits (Blasch et al. 2023; Xie et al. 2008). Hyperspectral imaging (HSI or imaging spectroscopy) captures light across a much wider spectral range in narrow contiguous bands, including UV (250- to 400-nm wavelength), visible (400 to 700 nm), near-infrared (NIR; 700 to 1,300 nm), and shortwave infrared (SWIR; 1,300 to 2,500 nm), and has a high spectral resolution (Brugger et al. 2023; Fiorani et al. 2012; Mahlein et al. 2019; Mishra et al. 2017; Rayhana et al. 2023; Sarić et al. 2022).

Very generally, plant and fungal pigments (e.g., chlorophyll, anthocyanins, carotenoids, melanins) affect reflectance spectra in the UV and visible ranges (Bohnenkamp et al. 2019b; Brugger et al. 2023; Gay et al. 2008). Reflectance in the visible and NIR/SWIR ranges carries information about foliar plant traits relevant to disease, including nutrient and water content, photosynthetic capacity, pigment, and phenolic compound concentration, as well as other physiological and morphological properties of plants, including leaf area index (Delalieux et al. 2008; Garrett et al. 2022; Gold et al. 2020b, c; Mahlein et al. 2019; Mishra et al. 2017; Singh et al. 2023; Vanbrabant et al. 2019). Reflectance in the red edge area (680 to 750 nm) is sensitive to plant stress because it is affected by chlorophyll absorption (Horler et al. 1983). HSI has been extended to retrieve passive solar-induced fluorescence in the field and with airborne hyperspectral sensors (Mohammed et al. 2019), in contrast to classical chlorophyll fluorescence, which is mainly limited to controlled environments (Ajigboye et al. 2016). This makes HSI more useful for disease measurement (Calderón et al. 2013; Mahlein et al. 2018; Zarco-Tejada et al. 2018) and monitoring

(Porcar-Castell et al. 2021). HSI can quantify subtle changes in plant constituents, and the rich information content of hyperspectral data is promising for disease detection and quantification.

Recent publications have established scalable detection of multiple economically important diseases caused by bacterial (Schoofs et al. 2020; Zarco-Tejada et al. 2018), fungal (Sapes et al. 2022), oomycete (Hornero et al. 2021), and viral (Galvan et al. 2023) pathogens asymptomatically with visible SWIR hyperspectral imagery collected via aircraft. Once the most discriminatory wavelengths are identified, hyperspectral sensors may be replaced with cheaper multispectral sensors that capture fewer spectral bands located at the most informative spectral regions sensitive to the biotic-induced physiological changes (Bohnenkamp et al. 2019b; Poblete et al. 2020).

Thermal infrared (TIR) imaging (aka thermography) captures radiation in the long-infrared, thermal range (8- to 14-μm wavelength), providing information complementary to HSI. Typical outputs include maps of canopy or leaf temperature normalized by air temperature (Still et al. 2019), thermal-based indices such as the crop water stress index (Jackson et al. 1981) and the index of stomatal conductance (Jones 1999). For foliar diseases, plant–pathogen interactions can disrupt stomatal function, leading to changes in temperature within affected leaf areas (Bassanezi et al. 2002; Hellebrand et al. 2006; Smith et al. 1986). Vascular pathogens can block plant vessels, which reduces transpiration rates, and this can also be quantified by TIR imaging (Calderón et al. 2015; Zarco-Tejada et al. 2018). TIR imaging in controlled environments has achieved presymptomatic detection in several pathosystems (Chaerle et al. 2004; Oerke et al. 2011), although reliable signals of presymptomatic disease appear absent for others (Pineda et al. 2021). In the field, higher severities of Dothistroma needle blight in pine trees and Septoria tritici blotch in wheat have been associated with increased canopy temperatures via TIR imaging (Smigaj et al. 2019; Wang et al. 2019). TIR imaging is potentially a powerful tool for detecting plant stress (Messina and Modica 2020). However, its outputs are not pathosystem specific and can be confounded with abiotic stress (Kuska et al. 2022; Pineda et al. 2021), and even without stress, temperature distributions in field canopies vary in space and time. Hence, TIR imaging is expected to be most useful in combination with other sensing technologies (Berger et al. 2022).

Light detection and ranging (LiDAR) is an optical sensing technology that uses reflected laser pulses to measure distances (Wang and Menenti 2021), generating dense 3D point clouds to map an environment. The technology is increasingly used to measure the structural characteristics of plants (Omasa et al. 2007), especially crops (S. Jin et al. 2021; Rivera et al. 2023). Applications include detecting individual plants, classifying them according to species (Fassnacht et al. 2016), and estimating plant height, leaf area index (Wang and Fang 2020), canopy density and volume, dry matter, and yield. Because structural and geometric plant traits captured by LiDAR can be affected by pathogens, in principle, LiDAR can also be used to measure plant diseases, although examples are rare (see, for example, Husin et al. 2020). More often, LiDAR has been used in conjunction with other sensing techniques, such as for Dothistroma needle blight (Smigaj et al. 2019) or wilt disease (Yu et al. 2021) and for vascular wilt ("Blackleg") disease in potato (Franceschini et al. 2024), because LiDAR provides information complementary to other sensing methods.

Platforms and spatiotemporal scales. Several platforms have been developed to gather proximal and remote sensing measurements (X. Jin et al. 2021). Some platforms are stationary, fixed in place by poles (Parmentier et al. 2021), cable suspension (Kirchgessner et al. 2016), or rails (Virlet et al. 2017). Others are mobile, ranging from handheld (Behmann et al. 2018; Cerovic et al. 2012) to those mounted on human-driven (Buelvas et al. 2023) and/or robotic vehicles (Cubero et al. 2020; Pearson et al. 2022; Underwood et al. 2017), UAVs (Aasen et al. 2018; Kim et al. 2019; Kouadio et al. 2023; Sankaran et al. 2015), piloted aircraft (Kampe et al. 2010; Wang et al. 2020), high-altitude balloons (Hobbs et al. 2023), and satellites (Paek et al. 2020; Qian 2021; Rast and Painter 2019).

The features of the sensor-platform combination determine the spectral, temporal, and spatial characteristics of the observations and typically trade off detail (resolution), scale (extent), and fidelity (precision and accuracy) (we discuss these trade-offs in more detail in Challenge Biii). We note that, because the sensors and platforms are undergoing rapid development, these trade-offs are continuously changing. Mass production of UAV components makes it possible to relatively cheaply and regularly collect spatially detailed plot or landscape-scale images that until recently required piloted aircraft. Thanks to the miniaturization of sensors, both piloted aircraft and UAVs can carry sensors chosen for their sensitivity to specific vegetation traits of interest to an epidemiological problem (X. Jin et al. 2021).

New and forthcoming imaging spectroscopy satellites include the German Aerospace Center's Environmental Mapping and Analysis Program (EnMAP) (Chabrillat et al. 2024; Storch et al. 2023), NASA's Surface Biology and Geology (SBG) (Cawse-Nicholson et al. 2021), the Italian Space Agency's PRecursore IperSpettrale della Missione Applicativa (PRISMA) (Tagliabue et al. 2022), and ESA's Copernicus Hyperspectral Imaging Mission for the Environment (CHIME) (Celesti et al. 2022). These will provide vast open datasets that can be used for plant disease measurement, with smaller missions such as CSIMBA-IPERLITE (a non-commercial in-orbit demonstration mission of the European Union) adding hyperspectral capacity at a higher spatial resolution ($\approx$20 m) (Livens et al. 2024). These systems provide high spectral and temporal resolutions (sub-monthly) but intermediate spatial resolutions ($\approx$30 m). Current thermal imaging satellites, such as NASA's ECOSTRESS, have insufficient spatial resolution for effective plant disease monitoring (>100 m). However, upcoming high-resolution TIR satellite sensors, such as NASA's Landsat Next and ESA's Land Surface Temperature Monitoring (LSTM), will offer improved revisit intervals (3 to 6 days) and spatial resolution (50 to 60 m).

These advances promise to improve the characterization of plant diseases, but the relatively coarse spatial resolution remains a challenge. The commercial satellite industry has sought to fill this gap. Recent developments in satellite design have improved the spatial-temporal resolution and scalability of spaceborne sensing platforms, making them more suitable for disease detection (Kanaley et al. 2024; Poblete et al. 2023; Raza et al. 2020). Largely, this has become possible thanks to developing satellite constellations, groups of satellites working together, often designed to complement each other in terms of coverage, revisit time, or other functions. For example, Planet Lab's cube multispectral satellite constellations provide global imagery with high spatial resolution and frequent revisit times. Planet's SuperDoves collect eight-band images at a 3-m resolution with a 24-h revisit time (Tu et al. 2022), and the SkySat C constellation captures four-band images with a 0.5-m resolution at revisit intervals set by tasking contracts (Planet 2023). In contrast, MAXAR's 16+ band Worldview-3 has a more traditional satellite design that offers a spatial resolution of 0.3 m for panchromatic imagery, 1.24 m for visible and NIR imagery, and 3.7 m for SWIR imagery (Longbotham et al. 2015). Other emerging systems offer moderate spatial resolution, but in the hyperspectral domain, including Planet Tanager (30 m, 420 bands; Planet 2024), Kuvaspace Hyperfield-1 (25 m, 150 bands; Kuvaspace 2024), PIXXEL (5 to 10 m, 250 bands; Petropoulos et al. 2024), and Orbital Sidekick GHOSt (8 m, 500 bands; Sanders et al. 2024). In the thermal domain, Hydrosat's 16 constellation promises TIR imagery targeted for agricultural use at a 30-m spatial resolution (Lalli et al. 2022).

Data preprocessing and analysis. To measure plant diseases using optical sensing, the data require preprocessing (Aasen et al. 2018; Bioucas-Dias et al. 2013) and extraction of disease measures (Behmann et al. 2015; Verrelst et al. 2019). The raw signal acquired by a sensor must be converted to a meaningful biophysical quantity, such as surface reflectance (for multispectral imaging and HSI; Daniels et al. 2023) or temperature (for TIR; Messina and Modica 2020), via radiometric calibration (Sterckx and Wolters 2019; Sterckx et al. 2020). To convert hyperspectral imagery into surface reflectance, it is essential to measure irradiance (the amount of incoming sunlight) at the time of image capture. To achieve this, irradiance should be recorded simultaneously with the imagery. This signal conversion should incorporate corrections for both the sensor and the local environmental conditions. Furthermore, plant canopies can have different patterns of sunlit versus shaded, depending on solar and view geometries. This can confound analyses when multiple images captured at different times are stitched together (mosaicking; Ghosh and Kaabouch 2016; Gómez-Reyes et al. 2022) or compared, although bidirectional reflectance distribution function (BRDF) approaches can correct for these effects (Collings et al. 2010; Queally et al. 2022). Terrain slopes may also distort the images, in which case topographic corrections are needed (Soenen et al. 2005; Vreys et al. 2016a, b). Open-source packages are available that implement BRDF and topographic corrections (Chlus et al. 2023). For high-altitude platforms, light travels large distances, making atmospheric correction essential (Bioucas-Dias et al. 2013; Sterckx et al. 2016). This can be done by inverting radiative transfer models (Verhoef and Bach 2003). In HSI, single pixels can contain spectra from different “pure materials,” or endmembers (e.g., soil, vegetation, and shadow; Galvan et al. 2023), and spectral unmixing can tease out the spectra of individual endmembers for each pixel (Bioucas-Dias et al. 2013; Gu et al. 2023). Each pixel also needs to be attributed to a spatial location by georeferencing (Aasen et al. 2018), which may require ground control points, inertial measurement units, global positioning systems, or a combination of these (Bryson et al. 2010; Turner et al. 2014). When multiple sensors are used, their spatial co-registration is desirable (Scheffler et al. 2017). Several studies offer examples of standardization and assessment of reliability of the data acquired using multispectral and hyperspectral sensors in controlled environments (Paulus and Mahlein 2020) via ground-based measurements (Detring et al. 2024) and on-board UAV platforms (Aasen et al. 2018).

After data preprocessing, meaningful disease measures must be extracted, such as disease presence/absence, incidence, or severity. To capture disease presence/absence or distinct qualitative classes of disease intensity (nominal scales; Bock et al. 2020), classification methods need to be used, whereas to capture quantitative measures of disease (e.g., incidence or severity), regression methods are more suitable. This can be done using parametric regression, machine learning (ML), radiative transfer modeling (RTM) (see Challenge Ai below), or a combination of these methods (Verrelst et al. 2019). A range of ML approaches have gained particular prominence because of their capacity to handle complex, high-dimensional datasets (Behmann et al. 2015), including penalized linear regression (e.g., partial least squares regression; Geladi and Kowalski 1986), kernel-based methods (e.g., support vector machine; Tuia et al. 2011), decision trees (e.g., random forest; Belgiu and Drăguţ 2016), and artificial neural networks (especially deep learning; Ispizua Yamati et al. 2024; Osco et al. 2021; Yuan et al. 2020). Each of the ML approaches mentioned above can be formulated as a classification or a regression method. Furthermore, in ML-based image analysis, we can train ML models to detect objects of certain types within images (e.g., diseased plants or fungal fruiting bodies) or perform image segmentation, in which we subdivide an image into multiple regions, according to certain criteria (e.g., to separate diseased leaf areas from healthy leaf areas). We mainly focus on supervised ML, which requires reference measurements of disease to be used as training and testing datasets, but we consider self-supervised ML, which requires minimal reference measurements in Challenge Bi below.

Current state of the art in optical sensing of plant diseases. Several studies have reported plant disease measurements using various combinations of platforms and sensors across a range of spatial and temporal scales. For example, ground-based hyperspectral radiometers were used to detect and quantify Septoria tritici blotch in diverse wheat cultivars (Anderegg et al. 2019; Yu et al. 2018). Further examples include detection and quantification of yellow (stripe) rust in wheat using UAV-based multispectral (Su et al. 2018, 2019) and HSI (Guo et al. 2021) and HSI using both a ground-based vehicle and UAVs (Bohnenkamp et al. 2019a). Wheat blast has been quantified using UAV-based multispectral imaging (Gongora-Canul et al. 2020). Several UAV-based studies reported quantification of potato late blight using RGB imaging (Sugiura et al. 2016), multispectral imaging focusing on quantifying low severities (Franceschini et al. 2019), and detection of the disease using HSI (Shi et al. 2022). Tar spot disease in corn has been quantified with the help of ground-based RGB imaging (Lee et al. 2021, 2025), UAV multispectral imaging (Oh et al. 2021; Zhang et al. 2023), and a combination of multispectral and thermal imaging (Loladze et al. 2019). Ground robotics and rovers that automate side and lower canopy disease data acquisition offer a promising complement to aerial imaging (Liu et al. 2022a, b, 2023).

For some pathogens at certain spatial scales, it is now firmly established that visible to SWIR imaging spectrometers mounted on piloted aircraft (e.g., AVIRIS-NG; Chapman et al. 2019) are capable of pre- and post-symptomatic disease detection (Galvan et al. 2023; Hornero et al. 2021; Sapes et al. 2022; Zarco-Tejada et al. 2018, 2021). Satellite data have been used to map and monitor host plants across large areas (e.g., citrus in China; Xu et al. 2021) and to detect both systemic (e.g., Huanglongbing in citrus; Li et al. 2015) and localized (e.g., foliar grapevine downy mildew; Kanaley et al. 2024) diseases. More recently, optical satellite data have been used to track the spread of rice blast, and ground-based hyperspectral reflectance was used to verify the satellite-derived predictions (Tian et al. 2023).

We highlight two research programs that have achieved encouraging success in sensor-based disease detection and/or measurements in two contrasting pathosystems (systemic versus localized): *Xylella fastidiosa* in olives (Box 1; a xylem-limited bacterial pathogen of a woody perennial crop) and *Cercospora beticola* in sugar beet (Box 2; a foliar fungal pathogen of an annual field crop). We note that the set of examples we have identified above is far from being complete. Many studies have achieved high accuracies of disease detection/quantification. However, with a few exceptions (Box 1), investigations have been conducted for a single disease in the absence of abiotic stress, and often in a single location. It is not clear whether the sensing signatures derived from these studies would be robust with respect to presence of other biotic and/or abiotic stresses (Challenge Aii) and to what extent the outcomes would be transferable to other host genotypes or other geographic locations (Challenge Aiii).

Epidemiological modeling

Data- versus process-based models. In categorizing model structure, a key distinction is between data- and process-based models (Madden 2006). Data-based models (aka empirical or correlative or statistical models; González-Domínguez et al. 2023) are driven entirely by data and do not attempt to capture or track the biological mechanisms underpinning disease or disease risk. This class of model has a long history, with mathematical and statistical methods becoming increasingly complex. Current work often emphasizes models including complex nonlinear responses and/or multiple predictor variables (Shah et al. 2019), as well as statistically sound treatments of different types of measurements and their associated error structures (Garrett et al. 2004; Madden et al. 2007). Promising recent developments echo trends in epidemiology more broadly (Li et al. 2017) to develop techniques for combining multiple predictions from ensembles of models (Shah et al. 2021) and to account for and weigh different sources of evidence using Bayesian analysis and decision theory (Hughes 2017).

Data availability is often a limiting factor for data-based models (Madden 2006). This makes linking with optical sensing attractive, as it increases the volume, range, and scope of data available for model parameterization and validation. In turn, these expanded datasets enable the direct application of recent developments in ML to disease prediction. Although some recent studies have shown the potential of ML for plant disease prediction (Hamer et al. 2020; Martinetti and Soubeyrand 2019; Skelsey 2021; Xu et al. 2018), applications have so far been predominantly focused on data analysis for disease detection (Gobalakrishnan et al. 2020; Xie et al. 2022) and/or quantification (Anderegg et al. 2019;

BOX 1

Aerial avengers: Remote sensing of *Xylella fastidiosa* on olives

The vector-borne, xylem-limited bacterium *X. fastidiosa* causes serious diseases in a range of cultivated and wild plants, including Pierce's disease in grapevines and variegated chlorosis in citrus (EFSA et al. 2022). In 2013, the first report of *X. fastidiosa* in the European Union came from Italy (EFSA 2013), where the pathogen was recognized to cause olive quick decline syndrome (OQDS; Martelli et al. 2016). OQDS has subsequently killed millions of olive trees in southern Europe (Bajocco et al. 2023), with reports now coming from several European Union countries. Nevertheless, remote sensing of OQDS represents an inspiring success.

Substantial reference datasets have been collected for OQDS by quantitative polymerase chain reaction (qPCR; Harper et al. 2010) assays and in situ inspections and linked to aircraft (Zarco-Tejada et al. 2018, 2021) and satellite (Hornero et al. 2020) remote sensing measurements. Combining results from visible to near-infrared hyperspectral imaging (HIS) and thermal infrared (TIR) imaging sensors onboard piloted aircraft, Zarco-Tejada et al. (2018) detected OQDS symptoms in individual olive trees, often before they were visible to the naked eye. Camino et al. (2021) extended this approach with images in the shortwave infrared region and showed how linking to dispersal processes from an epidemiological model could improve detection accuracy of *X. fastidiosa* in almonds at a pre-visual stage. Nevertheless, the confounding physiological effects caused by vascular pathogens and water stress in olive and almond required further work to reduce the detection of false positives. The evaluation of a wide range of spectral plant traits quantified from airborne hyperspectral and thermal images across host species (olive versus almond) and across vascular plant pathogens (*X. fastidiosa* versus *Verticillium dahliae*, a soilborne pathogen that causes analogous symptoms) demonstrated that there are specific spectral-based traits for each plant species and pathogen (Poblete et al. 2021; Zarco-Tejada et al. 2021). Accounting for distinct spectral plant traits associated with the dynamics of water-induced stress improved early and presymptomatic disease detection (Zarco-Tejada et al. 2021). Although detection of middle and advanced stages of OQDS development was reasonably successful using high-resolution multispectral satellite imagery, a critical conclusion is that the early (i.e., pre-visual) detection of *X. fastidiosa*- and *V. dahliae*-induced symptoms required a combination of HSI and TIR imaging from aircraft or uncrewed aerial vehicles at high spatial resolutions (40 to 60 cm) to capture pure tree crowns (Poblete et al. 2023).

However, the transferability of spectral signatures of OQDS to other olive-growing regions, and to other host species (e.g., coffee, citrus, and grapevines), is an outstanding challenge. Remote sensing may be particularly suited to the slower dynamics of vascular wilt disease progression in trees compared with annual crops. Trees are larger and persist for longer than annual crop plants in a fixed spatial location, making the multitemporal monitoring of orchards at the required resolution and frequency technologically and operationally feasible. This means higher temporal resolutions and quicker turnaround processing times are required to achieve similar success in optical sensing measurements of annual crop diseases.

BOX 2

Fifteen years of optical sensing of Cercospora leaf spot (CLS) in sugar beet

CLS, caused by the ascomycete *Cercospora beticola* (Sacc.), is a serious threat to sugar beet production worldwide (Rangel et al. 2020; Weiland and Koch 2004). This hemibiotrophic pathogen causes characteristic leaf spots with a reddish brown border and a necrotic center. Under favorable conditions, entire leaves become necrotic, causing reductions in the photosynthetically active canopy. Yield losses can reach 50% in regions with high disease pressure (Shane and Teng 1992).

Thanks to intensive research during the last 15 years, clearly defined symptoms, and the dicotyledonous growth with flat leaves of the host plant, *C. beticola* is now established as a model organism for plant disease detection using spectral sensors (Ruwona and Scherm 2022). Diverse studies have characterized and detected CLS at different scales, from the microscopic (Leucker et al. 2016, 2017) to the tissue (Arens et al. 2016; Mahlein et al. 2012), leaf (Mahlein et al. 2010), and single-plant scales (Günder et al. 2022). Hyperspectral imaging with high spectral and spatial resolution in the visible, near-infrared, and shortwave infrared ranges provided high-quality datasets of reflectance and transmittance complemented with reference data from visual monitoring or analytics. Studies under controlled conditions provide basic knowledge on the spectral characteristics of the disease (Mahlein et al. 2010), offer insights into sporulation and lesion phenotyping (Leucker et al. 2016, 2017), have linked disease etiology to biochemical and structural processes (Arens et al. 2016; Mahlein et al. 2012), and have permitted early detection before visible symptoms (Arens et al. 2016; Rumpf et al. 2010). Early studies addressed the differentiation of CLS from other foliar diseases, such as sugar beet rust or powdery mildew, and, for the first time, disease-specific spectral vegetation indices were developed (Mahlein et al. 2013). Due to recent innovations in robotics and the increasing availability of uncrewed aerial vehicles (UAVs) and spatially highly resolved red-green-blue or multispectral cameras, these studies are now complemented by field-scale studies on monitoring and detection of CLS (Barreto et al. 2023; Ispizua Yamati et al. 2022). Remote sensing using UAVs was successfully used for phenotyping of tolerant and resistant varieties (Görlich et al. 2021; Ispizua Yamati et al. 2022) and for extracting disease incidence and severity for decision-making in integrated pest management.

The progress and knowledge gained in detecting CLS are likely to be useful for other host pathogen systems, because similar experimental approaches and data analysis pipelines are expected to work for a range of foliar fungal pathogens of field crops.

Barreto et al. 2023; Leclerc et al. 2023; Lee et al. 2025; Oh et al. 2021; Zhang et al. 2023).

Process-based models. Process-based (or mechanistic) models instead aim to represent the biological basis of disease epidemics, focusing on the dynamics of disease in time and perhaps space (Madden 2006). The dominant paradigm is compartmental modeling, an approach also widely adopted for diseases of animals and humans (Keeling and Rohani 2008). Compartmental models divide a host population into mutually exclusive classes based on disease status. Levels of complexity vary, but the most common formulation distinguishes healthy and infected tissue, with a further partitioning of infected tissue into pre-infectious, infectious, and post-infectious. In plant disease modeling, this is often referred to as the H-L-I-R (Healthy-Latent-Infected-Removed) model (Madden et al. 2007), which—perhaps unhelpfully—obscures links with work on S-E-I-R (Susceptible-Exposed-Infected-Removed) models for pathogens of other host taxa (Keeling and Rohani 2008). For plant diseases, the unit of interest tracked by a compartmental model is often the individual host plant, although host tissue can be tracked at smaller (e.g., organs such as roots or leaves, or infectible sites) or larger scales (e.g., entire fields or farms, or even counties/states), depending on the scale at which predictions are required.

Much work using compartmental models is theoretical, aiming to develop strategic understanding, and therefore not explicitly tied to a single system. The focus is on understanding broad principles relevant to a class of pathosystems without detailed reference to any single pathosystem. Often, the key output is an improved understanding of epidemiological factors promoting the invasion and persistence of pathogens (Gilligan and van den Bosch 2008). Much work has also focused on how crop diversification affects disease dynamics, particularly for cultivar mixtures (Clin et al. 2022; Mikaberidze et al. 2015) and intercropping (Allen-Perkins and Estrada 2019; Levionnois et al. 2023). Other theoretical work focuses on the evolution and/or dynamics of adapted pathogen strains for fungicide resistance (Corkley et al. 2025a, b; Mikaberidze et al. 2014, 2017; Taylor and Cunniffe 2023a, b; van den Bosch et al. 2014), resistance-breaking pathogens (Rimbaud et al. 2021; Watkinson-Powell et al. 2020; Zaffaroni et al. 2024a, b), or both simultaneously (Carolan et al. 2017; Taylor and Cunniffe 2023b). Yet other work has concentrated on complex interactions, such as in the context of climate change (Jiranek et al. 2023), interactions between different pathogens (Allen et al. 2019; Hamelin et al. 2019), between pathogens and their biological control agents (Cunniffe and Gilligan 2011; Jeger et al. 2009), and between pathogens and their vectors (Donnelly et al. 2019; Falla and Cunniffe 2024). The socioeconomic implications of epidemics are explored by linking economic analyses or game theory with simpler models of exponential growth of disease (van den Bosch et al. 2018, 2023) or with full compartmental models (Hilker et al. 2024; Mikaberidze et al. 2025; Murray-Watson and Cunniffe 2022, 2023; Murray-Watson et al. 2022). Several studies have incorporated plant physiological processes into epidemiological models (Précigout et al. 2017). A final theme is the use of compartmental models to understand factors promoting disease detection (Lovell-Read et al. 2023; Parnell et al. 2015, 2017) and control (Bussell et al. 2019; Russell and Cunniffe 2025). Because underpinning compartmental models can easily be cast in stochastic as well as deterministic forms, work of this type often now also explicitly considers the risk of disease outbreaks (or, equivalently, the risk of failure of control) (Thompson et al. 2020).

Using process-based models to make predictions and/or assess disease management. Process-based models can also be used to make predictions—in time and in space—for a given disease (Cunniffe and Gilligan 2020). Similarly to data-based models, many process-based models target a single location—or set of distinct locations, with no consideration of the flow of the inoculum between them—focusing on how aspects of the abiotic environment drive rates of epidemiological processes (see González-Domínguez et al. 2023 for a recent review). Note that, despite the commonality of approach with compartmental models, in plant pathology, such models are—arguably unhelpfully—often framed as "simulation models" (Savary and Willocquet 2014) and presented in terms of visual systems dynamics modeling languages (Costanza and Voinov 2001), although we should note that these models can be readily translated into differential equations or discrete maps (Willocquet et al. 2020). Other process-based models, particularly when applied to emerging or invading pathogens, make predictions of the spatial spread of a particular named pathogen across a region through a landscape of hosts susceptible to disease, considering the effects of particular disease detection and control strategies (see Cunniffe and Gilligan 2020 for a review).

For applications to spatial spread, underpinning models must consider the flow of the inoculum and, thus, the disease transmission between locations. Although network approaches have been promoted (Garrett et al. 2018; Jeger et al. 2007; Shaw and Pautasso 2014), the large number of parameters that would need to be fitted means that full network-based models of dispersal tend not to be explicitly linked to data. Detailed spatial predictions instead tend to use the abstraction of the dispersal kernel, an idea used very widely in ecology more broadly (Nathan et al. 2012), to capture spatial dependencies via a parameterized functional form (reviewed in the context of plant disease epidemiology by Fabre et al. 2021). The challenge is then to parameterize dispersal kernels and infection rates from (often very restricted) disease spread data at different spatial scales. Broadly speaking, three distinct approaches are used to characterize dispersal kernels: (i) measurements of empirical disease gradients (Madden et al. 2007) in an experimental setting, using fungicide or other treatment to ensure there is only a single round of dispersal; (ii) using a separate detailed model of dispersal parameterized to capture the underlying mechanism of spread; or (iii) inferring the likely dispersal kernel from within a range of possibilities in process-based models using statistical approaches based on successive spatial snapshots of the pattern of disease (Cunniffe and Gilligan 2020). Several studies have estimated dispersal kernels from disease gradients but only at distinct geographic locations and often within individual crop fields (Karisto et al. 2022, 2023; Mikaberidze et al. 2016; Rieux et al. 2014). Explicit models of the dispersal process tend to be applied over large spatial scales, most often via computationally demanding spore trajectory simulations for windborne spread (Gilligan 2024; Meyer et al. 2017; Schmale and Ross 2015). Process-based models can be fitted using various statistical methodologies, ranging from simple least-squares or maximum likelihood techniques (Cunniffe and Gilligan 2020) to more complex Bayesian methodologies based on likelihood functions and data augmentation (Gibson and Austin 1996; Papaïx et al. 2022). For successful examples of doing so, see, for example, Soubeyrand et al. (2008), Cunniffe et al. (2014), Neri et al. (2014), Parry et al. (2014), Adrakey et al. (2017, 2023), or Nguyen et al. (2023). Some studies explicitly couple process-based and data-based approaches in the framework of state-space modeling or mechanistic-statistical modeling by defining a model of the observation process conditional on the model of the epidemiological dynamics and deducing from this construction a Bayesian inference scheme (Abboud et al. 2023; Papaïx et al. 2022; Pleydell et al. 2018; Saubin et al. 2024; Soubeyrand et al. 2009). When likelihoods are intractable or very complex, as can often be the case when fitting stochastic models at the landscape scale, the current vogue relies on approximate Bayesian computation via repeated simulation and the use of a distance between summary statistics computed from the observed and simulated data sets as a proxy for a formal likelihood function (Godding et al. 2023; Minter and Retkute 2019).

The current state of the art in epidemiological modeling often involves use of parameterized stochastic compartmental models to predict how epidemics will spread in time and space. Although some work focuses on spread within fields (Karisto et al. 2022, 2023; Mikaberidze et al. 2016) or relatively small production sites (Craig et al. 2018; Cunniffe et al. 2014; Parry et al. 2014), recent applications of these models tend to focus on large spatial scales and link spread modeling to optimization of disease detection (Mastin et al. 2020 for citrus greening and Martinetti and Soubeyrand 2019 for *X. fastidiosa*) or disease control (Cunniffe et al. 2016 for sudden oak death in California, Ellis et al. 2025 and Nguyen et al. 2023 for citrus greening, and Godding et al. 2023 for cassava viruses in sub Saharan Africa). The huge increase in availability of spatial data on sets of locations infected over time promised by optical sensing is incredibly attractive for predictive use of process-based models.

Opportunities in Linking Epidemiological Modeling and Optical Sensing for Plant Disease

How can optical sensing inform epidemiological modeling?

The vast amounts of data generated by sensing will greatly benefit the quality of models. The predictive power of any epidemiological model is limited by the amount and quality of data used for parameterization. Similarly, our confidence in model robustness depends on the range of data used for validation (Challenges Bi to Biii). Traditional methods to acquire plant disease data, whether in controlled environments or under field conditions, can be costly and often require expert assessors. Optical sensing promises to generate disease data at hitherto impossible spatiotemporal scales and resolutions while allowing for a much wider range of environmental conditions and locations to be sampled, including locations that are inaccessible from the ground. Increased data availability enhances the reliability and usefulness of any data-based disease model, meaning less extrapolation is required for model use in real-world settings (Madden 2006).

Optical sensing also has the potential to improve the parameterization of process-based models. More finely resolved spatiotemporal data then lead to more accurate parameter estimation and/or better prospects for (practical) identifiability of parameters (Cunniffe et al. 2024). Similarly, model selection (and model averaging) is often expected to become more powerful with an increased amount of data (Kuparinen et al. 2007). High revisit frequencies allow for the amount or spatial pattern of disease to be assessed repeatedly, leading to an improved understanding of disease dynamics over time. Focusing on spatial dynamics in particular, optical sensing would enable disease measurements over much denser and larger grids of locations (e.g., as disease gradients) with higher numbers of treatments and replicate experimental plots than is feasible by conventional visual assessments (Sackett and Mundt 2005). This would dramatically improve our capacity to quantify pathogen dispersal and reproduction via estimation of dispersal kernels (Farber et al. 2019; Karisto et al. 2022, 2023; Soubeyrand et al. 2007) together with strengths of infected source areas producing spores or other infectious propagules (Bousset et al. 2015) and basic reproduction numbers (Mikaberidze et al. 2016; Segarra et al. 2001; van den Bosch et al. 2024). Conducting such experiments characterizing disease gradients across diverse geographic locations would provide (in conjunction with weather data) detailed knowledge of how pathogen dispersal and reproduction depend on the three aspects of the disease triangle (i.e., the genotypes of the host and the pathogen as controlled by the experimental design and the environmental variables; Madden et al. 2007). This improved knowledge concerning dispersal and reproduction can then feed into spatially explicit process-based models, increasing their power to predict epidemics and evaluate disease management approaches.

Nondestructive and objective disease quantification by optical sensing will overcome difficulties and bias in human scouting and rating. However, optical sensing can do more than simply increase the volume of data. Certain diseases have symptoms that are difficult to recognize or distinguish from other diseases, or from more general signs of abiotic/biotic stress (Challenges Ai and Aii). It can also be quite difficult and time consuming even for trained assessors to unambiguously assess severity, that is, to measure the level of disease within a single host or group of hosts. These factors introduce subjectivity and bias into human scouting and rating (Bock et al. 2020; Nita et al. 2003; Nutter et al. 2006), in turn affecting the reliability of epidemiological models using these types of data for their parameterization, albeit in a way that is seldom, if ever, accounted for in the analysis (Challenge Ciii). Although lab-based molecular diagnosis is recognized for its sensitivity, accuracy, and reliability (Venbrux et al. 2023), it is typically destructive, requiring plant tissue to be removed for assessment, and may not be cost-effective (Mastin et al. 2020). Nondestructive, objective disease quantification—as would be generated by methods based on optical sensing—is therefore very valuable, even when sensors are not deployed over large spatiotemporal scales and resolutions, provided that the sensing and analytical approaches allow for correct disease diagnosis and quantification (Oh et al. 2021; Zhang et al. 2023).

Host maps and comprehensive environmental characterization provided by optical sensing will improve landscape-scale models. For landscape-scale spatial process-based models (Cunniffe and Gilligan 2020; Fabre et al. 2021), remote sensing also offers various classes of data that might be used directly as a model input, rather than as a source of data for model fitting. An important example is information on the location of susceptible hosts. Although maps have been produced for certain major crops (IFPRI 2024), location data are often either unavailable or are only available at a low spatial resolution. Sometimes only data relating to related host species are readily available. In all cases, host maps used as model inputs tend to be based on statistical inference (Ellis et al. 2025; Meentemeyer et al. 2011), losing small-grained but relevant features such as sizes and relative locations of individual fields or orchards. Because remote sensing can now reliably distinguish between different plant species (Ashourloo et al. 2022; Fassnacht et al. 2016; Kordi and Yousefi 2022) and in some cases even between different subspecies/varieties/cultivars (Lyu et al. 2024; Rauf et al. 2022), the level of biological realism in host maps could be increased. In the context of landscape epidemiology, locations of potential inoculum reservoirs might be particularly important (Plantegenest et al. 2007), such as populations of the same host species and/or of cultivated/wild alternative hosts (Emery et al. 2021; Morris et al. 2022), or crop residues from previous growing seasons (e.g., piles of potentially infectious tubers for potato late blight or pathogen-harboring standing stubble from previous host crops). Such reservoirs force epidemics, as well as potentially providing refugia for pathogens to persist between growing seasons/years. However, the potential for proliferation of species-specific parameters in epidemiological models would need to be carefully considered (Cunniffe et al. 2015). Models could also better reflect spatial variation in host plant density for a given growing season if they used real-time information from optical sensing, rather than—as at present—resorting to use of historical data or simple functions to parameterize growth over time. This would also allow for time-dependent ecophysiological information on plant status to inform epidemiological models.

Other biotic/abiotic factors affecting disease can be characterized by optical sensing (Dlamini et al. 2019) and so, in turn, could be included in disease models. This includes information on landscape topography, soil structure, and water availability, as well as the phenology of the host crop. An example of integrating phenological information with modeling is a regional-scale S-E-I-R model of Fusarium head blight (Xiao et al. 2022). There is also real-time information that can be remotely sensed and contribute to prediction when epidemiological models are used predictively for short-term forecasting (Gilligan 2024). Exciting examples include sets of currently infected locations (Allen-Sader et al. 2019), definitive confirmation of whether previously scheduled control by host removal has in fact occurred (Carnegie et al. 2023), and real-time information on meteorological driving variables as sensed by Global Navigation Satellite Systems (Bianchi et al. 2016).

How can epidemiological modeling inform optical sensing?

Model outputs will help to improve disease classification and interpretation of optical sensing data. Arguably most importantly, epidemiological modeling offers a mechanism to improve the accuracy of disease measurement via optical sensing. Optical sensing of plant disease often has a classification task at its core, in which a binary decision is made about whether a given location (i.e., a position in an image) is diseased or not. Outputs of epidemiological models could improve this classification by providing the classifier with additional relevant information. For example, positive confirmation from simple weather data-based models to estimate the risk of disease at a given location could provide greater confidence that an ambiguous signal from optical sensing in fact corresponds to disease.

There is also useful information in the spatial and spatiotemporal pattern of disease that can be used in interpreting optical sensing data. It is well known that plant diseases are clustered at a range of scales: accordingly, much statistical modeling work in plant disease epidemiology concentrates on quantifying these relationships (Madden et al. 2007, 2018). The corollary is that any location is more likely to be infected if its neighbors are also infected. This idea is at the core of the methodology used by Camino et al. (2021) for *X. fastidiosa* in almond orchards (Box 1) in which predictions from a static probabilistic model of disease risk (Parnell et al. 2011) were used to ascribe a probability of infection to different trees via a model based on an exponential dispersal kernel. These predictions were then combined with remote sensing results to come to an overall prediction of infection status on a tree-by-tree basis. Also, more complex, dynamic epidemiological models could be used in this framework, closely coupling interpretation of optical sensing data to the explicitly probabilistic predictions in space and time made by a process-based epidemic model. Similar improvement may be achieved by using convolutional neural networks to extract disease information from optical sensing data: convolutional neural networks use convolutional kernels with combination pooling to extract local features, potentially allowing the spatial topology and geometry of optical sensing data to be incorporated into predictions. However, in contrast to process-based models, the parameters of convolutional neural networks lack biological interpretation, and, hence, this approach would not provide as much insight into the processes driving epidemics.

Models will help to decide where, when, and how to deploy sensors, including guiding flight routes in near real time for surveillance. The other way in which epidemiological modeling might be useful for optical sensing is in establishing where, when, and how sensors should be deployed (Mahlein et al. 2024). Optical sensing is particularly promising for early detection, a key constraint in the "controllability" of an infectious disease outbreak (Fraser et al. 2004). The possibilities here range from being able to detect pathogens in near real time over hitherto unimaginable spatial scales (Challenge Aiii) to "anomaly detection," that is, characterizing spectral signatures associated with healthy plants and using any deviation from this to trigger ground scouting or other disease management (Challenge D). Real-time information could also be used to better guide disease surveillance, such as incorporating epidemiological models into automated flight route planning for UAVs or planning satellite surveillance patterns. In principle, each successive sample could then be taken from areas in which knowledge is weakest and so from which confirmation of disease positives (or negatives) would be most useful (see Cook et al. 2008 and Parisey et al. 2022 for examples of this broad idea). Of course, reliably detecting disease is only the first step in disease management, and many disease controls are applied reactively in response to detections of disease. Much modeling work focuses on how optimal patterns of reactive control can be identified based on observation patterns of disease until a given time (Bussell et al. 2019; Hyatt-Twynam et al. 2017). This raises the possibility of a moveable platform that combines optical sensing with disease control, such as a robotic ground-based vehicle that operates within a greenhouse or in the field (Oberti et al. 2016). This has obvious applications in precision agriculture (Yang 2020) and would echo well-publicized parallel developments for automatic weed detection and destruction mounted on tractors and other cultivation equipment (Zhang et al. 2022).

We summarize the opportunities presented above in Table 2. There, we list the relevant plant traits and features that could be estimated via optical sensing and indicate how this estimation could aid epidemiological modeling and how epidemiological modeling could aid the estimation.

Challenges in identifying a particular disease from optical sensing data (Challenge A)

Immature understanding of disease mechanisms underpinning spectral responses (Challenge Ai). Understanding spectral plant traits associated with disease is clearly important (Mahlein et al. 2012; Zarco-Tejada et al. 2018, 2021; Zhang et al. 2012). However, and with some exceptions, we lack knowledge of the mechanisms by which disease-induced alterations in plant physiology and biochemistry translate into detectable variations in spectral signatures (Oerke 2020). Additionally, the degree of conservation of spectral responses across plant genotypes and/or environments is unclear (Terentev et al. 2022). Other domains of spectral biology suggest that the more highly conserved the underlying processes are, the more likely their associated spectral features will be too, as shown for hyperspectral reflectance of healthy leaves across 544 plant species (Meireles et al. 2020). Divergent spectral pathways associated with shared physiological symptoms have been disentangled recently between major fungal foliar diseases of wheat (Bohnenkamp et al. 2021) and sugar beet (Brugger et al. 2023; Mahlein et al. 2012) in controlled environments and in other pathosystems in the field (Fallon et al. 2020; Gold et al. 2020a, b, c; Zarco-Tejada et al. 2021). Studying differences and similarities in spectral responses for pathogens affecting plant health via different underlying mechanisms is therefore essential.

A promising methodology to distinguish plant disease from other stress responses is based on plant functional traits, which has emerged as a unifying framework to understand natural and stress-induced variation in vegetation (Ustin et al. 2004; Wright et al. 2004). Plant pathogens damage, impair, and/or alter plant function, and their impacts on plant traits can be sensed both before and after disease symptoms appear. Methods to quantify functional traits from optical sensing data can be based on either statistical modeling (e.g., partial least squares regression, random forests, or Gaussian process regression) or RTM. RTM allows leaf and canopy traits linked to plant physiological processes to be retrieved from spectra (Essery et al. 2008; Kattenborn and Schmidtlein 2019), whereas partial least squares regression iteratively transforms predictor (spectra) and response variables (traits) to create predictive models (Serbin and Townsend 2020). Compared with empirical approaches based on single-band or vegetation indices, quantifying spectral traits linked to stress-induced biological mechanisms improves model accuracy and transferability (Camino et al. 2021; Hornero et al. 2021; Poblete et al. 2021; Zarco-Tejada et al. 2018). ML further allows for robust extraction of these traits from complex spectral data even under diverse conditions (Serbin and Townsend 2020; Verrelst et al. 2019). Combining partial least squares regression/RTM and ML should improve our ability to scale from controlled studies to the field (Challenge Aiii) and from foliar to spaceborne scales (Poblete et al. 2023; Zarco-Tejada et al. 2021).

Spectral signatures are inherently variable and unknown for some pathogens (Challenge Aii). Many spectral signatures of plant diseases have been reported. However, a given plant pathogen in an identical environment can very often show different symptoms. For instance, symptoms caused by *Phytophthora* spp. on citrus depend on the tissue affected (i.e., root rot, fruit brown rot, gummosis of bark, or twig desiccation) (Cacciola et al. 2007). Identifying specific signatures of presymptomatic infection remains particularly challenging (Gold et al. 2020c; Rumpf et al. 2010), requiring deep knowledge of the plant–pathogen interaction to determine physiological parameters that could be affected early in disease development. Diseases can also manifest differently depending on location (Calderón et al. 2014), pathovar (Gold et al. 2020c), and host genotype (Gold et al. 2020b; Surano et al. 2022), or depending on interactions between pathogen isolates and host genotypes (Kader et al. 2022), as well as when plant hosts experience abiotic stresses, such as nutrient deficiencies (Abdulridha et al. 2019) and water stress (Zarco-Tejada et al. 2021). Biotic stresses can also be confounding factors (Gold et al. 2020a; Poblete et al. 2021), particularly in cases of co-infection by distinct pathogen species (Bohnenkamp et al. 2019b). Differentiating between aboveground symptoms of abiotic stresses and diseases is particularly challenging for soilborne pathogens (Hillnhütter et al. 2011). Ontogenic resistance, as well as other effects of leaf age on spectral responses, may also play a confounding role (Chavana-Bryant et al. 2019). Anthropomorphic factors, such as mechanical damage and pesticides/fertilizers, may further mask spectral responses (Gambhir et al. 2024). Additional variation stems from interactions between these factors, as well as simply from the natural variability of agro- and natural ecosystems (Oerke 2020).

Even setting aside significant but unavoidable complications caused by variability, the optical spectral signatures of many pathosystems remain to be characterized. Of course, finding signatures may be intrinsically challenging for certain pathosystems. For example, shorter plant and pathogen life cycles may allow less time to characterize disease-associated signatures than for diseases in longer lived pathosystems, although in some pathogens with fast life cycles, this might be easier due to a lack of significant asymptomatic infection. Other aspects of any given pathosystem, such as whether symptoms are exhibited on foliar or woody tissue, as well as the size/pigmentation of affected plant organs, also clearly play a role.

Spectral libraries cataloging signatures across scales, diverse environments, conditions, host ages and species, stages of infection, and damage mechanisms (Boote et al. 1983) are sorely needed (Bohnenkamp et al. 2021; Zhu et al. 2023). This would allow us to investigate the transferability of spectral signatures given these potentially confounding factors.

Scaling from controlled to field conditions and from proximal to remote sensing (Challenge Aiii). Spectral signatures also depend on choices of sensors, platforms, and spatial/spectral resolutions, as well as lighting and exposure times, even under controlled conditions (see Current state of the art). Scaling to field conditions is therefore expected to be challenging. Additionally, signatures that are specific at the foliar scale are not necessarily most useful at the canopy scale (Bohnenkamp et al. 2019b, 2021; Calderón et al. 2013, 2014, 2015; Herrmann et al. 2018). If effective detection depends

TABLE 2
Plant traits and features that, once estimated via optical sensing, could aid in epidemiological modeling, and vice versa

Plant trait/feature (estimated via optical sensing)	How optical sensing aids epidemiological modeling	How epidemiological modeling aids optical sensing
Disease onset, incidence, and severity	Improves model parameterization and validation with objective, standardized, high-resolution data	Improves classification by incorporating risk estimates derived from models
Spatiotemporal patterns of infection	Enhances understanding of disease dynamics and spread (i.e., data for model fitting)	Informs contextual interpretation based on expected and/or modeled spatial clustering
Pathogen dispersal gradients	Improves estimation of dispersal kernels by providing additional data	Helps validate sensing-derived assessment of pathogen dispersal with models accounting for underpinning mechanism of pathogen spread
Real-time infection status or anomalies	Triggers surveillance or action based on spectral anomalies (underpinned by tests in models)	Optimizes sensor deployment (e.g., uncrewed aerial vehicle routes) to maximize information content in data
Host plant identity (species, cultivar)	Increases biological realism in host maps used in models	Informs whether there is a need for species-level resolution in host plant sensing
Host density and spatial distribution	Enables dynamic modeling of disease risk based on real host distributions in space	Focuses sensing efforts where areas of higher host density are expected to be most epidemiologically relevant
Host phenology and growth stage	Allows time-sensitive modeling of host susceptibility and epidemic timing	Highlights critical phenological windows (and spatial locations) for data collection using optical sensing
Environmental conditions (e.g., topography, water availability)	Adds environmental realism to models, potentially improving predictive accuracy	Identifies which environmental variables are most relevant to measure (i.e., have the largest effects on disease risk)
Presence of inoculum reservoirs or alternative hosts	Informs model structure by allowing models to account for hidden reservoirs	Suggests where to search for reservoirs based on persistence/spillover inferred with models
Confirmation of control implementation (e.g., host removal)	Improves tracking and evaluation of management interventions, then informing models	Targets verification efforts on areas of predicted but uncertain control (e.g., due to lack of stakeholder compliance)

on expensive sensors (e.g., with high detection sensitivity across narrow bands in the SWIR), lack of access to such sensors may hinder scaling to the field. Using openly available Earth observations from space agencies is appealing, with particular success for detecting defoliating insects (Dalponte et al. 2022), but other applications may be hindered by limited spectral and/or spatial resolution of the currently available satellite data.

In low to medium spatial resolution imagery (where the pixel size exceeds the size of the plant or plant unit of interest), it can be difficult to separate vegetation spectra from mixed signals of soil background, shadows, and understory vegetation (Hornero et al. 2020), although spectral unmixing techniques can disentangle spectral diversity at sub-pixel levels (Galvan et al. 2023). Nadir (straight-down) view systems are valuable for capturing visible symptoms on upper canopies but are less useful for diseases developing primarily in the lower canopy (Abdulridha et al. 2020; Carlier et al. 2023; Kanaley et al. 2024). Spectral signatures can become distorted when scaling the measurements from the leaf scale to the canopy scale, and systematic investigation of these changes is challenging (e.g., comparison of leaf versus canopy reflectance for cereals in the red edge region; Li et al. 2017). Although high-spatial resolution and multi-angular remote sensing enhance disease detection across canopy layers, operational challenges arise for regional-scale monitoring (He et al. 2021; Zhang et al. 2023). Various factors can introduce uncertainties, including canopy complexity, atmospheric conditions, sensor calibration inaccuracies, and radiometric correction (Daniels et al. 2023; Delalieux et al. 2009; Tanner et al. 2022). In particular, bidirectional reflectance effects, influenced by solar illumination and viewing geometry changes, pose difficulties with data collected at different times of day, under varying lighting conditions, and across different canopy structures. However, as described above, BRDF (Collings et al. 2010; Queally et al. 2022) and RTM approaches (Hornero et al. 2021; Zarco-Tejada et al. 2018) may be able to correct for these effects.

Challenges associated with data availability, quality, and resolution in optical sensing of plant diseases (Challenge B)

Insufficient reference data (Challenge Bi). Optical sensing requires accurate reference measurements of disease for training, testing, and validation (depending on the field, reference measurements are sometimes called "annotated data," "labeled data," or "ground truth"). However, as described in Opportunities above, such data are scarce, because they tend to be time- and resource-consuming to acquire. Visual assessments in the field can be cost-effective and, under certain conditions, can have high throughput but yet require skilled evaluators and can also be prone to error, most often due to inherent variability (Bock et al. 2022; Nutter et al. 2006). Attention needs to be paid to training of assessors, standardization of measurement protocols, data verification, normalization and calibration, and assessment of measurement uncertainties (Bock et al. 2022).

Crowd source annotation (e.g., Pl@ntNet; Joly et al. 2016), in which data labeling or classification is outsourced to a large group of people, could become a valuable additional source of reference data but also requires careful validation. Even with enhancements, visual assessment may overlook indicators not immediately apparent to the naked eye. Ideally, visual assessment should be confirmed by molecular laboratory analyses (Donoso and Valenzuela 2018; Martinelli et al. 2015). This can be especially important for pathogens not easily recognized in the field, or when multiple pathogens cause similar symptoms (Abdullah et al. 2018) (Challenges Ai and Aii).

RGB imaging provides a potential source of reference measurements (Anderegg et al. 2019). The methodology has been developed to measure foliar diseases in major crops, such as Septoria tritici blotch on wheat (Karisto et al. 2018; Stewart et al. 2016) and tar spot on corn (Lee et al. 2021, 2025), as well as bean angular leaf spot, rice brown spot, wheat tan spot, and soybean rust (Olivoto et al. 2022). However, with some exceptions, such as a recent study on red needle cast of pine (Fraser et al. 2022), acquiring RGB images of sufficient quality has thus far required destructive sampling and manual processing (Karisto et al. 2018; Lee et al. 2021; Zenkl et al. 2024) or noninvasive in-field imaging (Anderegg et al. 2024; Lee et al. 2025) of individual diseased leaves. This tends to be more resource consuming than visual assessments. A higher throughput will be achieved by capturing close-range images from within entire canopies, but several challenges need to be overcome, including variable lighting, blur due to canopy movement (for example, from wind or UAV downdraft), and extraction of relevant image parts (Zenkl et al. 2024). Most existing RGB imaging methods are yet to be used to produce reference data for optical sensing. Calibration and optimization for this specific purpose are therefore required.

Self-supervised learning (SSL) or foundation models may overcome insufficient labeled data in a different way (Culman et al. 2023; Moor et al. 2023; Y. Wang et al. 2022). SSL models can be formulated as convolution neural networks or vision transformers (Khan et al. 2023). First, an SSL model is "pretrained" on a large, unlabeled dataset, ideally capturing a wide range of conditions, according to automatically generated objectives rather than annotated data, as in conventional ML (Zhao et al. 2023). In this way, SSL models can extract useful, abstract, and generic high-level representations from unlabeled data (e.g., visual representations; Doersch et al. 2015). Next, the SSL models are trained for a specific task (i.e., "fine-tuned") using a limited amount of labeled data (Bengar et al. 2021). Similarly, foundation models can be trained on broad sets of unlabeled data and apply information about one situation to another (Moor et al. 2023). Both approaches can therefore learn from large volumes of unlabeled data, and this promises to improve model generalizability to unseen domains (J. Wang et al. 2023). However, it will be important to evaluate the outcomes to ensure accuracy.

Repurposing data originally collected for other purposes (Challenge Bii). Data potentially valuable as reference data could be sourced from growers, agronomists, or diagnostic clinics. However, disease severity is often not available, and geolocation is often absent. There can also be questions around reliability, as well as the willingness of stakeholders to engage and share data in a standardized format (Bührdel et al. 2020). As described in Challenge Bi above, severity is difficult to assess even for experts (Bock et al. 2022), and certain diseases can be challenging to distinguish from each other (Abdullah et al. 2018; Barbedo 2016), as well as from other stressors, especially when they occur together. However, apps for disease identification/detection (Siddiqua et al. 2022)—deployed on smartphones and so automatically geolocated—are promising, as are phone surveys (Allen-Sader et al. 2019). However, the potential for bias in citizen science observations in which public volunteers help to collect data (Baker et al. 2019) cannot be ignored. Another ever-growing source of data is social media/online news (Tateosian et al. 2023), the potential of which is highlighted by a system integrating internet media scraping into a predictive early warning system for wheat stem rust in South Asia (Smith et al. 2024).

At larger scales, global searchable repositories, including CABI (2023) and EPPO (2023), collate presence-absence data for plant diseases. However, spatial scales are far too coarse, and temporal resolutions too low, for epidemiological modeling applications. Despite this, large-scale crop health assessments have been used with Earth observation data, such as CIMMYT's multi-seasonal survey of wheat rusts (Pryzant et al. 2017). Data from long-term forest biosecurity and health surveys have also been used to validate identifying *Phytophthora pluvialis* from satellite imagery in New Zealand forests (Watt et al. 2024). For pathogens of crops, data from regulatory surveys of disease are sometimes becoming available (Turner et al. 2021 for cereal diseases in the

United Kingdom), and large-scale participatory surveillance efforts involving growers/agronomists are also appearing (Bregaglio et al. 2022 for grapevine downy mildew in Italy). However, potentially highly valuable field trial data collected by breeding/agrochemical companies tend to remain siloed for commercial reasons. Other potentially useful regional-scale data sources include daily disease risk maps (Shah et al. 2014), particularly when informed by real-time spore trapping data (Fall et al. 2015), although methods to integrate probabilistic disease predictions with optical sensing are needed (as discussed in Opportunities above).

Resolution and scales in time and space (Challenge Biii). Clearly, measurements should capture relevant scales in time and space to quantify traits of interest, which informs the choice of sensor-platform setups. As part of this decision-making process, host units of infection (e.g., individual plant organs such as leaves or inflorescences, individual plants, or groups of plants) must be identified based on the pathosystem in question. However, this raises trade-offs. Ground-based platforms and UAVs can capture images down to millimeter-scale resolutions (Bohnenkamp et al. 2019a), but only across a limited area. In contrast, measurements via aircraft and satellite platforms capture scales up to entire regions (Galvan et al. 2023; Poblete et al. 2023) or even continents (Kampe et al. 2010), but with lower resolution. A similar trade-off affects temporal resolution. With a fixed budget, any sensing platform can only be deployed a fixed number of times, requiring decisions over whether to sample densely over a limited time interval or more sparsely over a longer time (Mateu and Müller 2012). Commercial satellites now capture near-daily images of the entire globe with spatial resolution of ≈3 m (e.g., Planet; Y. Liu et al. 2022). Governmental satellites Landsat-8, Sentinel-2A, and Sentinel-2B together provide a global median average revisit time of 2.9 days (Li and Roy 2017), with a spatial resolution of 10 to 30 m for the multispectral sensors. On the other hand, currently operational hyperspectral satellites (e.g., EnMAP) can provide high spectral resolution (224 contiguous narrow bands) over a wider spectral range (420 to 2,450 nm) with a spatial resolution similar to that of Landsat-8, although the revisit time is coarser, at 4 days for off-nadir capture, and longer in nadir view mode (Chabrillat et al. 2024). Plant disease measurement projects need to adapt to these specific revisit times and other parameters of satellite imagery. However, the long-term, large-extent sets of satellite images will allow for modeling of long-term trends in disease dynamics, which would simply not be available using other data collection methods.

Combining datasets acquired using different sensing platforms and technologies can help to overcome these limitations and trade-offs in scales and resolutions (Berger et al. 2022), for example, via spectral and spatial unmixing (Delalieux et al. 2014). Multiple hyperspectral reflectance datasets acquired via both remote and proximal sensing have been merged to improve characterization of uncertainties and transferability of estimates of functional plant traits (Cherif et al. 2023; Singh et al. 2023; Challenge Ai). Also, results of small-scale proximal sensing confirmed via collection of reference data at a small number of tightly monitored sites could be combined with large-scale remote sensing, such as satellite imagery, to lead to more expansive inferences (Camarretta et al. 2024).

However, integrating data from different sources can be complex (Sisodiya et al. 2023; Y.M. Wang et al. 2023), particularly if some data are missing (Ekeu-wei et al. 2018; Zhao et al. 2018). Different datasets might not be aligned in space and/or time and might use different formats. Data fusion, defined as "the process of combining data from multiple sources to produce more accurate, consistent, and concise information than that provided by any individual data source" (Munir et al. 2021), is a potential solution (Barbedo 2022; Ouhami et al. 2021). Data fusion techniques, some applied to agricultural problems for almost three decades (Solberg et al. 1994), include regression methods, spatial and temporal adaptive reflectance fusion model (STARFM)-like statistical methods, geostatistical tools, principal component analysis, Kalman filters, and ML (Barbedo 2022). However, persistent challenges hinder the widespread adoption of data fusion. These include data variability and representativeness, integration complexity, overfitting, unrealistic assumptions, demand for high-performance computing, economic and technological constraints, and sociopolitical factors (Barbedo 2022). Data fusion should be used in conjunction with comprehensive model-data integration approaches to address the complexities and uncertainties inherent in plant systems data (Cui et al. 2024; Kofidou et al. 2023). In this context, data fusion might be developed in the framework of Bayesian hierarchical modeling (Bourgeois et al. 2012; Wang et al. 2018), allowing us to couple multiple observation models—corresponding to different types of optical sensing data—defined conditionally on a particular epidemic model.

Socioeconomic constraints including regulatory barriers and privacy concerns (Challenge Biv). A lack of access to data may drive new power relations around data (Kos and Kloppenburg 2019). Growers may lack the basic infrastructure required for measurements (Garske et al. 2021), may perceive the monitoring of their fields as revealing commercially sensitive data, or perhaps experience it as invasive in other ways (European Court of Auditors 2020), or may not trust the interpretation of the data (Purdy 2011). In some contexts, there are also concerns that data may be used for purposes other than those intended (Gardner et al. 2019; Kos and Kloppenburg 2019). Privacy legislation varies by country (Maniadaki et al. 2021), further challenging the application of the technologies. To address these concerns, governments and international organizations should focus on improving data regulation and legislation, as well as digital literacy (Kos and Kloppenburg 2019). Support by growers and other stakeholders might increase if efforts were made to communicate, develop data sharing agreements, and promote co-production approaches with them (Purdy 2011; van Rees et al. 2022). Thanks to technological developments in sensors and platforms, optical sensing data relevant to plant diseases can now be acquired at a much lower cost than before. Also, data storage and computing facilities for data processing have become more affordable. All these factors promise to make commercial deployment of optical sensing more profitable (Weiss et al. 2020; Wolfert et al. 2017).

Challenges in linking optical sensing and epidemiological modeling (Challenge C)

Compatibility between optical sensing data and epidemiological models (Challenge Ci). Optical sensing data may inform state variables of epidemiological models (e.g., susceptible, infected, or symptomatic states), particularly when models are spatially explicit. However, the spatial and temporal resolutions of the data must then match the spatial and temporal resolutions tracked by the model. Super-resolution methods can improve the spatial resolution of sensing data, at least to some extent (P. Wang et al. 2022), and signal processing methods (Li and Revesz 2004; Yang and Hu 2018) can be used to interpolate sensing data to achieve desired resolutions in space and time. However, handling high-resolution data may become computationally demanding. Statistical downsampling can be used if coarser resolution is needed (Atkinson 2013). Optical sensors can be used to characterize aspects of plant physiology (e.g., photosynthesis or water relations) (Zhang et al. 2021), whereas these aspects are omitted by most current epidemiological models. However, integrating plant physiological processes into epidemiological models is an active area of research (Précigout et al. 2017), suggesting that physiologically designed sensors will likely inform future epidemiological models. In general, statistical methods for spatiotemporal designs (Mateu and Müller 2012) could be used to efficiently design plant disease monitoring via optical sensing for compatibility with epidemiological models, but these may require heterogeneous data acquisition across different spatial scales, meaning data fusion becomes challenging (see also Challenge Biii; Barbedo 2022; Berger et al. 2022).

Using data assimilation methods for model fitting (Challenge Cii). A major opportunity for combining epidemiological models and optical sensing data is to obtain estimates of epidemiological parameters. This problem is referred to as parameter estimation or identification, or in some cases as inverse problems. Several methods are available. As epidemiologists often already must tackle sparse and noisy data, they routinely formulate suitable observation processes (e.g., zero-inflated) and methods (e.g., Markov chain Monte Carlo, likelihood, or nonlinear least-squares optimization) for inferring parameters when potentially useful information is unavailable (Gibson 1997; Soubeyrand and Roques 2014), in both frequentist and Bayesian statistical frameworks. Alternatively, model parameters or states can be estimated using data assimilation (Asch et al. 2016; Pandya et al. 2022). These methods may prove particularly suitable for fitting epidemiological models to optical sensing data because they have been adapted to handle image data (Mang et al. 2020; Papadakis and Mémin 2008). Data assimilation is broader than parameter estimation and is well suited for sequential data acquisition, meaning model parameters and predictions could be automatically updated as new image data are acquired. Finally, we can draw inspiration from recent ML methods developed to solve data assimilation problems in physics (physics-based deep learning; Cheng et al. 2023; Thuerey et al. 2021), which are increasingly used in epidemiology (Ye et al. 2025), to fit mechanistic epidemiological models to optical sensing data.

Accounting for data uncertainty in epidemiological models (Challenge Ciii). Although optical sensing data offers new opportunities for epidemiological modeling, additional uncertainties and errors will also be introduced. For example, environmental conditions (e.g., cloud cover, aerosol loading) can influence sensor measurements (Daniels et al. 2023). The frequency of data acquisition can also vary (Challenge Biii), meaning sensors may fail to capture important events, such as early infections (Gold et al. 2020c; Rumpf et al. 2010). Similarly, spatial heterogeneity in host topology and species/cultivar can only ever be partially captured by optical sensing. Preprocessing techniques applied to raw data from optical sensors (as described above in Current state of the art) may introduce further uncertainties.

Following preprocessing and analysis, it is now established that optical sensing data can be used to obtain point estimates of the spatial distribution of infections (Boxes 1 and 2). However, predictions have two main sources of uncertainties. First, prediction of disease occurrence and severity from remote sensed data is subject to several, known and unknown, potential confusions between biotic and abiotic causes (Challenge Aii). We note that the types of errors in optical sensing data may be different from those in reference measurements (e.g., human observations of symptoms, molecular detection), and this will require specific treatment. Second, ML algorithms used for processing optical sensing data themselves make errors. This may make epidemiological parameters as inferred from optical sensing data either potentially unreliable or difficult to interpret (Leclerc et al. 2023). Furthermore, there are challenges associated with intra-class variability (where it can be difficult to establish a boundary between classes) and inter-class similarity (where the inherent similarity between certain classes means that the class of an individual pixel can be difficult to determine unambiguously) (Bi et al. 2021; Qin and Liu 2022).

Both types of error should be considered for forward predictions from epidemiological models. Promising methods have been developed in the environmental sciences, where spatial models are fitted to remote sensing data (Chabot et al. 2015; Janjić et al. 2018), and these could be co-opted to this use case. In principle, the Bayesian statistical framework used in parameter inference in plant disease epidemiology also provides a mechanism by which these types of uncertainty can be propagated. However, despite some promising successes in related fields (Bauer-Marschallinger et al. 2022), methods to do this specifically for optical sensing data and plant disease will require more research.

Particular challenges associated with emerging diseases (Challenge D)

Reacting rapidly to invasion of a region hitherto unaffected by a plant pathogen is important to give disease management the best possible chance of success (Epanchin-Niell and Hastings 2010; Fraser et al. 2004). However, because spread data only become available as any outbreak unfolds (Thompson et al. 2018), pathogen biology and transmission become more precisely characterized the longer any epidemic has been spreading in the region of interest (Neri et al. 2014). This unavoidable tension between when models are most useful and when the data to drive them become available leads to challenges characteristic of emerging plant disease epidemics, affecting both optical sensing and epidemiological modeling.

A challenge is that reference data are almost always more limited for emerging than for established diseases. The probability a disease will truly be present if detected—the "positive predictive value" (PPV) (Bours 2021)—is likely to be low. Indeed, the PPV depends on the prevalence of the disease (a priori low for an emerging disease) and the sensitivity and specificity of the detection method. With a sensitivity and specificity of 90%, the PPV is 0.083 for a prevalence of 1%, meaning that the disease is truly present in only 8.3% of detections. This value drops to 0.89% for a prevalence of 0.1%. Nearly perfect sensors with 99% sensitivity/specificity are necessary to reach a PPV of 50% (at prevalence 1%) and 9% (at prevalence 0.1%). The levels of sensitivity and specificity of optical sensing in the field depend on many factors, but values higher than 90 to 95% are currently unlikely (Terentev et al. 2022).

Arguably the larger challenge for optical sensing of emerging pathogens is that spectral signatures are often not characterized. It would, of course, be plausible to use signatures from geographic regions where the pathogen of interest is well established and well characterized (Gongora-Canul et al. 2020; Negrisoli et al. 2022; Zhang et al. 2023). However, this raises challenges around the robustness/transferability of the signatures from different geographic areas. A second approach could be to use proximal sensing and reference disease intensity data from controlled environment experiments. However, here, the related challenge is the robustness/transferability between controlled environments and epidemics in the field (see Challenge Aiii).

An approach that simultaneously targets a range of potential invading pathogens while sidestepping the need to obtain disease-specific spectral signatures in a novel environment is "anomaly detection." Spectral signatures associated with healthy plants are characterized, and deviation from typical signatures then acts as a trigger to initiate ground scouting or other efforts (Kanaley et al. 2024). It may be possible to derive robust and species-specific spectral signatures of plant health based on foliar functional plant traits (Reich et al. 1997; Wright et al. 2004). Some of these traits (e.g., leaf mass per area, chlorophylls) may reflect overall plant health, whereas others (e.g., lignins, carotenoids) hint at diseases. Robust estimation of many of these traits via optical sensing has been achieved (Cherif et al. 2023; Singh et al. 2023; Wang et al. 2019, 2020; Zhang et al. 2021). Measuring abnormal plant mortality (Wegmueller et al. 2024) and detecting abnormal changes in plant traits (Fekete and Cserep 2021) via optical sensing combined with novelty detection classification techniques (AlSuwaidi et al. 2018) may provide valuable information about emerging diseases. These approaches may become especially effective in nursery and greenhouse production: a relatively small footprint and controlled growth conditions make it easier to characterize and monitor spectral signatures of healthy plants. However, going from characterization of functional plant traits to a robust assessment of plant health requires a nontrivial synthesis of existing knowledge/data and dedicated new datasets.

Parameterized mathematical models will also tend not to be available when a pathogen is emerging and spreading in a new region. Indeed, fully parameterized predictive models have often only become available after control has ceased to be a viable proposition (e.g., sudden oak death in California; Cunniffe et al. 2016; Meentemeyer et al. 2011). Similarly to the trade-offs for optical sensing above, options for making models available before or during outbreaks tend to require either significant assumptions on pathogen spread (Hilker et al. 2017) or direct transfer of models originally parameterized for spread in other locations (Ellis et al. 2025). Both options introduce uncertainties and potentially inaccuracies in spread predictions. Predictive models of emerging pathogens are therefore particularly challenging to develop (Cunniffe and Gilligan 2020; Cunniffe et al. 2015), and links with optical sensing must be alert to this. Where possible, a combination approach—use of predictive models along with anomaly detection, described above—may help to improve timely detection of emerging diseases.

Finally, ethical considerations, including privacy and data sharing concerns, can pose particular challenges for emerging diseases (Challenge Biv). Emerging diseases tend to require interdisciplinary collaboration between remote sensing specialists, epidemiologists, and plant pathologists, sometimes under significant time pressure, and this may not be easy. In many developing countries, limited infrastructure and resources, a lack of experts in relevant fields, or limited funding might reasonably be expected to lead to particularly extreme challenges in this regard.

We summarize the opportunities and challenges presented above in Figure 1.

Recommendations

Establish standards

There is a critical need to standardize methods for optical sensing in plant health monitoring to acquire data comparable across sensors, sites, and dates. This includes developing common protocols for data acquisition, processing, and interpretation; ideally, this should be led by experts in these fields. Assuming they are widely adopted, consistent, reproducible, and reliable practices will help minimize bias, improve accuracy, and enable comparability across studies. This is critical for HSI due to the complexity of the sensors' operation, data acquisition, and processing (Aasen et al. 2018). To convert hyperspectral imagery into surface reflectance (the proportion of incoming light reflected by a surface), it is essential to measure irradiance (the amount of incoming sunlight) at the time of image capture. This requires recording irradiance data simultaneously with the other imagery captured by measurement platforms. Radiometric calibration of the sensors and standard models (such as RTM; Verhoef and Bach 2003) need to be optimized for local conditions to enable atmospheric correction of the imagery. For UAV platforms, Chakhvashvili et al. (2024) proposed a structured approach to multi-sensor campaigns encompassing mission planning, calibration, and spatial referencing and using additional sensors to assess ambient environmental conditions (e.g., weather stations, Internet of Things environmental sensors). A recent positive development is the publication of a European and Mediterranean Plant Protection Organization (EPPO) standard on "Adoption of digital technology for data generation for the efficacy evaluation of plant protection products" (Anonymous 2024).

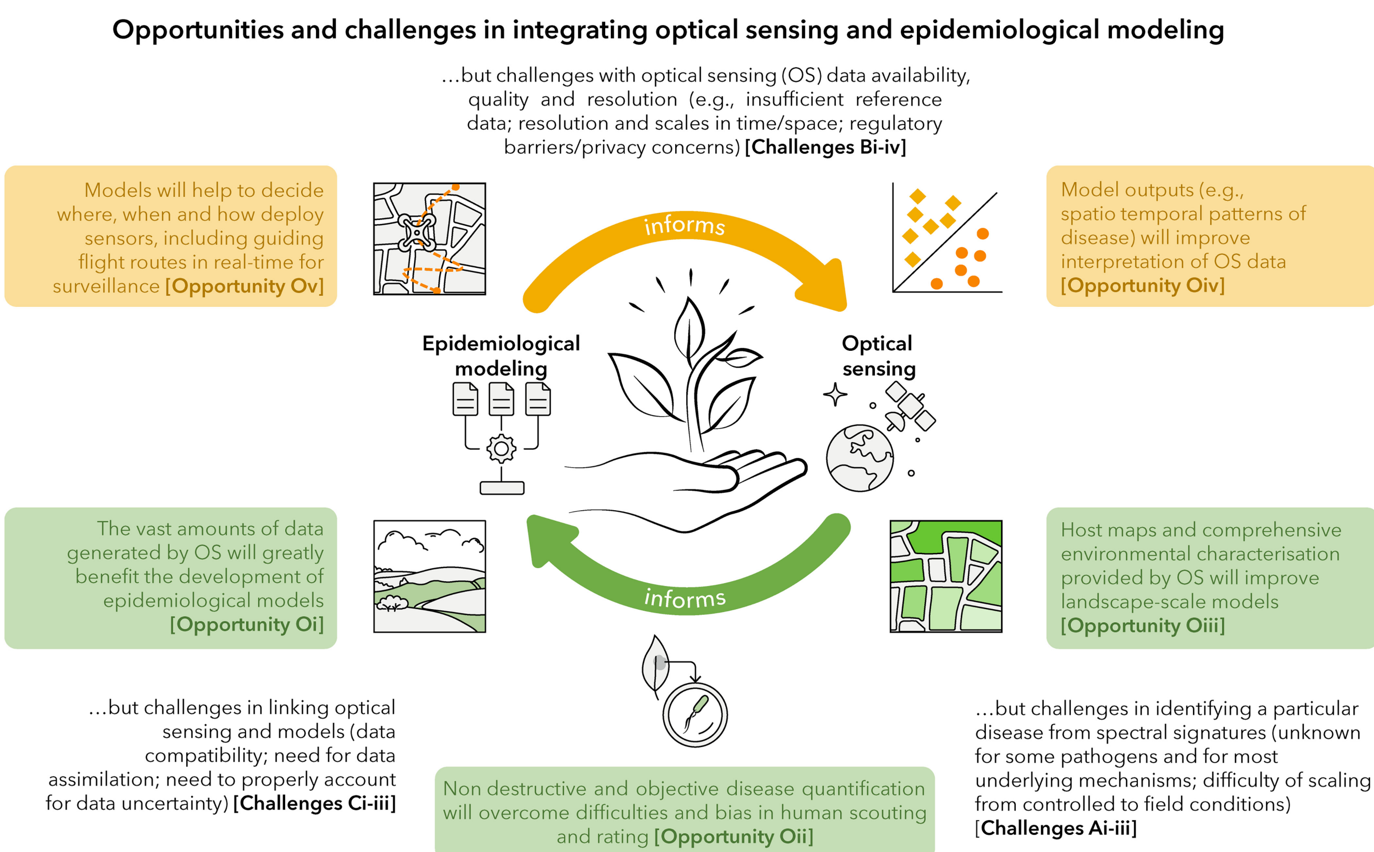

FIGURE 1
Summary of opportunities and challenges in integrating optical sensing and epidemiological modeling.

Develop, maintain, and use open access databases

Open access, standardized databases including optical sensing data, epidemiological models, and reference data would foster cross-disciplinary work (Sparks et al. 2023). However, data privacy and intellectual property implications would need attention (Kaur et al. 2022), as would long-term funding to maintain such a system. To achieve this, we can draw inspiration from genomics, where open access data repositories are well established (e.g., GenBank of the National Center for Biotechnology Information). Using openEO (https://dataspace.copernicus.eu/analyse/apis/openeo-api) in remote sensing of plant diseases would provide a standardized, scalable, and interoperable platform that simplifies access to diverse Earth observation datasets (Schramm et al. 2021).

Develop awareness by working with stakeholders

To address socioeconomic constraints, governments and international organizations should improve data regulation, legislation, and digital literacy (Kos and Kloppenburg 2019). Our research communities need to work with social scientists and stakeholders to find ways to reconcile data availability with respecting data privacy and intellectual property (Everts et al. 2012; Kaur et al. 2022).

Routinely capture a range of conditions to improve generalizability and transferability

Many studies report disease measurement via optical sensing, but the outcomes may not be robust with respect to other biotic or abiotic stresses and may not be transferable to other host genotypes or geographic locations. To address these challenges, comprehensive ranges of conditions (related to host plant, pathogen, and the environment) need to be captured in both reference and optical sensing measurements, which need to be georeferenced. Possible abiotic and biotic confounding factors also need to be assessed in the field.

Use crowdsourcing and gamification to improve annotation of data when possible

Annotated reference data for model training is a key limiting factor, and crowdsourcing may help to overcome this (Wazny 2017). However, despite the emergence of various paid-for platforms, such as Amazon's Mechanical Turk (Mason and Suri 2012), and the possibility to use gamification to reduce costs (Khakpour and Colomo-Palacios 2021), the necessary specialist knowledge required to annotate plant diseases might make this challenging (Bock et al. 2020). However, these efforts would be of great educational value and help to promote plant health to wider audiences.

Optimize optical sensing data collection both for use with models and by using models

Spatial and temporal scales and resolutions and trade-offs between them need to be considered when combining optical sensing and epidemiological modeling. Acquisition of optical sensing data can be optimized using epidemiological modeling, but model development needs to be informed by the characteristics of the available optical sensing data.

Identify signatures of plant health beyond the one host-one pathogen paradigm

Linking epidemiological models and optical sensing data is difficult because it is hard to identify a given disease, particularly given the range of biotic and abiotic conditions that must be handled (Challenge A). Focusing on anomaly detection is therefore very attractive, although it requires us to overcome the significant challenge of robustly assessing plant health from measured traits (while accounting for multiple pathogens).

Ensure uncertainties are captured and propagated through analyses

Uncertainty can be introduced at various stages in analytic pipelines, from uncertainty in measurements (e.g., due to cloud cover) to confusions caused by interactions with biotic and/or abiotic factors (Challenge Aii), errors or imprecision in ML methods for processing data (Qin and Liu 2022), uncertainties in model parameters as fitted to data (Minter and Retkute 2019), and sampling effects when using stochastic models predictively (Cunniffe and Gilligan 2020). Sorely needed are methods to capture and propagate these uncertainties forward, building on promising methods from related fields.

Establish multidisciplinary collaborations

We need to foster multidisciplinary and interdisciplinary collaborations, bringing together optical sensing experts, computer scientists, plant pathologists, plant physiologists, crop modelers, and epidemiological modelers (Camino et al. 2021). Encouragingly, a growing body of work in phytopathometry (Gongora-Canul et al. 2020; Kanaley et al. 2024; Lee et al. 2021, 2025; Oh et al. 2021; Zhang et al. 2023) exemplifies this and shows how integrated methodologies can enhance the reliability and scalability of plant disease detection, quantification, and assessment under field conditions. In going further and linking optical sensing with epidemiological modeling, we should not reinvent the wheel but instead draw inspiration from disciplines such as environmental sciences (Liu 2015; Weng 2009) and meteorology (Bevis et al. 1992; Mittaz et al. 2019), which have long coupled optical data with mathematical modeling. We can also reflect on other uses of new sources of data in epidemiological modeling. Notable examples include phylogenetic data (Gougherty and Davies 2021; Pybus and Rambaut 2009) and human mobility data from mobile phones and social media (Grantz et al. 2020; Kostandova et al. 2024).

Teach basic sciences and modern data analysis in plant pathology training

A major obstacle to integrating optical sensing and epidemiological modeling is the inconsistent and often insufficient training in basic sciences and modern data analysis at the bachelor's and master's levels in agricultural and biological sciences. Although addressing this requires systemic changes and broader discussions across the academic community, there are practical steps we can take to train the next generation of plant health researchers. These include (i) designing and teaching courses on digital plant health, incorporating necessary elements of basic sciences (mathematics, physics, chemistry, and biology), programming, data sciences, and mathematical modeling; (ii) organizing summer schools on interdisciplinary approaches to plant health; and (iii) organizing informal study groups and other communities that bring together students and researchers from different disciplines, perhaps leveraging internet technologies to do so. Ensuring accessibility to these opportunities—particularly for researchers from the Global South and underrepresented communities—should be a key priority. In doing this, we can draw inspiration from similar discussions in related multidisciplinary fields such as bioinformatics (Mulder et al. 2018) and big data/artificial intelligence (Luan et al. 2020).

Promote opportunities to funding agencies, governments, plant protection organizations, and technology companies

Interdisciplinary and transdisciplinary research in digital plant health must be supported more strongly by funding agencies. Traditional 3-year funding periods are often too short to perform the necessary field trials or observational studies, collect and analyze data, and publish the outcomes. More comprehensive support, longer-term funding, and interdisciplinary projects are needed to collect these datasets, transform them into meaningful interpretations, and publish them open access in accordance with the findable, accessible, interoperable, and reusable (FAIR) data principles (Kumar et al. 2024). This approach is data intensive, and, therefore, we need to establish the necessary infrastructure to develop sophisticated artificial intelligence models (e.g., SSL or foundation models)

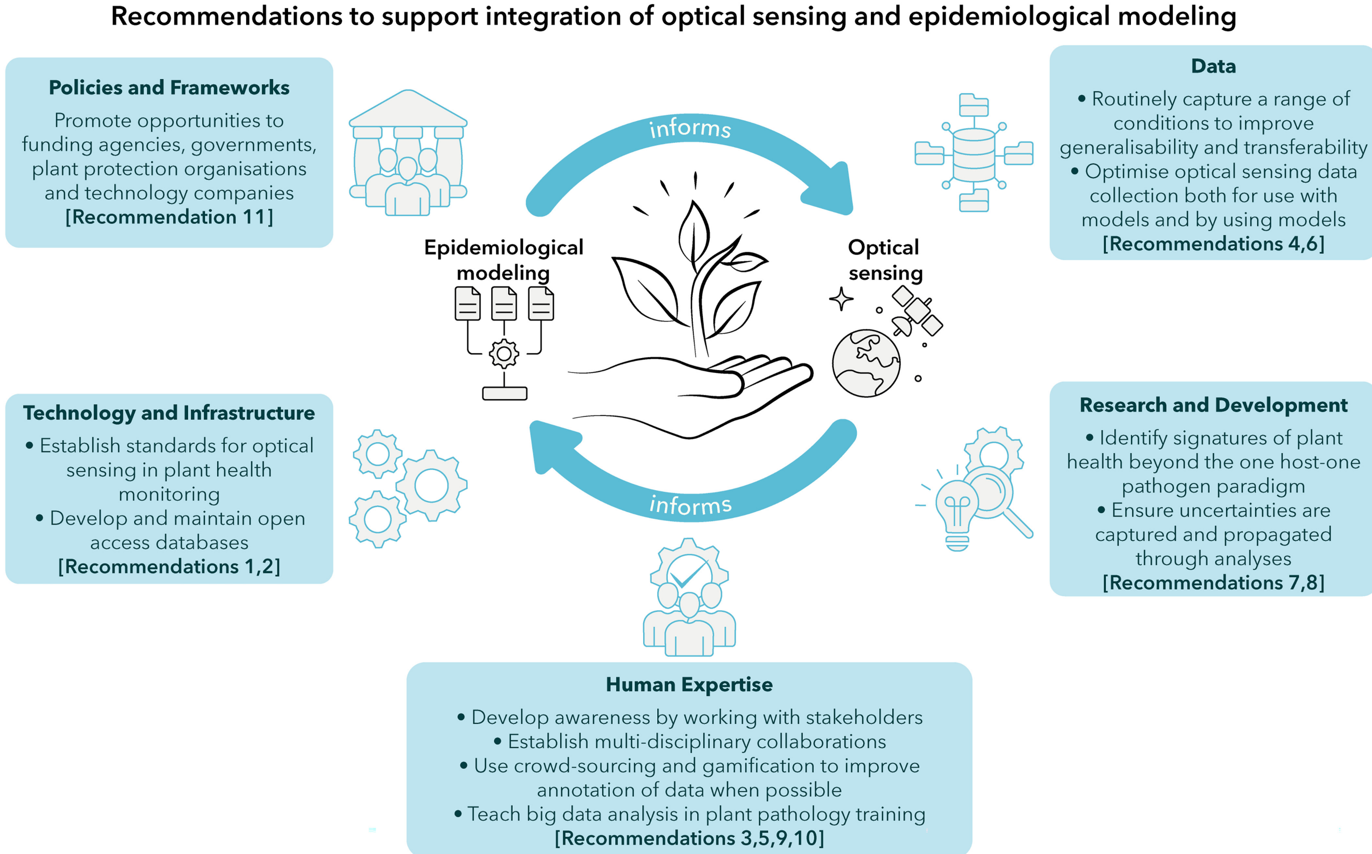

FIGURE 2
Summary of recommendations to support integration of optical sensing and epidemiological modeling.

in cooperation with ML experts. Furthermore, we need to collaborate with plant protection companies and technology companies to make the applications rapidly accessible and to foster their adoption by growers. A particular challenge is to communicate with political decision-makers and convince them of the many possibilities and necessary steps, as well as the commensurate need for investment.

We summarize the recommendations presented above in Figure 2.

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