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EDITORIAL

# A special issue on phytopathometry — visual assessment, remote sensing, and artificial intelligence in the twenty-first century

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Phytopathometry is fundamental to plant pathology and related disciplines (Large 1966; James, 1971; Bock et al., 2010; 2020). Epidemiology, disease management, and aspects of agronomy and plant breeding (phenotyping) all rely on measuring or estimating disease (Bock et al. 2010). Although both, incidence and severity of disease, are important variables, disease severity might be considered a more challenging variable to obtain for visual or sensor-based systems but is crucial to understanding many facets of disease for many pathosystems (Madden et al. 2007). A quantitative approach to visual assessment was first attempted by Cobb in the late 1800s (Cobb, 1892), and visual assessment has since become better understood and refined (Bock et al. 2010, 2020; Nutter et al., 1993; Nutter 2001). Instrument-based remote sensing is more recent: although aerial photography and various cameras were used early in plant disease measurement (Neblette 1927; Bawden, 1933), the earliest studies reporting sensors being used as proximal tools were performed late in the twentieth century; for example, Pinter et al. (1979) established an approach for discrimination of disease using close-range thermal spectrometers. Lindow and Webb (1983) were among the first to use red–green–blue (RGB) image analysis and Nutter et al. (1985) were first to apply a multispectral radiometer to measure disease. Remote sensing is now a burgeoning field and optical sensors are becoming more sophisticated and more capable of detecting and measuring disease (Mahlein et al., 2018; Bock et al. 2020). In several cases, especially in controlled conditions, measuring severity has been realized, but challenges remain (Barbedo 2018, 2021). Nonetheless, visual estimates of disease severity remain the most commonly used method of assessment for most practical experiment situations and applications. We believe this is the first time a journal Special Issue was tasked with phytopathometry as a subject area, although there have been other journal issues that have addressed more narrow topic areas, for example, sensor-based imaging of diseases.

Considering the central position of phytopathometry in plant pathology and related disciplines, it is particularly timely that we give over an issue to the subject, to pause and look back and assess what has been achieved, and consider what challenges and opportunities lie ahead. For visual disease assessment, the methods and approaches have maintained some constancy, but are now based on a firmer scientific understanding and can be applied in a more informed and nuanced manner to ensure appropriate methodology to maximize accuracy and reliability. The development and use of ordinal disease scales (Chiang et al. 2014) and standard are diagrams (SADs, Del Ponte et al. 2017) are well established examples. But a whole new suite of sensor-based digital technologies underpinned by up-to-date approaches from data analysis and interpretation including machine learning or in a broader sense "artificial intelligence" has arrived and offers incredible opportunities for measuring plant disease severity (Mahlein, 2016). The science is advancing at a pace (Gold 2021; Mahlein et al. 2022). Thus, RGB, multispectral and hyperspectral imaging, chlorophyll fluorescence, thermal imaging, and other approaches are all poised to become practical assets for disease quantification. Recently,

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innovations from robotics further improved the flexibility of their application, for example, the use of unmanned aerial vehicle (UAV)-platforms in combination with optical cameras is on the cusp of practical application (Mahlein et al. 2022). Indeed, the digital technologies will eventually be critical to, and integral to precision agriculture and phenomics (Mutka and Bart 2015; Mahlein 2016; Gold 2021; Mahlein et al. 2022). Machine learning or artificial intelligence has only relatively recently been applied to phytopathometry, but is vital to the success of field applications of sensor-based digital technologies (Behmann et al. 2015; Barbedo 2018; Barbedo 2016; Ferentinos 2018; Mohanty et al. 2016; Schramowski et al. 2020). And with the progress and new technologies, come new terms and concepts previously alien to plant pathologists but which are rapidly being acquired by the discipline and becoming part of a twenty-first century plant pathologists' lexicon.

It is our pleasure to present a balance of review articles and original research on phytopathometry in this Special Issue, which is divided in three sections. In the first section, we recognize Dr. Forrest W. Nutter, Jnr. (Madden et al.) and present an updated glossary of terms used in phytopathometry (Bock et al.); in the second section of articles, we embark on a review of visual assessment and methods (Bock et al.; Chiang and Bock), including original research (Del Ponte et al.); and in the third section, we explore the use of sensors, digital technologies, and artificial intelligence with a series of reviews (Barbedo) and original research articles (Ruwona and Scherm; Alves et al.; de Carvalho Alves et al.; Khaled et al.; León-Rueda et al.; Pozza et al.).

In the first section, the first article is a tribute to, and recognition of Dr. Forrest W. Nutter, Jnr., who spent a career pushing knowledge and understanding of disease assessment forward. Madden et al. outline Dr. Nutters' remarkable career and contributions, particularly those aligned with phytopathometry, although his contribution went way beyond the topic of this issue. His work in phytopathometry is described, from his early use of radiometers to measure plant disease in 1983, through his early experiments on accuracy and reliability of plant disease assessment and computer-based training. Dr. Nutter and colleagues were the first to provide evidence of the short comings of the much-used Horsfall-Barratt scale, and demonstrated it improve neither accuracy nor reliability of estimates. The scale continues to be used, but we believe that its use is now with greater caution and understanding of its shortcomings. Much of Dr. Nutters' work underpins modern phytopathometry.

The need for a within-discipline and cross-discipline understanding of the terms and concepts used in modern phytopathometry requires that they be clearly defined and correctly used to avoid confusion and misunderstanding. To this end, Bock et al. have compiled an updated glossary of terms used in phytopathometry. The glossary tackles updated definitions for the term "severity" and introduces a suite of other terms used in sensor-based methods of disease measurement.

The second section, on visual assessment, is introduced by an overview of the history, development and current status of visual disease assessment, changing paradigms, sources of error, and the methods used that aim to maximize accuracy and reliability (Bock et al.). The status of visual assessment is discussed, and it is suggested that overall, further gains in accuracy and reliability of visual estimates are likely to be slight if best operating practices (based on our current knowledge of visual assessment) are followed as outlined in the review.

Continuing with the topic of visual assessment, SADs are fundamental to improving the accuracy of plant disease estimates. Del Ponte et al. present a meta-analysis of SAD studies that used linear regression coefficients to ascertain the improvements in accuracy and precision when using the tool. The meta-analytic model determined a gain in precision from using SADs, a reduction in constant bias, although systematic bias was less affected by use of SADs. Less accurate estimates were associated with numerous small lesions and for those diseases where maximum severity was < 50%. The study not only demonstrates the utility of SADs, but provides novel insights into the symptom characteristics affecting precision and bias, and SAD illustration number and design.

Also related to visual assessment, ordinal scales have been used to indicate the severity of plant disease since the earliest attempts at quantification. Ordinal scales have been seriously misunderstood, misused, and misanalysed by generations of plant pathologists. To this end, Chiang and Bock have reviewed the use of ordinal scales, and studies that have contributed to our understanding of the scales, and what actually constitutes a quantitative ordinal scale that maximizes accuracy and reliability when choosing to use the tool.

The third section focusses on sensor-based methods of disease detection and quantification, associated digital technologies, and artificial intelligence. Ruwona and Scherm review the application of these technologies in plant pathology and disease management using a systematic approach to explore research trends, the evolution of research topics, and publication. They do this using a structured, bibliometric approach with VOSviewer software and make the interesting observation that China, the USA, and Germany dominate the field. Most journals publishing plant pathology-related studies were in the realm of remote sensing (9 out of 10 journals). Research themes were identified that included wheat diseases, aspects of plant physiology, analytical approaches, and data acquisition sources. Analysis showed that articles associated with analytical approaches and data acquisition sources tended to have later publication dates, suggesting that knowledge of pathogen biology and plant physiology had to be established prior to involving engineers and computer scientists in more recently emerging areas such as machine learning and big data analytics. The research shows research habits, publication trends, and collaboration patterns and provides a baseline for future research on scientific networks in the interdisciplinary domain of disease measurement using sensor-based technologies.

The rise of deep learning techniques has impacted both research and applications of pattern and object recognition in digital images. Barbedo reviews the current status of deep learning for disease classification. Some studies provide promising results with classification accuracies of prediction models approaching 100%, and suggests that provided the training set is enough, deep learning models can solve most image classification issues. However, determining “enough” is not trivial and involves sample size, the quality, and representativeness and appropriate variability of the training dataset. It is particularly challenging due to the variable nature of plant diseases in space and time due to innumerable factors that introduce variability to the issue. Most studies have been limited in scale, but application of deep learning to disease measurement is burgeoning. Barbedo suggests that the data gap problem needs to be filled to satisfy existing limitations and discusses technical and practical issues to be addressed to achieve this goal.

RGB image analysis has been a research tool and a subject of research since at least the early 1980s. Indeed, image analyzed samples are often considered the “gold standard” against which other measurements, particularly visuals estimates, are compared. An object of research using RGB image analysis is to strive for adequate accuracy and reliability of measurements, particularly under field conditions. Olivoto et al. introduce a new R package software, *pliman*, the first R program written for analysis of disease severity on images of plant specimens. In the automated system, the RGB values are used as predictor variables in a binomial logistic regression fitted to binary outcome for both the background/organ and health area/diseased area. Compared to other industry standards, *pliman* was both accurate and reliable. The program should be a valuable tool for plant pathologists and scientists from related disciplines needing to batch process large image collections.

Diseases induce visible modifications on leaves with the advance of infection and colonization, thus altering their spectral reflectance pattern. Alves et al. evaluated RGB reflection from leaves symptomatic for five diseases: soybean rust, Calonectria leaf blight, wheat leaf blast, *Nicotiana tabacum-Xylella fastidiosa*, and potato late blight. Ten RGB spectral indices were calculated from images of leaves with varying severity. There was a correlation between severity and most spectral indices. Boosted regression tree models were trained to predict severity for each disease with prediction accuracies up to > 97%. The potential for these systems to eventually be adapted for practical field use is discussed.

De Carvalho Alves et al. used topographical factors and satellite-based remote sensing variables to describe and predict patterns of bacterial blight (*Pseudomonas syringae* pv. *garcae*) in coffee based on machine learning and geostatistics implemented with geocomputation and digital image processing algorithms. Utilizing these big data, and applying machine learning, epidemiological information and insights were obtained that has the potential for guiding more precise management of bacterial blight of coffee.

Khaled et al. investigated the feasibility of applying a genetic algorithm (GA) to select the most significant frequencies of dielectric spectral data for identifying basal stem rot (BSR) of oil palm. Four classifiers were compared: linear discriminant analysis (LDA), quadratic discriminant analysis, *k*-nearest neighbors, and naïve Bayes. Applying the GA and using LDA classifier, the highest accuracy was 86.36%. The results show that using a GA for feature selection enhances classification accuracy of BSR in oil palms using dielectric spectroscopy measurements.

Timely and accurate detection and differentiation of diseases from other stressors are the basis for effective management. León-Rueda et al. evaluated UAV acquired multispectral data to detect vascular wilt of potato caused by *Verticillium* spp., waterlogging stress, and a symptom of unknown cause. Five spectral band images were acquired, and vegetation indices calculated and evaluated for ability to discriminate between diseased and healthy plants based on a generalized linear model and Kappa index. A supervised random forest algorithm was also implemented. Accuracy ranged from 37.5 to 82.5%, depending on experiment. The tool has potential for detection and differentiation of diseases and physiological disorders in commercial potato crops.

Finally, computer vision and machine learning offer great potential to evaluate seed health. Traditional methods are labor intensive, and the assays take time to perform. Pozza et al. used computer vision combined with different machine learning algorithms to detect and identify seed-borne fungi associated with common bean seeds based on RGB spectral data. After a fivefold cross-validation process and a confusion matrix, the random forest algorithm had the highest prediction success to detect the targets correctly to species. In light of the reported results and other studies, the authors discuss the use of computer vision and machine learning to augment traditional tests.

We believe this collection of articles by prominent scientists in the area will be a valuable resource for those working in the field of phytopathometry, and for those needing more information regarding the state of the art of tools, methods, and techniques available for estimating or measuring plant disease. The area is fast moving and will continue to evolve. In conclusion, the resource is a repository of information for those already deeply engaged, and those desiring to learn more about phytopathometry using a range of available approaches.

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