Direct Research Journal of Agriculture and Food Science

Vol. 11(12), Pp. 339-349, December 2023
ISSN: 2354-4147
DOI: https://doi.org/10.26765/DRJAFS604179266
Article Number: DRJAFS604179266

https://journals.directresearchpublisher.org/index.php/drjafs

Standard Methods and Innovative Techniques in Phytopathometry, the Art and Science of Plant Disease Measurement

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Received 19 September 2023; Accepted 21 November 2023; Published 13 December 2023

ABSTRACT: Agriculture remains a mainstay gross domestic product earner and key contributor for public health nutrition of various economies in sub-Saharan Africa. Pests and disease attacks, and ecological health effects are some of the vital challenges to agro-productivity and sustainability. Early detection, proper diagnosis, accurate and precise measurement or correct estimation of disease would help mitigate the losses encountered by the farm economy from these bio-pressures which already are known to exceed 50% postharvest. Classical and conventional approaches to crop loss assessments though useful but whose accuracy depends largely on the skill of the assessors is on the other hand time consuming and prone to some forms of biases. Modern technology through remote sensing techniques and various other forms of satellite-based or airplane-borne sensing systems including radar, GIS, GPS and drones hold strong potentials for improving disease detection, disease or damage assessment and crop loss estimation. Herein, a review highlighting some of the standard and innovative techniques of plant disease, biotic and abiotic stress detection, assessment, measurement and crop loss estimation is presented.

Keywords: Plant disease, Phytopathometry, Crop loss assessment, Crop disease estimation, Remote sensing, Visual assessment, Internet of Things (IoT)

Citation: Enyiukwu, D.N., Chukwu, L.A., Bassey, I. N., and Nwaogu, G. A. (2023). Standard Methods and Innovative Techniques in Phytopathometry, the Art and Science of Plant Disease Measurement. Direct Res. J. Agric. Food Sci. Vol. 11(12), Pp. 339-349. https://doi.org/10.26765/DRJAFS604179266. This article is published under the terms of the Creative Commons Attribution License 4.0.

INTRODUCTION

Phytopathometry refers to the quantitative study of the suffering plant (Anonymous, 1991). It is the branch of plant pathology associated with plant disease appraisal, measurement and quantification (Large, 1966; e-Concise Dictionary of Plant Pathology, 2004). Phytopathometry is defined as the estimation or measurement of the amount of plant disease expressed by disease symptoms or signs of a pathogen on a single or group of host plants (Bock *et al*., 2022). Plant disease measurement therefore aims at quantitative rather than qualitative reportage of plant diseases (Large, 1966). Methods for disease assessment involve a detailed knowledge of the disease and all the ways it affects the plant (Large, 1966). Some workers suggest that thorough knowledge of morphology, physiology, and stages of growth of the healthy host crop etc. coupled with the entire sequence of host-pathogen interaction leading to development of disease must be clearly understood, before any assessment can be gainfully conducted on the plant. Similarly, knowledge of plant disease prevalence, severity, and spatial and temporal distributions underpins crucial economic decisions in agriculture. This information is needed by agro-allied stakeholders to evaluate disease management decisions, investment targets, and resource allocations (Anonymous, 1991). Phytopathometry also forms crucial aspect of plant disease surveillance or disease forecasting programmes, and spurs development of disease warning systems or resistant varieties (Bock *et al.,*2010).Inaccurate disease assessment affects disease management decisions such that underestimation of disease-induced losses gives false impression that the disease is of no economic importance while overestimates results in concentration of limited resources on a particular disease to the neglect of other destructive ones. Hence, proper disease assessment enables stakeholders to weigh and decide whether the monetary losses attendant from a disease warrant the rigours and expense of control measures so as to apply limited resources to the best advantage of the farm economy (Tarr, 1972). Disease offers three fundamental parameters for measurement – prevalence, incidence and severity (Anonymous, 1991). These terms are defined thus by Bock *et al.* (2010).

Prevalence - the proportion (percent) of fields, states, and countries etc. where the disease is detected. It reveals diseases at a grander scale than incidence.
Incidence - the proportion (percent) of plants or plant parts (leaves, roots, stems) affected by disease out of a total number assessed.
Severity (otherwise called intensity) **-** the areas (relative or absolute) of the sampling unit (leaf, fruit etc) showing symptoms of the disease it is often expressed as percentage or proportion (Anonymous, 1991).

Hence, Wheeler (1969) and Tarr (1972) argued that plant disease appraisal not only seek to measure but also to quantify the three foregoing parameters, and relate the amount of disease present in a population of plants to the loss of the crop in terms of quality and quantity of yield. It also seeks to evaluate crop loss in relation to finance and assess its effects on the economy of the farm.
This paper reviews the antique and technology-assisted approaches used in measuring plant diseases, quantifying crop yield reductions and estimating losses to farm economy.

MATERIALS AND METHODS

Data used in this review were generated from old articles written between 1947-1989 retrieved from the archives of the Michael Okpara University of Agriculture, Umudike Library and from current techniques written from 1991-2023 obtained from searching online databases such as google, google scholar, Researchgate, etc. Only materials written in English were included in the review while others written in languages other than English were excluded (Enyiukwu et al., 2017).

Methods in phytopathometry

Antique techniques (Visual assessment methods)

Visual disease assessment practice is well over 100years old and is now very reasonably understood. Visual tactics of disease measurement may vary according to the nature of the disease (Bock *et al.,* 2010). Some of the visual assessment methods used in plant pathology include:

Percentage of Diseased Plants, Organs, or Tissues

This method is particularly essential and applicable to diseases which kill plants rather quickly or which cause about the same amount of damage to all the infected plants. Such diseases include damping-off, root rots and wilts, as well as virus diseases which originate from infected planting materials, for example tuber-borne virus disease of potato and diseases which cause total destruction of the affected organ such as smuts of inflorescences and ergot. Recording of the percentage of diseased organs or plants is a direct measure of the crop loss (Tarr, 1972; Anonymous, 1991).

Descriptive Scales

This is used for such diseases where the amount of disease varies greatly on different plants in the population – rusts, mildews, blights, leaf spots etc – with many arbitrary indices and ratings being in practice. They are widely used on a numerical quantitative (numerical) scale to qualitative (subjective) estimates such as moderate, severe etc. These qualitative scales no doubt are meaningful to the observer using them; however, they are of little value to other workers unless they can be more precisely defined. For instance, moderate disease in a region or season in which the disease is very prevalent may correspond to severe disease in a year or location with less abundant disease. Hence, qualitative scales cannot be realistic, well described, usable in practice and comparable from one worker location or season to another. Another shortfall of these scales is that the grades are rather wide and takes no account of the fact that the eyes asses diseased area in logarithmic steps (Tarr, 1972; Anonymous, 1991).

Assessment Keys

A field key is used for rapid assessment of a leaf disease, on whole plants or plots or on sampling areas of a standing crop. Field keys must refer to the area covered by the disease lesions and also to any death of tissues attributable to the disease (Tarr, 1972). According to Anonymous (1991), these keys can be used for comparing samples collected from the field and calculating the mean percentage area damaged by the disease. It can also be used for calculating infection index, coefficient of infection, disease intensity etc. by assigning grades to the keys i.e. giving a number to each range of percentage area affected (Anonymous, 1991).

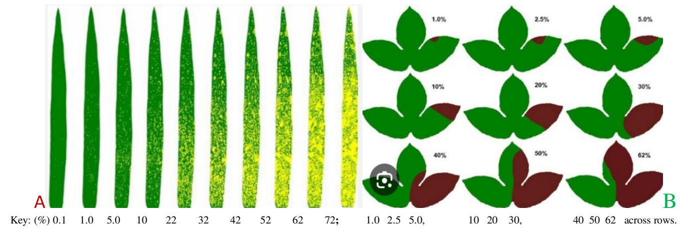

Figure 1 Standard area diagram A: Narrow leaf disease, B: Broad leaf disease. Sources: Rios *et al*. (2013); Monzani *et al*. (2018).

Standard Area Diagrams (SADs)

The original Cobb scale in 1892 was the first standard area diagram (SAD) used in plant pathology – the rater compared samples to the five standard disease areas illustrating rust pustules on the leaf of wheat in Australia, and placed it in the category to which it was most similar in severity as 1, 5, 10, 20 and 50% of the visible areas of the leaves occupied by visible or sporing parts of the rust pustules. This was later modified by Melchers and parker (1922) as 5, 10, 25, 40, 65 and 100% of leaf area covered by pustules. According to Large (1966) grades of between 1-100% illustrated on the diagram should be clearly distinguishable by eye. This is essential since visual scale progresses in logarithmic steps such that up to 50% the eyes tend to judge the total area that is diseased, while above 50% it judges the percentage that is healthy (Anonymous, 1991). Large (1966) noted that the grades chosen from Cobb (1892) onwards for the definition or illustration of standard diagrams have in fact conformed rather closely in equal increments to van der Plank's exponential log (9/100 –a) model.

Standard area diagrams (SADs) provides uniformity for rating disease intensity by researchers (Anonymous, 1991). These SADs may be drawings, photographs or preserved specimens of diseased plant parts. The researcher visualizes what area the lesions would cover if he could gather them all together and then estimate this area as a percentage of the total area of leaf (Figure 1).
Many researchers have developed and applied SADs to improve ability of assessors to assess disease on various plant organs either in interval scale (Large, 1966) or for aiding in assessment on the percent ratio scale (James, 1971; Nutter et al., 2006).

The severity of blast disease of wheat leaves and bacterial blight of yellow passion was reliably assessed and validated using SADs (Figure 1). SADs improved the reliability and accuracy of disease raters in experiments of assessing the images of diseased alfala, wheat and yellow passion leaves (Bock *et al*., 2013; Rios *et al*., 2013; Monzani *et al.,* 2018). Andrade *et al.* (2005) on the other hand developed a set of SADs to assess leaf spots (*Quambalaria eucalypti*) of eucalyptus and found improvements in the precision, accuracy and reproducibility of disease assessments against actual figures obtained by image analysis. Standard area diagram in recent times, can be generated in various ways, using computer program such as SEVERITY, and PRO. Computer-aided SADs allow for choice of types of leaves and kinds of disease symptoms (type and lesion size). SADs can also be constructed from scanned images of diseased leaves. Bock *et al.* (2010) revealed that computer-based training such as AREA-GRAM is developed to train assessors by generating SADs rather than a full range of possible disease severities. Other useful SAD-generating programs used in training assessors are DISTRAIN ESTIMATE, DISEASE.PRO, ALFALFA.PRO and SEVERITY.PRO (Shane *et al*., 1985; Bock *et al*., 2022).
Nevetheless, as good and easy to adopt as it is on the other hand however, Nwauzoma (2016) was of the opinion that similarity of symptoms presented by different plant pathogens/diseases pose a very serious challenge in visual disease assessment. More so, lesion mimics, leaf speckling, heat stripe or genetic stripes and can be so similar to pathogenic symptoms and could mislead especially inexperienced raters.

Pathogen quantification

Although measurements of plant diseases by way of symptoms are very informative in some cases, quantification of the pathogen is more powerful (Bock, *et al.,* 2010). This may be achieved by the following relationship measurements.

Incidence – severity measurement

The relationship between incidence and severity of plant diseases is a significant concept in epidemiology. Since measurement of incidence of a disease is much easier than severity, any quantifiable relationships between the two parameters remarked Anonymous (1991) would permit estimation of severity based on incidence data. Data thus generated by incidence studies may then be analyzed by correlation – regression, multiple infection model or measurement of aggregation.

Inoculums – Disease Measurement

Courting of spores has been used in phyto-fungal diseases to estimate disease severity. For example, number of uredospores, besides other variables such as measuring diseased area is used to predict rust severity on wheat, while sclerotial courts in soils have been used to predict root rot of sugar beet caused by the pathogen *sclerotium rolfsii*. Though this method has been justified by many workers (Zadocks, 1972), others deem it essential to distinguish between inoculums – incidence and inoculums – severity relationships (Anonymous, 1991).

Classical Crop Loss Assessment Methods – An Overview

Disease assessments according to Wheeler (1969) are of little value to the pathologist unless related to crop losses. Having determined the intensity of attack, the next step (probably more difficult one) is crop loss. It is therefore imperative to highlight some methods used in estimating crop loss. Many of the methods used in relating crop loss to disease intensity are of two main types – statistical and experimental (Tarr, 1972):

Statistical methods: This is done by assembling and analyzing numerous reports of disease incidence, estimated crop losses and yield figures. It is very useful and valid where large and extensive data are available. Generally, however, results from carefully and specially designed field trials with controls kept free from disease rarely match statistical outputs; constituting a major drawback.

- Crop yields in years of different disease incidence? This involves analyzing yield in relation to estimated disease incidence over many seasons. This method is useful where one major disease is largely responsible for yield fluctuation per season or when disease is particularly severe compared to when it is negligible. The limitation here is that other factors impact crop yield such as weather, pests, farming systems, and crop varieties and not only diseases.
- Comparing expected to actual yields: Quite early in the season, growers and farmers or extension workers with long experience of the crop can make reasonably accurate forecast of the crop yield. Statistical differences between actual to projected, expected or forecast yields from these stakeholders provides indication to the crop loss due to the pathogen; provided all other limitation remain unchanged during the period under consideration.
- Analysis of yield before and after the application of control measure. This gives interesting information about several years and over large hectares. For example in Bavaria, Germany, downy mildew (*Pseudoperonospora humuli*) reduced hop yield from 720 kg ha^{-1} to 320 kg ha^{-1} in 1726 and fungicide spraying increased yield to 1440 kg in 1927 – 1935. This was so on the assumption that limitations of improved crop varieties, improved cultural practices and other pests and diseases remained constant.
- Use of questionnaires: Information from numerous growers and extension officers on a particular disease or pest as on prevalence, severity, date of appearance, estimated crop loss, weather conditions, varietal susceptibility etc where properly organized and analyzed become reliable sources of valuable information on yield and allied issues, provided the grower are reliable enough.

Experimental methods: In a nutshell, these methods of plant disease loss assessment include:

- Comparing yield from artificially or naturally infected plants to uninfected ones or different grades of infected ones.
- Comparing yields between resistant and susceptible varieties
- Comparing yields from infected plants and plants mutilated to stimulate disease.
- Comparing yields from diseased plants and those kept free from disease by protective chemicals or some other ways – this being probably the best way of relating yield reductions to disease incidence.
- Surveys: Surveys made over large areas, regions, countries etc. by growers or trained professionals.

It may be ground surveys or aerial surveys. Surveys are affected by available resources, time etc. aerial surveys may be by colour photography using cameras borne on helicopters or winged air jets, however the former is preferred being able to manuover small and large heights and moves much slowly than aircrafts (Tarr, 1972).

Upstart tools for plant disease assessment

Plant pathology goes beyond just maintaining plant health to environmental and public health. This is so because food quality and security form the twin determinants of human welfare and public health. Lessons drawn from disease attacks on staple crops over time, makes it imperative to look to application of technology as a possible means to improving yields and nutritional quality of foods. Against the back-drop to ensure abundant and affordable foods for all persons, precision agriculture uses technology that seeks to improve plant health and reduce environmental impacts by adopting GPS, satellite imaging, meteorological data to monitor, forecast and control disease conditions and weed effects (Schothof, 2003). Bock *et al.* (2010) maintained that visual rating methods will continue to be the single most important way of assessing plant diseases for the foreseeable future having direct physical contact with it. Thus both visual estimations of disease and using cameras or other imaging techniques to measure the disease are considered remote sensing. The application of technologically advanced remote sensing techniques to locate and measure plant diseases started early with aerial photography – and has been applied to various pathosystems (Bock *et al.,* 2010).

Remote sensing and image analysis

Aerial photography can detect objects on land over large areas. It dates back to about 1860 – 1956 when Colwell demonstrated its potential usefulness in plant disease work. He showed that especially infra-red photography could be used to detect rusts and viral diseases of small grains and certain diseases of citrus. Its usage has expanded for many types of assessment and detection work in agriculture, including survey of plant diseases. Diseases caused by pathogens can also be detected and quantified as symptoms by other methods of remote sensing such as radar, microwave, laser induced florescence, thermography, hyperspectral imagery, and nuclear magnetic resonance (NMR) imaging amongst others.

Remote sensing is a rapid non-invasive efficient technique which can acquire and analyze spectral data from various properties of earth surface from various distances; ranging from satellites to ground-based platforms (Gogoi *et al*., 2020). As such remote sensing techniques have been reported to have myriads of potentials in crop production, protection and yield estimation (Gebeyehu, 2019; Mathenge *et al*., 2022). Variability and/or differences in reflectance spectra of plants resulting from occurrence of diseases or pest populations allows the RS systems to differentiate and identify those bio-challenges (Gogoi *et al*., 2020).

Against the backdrop that visual disease assessment is time consuming and outcomes could vary widely amongst assessors, remote sensing holds significant potential for assessing crop diseases over large hectare of land without physical contacts with the sampling units in a non-destructive manner (Bayoumi and Abdullah, 2016). The major advantage of remote sensing is that it eliminates subjectivity to raters, biases and ensures reproducibility (Nwauzoma, 2016). However, it is necessary to choose methods appropriate to estimate the correct variable and compatible with the available resources as effectively and efficiently as possible (Bock *et al.,* 2010). Anonymous (1991), remarked that high costs and especially inconvenience of taking and analyzing colour infra-red photographs for example, has limited the employment of this method. Digital photography is increasingly being applied in forestry, agriculture and horticulture to assess not only disease severities, but also for the diagnosis of plant diseases and disorders (Holmes *et al.,* 2000).

According to the e-concise dictionary of plant pathology (2004), remote sensing and image analysis are important tools in disease assessment. Digital image analysis has been applied to quantify pathogen population, host resistance, pathogen effects on different host species, relate disease severity to yield loss or disease control to improve yield (Bock *et al*., 2010). Though aerial film photography has been used and developed in plant pathology, it has been used at the microscopic level to measure and observe pathogen and host physiology and development. In the early days of photography of plant diseases, most of the images were acquired from aircraft borne cameras. Nelson (1980) pioneered the application of remote sensing and image analysis by using Leitz texture analysis system to measure disease severity. Blanche (1982) used VP-8 image analyzer system to measure root decay in pines. Lindow and Webb (1983) also used image analysis to measure disease severity on complex leaves. Several workers have found digital image analysis of diseased plant superior to visual ratings in several pathosystems (Kokko *et al*., 1993; Price *et al.,* 1993). However, image analysis has been reported to be more time consuming than visual assessment, and this constitutes a major drawback.

One of the major outcomes of any disease assessment activity is to relate damage resultant from disease to yield or disease control (Bock *et al*., 2010). Shaw and Royal (1989) used image analysis to accurately measure the area (actual area) of wheat leaves infected by *S. tritici* and was able to estimate and validate a function describing the rate at which *Mycosphaeralla graminicola* caused yield loss in winter wheat and demonstrated that yield was best predicted by the integer of the square root of the disease severity on the leaf alone. Image analysis has been used to gauge the efficacy of fungicides. Vincent *et al*. (2007) used image analysis to assess the percentage leaf area diseased on Mandarins (*Citrus sp.*) caused by brown spot of citrus (*Alternaria allornata*) and showed clear differences in rain fastness and persistence amongst various fungicide used in the study.

Image devices include slides, scanners, flat-bed scanners, video cameras, and digital cameras which is becoming the primary source of imaging due to tremendous range of compatibility. Images are captured as tagged image file format (TIFF) or joint photographic expert group (JPEG). High resolutions (2-11.1 megapixels) are necessary for phytopathometric image analysis. Shadows and leaf veins constitute interferences to lesion (image) quality and hence shadows must be avoided for better quality. Images are processed in many image analysis and processing software where colour and contrast can be corrected, rotated, sharpened, inverted and manipulated such as Adobe photoshop and Access (Bock *et al*., 2010).

Hyperspectral Imaging (HIS)

This is a young science in smart agriculture (Knauer *et al*., 2017) and its appreciation in plant pathology is particularly recent. Several studies done with it have concerned themselves with disease detection rather than quantification – but there is strong evidence suggesting that it can be a powerful disease assessment tool. Plant stressors – biotic and abiotic – significantly reduce crop productivity. Hence, in order not to exceed critical thresholds, early detection of diseases is undoubtedly imperatives to minimizing acute or chronic loss of productivity to the farm economy, bearing in mind that the severity of crop damage is affected by time of observation and/or intervention (Kim *et al*., 2011).

A hyperspectral image relies and is created from many high spectral resolution, contiguous spectral wave bands or sections of the full electromagnetic spectrum on an image scale. The HIS is acquired using a spectrograph coupled with a digital sensor (CCD, CMOS, INGAS etc.) effectively enabling each picture element (pixel) of the integrated circuit to become a separate spectroradiometer – producing a 3-dimensional image called a hypercube (or data-cube); with spatial x and y axis and a spectral z-axis (Knauer *et al*., 2017). According to Bock *et al.* (2010), because HSI possesses high spectral resolution it allows a target to be delineated from its background, however it generates very large data when compared to standard red, green and blue RGE digital images, requiring therefore more computing power to analyze the data. HSI operate within broad spectrum of wavelengths ranging from 450 – 700nm. However, within plant disease detection and measurement of severities, a range of 350 – 2900nm have been explored to study various pathosystems.

Reflectance of leaves are taken as functions of the interactions between incoming irradiation and biophysical and/or biochemical characteristics of plants. HIS is an emerging means of assessing plant vitality and holds the strong prospects of sensing leaf reflectance in order to detect changes in plant vitality, health, physiology and disease symptoms (Mahlein *et al*., 2012).These authors believes that HIS offers high potential as non-invasive diagnostic tool for disease detection. Cercospora leaf spot, leaf rust and powdery mildew of sugar cane have been assessed using HIS. HSI has also been used to detect yellow rust of wheat in wheat fields with a success rate of 96% (Bravo, *et al.,* 2003). Apan *et al.* (2005) used the technology of HIS at 350–2500nm to detect early blight of tomatoes and demonstrated good spectral severability between infected and healthy tissues of the plant, based on the “red-edge” and green regions of the visible spectrum. In another study, Quin *et al.* (2008) used HIS technology based on PGP at 400–900nm to different citrus canker on grape fruit from healthy ones at 93% success rate. Coops *et al.* (2003) used aircraft-borne HIS systems to assess severity of needle blight in Australian pine and found the accuracy of the system greater than 70% on a 4-point scale.

Though HSI generates massive amounts of data and information about a target at one time, the file size is usually voluminous and can be slow to capture and process. It is also de-merited in being an expensive technology requiring substantial training and expertise before using to its full potential and obviously out of each of resource-limited farmers compared to visual assessment (Bock *et al.,*2010).

Again traditional phenotyping is time consuming, destructive in nature, and labour intensive, HIS offers high throughput non-destructive strategy for desired characteristics of plants. In recent years HIS has been applied to other areas of agronomy to assess quantitative and qualitative functional plant traits, plant phenotypes, and to monitor the interaction between a host and its environment (Mishra *et al*., 2016). These authors noted that environments influenced structural and functional characteristics of plants, which in turn affected biomass accumulation and yield potentials. Mishra *et al*. (2016) utilized HIS images generated at 400-100nm with Phenovision software (Inspector VIOE, Finland) to effectively measure drought or water stress challenges in maize crops.

GIS analyzes the relationship between features and associated data. Information about earth or its manufactured features are stored in layers and can be separated to targets, therefore GIS allows users to collect and interpret location-based information in a planned and systematic way. Early detection of pathogens, accurate disease diagnoses and assessment and surveillance are necessary for vibrant agricultural productivity and food security. And as such GIS holds strong potential to improve speed and accuracy of plant disease assessments, diagnosis and detection (Nwauzoma, 2016). Remote sensing has commonly been used to estimate the extent and severity of damage caused by a disease, especially if the disease causes substantial morphological and physiological alteration of the affected crops. In addition geospatial techniques involving GIS, RS and artificial intelligence (AI) could provide basis for sustainable management of several agricultural and environmental resources such land use, land cover, crop yield forecasting, underground water movement, as well as flood monitoring and management at the local, national or regional scales (Zahra *et al*., 2023). It is noteworthy that satellite imagery has been variously applied to detecting and mapping crop diseases. For instance, LandSat and QuickBird satellite imagery were effectively used to detect severe and late stage powdery mildew and leaf rust in wheat with high accuracy, and basal stem rot in oil palms (Yang, 2020). However, this author believe that in most cases, by the time remote sensing imagery can reveal symptoms of diseases, damage may have already been inflicted on the affected crops.

Internet of things (IoT) and Cell phone Image-based Plant Disease detection

Over the years plant disease detection in sub-Saharan Africa has been classically and traditionally carried out by on the spot assessment of visible plant parts due in large part to limited or non-existent access to user-friendly advanced technologies (Asani *et al*., 2023). Internet of things refers to collective network of connected devices and technology that facilitates communication between devices and the cloud as well as between devices themselves (Amazon, 2023). IoT could help farmers at any time during their farming activities, and could assist them to remotely monitor their fields by keeping them updated on weather conditions and their crop health status (Orchi *et al*., 2022). Cellphone image-based plant disease detection tools comprised integrated systems coupled to smartphones and used to detect, and deploy targeted control which seek to minimize water and environmental hazards associated with conventional agro-crop protection techniques. Researchers say that a novel AI-based mobile phone application could provide an effective low-cost and easy-to-use diagnostic solution. Such system captures processes and reliably identifies crop disease conditions (Figure 2). Given that low-cost cellphones and their coverage are increasingly available in rural tropics of sub-Saharan Africa, such digital applications (Apps) and AI-devices can be connected with other devices such as cellphones as well as to cloud and communicate through embedded sensors. Internet of things applications help in early stage detection of crop pests and diseases; and as such aid farmers to curb their spread and save yield of the season. Many such IoT may be integrated with disease image processing and may feature SMS alerts to cellphones or palmtops of connected farmers (Orchi *et al.,* 2022). For instance Ai-based image recognition from mobile phones pictures has recently been demonstrated to be both practical and easy to use option for detecting amongst others cassava brown streak virus, potato late blight and banana bunchy top virus diseases. The AI recognizes and distinguishes shapes and patterns which ordinarily are difficult for the human eye to distinguish (IITA, 2017; CIP, 2023). Information thus generated is easily disseminated to rural farmers (Neuman *et al*., 2016). Furthermore, the application provides latest management advice for all major diseases and pest of root, tuber and banana crops as well pinpoints location of the nearest extension support for farmers (IITA, 2017). Shrimali (2021) reported that a convolutional neutral network based mobile phone application-PLANTIFY - was developed to correctly detect and identify and diagnose 26 different diseases of 14 crop species with 95.7% accuracy. The author emphasized that the application is good for assisting rural farmers to diagnose disease problems where infrastructure and necessary expertise may be lacking. Similarly, mobile phone embedded application (YOLOv8n) demonstrated 93-99.04% accuracy in identifying and diagnosing sugarcane mosaic disease, and blights and leaf spots of maize, and provided real time detection of these diseases to end users within seconds and out-performing traditional systems of disease detection (Khan *et al*., 2023; Kirti and Rajpal, 2023).

Figure 2: A cellphone-based application being tested for cassava mosaic virus disease identification. Source: IITA (2017).

Thermal Imagery Sensing

Modern agriculture aims at not only to increase and optimize production but also to produce safe and healthy high quality food in a manner compatible with sustainability. Thermal remote sensing a branch of remote sensing concerned with the acquisition, processing and interpretation of data obtained in the thermal infrared (TIR) region of the electromagnetic spectrum has been variously applied to monitor, assess and quantify plant diseases such as powdery mildew of wheat (Bayoumi and Abdallah, 2016). Thermal remote sensing differs from optical remote sensing by measuring emitted radiations from the surface of the target crop, whereas optical remote sensing measures reflected radiations of the target object under consideration. Thermal properties of plant leaves are affected by a complex heterogeneous internal structure that contains a certain amount of water per unit area. For that reason, it is possible to have research on individual plant with thermal remote sensing because of the versatility, accuracy and high resolution of the infrared thermography (Bayoumi and Abdallah, 2016). These authors used TIS to sense variations in temperature between infected and healthy leaves of wheat and the variation between air and leaf-surface temperatures on its precincts for early detection of disease and their observations revealed that infection with powdery mildew pathogen induced changes in leaf temperature from 0.37 ◦C (after one hour from the infection) to 0.78 ◦C at (21 days after infection with the pathogen) and metabolism, contributing to a distinct thermal signature characterizing the early and late phases of the infection. According to them, the maximum temperature difference within thermogram of wheat leaves allowed the discrimination between healthy and infected leaves before visible symptoms appeared. Nevertheless, accurate thermal measurements depend on environmental conditions, which influence the thermal properties of the visualized crop. Abdullah and Bayoumi (2015) studied the relationship between disease severity of powdery mildew and leaf temperature of infected wheat plants by thermal imagery technique, using Flukes thermal imager (Ti32) fitted with SmartView software (V). Images were captured before, during and after emergence of powdery mildew symptoms. Temperature differences within healthy and infected leaves were obtained by thermal and colour reflectance images between control and inoculated leaves compared to records from daily disease severity. Powdery mildew pathogen induced decrease in leaf temperature at points of effective infection and emergence of symptoms during early infection, and increases in leaf temperature due to dense colonies, decreased leaf physiology, poor open close mechanism of stomata and poor water conductance in late infection. Disease severity was taken as the difference between total leaf area x infected leaf area which was estimated from captured images using Image J software (Version 1.48s, USA).

Some applications of GIS, GPS and remote sensing in precision agriculture

1. GIS enables early detection of potential issues affecting crop health. By analyzing remote sensed data and satellite imagery, stressors including nutrient deficiency or disease outbreaks can be identified, and made for targeted interventions.
2. Modern satellite based systems such as the GIS and GPS allow for accurate prediction of crop yield by integrating and analyzing data from soil composition, weather patterns and other variables. Armed with such information, farmers make informed decisions regarding proper time of planting, resource allocation, irrigation programmes and marketing strategies. For example Geopad is a GIS- based software which allows prediction of crop yield with up to 90% accuracy.
3. Geopad also allows for proper pest distribution mapping, and as such makes for precise rather than blanket applications of pesticides.
4. LandSat 8, a GIS-based system not only helps in assessing crop health, nutrient status, pest infestation, but also determines soil moisture levels using both visible and invisible thermal infrared radiation (TIR). Abnormally high crop temperature could be an indication of pest infestation, disease or dehydration (Hammonds, 2017; EOS, 2023).
5. GIS, drone-borne remote sensing and global navigation satellite systems (GNSS) are invaluable tools used for data collection, mapping and to analyze the distribution of critical factors that potentially affect crop productivity and ecological health such as drought, poor soils, unfavourable temperatures, pest, disease and target weeds distribution (Sabtu *et al*., 2018).
6. GIS allows for high fidelity real time collection and analysis of data concerning all stages of agricultural value chain, Hi-Fi crop and ecological health monitoring or surveillance and tracking of crop or animal residues and estimating availability and composition for renewable energy generation based on variables of time and seasons (Ghosh and Kumpatla, 2022).
7. Above all, GIS and remote sensing programs and platforms besides making for quick and easy identification of soil and crop health status or level of pest infestation, it aids in potential crop yield and yield estimation (Gebeyehu, 2019; Mathenge *et al*., 2022).

Yield estimation by remote sensing – some practical applications

Accurate and timely crop mapping, planting area statistics and crop growth status and yield predictions are required for sound agricultural management and increased speed for decision making related to harvesting, storage, transporting operations and to ascertain farming profitability. Crop yield estimation is a crucial aspect of modern agriculture; and could be obtained traditionally by field visits and consulting published reports. However, this approach has the

Table 1: Some practical applications of satellite data and remote sensing for yield prediction.

Remote sensor	Programme Used	Crop, Country	Purpose
LanSat 8	Sentinel-2	Wheat, karbala– Iraq	Yield prediction
LanSat 8	Sentinel-2	Coffee, Minas – Brazil	Yield prediction
LanSat 8	Sentinel-2	Tea - Indonesia	Yield prediction
SPOT 4	-	Wheat – Egypt	Yield prediction
MODIS-NDVI	-	Barley, spring wheat, canola	-
MODIS	AVHRR-SPOT 4	Different crops – Global	Yield prediction
-	Sentinel-2	Winter wheat – China	Yield prediction
-	Sentinel-2	Wheat – United Kingdom	Yield variability
-	Sentinel 2A	Corn – North China	Growth monitoring

Source: Abul-Jabbar et al. (2004).

drawbacks of being laborious and time consuming (Paliwal and Jain, 2020; Udemy, 2023), and in some cases outputs might be constrained by field topography, weather conditions or natural disasters (Ilyas et al., 2023). In China, Cheng et al. (2022) affirmed that field observation and traditional linear regression crop yield models gave poor approximations of winter wheat yield.

Remote sensing (RS) on the other hand can be used to effectively assess crop conditions timely and reliably (Table 1); and estimate its yield based on very high resolutions of the spectral, textual and structural characteristics of the crop than conventional approaches (Singh and Kumar, 2020; Seklar, 2020; Gumma et al., 2022; Udemy, 2023). This technique allows for large scale continuous crop and field monitoring throughout the growth cycle per season (Khaki et al., 2021). Such pre-harvest prediction of crop yield could help in preventing disastrous situations and help stakeholders apply more reliable and accurate strategies to avert food insecurity (Ali et al., 2022).

RS estimates crop yield by capturing crop biomass accumulation through pre-harvest vegetation index, temperature condition index, enhanced vegetation index, leaf area index, land surface temperature and normalized difference vegetation Index (NDVI) which are strong indicators of total greenness in plants (Abul-Jabbar et al., 2004; Seklar, 2020; Campos et al., 2023) and these satellite-based techniques outperformed traditional vegetation indices (Cheng et al., 2022). RS techniques used for crop monitoring and yield prediction include multispectral, hyperspectral data, radar and lidar imagery, random forest and decision tree regressor and gradient boosting predictors, AI and ML, GIS, GPS (Ioraiswamy et al., 2000; Singh and Kumar, 2020; Ilyas et al., 2023) and may be applied to more than one crop simultaneously (Khaki et al., 2021). These workers utilized this approach to estimate the yield of corn and soybean at the same time. And this may be very helpful in crop yield forecasting especially in sub-Saharan Africa where intercropping is commonplace. Satellite and remote sensing programs like Lansat, Sentinels 1 and 2, and moderate resolution imaging spectroradiometer (MODIS) are used for crop assessment and monitoring and yield prediction on small land areas while large areas are covered with MODIS (Abul-Jabbar et al., 2004).

In India, the National Oceanic and Atmospheric Administration used advanced very high resolution radiometer data to effective estimate yield for 8 different crops on a region-wide scale, and the method 84-87% accuracy. These workers consider this approach as simple and affordable by developing nations. (Ferenc et al., 2004).Furthermore, some approaches involving remote sensing and machine learning models could predict the yield of over 100 different crops within 2 weeks and 3 months in advance of the crops' complete life cycle with accuracy of 95% using both biophysical and statistical methods (EOS data Analytics, 2023).In South Africa, Satellite Pour l'Observation de la Terre - 5 (SPOT-5) was used to assess maize crop growth parameters and yield captured in 2 different locations of the country through canopy reflectance from multispectral sensor after 7-8 months' period with 90-92% accuracy (Ngie and Ahmad, 2017).Against these backdrops, Ali et al. (2022) is of the opinion that satellite-derived data with high spatial, temporal and thermal resolutions are amongst all approaches still the most powerful tools for crop monitoring and monitoring crop parameters of interest including yield.

A brief summary

Phytopathometry is that branch of phytopathology involving and dealing with plant disease assessment. Plant disease assessment is sometimes synonymously taken as crop loss assessment; however Large (1966) regarded this as misleading. Disease assessments have their central objective as quantitative reportage of phyto-diseases rather than qualitative presentation (Large, 1966). Tarr (1972) noted that one of the most difficult problems of plant pathology is that of accurately assessing the incidence of diseases in crops and relating this to the subsequent loss in terms of yield and money. Hence, disease assessments are of little value to the pathologist unless related to crop losses (Wheeler, 1969). Bock *et al.* (2010) remarked that assessments may be by "measurement" through visual assessment or by “estimation” by remote sensing, image analysis, hyperspectral investigation or satellite scanning. Accurate disease assessment helps in predicting the development of epidemics and formulating a decision support system for timing the application of pesticides for control of diseases (Econcise Dictionary of Plant Pathology, 2004). Bock *et al*. (2010; 2022) adds that reliable and precise estimates of disease severities are important for predicting yield loss, assessing crop germplasm for disease resistance and understanding fundamental biological processes including co-evolution. Plant disease assessment is a three stage operation (Wheeler, 1969; Tarr, 1972) namely:

- Measuring the amount of disease in the population by its prevalence, incidence and severity
- Translating the above disease parameters into crop loss and finally
- Interpreting the loss in terms of the crop farm economy.

CONCLUSION

Though classical crop disease assessment by visual assessment had proved very useful over the years, it is time consuming and prone to biases. However, modern digital technologies and remote sensing techniques for disease assessment and yield loss estimation begs for use and integration within the confines of available resources and expertise amongst students and researchers in our higher institutions and governments in sub-Saharan Africa.

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