Review

Actual Pathogen Detection: Sensors and Algorithms - a Review

Federico Hahn

Irrigation Department, Universidad Autonoma Chapingo, Km 38.5 carr. Mexico-Texcoco, Texcoco, Mexico; E-Mail: fhahn@correo.chapingo.mx; Tel.: 52-595-9521551; Fax: 52-595-9521551

Abstract: Pathogens feed on fruits and vegetables causing great food losses or at least reduction of their shelf life. These pathogens can cause losses of the final product or in the farms were the products are grown, attacking leaves, stems and trees. This review analyses disease detection sensors and algorithms for both the farm and postharvest management of fruit and vegetable quality. Mango, avocado, apple, tomato, potato, citrus and grapes were selected as the fruits and vegetables for study due to their world-wide consumption. Disease warning systems for predicting pathogens and insects on farms during fruit and vegetable production are commonly used for all the crops and are available where meteorological stations are present. It can be seen that these disease risk systems are being slowly replaced by remote sensing monitoring in developed countries. Satellite images have reduced their temporal resolution, but are expensive and must become cheaper for their use world-wide. In the last 30 years, a lot of research has been carried out in non-destructive sensors for food quality. Actually, non-destructive technology has been applied for sorting high quality fruit which is desired by the consumer. The sensors require algorithms to work properly; the most used being discriminant analysis and training neural networks. New algorithms will be required due to the high quantity of data acquired and its processing, and for disease warning strategies for disease detection.

Keywords: Non-destructive sensors, algorithms, remote sensing, disease warning systems.

1. Introduction

Sensors and algorithms have been developed to detect fruit and vegetable diseases. Diseases can be encountered during the growing stage, the postharvest storage, and at the point of retail where the consumer comes in contact with the product. Crop residue-borne fungi and other soil-surface-

inhabiting microbes, including numerous plant pathogens, are encountered during the production stage. These microbes rely on water at or near the soil surface for survival, growth, and reproduction [1,2] The presence of wetness (moisture) at the soil-air interface or within the top few millimeters of soil is thought to be a very important factor in the development of certain plant pathogens and plant diseases [3,4]. Soil surface moisture, often associated with precipitation events or dew formation in the canopy [5], is presumed to be one of the critical environmental factors affecting the development of these and other residue-borne pathogens [2].

Leaf wetness influences the initiation and development of many fungal and bacterial plant diseases. Bacterial diseases increase in severity in direct relationship to the length of time the leaves are wet [6]. Most foliar fungal disease pathogens require specific leaf surface conditions for their spores to germinate; favorable temperature and a film of water on the leaf surface are required [7]. The longer the leaf surface is wet, the greater the risk of infection and the greater the number of infections per leaf. Even patch diseases have been reported to be more severe with prolonged periods of leaf wetness [8,9]. Thus, disease management prediction requires leaf wetness assessment. Trees and orchards suffer damages by fungi that decay live or dead trees. It is estimated that for every 100 million board feet of timber harvested every year in the United States, heart decay fungi destroys about 30 million board feet of timber volume [10]. Bacterial wet-wood infections are present in hardwood and some conifers causing annual losses due to drying defects in oak lumber of about 500 million board feet [11].

The battle against postharvest decay of fruits and vegetables has been fought for decades and consumers who shop for quality fresh fruits and vegetables must often discard spoiled produce [12]. Harvested fruits have to be sorted in order to eliminate those with disease. If one rotten fruit is present inside a box, a high probability of infection in healthy fruits exists. Although the development of modern fungicides and storage technologies have greatly extended the shelf life of fruit after harvest, postharvest losses vary from an estimated 5 percent to more than 20 percent in the United States, and can be as high as 50 percent in developing countries [13]. Postharvest losses were measured in Costa Rica at rates of 44%, 35%, 32% and 30% for mango, avocado, melon and papaya, respectively [14]. Losses between 40 and 50% occurred in retail shops. Fungicide efficiency has decreased with the development of pathogen resistance and to public perception that pesticides are harmful to human health and the environment [12]. Thus, alternative methods to control postharvest diseases are urgently needed.

The structure and physiological status of a plant is represented by reflectance patterns. The amount of reflected light depends on an amount of leaf-related factors, such as external morphology, internal structure, concentration, and internal distribution of biochemical components. Much remote sensing research has been done at plant leaf-level to ascertain the amount of stress in plants. Alteration of the interaction of light with the foliar medium and its effect on physiological changes has been studied [15]. The most common and widespread change occurs in the proportion of light-absorbing pigments [16], most notably chlorophylls *a* and *b* which absorb light in the 430–660 nm region. Investigators have observed differences in reflectance due to stress induced changes in pigment concentration in the green peak (525-605 nm) and along the red edge (~750 nm) [17,18] .

Plant resistance responses to pathogen attack commonly involve the accumulation of specific compounds with either signaling or antimicrobial properties. The latter can include both structural

modifications to impair pathogen ingress and direct toxic effects on the pathogen (e.g. phytoalexins). Key components in plant disease resistance include salicylic acid [19] and phenolic compounds, including flavonoids [20]. As phenolic compounds generally have the property of emitting fluorescence after UV excitation [21], they provide an elegant way to reveal stress symptoms [22,23]. Ethylene involved in systemic plant resistance, is a plant growth regulator and its molecular simplicity is in contrast with its complex role in the physiology of plants [24]. An ethylene sensor based on laser photo-acoustic spectroscopy (LPAS) was designed [25]. LPAS technique offers an elegant and accurate solution to perform high sensitivity trace gas detection (typically under 1 ppb) for small molecules and posses a time resolution of only a few minutes.

Disease warning systems have been developed as tools for Integrated Pest Management (IPM) to help growers decide when to apply a fungicide spray. The systems use data about the weather, crops, and/or pathogens and provide outbreak risk information. Warning systems can save fungicide sprays and reduce production costs. Weather data is the main component of the disease warning system, but depends on accuracy, costs and logistics. Weather stations usually have air temperature, radiation, relative humidity, rainfall, and wind speed sensors. An additional sensor important for disease detection is the leaf surface wetness sensor (LSW) which works both on the soil-air interface and as an electronic leaf sensor. The capacity to detect wetness at the soil-air interface and to estimate wetness duration would be used in future disease development models [26,27].

Airborne remote sensing technology has been employed for detecting crop disease and assessing its impact on productivity [28,29]. Satellite remote sensing has been used to detect some pest problems. QuickBird imagery was evaluated for detecting citrus orchards affected by sooty mould [30]. Researchers have used Landsat [31] and SPOT [32,33] satellite imagery with coarse spatial resolutions to detect and assess insect damage to forests.

This review analyzes the main non-destructive technologies for fruit and vegetable disease detection, both in field and for postharvest management. Field diseases have to be predicted just in time to avoid losses while infected fruit have to be removed. It is impossible to analyze all the fruits and vegetables, so the most important detection techniques (mango, avocado, potato, tomato, cucumber, apple, orange, lemon and grapes) are mentioned together with risk-disease management and remote sensing.

2. Non Destructive Sensing

Technology measurements for quality evaluation and sorting of products such as ultrasound, X-ray, magnetic resonance, hyperspectral imaging and fluorescence based on physical properties are carried out. Research has been done on developing sensors for real time, non destructive sorting of fruits and vegetable maturity, defect and disease detection.

2.1. Non Destructive Measurements

Ultrasound technology is used in a limited range in the food industry. Ultrasonic waves can be transmitted, reflected, refracted or diffracted as they can interact with the material. Wave propagation velocity, attenuation and reflection are the important ultrasonic parameters used to evaluate the tissue

properties of horticultural products. Ultrasonic measurements could be used for firmness determination in some fruits but that a more powerful ultrasonic source is required to penetrate them [34]. Acoustic tomography quantified red oak decay and the tomograms could not distinguish between large internal cracks and heartwood decay [35]. Ultrasonic transmission through potatoes was used for hollow heart detection [36].

Three X-ray techniques are used to measure the interior quality of fruits and vegetables: two-dimensional radiography, line scan radiography and X-ray computerized tomography (CT). The application of X-ray CT for quantifying physical properties of fleshy fruits requires appropriate correlations between the physical property and X-ray absorption have been demonstrated by many researchers [37-39]. X-ray techniques has been applied for detecting watercore in apple, split pit in peach, the presence of pits in processed olives and cherries, freeze damage in citrus, bruises, and the presence or feeding of insects on fruits [38,40-42]. Internal changes during peach ripening and different maturity can be clearly monitored through X-ray imaging [43]. X-ray spectrometry combined with chemometrics presents high potential to discriminate conventional from organic grown tomatoes and coffee beans [44].

In the nuclear magnetic resonance (NMR) imaging technique, water in the material is subjected to both static and oscillating magnetic fields at right angles to each other and areas with greater free water appear brighter (MRI). Disorders involving water distribution as watercore, chilling injury, bruising, decay and presence of insects can be visualized [45-49]. MRI has been used to show ripening [50], seeds or pits [51], pathogen invasion [52], bruises [53], and ripening changes due to freezing and chilling [48,54]. A study of red cherries correlated firmness, dry matter, soluble solid content, total acidity and brix acid ratios [55]. However, NMR imaging has a number of disadvantages: the high cost of the instruments, radiation hazard, insensitivity near the surface, variation in readings due to density changes, which may cause error rates up to 15%. Actually those equipments are of no practical use as they are expensive and difficult to operate, but have a great potential for evaluating the internal quality of fruits and vegetables.

Imaging techniques have been developed as an inspection tool for quality and safety assessment of agricultural food products. Imaging is generally non-destructive, reliable, and rapid depending on the specific technique used [56]. Inspection of tomatoes, apples, peaches with respect to size, color and shape by machine vision is already automated in the industry [57-59]. Studies with different fruits indicated that the decay of chlorophyll parallels the ripening process [60,61].

Hyperspectral imaging systems combine conventional imaging techniques and spectroscopy to acquire both spatial and spectral information from fruits and vegetables for determining important quality parameters [56,62-65]. However, the technology thus far is very slow and cannot be implemented in a real time detection system. Starch or soluble solids [66,67] contents can be determined in intact fruit (apple, citrus, kiwifruit, mango, melons, peach, potato and tomato). Oil content in seeds, nuts and avocado can be determined using near infrared (NIR), while differences between healthy and damaged tissues in visible and NIR diffuse reflectance are useful for detecting bruises [68,69] chilling injury [70], scald [71], decay lesions and numerous other defects.

Fluorescence results from excitation of a molecule by a high energy light (short wavelength) and its subsequent instantaneous relaxation with the emission of lower energy light (longer wavelength). Fluorescence measurements of chlorophyll containing tissue are routinely used for investigations of

photosynthetic activity in plant leaves [72]. Chlorophyll content and its photosynthetic capacity are often related to maturity of plant organs and can detect defects or injuries. Physiological stresses that affect chloroplast or photosynthesis, such as temperature, salinity, moisture [73], atmospheric pollutants [74] and mechanical damage can also be detected [75]. Fluorescence or delayed light emission (DLE) imaging is used on physiological studies of chilling injury and similar stress responses on fruits and vegetables [76,77]. Fluorescence and DLE have been studied as possible methods for evaluating maturity in fruits and vegetables that lose chlorophyll as they ripen or mature [78]. Fluorescence detected citrus rind based on fluorescence of oils that leaked from damaged cells.

2.2. Disease Warning Systems

In a susceptible crop, the increase of a foliar parasite during a growing season often is determined primarily by weather factors, particularly duration of wetness and air temperature [79]. Consequently, the effects of these factors on foliar parasites have been investigated extensively [80]. In many experimental studies [81,82], wetness duration and temperature are manipulated under controlled conditions to evaluate their effects. Variation in some measure of the parasite's response, such as rate of sporulation or germination, infection efficiency, latent period, lesion density, disease incidence, or disease severity, is assessed [83].

Forecasting systems are useful for diseases that are important but sporadic. Mango anthracnose forecast in the seasonal tropics would be most useful in dry seasons, when sporadic rain is possible, or during transitional periods between dry and wet seasons. Once the rainy season is established, calendar-based fungicide applications are the best strategy for chemical control, since conditions are usually favorable for disease development. The most advisable strategy would depend on the time of flowering of a given orchard in a given region of production [84].

Electronic leaf wetness sensors (LSW) determine surface water deposition by a change in sensor resistance or capacitance, ranging in size from crude wires to fine grid networks etched on a printed circuit board [85,86]. Direct LSW measurement was obtained by placing an electronic grid directly on the leaf [87]. These sensors have not gained widespread adoption as daily maintenance is required to ensure that they have good contact with the leaf surface [88]. The LSW size and shape sensor should be similar to that of the leaf or organ. In onions, a cylindrical shaped sensor has been found to be useful [89], although it was proved with a form similar to the fruit shape [88]. The wetness sensor represented leaf wetness reasonably well, although most sensors over-predicted canopy wetness. The drawback is that it gets the measurement of only a single location in the production area, which may not be a complete representation of the entire crop zone.

2.3. Remote Sensing

Remote sensing technology from ground, air, or space-based platforms is capable of providing detailed spectral, spatial and temporal information on vegetation health, and vigor; and it has significant crop yield estimation applications [90-92]. Spatial resolution is a measure of the smallest object detectable on the ground. The number of available image-forming pixels in the sensor itself, and its distance from the ground, contribute to determining the pixel-size on the ground and the overall

image footprint. The smallest object that can be directly detected by the sensor is 30 m (Landsat) or 20 m (SPOT) in each dimension [93]. More recently, high resolution satellites such as IKONOS, which provides 4 m resolution multispectral imagery are available, but the cost of such data remains a significant impediment to its widespread use [94] IKONOS- panchromatic can provide 1 m resolution. Airborne mounted sensors such as airborne digital cameras or video systems, which are flown up to 3 km above the ground, generally have 1- to 2-m pixels and corresponding image footprints of the order of 100 Ha [94].

Radiometric resolution specifies the number of discrete spectral levels available to individual pixels to record the intensity of measured radiation from a target in a given waveband. In practice, however, n-bit systems tend to only have (n-2)-bits of information in image pixels as usually the lowest 2-bits of data carries the system noise, including dark-current and thermal noise [95,96]. Temporal resolution or, more simply, revisit-frequency is an important attribute of any sensor when used for commercial monitoring or management purposes. Typical commercial satellites like the American Landsat and French SPOT satellites have revisit intervals of 16 and 26 days, respectively. IKONOS revisit timing ranges from 1 to 3 days. Aircraft mounted sensors, on the other hand, are more amenable to user-defined visitations, and have the added advantage of being able to operate under a high-cloud base.

The spectral resolution is the number of wavebands of data that can be simultaneously recorded at each pixel. The amount of sunlight reflected off a target is described in terms of the target's reflectance profile. All photosynthesizing plants do not reflect much light in blue or red wavelengths because chlorophylls (and related pigments) absorb much of the incident energy in these wavelengths for the process of photosynthesis [97]. In the near infrared wavelengths (wavelengths greater than about 700 nm) photosynthesizing plants reflect large proportions of the incident sunlight (in excess of 65%). These wavelengths, to which the human eye is insensitive, can be detected by appropriate instruments. The amount of sunlight reflected in these wavelengths is very sensitive to leaf cell structure and this is influenced by water content [98].

A consequence of the upper limit on the amount of data that can be processed and stored in real-time by any remote sensing system is the compromise between spatial, radiometric and spectral resolution. In general, this equates to a trade-off between spatial and spectral resolution. The terms multispectral and hyperspectral are often interchanged, although they usually define instruments according to the number of wavebands of information that is recorded for each image pixel [97]. The more general adjective 'multispectral' is used to describe instruments that record information in only a small number of wavebands; typically 2-10. Hyperspectral instruments record information in a large number of wavebands, typically greater than 10.

Spectral vegetation indices reduce the multiple-waveband data at each image pixel to a single numerical value (index), and many have been developed to highlight changes in vegetation condition [99,100]. Vegetation indices utilize the significant differences in reflectance of vegetation at green, red and near infrared wavelengths.

Predicting the probability of biological invasion and probable invaders has been a long-standing goal of ecologists. A major challenge of invasion biology lies in the development of pre and post predictive models and understanding of the invasion processes. Introduced species vary in their invasive behavior in different regions [101]. Predicting the ecological behavior of a species in a new environment may be effectively impossible [102]. Estimating animal species numbers, population size

and related features is rather difficult in comparison to plants. However, indicated clear relationships between the characteristics of releases and the species involved [103], and the successful establishment and spread of invaders. A modified change vector analysis (CVA) was developed using normalized multi-date data from Landsat TM and examined *Adelges piceae* infestation.

Although high spectral and spatial resolution provide the ability to classify canopy species, precise classification of a species is still difficult. Several such studies of the spectral properties of invasive species have been derived, mostly from low altitude aerial photography or field spectrographs, but minimum information will reach the remote observer. Other factors like atmospheric noise, humidity, shadow, contribution from soil add to the confusion and the low chance of discrimination of separate species [105]. Furthermore, variation in orientation of leaves, age of a leaf, variation in leaf area index, different slopes of the locations where the individuals are found could make the spectral signature of a species difficult to define. Also, all leaves are not exposed to the same level of incoming radiant energy and often do not reflect back to the sky due to distortions in the leaf surface. It is not however practically feasible to determine the ideal wavelengths for discrimination when large numbers of invasive species are present. Furthermore, if the presence of number of invasive species per pixel increases, the difficulty in identifying the individual components that contribute to the mixed spectrum also increases. These problems will be further aggravated if species variability in spectral signatures is high. For large scale direct remotely sensed monitoring of several invasive species, the possibility of correctly identifying all individuals through direct mapping thus appears doubtful.

Absorption of incident light in the visible range and in the NIR range changes when plants are disease-stressed [106,107]. Damage of foliar internal structure, intracellular water content, decrease of chlorophyll content and pigment changes result from plant-disease interaction. This consequently influences their reflectance obtained from airborne remote sensing. Therefore, comparing the spectrum difference of plants in stress from the healthy ones, theoretically we are able to identify the stress severity of green vegetation. Reflectance tends to increase in individual leaves as the leaf matures but the changes are wavelength dependent. Water stress by reducing the internal water content increases the reflectance from an individual leaf. Information gathered from individual leaves provides a basic set of information about the mechanism of the changes occurring within a plant [108,109]; however, to be of practical application it must be extended to a canopy or field level [110]. Canopies exhibit the same properties of individual leaves but several variables that now must be considered. Leaf surfaces often act as polarizing filters and reflect back to portions of the sky that are not always detected by viewing the canopy only from the vertical direction. Leaf fluorescence has been observed in all plants and can be related to the efficiency of the photosynthetic process. It is possible that leaf fluorescence could be used to assess the impact of diseases on the physiological status of a plant. This technique has only been used on individual leaves; however, it could be extended to canopies through the use of laser-induced fluorescence [110].

Non-contact sensing methods for estimating surface moisture cheaply and faster over large areas are being studied in order to replace contact sensing field instruments. The heat generated as water in a leaf freezes can be readily imaged [111], while in extreme cases raised temperatures can be used as a measure of these increased respiration rates [112]. In most cases, however, the heat generated by respiration is too small in quantity to have a detectable effect on leaf temperature. Thermal imaging

can be used to study plant water relations, and specifically stomatal conductance, because a major determinant of leaf temperature is the rate of evaporation or transpiration from the leaf [109].

Scientists have evaluated radio detection and ranging (RADAR) [113], nuclear magnetic resonance (NMR), and microwave transmission [114] as tools for LSW estimation. Leaf surface water can be measured by the reflectance of the canopies, which is influenced by the total amount of water (both surface and internal water) in the sensor's field of view [115]. The thickness of the surface water could be detected by comparing the reflectance measurements of plant canopies with and without surface water [116].

2.4. Algorithms

The use of algorithms began in the 1970s with least squares. From 1981 – 1985, the usage of RLS and Entropy began. Maximum Likelihood and Least squares were popular during 1986 – 1990. Maximum Likelihood, Least squares and Entropy were popular during 1991 – 1995 [117]. There was a drastic change in the usage of algorithms from 1996 – 2000 and this might be due to the introduction of hyperspectral imagery. Maximum Likelihood still seems to be popular, followed by Least squares and Entropy. The usage of principle component analysis (PCA) and Genetic algorithms has increased. From 2001 to the present year, the usage of Least squares has decreased compared to previous years, but Maximum Likelihood and Entropy are still widely used.

Partial least square regression is a multivariate statistical method for establishing models combining the features of principle component analysis and multiple regressions [118]. The decomposition of data is similar to the principle component analysis with an additional advantage of data reduction on both spectral and concentration data. When the spectral data is processed using the PLS algorithm two eigen-vectors are formed representing variation in spectral data and changes in spectra due to variations in concentration.

Linear discriminant analysis (LDA) is a method of predicting a classification based on known values of the variables. LDA is a statistical, supervised method used for dimensionality reduction and feature optimization. The technique is based on how close a set of measurement variables are to the multivariate means of the levels being predicted [119,120]. Based on the discriminant analysis of the training data set, the Mahalanobis distance to each class cluster is computed. Based on this distance a probability can be calculated providing the likelihood that the sample is classified with a class label. The contribution of individual variables to the accuracy of prediction was assessed using the magnitude of the ratio of variances between consecutive stepwise additions to the model (F-ratio statistic).

Principle component analysis is a multivariate statistical method to reduce the large number of original variables into some linear combinations of transformed variables [121]. These transformed variables represent the constituents from the spectral information and represent the largest variations among the values of the spectral data.

An Artificial Neural network (ANN) is an information processing concept constructed by a large number of individual, locally connected processing elements or units called neurons similar to the biological nervous system or human brain [120,122,123]. These neurons in the network sum up the results of the respective input connections, weight them and transform the weighted sum by a non-

linear function of variables. ANN is applied in many complex real-world problems like pattern recognition, forecasting and data classification. The use of ANN in the field of image processing, remote sensing and weather forecasting is increasing rapidly because of the ability of ANN to handle large volume of complex data for processing and classification.

Remote sensing uses these algorithms but they have to be optimized due to the high quantity of data acquired. Several types of data are available, but most use images which could be visible, NIR, infrared, ultraviolet or radar. Image classification is defined as the process of creating thematic maps from satellite imagery [124]. Image classification classifies each pixel of an image into land cover categories. In the case of crisp or *hard classification*, each pixel is assigned to only one class. However, in fuzzy or *soft classification*, a pixel is associated with many land cover classes. In general, classification techniques may be supervised or unsupervised. Supervised classification procedures tend to require considerable interaction with the analyst, who must guide the classification by identifying areas on the image which are known to belong to each category of interest [125]. This control is essential if it is the specific task to compare one classification with another of the same scene at different dates, or if the classification must be compatible with those of adjacent regions. Serious classification errors are detectable by field verification to determine whether they have been correctly classified.

Supervised classification has numerous disadvantages, as the analyst imposes a classification structure upon the data based on predefined classes instead of finding natural classes in an image. In supervised classification, training sites and classes are based primarily on the information categories and only secondarily on spectral properties. Another source of error is the selection of training data, since these samples of pixels may not be representative of conditions encountered throughout the image. Moreover, supervised classification is not able to recognize the specific or unique categories which are not represented in training data due to the small areas they occupy on the image or simply because they are not known to the analyst.

Unsupervised classification involves the process of automatically segmenting an image into spectral classes based on the natural groupings found within the data set. Multi-band spectral response patterns are grouped into clusters which are statically separable. In supervised classification, any individual pixel is compared to each discrete cluster to select the one which is closest in terms of spectral values. The two most frequently used grouping algorithms are K-means and ISODATA cluster algorithms, which are iterative procedures. Three advantages of unsupervised classification are: no extensive prior knowledge of the region of interest is required; the opportunity of human error is minimized; unique classes are recognized as distinct units in unsupervised classification. Since unsupervised classification identifies spectrally homogenous classes within the data, such classes do not necessarily correspond to the informational categories which are of interest to the analyst.

Unlike supervised and unsupervised image classification, SMA did not rely on the detection or identification of pixel clusters with similar reflectance spectra. Rather, it is possible to consider each pixel individually and assess the presence and proportion of selected end-members. The fraction images produced by SMA refer to a pixel- by pixel measure of the percentage composition of each end-member in the spectral mixing model. The SMA technique is able to generate more accurate estimates of the end-member classes and appeared to be an effective means of mapping vegetation cover. Since supervised and unsupervised methods are based on predefined classification schemes

classifying entire pixels, this causes an error which often produces too high or low estimates of land cover classes due to the inability to distinguish sub-pixel covers. From these facts it is clear that the application of SMA and the production of end-members fraction images for land cover classification allow for a more detailed analysis of individual pixels in the image. Thus, it can maintain higher accuracy in classification and provide more realistic representation of landscape, as opposed to the patchy and discrete nature of traditional classification techniques.

Change Vector Analysis (CVA) is an effective approach for detecting and characterizing land cover change. Processing and analyzing is applied to multi-spectral/multi-temporal data layers [126,127]. The vector describing the direction and magnitude of change from the first to second date is a spectral change vector. This time trajectory is represented as a vector in multidimensional measurement space. The length of the change vector indicates the magnitude of change, while its direction indicates the nature of the change [128].

3. Sensing Per Crop

Studies are being carried out for each fruit and vegetable around the world, depending on the importance of crop yields per country. It is impossible to write a review that covers all these researches so the main fruits and vegetables around the world would be covered, including apple, grapes, avocado, mango, citric, tomato and potato (Table 1). The latter botanically is not a fruit or a vegetable, but developed countries consume potatoes in huge quantities, so a lot of funding is available to detect diseases and increase its quality.

Table 1. Pathogens attacking selected fruits and vegetables.

Fruit or vegetable	Pathogen common name	Pathogen scientific name
Mango and avocado	Anthracnose	*Colletotrichum gloeosporioides*
	stem-end rot	*Lasiodiplodia theobromae*
Potato	Fusarium wilt	*Fusarium oxysporum*
	Late blight	*Phytophthora infestans*
Tomato	Fusarium wilt	*Fusarium. oxysporum*
	Rhizopus rot	*Rhizopus stolonifer*
	Downy mildew	*Pseudoperonospora cubensis*
Apple	Apple scab	*Venturia inaequalis*
	Fire blight	*Erwinia amylovora*
	Black rot	*Physalospora obtuse*
Citrus	Black spot	*Guignardia citricarpa*
	Gummosis	*Phytophthora parasitica*
	Trizteza	*Toxoptera citricidus*
	Sooty canker	*Hendersonula toruloidea*
Grapes	Downy mildew	*Plasmopara vitcola*
	Bunch rot	*Botrytis cinerea*

3.1. Sensing Mango and Avocado Diseases

Anthracnose, the most important mango disease, is caused by the fungus *Colletotrichum gleosporioides*. Flower blight, fruit rot, and leaf spots are among the symptoms of this disease [129,130]. Fruit infection commonly occurs and can result in serious decay problems in the orchard, in transit, at the market, and after sale [131]. The fungus invades the skin of fruit and remains in a "latent" state until fruit ripening begins. Ripe fruit, both before or after picking, can then develop prominent dark-brown to black decay spots and can result in extensive fruit rotting. Anthracnose is usually more serious in years when rain and heavy dews are frequent, from the onset of flowering until fruit are about half size.

Stem-end-rot causing fungi in mango are endophytic, and such pathogens are activated when fruits begin to ripe and continue until complete degradation of the tissues [132]. The long time taken for natural ripening allows fungi to multiply rapidly producing stem-end-rot before ripening process is completed [133-135]. The major fungus responsible for stem-end-rot *Lasiodiplodia theobromae*, cannot directly penetrate into the plant tissue and hence requires wounds to facilitate penetration.

3.1.1. Sensors and Algorithms

A NIR model was developed to predict mango anthracnose in fruits still hanging in the trees [136]. Discriminant analysis was used to determine the best wavelengths (690 nm, 710 nm and 515 nm) and predicted the disease when it was still not visible (Table 2). A better model used HSI together with the spectral bands to increase the prediction accuracies [137]. Black pulp is another disease that is not visible until the fruit ripens; and it was detected with a thin needle which pushed the pulp towards a photo detector which was able to detect the disease [138].

Mangoes could be sorted by firmness [139] as hard, soft and very soft with 90% accuracy at a speed of one fruit per second (Table 3). NIR reflectance spectra on the 760 –2500 nm spectral range were used to measure mango flesh dry matter [140]. The best correlating wavelengths found by discriminant analysis were 904, 872, 1660 and 1516 nm, providing a $R^2 = 0.90$ with flesh dry matter (Table 4). Hyperspectral imaging for estimating total soluble solids, water content and fruit firmness in mango was obtained [141]. The correlation coefficient for total soluble solids and water content prediction was 0.78 and 0.81, respectively, while firmness correlation coefficient was 0.88.

Table 2. Sensors used for post-harvest detection of diseases and defects.

	Ultrasonic	Magnetic resonance	Machine vision	Spectral analysis	X-ray	Others
Mango and avocado		◘	◘	◘	◘	
Potato	◘	◘	◘	◘	◘	
Tomato			◘	◘		Electronic nose
Apple			◘	◘	◘	
Citric			◘	◘		
Grapes		◘				Chlorophyll fluorescence

Table 3. Post-harvest operations where sensing is applied.

	Maturity & Bruise	TSS, firmness	Disease det.	Freezing & chilling injury
Mango and avocado	◘		◘	◘
Potato		◘	◘	
Tomato	◘	◘	◘	
Apple	◘	◘	◘	◘
Citric		◘	◘	
Grapes		◘		

Table 4. Algorithms used for the different operations on postharvest.

	PCA	LDA	Neural networks	Others
Mango and avocado	◘	◘		
Potato	◘	◘	◘	
Tomato	◘	◘	◘	Fuzzy
Apple	◘	◘	◘	Fuzzy
Citric	◘	◘	◘	Fuzzy
Grapes		◘		

	Disease warning systems	Remote sensing		
		Spectral ratios & NDVI	Infrared	Fluor & Thermog.
Mango and avocado	◘			
Potato	◘	◘		
Tomato	◘	◘	◘	◘
Apple	◘	◘	◘	
Citric	◘	◘	◘	
Grapes	◘	◘	◘	◘

X-ray imaging was proven to be reliable when the mango is cut open [142,143]. MRI images obtained of mango fruits infected by the fruit fly showed dark areas in the seed eaten by the weevil, meanwhile healthy fruits showed a uniform light grey area [49]. X-ray can be considered a better technique for weevil detection in mango than MRI due to its lower cost [144].

A useful relationship between dry matter and the ratio of the oil/water were obtained with NMR in intact avocado that had desirable features for high-speed sorting [145]. Hass' avocado harvested at four different times during a growing season was analyzed by both reflectance and NIR spectroscopy to determine fruit dry matter. The model gave a $R^2 = 0.88$, suggesting NIR avocado grading on the basis of their DM content, to improve taste and oil content. Three of these wavelengths were obtained in the vicinity of 900-920 nm [146].

Low-altitude aerial color infrared (CIR) imagery identified *Phytophthora cinnamomi* infestation in avocado orchards [147]. Two anthracnose predictive models based on temperature and moisture were developed in Australia and Phillipines. The Mango Anthracnose Estimator (MAE) uses as variables the temperature and wetness duration for the prediction of dark appressoria production from conidia applied to detached mango leaves [148]. The use of the model resulted in a reduction of four to eight

fungicide sprays pear season to control flower anthracnose as compared to weekly spraying [149]. The Philippine model includes relative humidity in addition to wetness and temperature and was tested under field conditions [150]. Comparing both models present important differences in level of infection predicted from a given combination of temperature and wetness duration. High discrepancy indicates that weather-based forecasting systems for anthracnose should not be extrapolated from one region to another and the infection should be elucidated locally [84]. Although disease warning models have been developed, remote sensing is in its initial stage.

3.2. Sensing Apple Diseases

Apple scab is caused by the fungi *Venturia inaequalis* and is an economically important disease for apple producers. This disease causes almost as much loss to apple growers as all the rest of the apple diseases put together [151]. The scab fungus attacks leaves, stems, and fruit. The apple scab fungus overwinters in the dead apple leaves under the trees [152]. Depending on the temperature, first visible symptoms may show as soon as 8 days after the initial penetration by the ascospore. Hundreds of new spores are formed in the infection lesion and rain disperses the spores from the infection lesion to healthy leaves and to the young developing fruit, where they start a secondary infection.

The apple Black Rot is a fungus disease caused by *Physalospora obtuse* that occurs throughout the warmer regions of the world. The fungus attacks fruit, leaves, and limbs. Infection of the fruit may occur from the time the fruit is initiated until harvest, causing postharvest decay. The disease first appears as a small brown spot any place on the surface of the fruit. The black rot infection develops slowly, and complete decay of the fruit usually does not occur until the fruit is mature and turns black [153]. As the rot progresses, the decayed tissue is firm and leathery. Symptoms first appear on the leaves as small, dark purplish spots.

Fire Blight, caused by the bacterium *Erwinia amylovora,* is one of the most destructive diseases of apple and pear in the United States. The fire blight bacterium may attack any part of the tree from the roots to the leaves. The disease usually appears in the spring as blossom, leaf, and twig blight. Infected blossoms suddenly wilt and soon turn light to dark brown. As the disease progresses beyond, it invades the fruit spur and spreads out into the leaves. The leaves wilt and the entire spur growth turns brown on apple or dark brown to black on pear and dies [154]. The invading bacteria progress more rapidly down the shoots or twigs than in the fruit spur. A severely infected apple or pear tree may have so many blighted terminals that it has the appearance of being scorched or burned by fire. The diseased fruit is firm and later leathery, shriveling and turning brown on apple or black on pear and usually remains attached to the spur.

3.2.1 Sensors and Algorithms

Post-harvest detection of defects are carried out in automatic sorting lines (Table 2). Different researchers [56,71,155-157] analyzed apple diseases mainly for fruit quality sorting and detection of the three diseases at the same time. Differences in spectral responses at 450, 675 and 686 nm with a 6 nm bandwidth provided excellent apple scab detection independent of apple cultivar and color [56]. This study showed that the asymmetric second difference method and principal component analysis

(PCA) gave very similar results for the disease detection, fungal contamination, bruises and soil contamination on apples (Table 4). A neural network using up to 200 neurons was used to detect diseases on apples using entropy, local homogeneity, energy and inertia as image parameters and achieved an 89% success rate on the detection of damaged apples [158]. An automatic near infrared vision system was developed for apple defect inspection using a monochrome CCD camera attached with a 700 nm long-pass filter. The inspection procedure consisted of four steps: blob extraction, feature extraction, rule base construction and recognition [58]. A near-infrared (NIR) and a mid-infrared (MIR) dual-camera vision system was also used for quality inspection on refrigerated apples [159]. The MIR cameras had a sensitive spectrum range from 7.5 to 13.5 μm and detected only stem-ends and calyxes (Table 3). Recognition rates on refrigerated Red Delicious apples of about 94% for stem-ends and 92% for calyxes were achieved. The correct classification rates of good and defective apples were, 100% and 92%, respectively.

A line-scan X-ray imaging device detected bruises in Red Delicious and Golden Delicious apples [59]. One day and one month old bruises were analyzed, testing spatial and transform features. Best classification results were obtained using an artificial neural network and two kinds of features: spatial edge features and discrete cosine transform coefficients (Table 2). For old bruises, accuracies of 90% and 93% were achieved, respectively, for Red Delicious and Golden Delicious apples. New bruises were not adequately separated using this methodology (accuracy was approximately 60% for both apple varieties).

Remote sensing of scab infection plots throughout the vegetation period applies a standardized difference vegetation index (SDVI) to it. A combination of visible bands gives a much lower detection level than combinations of wavebands in the NIR. Symptoms of the infection leaves at the beginning did hardly show any visual infection (brown spots) but apparently the fungus was already present in the leaves affecting its internal structure [92,160,161]. Three months later the disease in the visible part of the spectrum was clear, as the damage to the internal structure of the leaves became larger. Out of these results it was concluded that a common vegetation index such as the normalized difference vegetation index (NDVI) is not the ideal one for early scab detection; combinations of NIR bands will perform much better (Table 4). Early stress detection for scab, making use of SDVI's can best been done using as second wavelength a waveband situated between 750 nm and 1,400 nm and first wavelength between 750 nm and 850 nm [162].

More recently in Germany, the apple scab model ASCHORF was developed and can provide practical recommendations to plant protection services and apple growers [163]. The modeled infection risk is dependant on temperature and leaf wetness duration. Leaf wetness duration is calculated but not measured and is based on energy balance principles. The model uses a sliding 10-day time series and acquires data for the previous four days from the standard meteorological network and then inputting grid point data from numerical weather prediction models.

3.3. Sensing Citrus Diseases

Blight affects mainly grapefruits and oranges, and incidence is lower on lemons and mandarins. Water transport in the xylem of blighted trees is impaired. The failure of water transport [164] seems to be attributable to the amorphous plugs [165], and symptoms appear to be due to lack of water

transport to the canopy. Blight symptoms are somewhat like those of vascular wilt fungi diseases caused by soil-borne systemic agents. However, no specific vascular wilt pathogen has been identified, although there were early claims that hyphae could be found associated with vascular occlusions.

Phytophthora foot rot or gummosis of citrus is caused by two soil microorganisms: *Phytophthora parasitica* and *P. citrophthora*. Disease incidence is especially high in trees established with the graft union at or below the soil surface, exposing susceptible scion tissue to the two pathogens [166]. Severe losses also can occur in groves subjected to flood irrigation if trees are planted on susceptible rootstocks. Longitudinal cracking of bark, accompanied by profuse gumming, usually is positive evidence of infection. Advanced stages of infection will result in yellow, sparse foliage and is named brown rot as diseased areas on the fruit are brown in color. Trees may later collapse and die due to the girdling action of the fungal infection.

Citrus Tristeza Virus (CTV) is one of the most destructive of the many viruses that affect citrus, (Table 1). The virus pathogen has been responsible for the death of 18 million trees in Argentina and 10 million trees in Brazil. In 1946, American and Brazilian plant pathologists reported that tree failure was caused by a virus disease [166]. The Brazilians found that an aphid, *Toxoptera citricidus*, was a vector of the virus. Common symptoms include reduced fruit size, leaf vein-clearing, yellowing and cupping of leaves, and stem pitting. Infection of sweet orange, mandarin, or grapefruit trees on sour orange rootstock causes necrosis in the phloem of the sour orange rootstock just below the bud union. This girdling causes eventual decline and death of the infected tree.

The sooty canker or limb wilt disease is caused by the fungus, *Hendersonula toruloidea*, a wound pathogen that invades citrus bark that has been damaged by freezing injury, sunburn, or mechanical injury but does not infect uninjured bark tissue [166]. The most common symptom of sooty canker is the sooty, black growth that develops beneath bark tissue, due to the presence of black masses, fungal spores that appear under the bark and on the surface of the canker. The leaves on branches with cankers wilt, turn brown, and die, as well as the branches on to the cankered area. Most cankers develop on unshaded trunks or limbs that face toward the sun. Sunburned trunks and limbs are highly susceptible to infection.

3.3.1. Sensors and Algorithms

A machine vision system [167] discriminated normal and diseased citrus leaf samples with greasy spot, melanose and scab (Table 2). The leaf sample discriminant analysis using Mahalanobis statistical classifier achieved over 95% accuracy for all classes when using hue and saturation texture features (Table 4). A back-propagation neural network algorithm achieved accuracies over 90% for all classes with the same texture features. Windscar was the most prevalent defect ranging from 23% on tangerine to 32.6% for grapefruit [168]. Classification was based on either Bayesian parametric techniques or on back propagation neural networks. Yielding the highest percent correct classification was the Bayesian approach. The parameters used for disease detection were HIS (Hue, Intensity and Saturation). RGB color systems using artificial neural network for orange-sorting are used in Brazil [169]. The feasibility of using machine vision system with neural networks to predict the sugar content or pH of orange fruit was tested [170].

The possibilities of adopting VIS/NIR spectra for measuring the quality characteristics of Satsuma mandarin was explored and developed a relationship between the VIS/NIR spectral measurements and major physiological properties like firmness [171], soluble solid content and acidity of the fruit (Table 3). The study concluded that the full spectral range of 400-2,350 nm has great potentials to assess the quality characteristics of mandarin fruit. An electronic nose was used to distinguish the maturity stage in mandarin [172]. Linear discriminant analysis was able to classify correctly 92% of the samples, while principal component analysis did not work properly. Spectral reflectance of citrus leaves changed as citrus canker lesions developed, being more pronounced in the 600-700 nm [173].

Typically absorption of pigments in the UV and in visible spectral range up to 500 nm is very high in the citrus peel, and low reflectance values are mainly originating from scattering in this range. From 720 nm up to the water absorption band centered at 980 nm, citrus peel has reflectance values around 70-80%, and decrease of the NIR reflectance due to softening (pre-necrosis stage) are obtained. Peel damage seen as tissue browning decreases the NIR reflectance. Changes in reflectance spectra can be seen already after 1-2 days after inoculation of orange fruits infested with *P. italicum* and *P. citrophtora* [174]. MIR images of internal rots produced by *Alternaria citri, Diplodia natalensis* and *Botrytis cinerea* in oranges var *Navel Barnfield* detect fruits with healthy external appearance [46].

The black spot of citrus (*Citrus* sp.) is caused by *Guignardia citricarpa* with ascospore production depending on temperature, leaf wetness, and rainfall. Ascospore production was related to leaf wetness only in the orange orchard but was not related to total rainfall or temperature [175]. Temperature and relative humidity were not important factors in post-bloom fruit drop caused by *Colletotrichum gloeosporioides*. Leaf wetness 4-8 days before the target day was a significant factor and rainfall acts as a conidia disperser and as a provider of moisture for spore germination [176].

Citrus foot rot foliage loses their chlorophyll and become chlorotic (yellowish-white) in contrast to the dark-green foliage of healthy trees [177]. For quick assessments of vegetation stress in citrus crops in the visible and near infrared region of the electromagnetic spectrum, an inexpensive multi-band video system was used to distinguish between grapefruit and orange trees in the yellow-green band [178]. Aerial photography and videography have been found useful for tree inventory in the Merritt Island National Wildlife Refuge citrus groves [179]. Remote sensing evaluates plant stress monitoring salinity [180], delineation of saline soils [181], and the detection of insect infestations [182]. In studies of general vegetation spectral reflectance, the near-infrared (IR) band (0.75 μm–1.35 μm) is important in detecting healthy and stressed trees based on leaf air content; healthy leaves with more air and a thicker mesophyll increase near-IR scatter [183]. In the visible region of the spectrum, especially at 0.45 μm, reflectance of citrus (Valencia orange) leaves was found to be influenced by leaf water content, chlorophyll content and leaf air volume [184], more than by leaf thickness (Table 4).

These positive forecasts of citrus production in Florida, however, face threats from virus and insect infestations. The 2002 Commercial Citrus Inventory showed a 4.2% decline in total citrus area coverage from 2000 due in part to diseases such as citrus canker (*Xanthomonas axonopodis pv. citri*), tristeza (Citrus Tristeza Virus). Little leaf notcher (*Artipus floridanus*), and the Diaprepes root weevil (Diaprepes abbreviatus) are of economic significance to citrus growers [184].

3.4. Sensing Tomato and Cucumber Diseases

Fusarium wilt is caused by the *F. oxysporum* fungi. Symptoms of *Fusarium* diseases are rots, leaf spots, blights or wilts [186] and once the soil is infested, the pathogen is difficult to eliminate since it survives in the soil for long periods [7]. The optimum temperature for growth of *F. oxysporum* is 28-29°C. There are no symptoms of infection if the soil temperature is below 20°C or above 30°C [187].

Rhizopus rot is a fungal soft rot requiring injuries caused by insects, hail, or cracking for infection to occur. The early appearance of the fungal mycelium is as a fluffy white mass [7]. Rot progression is temperature related with rapid fungal growth at 27°C, and no spore germination at 4°C. To minimize the incidence of Rhizopus rot, fruit has to be carefully handled to avoid wounds while keeping clean storage containers, warehouses, and hydrocooling water (Table 1). Rhizopus rot is more likely to be a problem when fruit is allowed to fully ripen on the plant and when poor sanitary conditions are found on field bins and at the packinghouse. Other diseases that attack tomato plants are anthracnose, early and late blight, Septoria leaf spot.

Downy mildew of cucurbits is a devastating disease, especially in temperate regions of the world [188] where humid conditions favor disease spread; infection by zoospores requires free water on the lower leaf surface for at least 2 h, and production of zoosporangia in the dark occurs at an RH of >90% for at least 6 h [189]. After penetrating the leaf through stomata, this pathogen rapidly colonizes the mesophyll of its host cell producing intercellular hyphae and intracellular haustoria for the uptake of nutrients [190]. First symptoms on leaves are small, slightly chlorotic to bright yellow areas on the upper surface without loss of vitality in plant cells.

3.4.1 Sensors and Algorithms

It is a challenge to detect surface defects on tomatoes in an automatic sorting line. In comparison with bruises, the other surface defects, such as the blossom-end rot, sunscald, mold and cracks are not so difficult to recognize for a vision system. Tomato bruises were detected using a hyperspectral imaging setup [191] in the wavelength region between 400 and 1,000 nm (Table 2). Chemometrics tools were used to extract the effective wavebands for surface defects detection and for identifying the stem-end.

F. oxysporum was detected on tomatoes using spectral Fourier signatures with an accuracy of 91% [192,193]. Spectral signatures were analyzed by a Fourier program providing different harmonics, which were discriminated to obtain differences between healthy and diseased plants. An automatic conveyor belt was developed to sample the inoculated tomatoes on-line using 1 nm spectral bandwidths acquired with a computerized spectrometer [194]. Four different concentrations were applied encountering 92% on detection accuracy for a concentration of 6.5 x 10^4 sporangiospores/mL. Reflectance at 670 and 960 nm [195] was used to detect mold and other surface defects.

An electronic nose was used to evaluate the maturity [196] and to monitor the shelf life of tomatoes (Table 3). Results showed that pink-stage fruit could be distinguished from light-red stage and red-stage ones based on the E-nose using principal component analysis (PCA) and linear discriminant analysis (LDA). E-nose sensor response signals were predicted and the coefficients were 0.981 and 0.968 for initially light-red stage fruit and red-stage fruit, respectively (Table 4). A sensor was

developed to sense *Rhizopus stolonifer* by the peduncle scar. The tomato peduncle scar acts as a membrane to decrease water loss in harvested fruits. Air is sucked and the relative humidity measured. A controlled pressure was applied to green and red infected tomatoes obtaining 91% and 89% on detection accuracy, respectively. The advantage of this method is that monitoring is non-dependent on its maturity stage [197].

Disease-warning systems are the most effective ICM option for tomato disease control. These systems use research-based information about weather conditions that increase the risk of fungal disease outbreaks. Disease-warning systems allow growers to spray fungicides only when the risk of an outbreak (and accompanying potential economic loss) is sufficiently high. Daily weather data (maximum and minimum air temperature, hours of leaf wetness, maximum and minimum air temperature during the wet period, hours of relative humidity > 90% and daily rainfall) were the environmental inputs to FAST. Because epidemics of late blight (causal agent: *Phytophthora infestans*) sometimes appeared in Pennsylvania tomato field, the BLITECAST model [198], a disease-warning model based on air temperature and hours of HR > 90%, was run in tandem with the FAST model.

In Ontario, growers use another model called TOM-CAST, which provides disease-risk ratings as Daily Severity Values (DSV's) to apply fungicide spray only when the sum reaches a predetermined threshold. At each site, temperature, relative humidity, rainfall amount, and duration of wetness periods were recorded by electronic sensors at 5-minute intervals and summarized hourly by an automated datalogger. Data were downloaded to a PC via modems and telephone so that DSV's for TOM-CAST could be calculated for the period from noon to 11 a.m. each day. It saves from 2 to 3 sprays per season which corresponds to fungicide sprays up to 50%, saving 125 US/ha [199]. Percent incidence of anthracnose was not significantly higher for thresholds of 20 or 25; with a DSV's threshold of 15, anthracnose incidence was affected neither by sensor location nor by distance from the field to a weather station. Marketable yield for DSV's thresholds of 15 or 20, but not 25, was not significantly lower than for the weekly-spray treatment [200].

The TOM-CAST system can be used to schedule fungicide sprays for controlling early blight where weather data is available. The first fungicide application after transplanting should occur when 25 DSV's have accumulated [200]. If 25 DSV's have not accumulated before mid-July, the first fungicide should be applied at that time. Subsequent applications should occur when 18-22 DSV's have accumulated since the previous application. Scheduling fungicides using TOM-CAST provide good control of Septoria leaf spot. Those leaves sampled for the presence of Septoria lesions on leaves and stems were inspected. The fungus prefers cool, wet springs for early disease spread.

Spectral ratio analysis based on principle component analysis [201] and clustered analysis was used in remote sensing of diseases (Table 4). They observed that the sensitive spectral wavelengths and reflectance values enabled them to discriminate *Phytophthora infestants* infection on tomatoes. Multi spectrum imaging detected the diseases and insect pests of tomato [202]. The experimental results showed that near infrared band (0.7-1.3 μm) is more significant than visible light band in monitoring the crop diseases and insect pests. The 0.75-0.93 μm band is useful for inspecting the tomato late blight. The spectral band of 750-930 nm is, statistically, the best for the remote sensing of tomato disease, followed by that of 950-1,030 nm and 1,040-1,130 nm [203]. Five narrow ranges are especially important for development of approaches to identify the diseased plants from the healthy

ones: two peaks centering respectively at 850 nm and 1,050 nm, and three valleys respectively at 625 nm, 1,500 nm and 2,100 nm. Leaf reflectance spectra of tomato leaves damaged by leaf miner were obtained [204]. Spectral reflectance decreases significantly with the increasing severity level of infestation at the short wavelengths of near infrared 800–1,100 nm but changes for individual bands of 1,450 and 1,900 nm where spectral reflectance increases with the increasing infestation severity.

Digital infrared thermography has been shown to be a useful tool for the prediction of diseases. Infrared thermography was tested on the detection of cucumber downy mildew caused by *Pseudoperonospora cubensis* [205]. The maximum temperature difference (MTD) within a leaf or a canopy turned out to be suitable for the differentiation of infected and non-infected tissue under controlled conditions. Environmental conditions during thermographic measurement, in particular air temperature and humidity, as well as water content and age of the leaf influenced the temperature of its surface. In some studies, conditions that enhance transpiration rate facilitated the detection of changes in leaf temperature of infected leaves. However, as modified by environmental conditions, digital infrared thermography alone is not suitable for the quantification of diseases in the field.

Measurements of stomatal aperture during the early stages of pathogenesis indicated that the decreased water content of infected tissue 2 d after inoculation coincided with a slight increase in stomatal opening. In darkness, the aperture of stomata which had an average area of 25.5 μm^2 in non-inoculated leaves dramatically increased due to the development of downy mildew and reached 160% and 280%, respectively, 3 d and 6 d after inoculation [206]. Two to three days after inoculation, the heterogeneity of the transpiration rate within infected leaves was significantly higher than for healthy leaves. Digital infrared thermography proved to be a simple but reliable parameter for this heterogeneity and may be used for the discrimination of healthy leaves or canopies [207] and those with downy mildew (Table 4). At later stages leaf tissue became necrotic, associated with a transpiration approaching zero and a drastic increase of local temperature; the average leaf temperature may be largely unaffected. The simultaneous presence of chloroses and necroses in leaves results in the highest values of the thermograms, which slowly decreases when the leaf becomes completely necrotic.

3.5. Sensing Potato Diseases

Despite a century of research, potato late blight (caused by *Phytophthora infestans)* remains a constant threat to potato production in many parts of the world. In high rainfall growing areas, control of late blight is by frequent application of fungicides, but consumer concerns over chemical residues may force modifications to current practice. Late blight appears on potato leaves as pale green, water-soaked spots, often beginning at leaf tips or edges (Table 1). Lesions enlarge rapidly and turn dark brown to purplish-black. During periods of high humidity and leaf wetness, a cottony, white mold growth is usually visible on lower leaf surfaces at the edges of lesions. In dry weather, infected leaf tissues quickly dry up and the white mold growth disappears. Late blight appears on potato tubers as a shallow, coppery-brown dry rot that spreads irregularly from the surface through the outer tissue. On tuber surfaces, lesions appear brown, dry, and sunken, while infected tissues immediately beneath the skin appear granular and tan to copper-brown [208].

3.5.1. Sensors and Algorithms

Tuber physiological disorders such as brown center, hollow heart, and translucent end, as well as secondary growth, growth cracks, bruise susceptibility, and heat necrosis have been associated with water stress and/or wide variations in soil moisture content [209-212].

A vision system graded potatoes by size, and detected external defects such as greening, mechanical damages, rhizoctonia, silver scab, common scab, cracks and growth cracks [213]. Mirrors were used to obtain a 360° view of the potato with a 3-CCD line-scan camera to inspect the potato in flight as they pass under the camera (Table 2). The color segmentation procedure used Linear Discriminant Analysis (LDA) and a Fourier Transform based shape classification technique based on the boundary distances and the centroid of the potato. A color machine vision system was trained to distinguish between good and green potatoes [214]. The vision system achieved over 90% accuracy in inspection of potatoes with hue histograms and multivariate discriminant techniques (Table 3).

NIR detected defective potato tubers [215] which are *Phytophthora* infected using discriminant analyses of reflectance rates (Table 4). As a result, for the ranges of specific wavelengths, there were clear differences between untreated and defective potato tubers. The light source was applied not only to the defective side, but to the entire surface of the potato tubers.

Magnetic resonance imaging was applied to detect non-visible internal bruise and spraying symptoms caused by a virus and to get insight on the chemical and anatomical causes of such defects [53]. *P. infestans*, *Phoma foveata*, *Fusarium sulphureum* y *F. coeruleum* fungus were detected using magnetic resonance [216]. Previous X-ray methods were modified to enhance the contrast of the hollow heart potatoes [217]. A potato was placed in an X-ray field and a scanning detector traversed the length of the potatoes. The output of detector was amplified, digitized, and transferred to a computer for analyzing and recording.

Ultrasonic transmission through potatoes is possible for the detection of hollow heart at a frequency of 50 kHz with a power level of 0.22 W [36]. At this frequency, ultrasound penetrated the whole potato tuber in the transverse direction along the longitudinal axis of the tuber, and yields information about the inside of the potato tuber. The analysis of the waveform of transmitted signals in time domain is sufficient to indicate the presence of hollow heart in potatoes. Average transmission losses of hollow heart potatoes were found to be greater than 0.28 dB/mm, and when this value was used as threshold, a predictive accuracy of 98 percent was achieved.

Forecasting of late blight uses data from in-field automatic weather stations for limiting agrochemical use during the potato growing stage. Ideal conditions for *Phytophthora infestans* spore production are relative humidity greater than 95% and temperature over 10°C at nighttime [218]. Serious infection occurs when free water is available on the crop surface, being rainfall and prolonged high relative humidity required after spore production. Critical periods can be predicted when minimum temperature is over 10°C, relative humidity greater than 90% for a period from 12 to 48 hours and rainfall is present in the period following up to 10 days. Prediction should be based on hourly observation of temperature and relative humidity.

Consistently rainy summer or fall weather promotes late blight. However, in the 1990's, epidemics of late blight developed in potato crops in arid production areas of the Pacific Northwest where late blight had not been a problem [219]. Irrigation that tends to keep the foliage wet may contribute to this

developing risk. Potatoes cultivated under center pivot irrigation can receive a relatively low volume of irrigation water for a long time near the pivot, favoring late blight occurrence. Late blight tuber rot increased significantly as more irrigation water was applied, and was significantly greater within 30 m of the pivot than at greater distances [220]. Long duration sprinkler irrigation also favored late blight in Oregon and California [221]. Under overhead sprinkler irrigation the proportion of potato leaflets containing late blight oospores and the number of oospores per leaflet were dependent on the soil water regime [222].

Potato vines that remain wet for long periods create a propper microenvironment for early blight (*Alternaria solani*), late blight (*Phytophthora infestans*), white mold (*Sclerotinia sclerotiorum*), and blackleg (*Rhizoctonia solani*) [223]. The timing of these diseases and associated crop losses vary regionally with yearly weather patterns, and can be affected by irrigation methods, which increase or decrease the duration of high humidity in the crop canopy. Long periods of leaf wetness or high relative humidity within the potato canopy favor infection by white mold [224]. Avoiding light, frequent irrigation of coarse-textured soils, and avoiding heavy, less frequent irrigation of fine-textured soils can diminish the risk of white mold.

3.6. Sensing Grape Diseases

Downy mildew *(Plasmopara vitcola)* is one of the most important fungal diseases for wine grapes and can lead to considerable losses in grape yield and quality. Downy mildew attacks all green parts of the grapevine (Table 1). On young leaves, the disease will appear on the upper surface as small yellow spots referred to as oil-spots [225]. As these spots enlarge they may appear to cover most of the leaf, especially if there is more than one spot on the leaf. Total crop loss may occur if severe infection is not managed, especially near flowering. Under warm, humid conditions (>98% humidity and > 55°F) at night, white, fluffy sporulation develops on the lower surface of the leaf. White spore masses also develop on infected flower and fruit clusters eventually wither and die [226]. Spores are spread to new leaves and clusters by wind and rain and the fungus require a film of water for infection. The disease can spread rapidly under warm conditions with frequent rain or dew.

Botrytis cinerea can infect all green parts of the vine being bunch rot the biggest problem. Early in the season, buds and young shoots may be infected and turn brown. Inflorescences may also be blighted and wither away. The fungus can infect grape berries directly through the epidermis or through wounds, and may continue to invade the entire cluster. Infected white grapes turn brown and purple grapes become reddish. During dry weather, infected berries dry out; in wet weather, they tend to burst and become covered with a grayish mold, which contains millions of spores. These spores are spread during moist periods by wind to new infection sites. The disease is favored by temperatures of 59-68°F and free water or at least 90% humidity [227].

3.6.1 Sensors and Algorithms

By using an imaging system, higher chlorophyll fluorescence (F690) was found for unripe white grape clusters than for ripe grapes [228], as expected, since the chlorophyll content decreases during the ripening of the grapes, Table 3. Magnetic resonance (Table 2) was used to study grape growth,

visualizing internal characteristics and obtaining total volume of the grape cluster [229]. Contamination of grapes by different diseases has also been studied by magnetic resonance [230].

The PERO model was developed to calculate the start of infection of the grapevine disease *Peronospora* that is determined by temperature and leaf wetness [163]. The model inputs hourly air temperature, relative humidity, calculated leaf wetness, daily extreme temperatures, and daily rainfall. The model output probable infection dates and oilspot lesions were used for agro-meteorological advice. The PLASMO (Plasmopora Simulation Model) model was developed to simulate the biological cycle and the disease leaf area of grapevine downy mildew allowing for the best timing of fungicide treatments [231]. Data inputs are hourly temperature, relative humidity, rainfall and leaf wetness. The results are expressed in percentage of leaf area covered by oil-spot lesion.

Relationships between yield and quality indicators are often inferred; however these relationships do vary significantly between vineyards [232,233], and possibly within vineyards. Moreover, preliminary data suggest regions of high and low-yielding vines in a vineyard tend to remain stable in time, inferring that soils play a significant role in such variability [234]. The accurate characterization of spatial variations in those parameters that influence vineyard productivity requires a considerable amount of data. Traditional methods of generating such data are generally time consuming and expensive. For example, measuring basic fruit quality and yield parameters of sixty sample sites in a one hectare block requires more than thirty work-hours. The move toward *on-the-go* sensing of yield and quality parameters by combining the latest sensor technology with GPS-equipped vehicles is slow and currently limited to grape yield. However, rapid sensing techniques such as measurement of baume using near infrared (NIR) spectroscopy [235] and grape phenolic composition using visible-NIR spectroscopy [236] are potential candidates for on-the-go sensing. The use of rapid electromagnetic induction or EM-survey techniques to accurately characterize soil structure is also becoming more widely used in the grape and wine industry [237].

Grape phylloxera (*Daktulosphaira vitifoliae* Fitch) infestation affects a number of California grape regions and in recent years devastated many vineyards [238]. An airborne multispectral digital imaging system related crop canopy reflectance and canopy density under various degrees of phylloxera stress [239]. Decreased foliar nitrogen and chlorophyll concentrations are also known symptoms of phylloxera stress. A new approach for calculating stress indices [240] used the shaded portion of the canopies, particularly useful for row or tree crops (Table 4). Its limitation is the tendency for stomata to be more closed in the shade and the smaller range of temperatures expected for a given range of conductance. Evidence was provided for grapevine that, not only leaf or canopy temperatures but also the temperatures of other surfaces within the canopy (including wet or dry reference surfaces), were dependent on the water relations of the crop.

4. Pathogen Detection in the Future

Sensors for disease detection and food quality will evolve in the following decade with the aids of nanotechnology and MEMS. Actual NIR, fluorescence and vision sensors can detect more accurately fruit quality and predict diseases better than our eyes. Sensor spectral range is broader than eye's spectral response and sensors are capable of detecting polarized light. Nanotechnology cells will be able to capture gases in bubbles creating internal reactions without affecting fruit or vegetable quality.

Ethylene, pigment status, diseases and enzymes will be predicted temporarily and spatially throughout the fruit.

MEMS are nanotechnology chips which can sense and take control actions. MEMS produced extensively have low costs and could help to optimize precise fruit ripening harvest, reducing post harvest costs. The author visualizes the future with a MEM plastic unit added per fruit, memorizing its history and growth characteristics with detail. The MEM will acquire fruit internal nutrient concentration (e.g. calcium and nitrate ions), type of soil, applied fertilization, and pesticide usage. The information will also include commercialization details as transportation, cooling, texture and firmness during controlled atmosphere treatments. Retail daily analysis of ripeness, rots, impact damage, chlorophyll, carotenoids, and water status should be monitored on real time for consumer safety.

Biosensors will also evolve and will be used together with intelligent biological agents as wasps, spiders or bees providing intelligent crop status sensing. Their attraction or repulsion to fruits can help on detecting fruit ethylene production, respiration rate and fruit ripeness. Even trained parrots could be used as indicators of mango ripeness. Fruit bio-security will be a big issue to assure that consumer health can be guaranteed.

As sensors improve and provide more information higher data acquisition will be required but algorithms will tend to become simpler. Supervised algorithms will be used if they continue to be trained during their operation; these algorithms would be iterative and will replace multiple regression equations which are used at the present on most processes. Genetic algorithms will be used more often while fuzzy algorithms will disappear as a prediction tool.

Although remote sensing is a strong tool its view is reserved to the top of the crop-tree canopies. With controlled mirrors crop status within the entire plants could be observed. The mirrors should be controlled to avoid sensor saturation with radiation. By the next decade, entire plant measurements will be placed on the top of the canopy using codes easily interpreted by satellites, avoiding excessive data transmission.

5. Conclusions

A lot of work has been carried out to save farms from pathogen attacks, although some attacks have been really devastating, as in the citric industry in Florida. Research is being done locally in each country or through grants with developed countries where sophisticated equipment is available for doing the tests. Results have saved million of hectares from its premature damage, and research will continue if we need to provide food for the world inhabitants in the future.

Disease warning systems are being used all around the world for all the existing crops requiring only a net of meteorological stations. Conventional stations require the addition of the wetness sensor which has the ability to determine the humidity in the canopies and fruits, being the essential component of the risk system. Although there are a lot of sensor designs its trend is to find a non-contact sensor which can provide the information quickly and accurately. Programs and algorithms are not sophisticated and software properly designed for tomatoes is being also used in apple orchards (TOMCAST). This software has the advantage that it predicts the disease but it cannot be used in a general approach to detect all type of diseases on an orchard. These warning systems provide huge

savings on fungicide application reducing fruit contamination for the consumers. Its maintenance is high, loosing accuracy with time so research is being carried out to find other risk systems.

Remote sensing technology is advancing quickly and soon will be able to predict farm diseases if the temporal resolution can be reduced to a maximum of one day. Its spatial accuracy should be reduced to 10 cm increasing the quantity of data collected. A hyperspectral imaging, thermographic and chlorophyll fluorescence setup is the optimal system required to predict diseases from the sky, but environmental variables and canopy structures affect measurements and require special algorithms for proper operation.

Disease detection of fruits on vegetable in sorters is in a more advanced stage. Defect products can be separated from healthy ones with high accuracies avoiding higher losses during transport and user consumption. In some cases NMR has been used and its application on real-time systems is not economically feasible at the moment, as well as the electronic nose. X-ray systems are getting cheaper and can be used to detect weevils inside fruits in a continuous sorter system. Throughout all this review advances on sensor technologies and their algorithms have been analyzed, although it was impossible to include all fruits and vegetables. In the future NMR high speed on-line systems will be available and all the internal properties of the produce will be known, while remote sensing will have to work in order to avoid farm damaging by diseases.

This paper has reviewed important applications carried out during this century and important changes will come with nanotechnology sensors, biosensors and MEMS. Algorithms will be simpler and always iterative, changing as fruits evolve naturally. Even intelligent ants, spiders, wasps and birds can be used to assess crop status in the field.

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