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Review article

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Abstract – Interest is increasing in the development of methods to automatically and continuously detect crop stress, water use, growth and nutrition in greenhouse crops. Some of these techniques are now being tried in commercial greenhouses and hold the promise of improved climate management for better yield and quality, and reductions in environmental impact. However, integration of automated crop monitoring with computer environmental control systems is not yet commonplace, and will depend on the development of computer programs which incorporate the most appropriate real-time crop data into dynamic models.

greenhouse / crop monitoring / climate control / sensors /environmental sustainability

Résumé – Suivi automatique des cultures sous serre. Il existe un intérêt croissant pour le développement de méthodes qui permettent de détecter automatiquement et en continu les contraintes subies par les plantes, l'utilisation de l'eau, la croissance et la nutrition des cultures sous serre. Certaines de ces techniques sont maintenant en essai dans des serres commerciales et tiennent leurs promesses en ce qui concerne l'amélioration de la conduite du climat, pour un rendement et une qualité meilleurs et une réduction de l'impact sur l'environnement. Cependant l'intégration d'un suivi automatique de la culture avec des systèmes de contrôle de l'environnement par ordinateur n'est pas encore banalisé, et dépendra du développement des programmes informatiques qui intègreront dans des modèles les données en temps réel sur la culture les mieux appropriées.

serre / suivi des cultures / contrôle du climat / capteur / durabilité de l'environnement

1. INTRODUCTION

In order to control climate, greenhouse environmental control systems have traditionally relied heavily on information collected from sensors which monitor climate parameters, especially temperature, humidity and light. These sensors provide information used by the control algorithms to modulate ventilation, heating, shade curtains, fog systems, supplemental lighting or other physical features of the greenhouse. Most of these sensors, such as thermistors and light meters, are reliable, inexpensive, readily available and constantly improving [19]. In a similar manner, the water status of the root zone may be monitored with tensiometers, moisture blocks, time domain reflectometry, or electrical conductivity (EC) probes in order to control irrigation, and nutrient composition may be measured with chemo-sensors such as ion specific electrodes [19]. In all cases, the instruments monitor some aspect of the crop environment but not the crop itself. Although this provides a useful way to control the environment in the greenhouse, it lacks precision because it relies on basic assumptions

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(models) about the effects of the environment on crop functions. For example, light level is positively correlated with transpiration rate, and is often monitored in order to control irrigation. However, crop transpiration is also affected by the stage of crop development, vapor pressure deficit (vpd), root mass, leaf area, leaf temperature, and perhaps cultivar. Not including this information decreases the precision of light-based irrigation. Direct monitoring of the crop would seem preferable because it does not require that these factors be fully known.

This review will describe current trends in the use of instruments to measure crop status directly (Fig. 1), and will discuss their potential application in commercial greenhouses to improve quality and yield and to conserve resources.

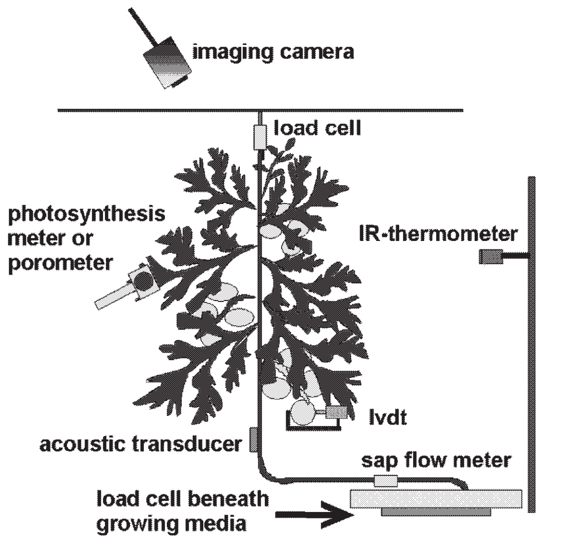

Figure 1. Schematic diagram of a few of the instruments which may be used to continuously monitor a greenhouse crop, in this case tomato. Remote sensing methods: imaging or infra-red camera and infra-red thermometer; direct methods: sap flow meter, lysimeter (load cell), linear variable displacement transducer, suspended load cell, photosynthesis meter and acoustic transducer.

2. REMOTE MEASUREMENTS

In general, remote sensing refers to a quantification of some plant canopy attribute (such as phytomass or leaf area index) obtained through non-contact, usually involving the measurement of electromagnetic radiation in specific wavelengths reflected or emitted by the plants [42]. Major developments have occurred recently in large-scale remote sensing of field crops [36]. These new approaches make use of aerial (aircraft and satellite) imagery to detect long-term changes in the crop, and are therefore inappropriate for day-to-day greenhouse crop management. However, the principles of field crop remote sensing apply in a greenhouse context.

2.1. Crop growth

Image processing has been a promising technique for measuring growth and development of a plant canopy since the early 1990s [62]. A recent example involved analysis of images of a canopy of broccoli seedlings taken with a video camera [61]. The camera was fixed 50 cm above the seedlings, which were illuminated with artificial light. The RGB (red, green, blue) signals outputted from the camera were resolved into 256 gray-tone levels by the image processor, from which the chrominance (difference between a given color and a reference color with the same degree of brightness) was calculated. Pixels with a threshold green chrominance level were considered to be plant material and could be used to determine leaf area and top fresh weight of the seedlings. Chlorophyll content was also correlated with chrominance green level (g-level). In another example, a finite element method of image processing using a unique data compression that is similar to the functioning of the human retina was used to calculate numerical values (contrast, homogeneity and local homogeneity) from original video images to determine the growth of a radish sprout canopy [49].

Seedling characteristics can be extracted from images obtained by machine vision. (Machine vision is the automated acquisition and analysis of video images for the purpose of decision-making or control). Lin et al. [38] used the motion of a rotary stage controlled by a computer for image acquisition. Seedling height, total leaf area, top fresh and dry weights were fitted into logistic and Richard functions. The relative growth rate was derived from logistic functions and growth curves were then modeled. The authors found that growth response could be adequately predicted under various conditions. In a more indirect approach, the dry weight of aerial portions of tomato plants in a growth chamber was correlated with machine vision images [55]. According to the model, these correlations can be used for developmental prediction (time to first flower) and for maintaining plant scheduling of a single truss tomato crop. However, the model did not account for a delay of 4–6 days in plant response to change of air temperatures.

An image processing system was developed for measurement of lettuce growth under greenhouse conditions [35]. Fresh weight was estimated by a model using average top-projected areas obtained by a video imaging system. The system can also generate control signals to adjust nutrient EC according to the stage of lettuce growth.

Itoh [32] used a fixed stand to acquire a top view image of lettuce under artificial lighting conditions. Each image was separated into three frames in RGB, and 27 image features were calculated. Fifteen were found useful in determining the growth of the plants. Using these 15 features, a neural network was used to assign a lettuce plant to one of three age groups (namely 10, 20, or 30 days after planting). The author concluded that machine vision in conjunction with a neural network algorithm can detect whether a lettuce crop is ahead or behind the expected size at a specific age.

2.2. Fruit quality

A video imaging system using two video cameras in fixed positions was used to analyze the growth rate, shape and color of greenhouse tomatoes [25]. The system was able to detect the early stages of blossom-end-rot in the fruit and it was suggested that this diagnostic system could be incorporated with an artificial intelligence expert system to avoid blossom-end-rot. However, this may be impractical in a commercial setting, where a large number of fruit would need inspecting.

Among the many physical and chemical attributes of tomato ripening, skin color is an accepted index of maturity. One problem with spectrophotometric methods is that they are limited to either a few locations around the fruit, or to average light reflectance values taken from the entire fruit surface. Color image analysis has been used to overcome these limitations. Choi et al. [5] used a cylindrical illumination chamber to provide uniform lighting that eliminates shadows and specular reflection from the tomato surface. The RGB values from the images were transformed into HSI (hue, saturation, and intensity) values and used to identify six classes of tomato maturation (USDA standard classification). Seventy-seven percent of tomatoes were correctly classified into the six standards, which improved to 98.8% if green/breaker, turning/pink, and light red/red standards were used.

2.3. Physiological status

Imaging techniques have been used to detect various aspects of plant status, including leaf mineral content. Meyer et al. [43] used a spectroradiometer to identify wavelengths of near-infrared radiation (800–1000 nm) which correlated with nitrogen deficiency in poinsettia. In lettuce, color image processing techniques were used to relate nutrient (N, Fe, Zn) deficiencies to leaf discoloration and plant size changes [27]. In this study, individual plants were brought into a chamber and images were taken every two days during the life of the crop. Using pixel number (size of a plant) and RGB channels of each object pixel, a counter-propagation neural network was applied to determine relationships. Ling et al. [40] used a machine vision system to correlate specific wavelengths with specific types of stress. Nutrient stress of a lettuce plant could be detected within two days of nutrient depletion by monitoring top projected canopy area (TPCA). Plant response to high levels of Zn and Cu was detected by a Normalized Difference Vegetation Index calculated from a hyperspectral video imaging technique [63]. Near-infrared wavelengths were more useful in detecting such response than were wavelengths within the visible region of the spectrum. Giacomelli et al. [18] used machine vision to detect lettuce plant response to nutrient deficiency by monitoring TPCA. Nutrient stress (achieved by providing water with no nutrients) was detected within 17 hours after initiation of the treatment based on differences in growth rate between treated and control plants.

Water status has been measured by video imaging using wavelengths in the visible regions [50]. Plant leaf water potential was measured destructively and related to tonal variations (contrast, homogeneity, and local homogeneity) of an RGB image taken over a canopy of chrysanthemum. Plant water status was then monitored on an ongoing basis by a neural network based on the textural features of pictorial information obtained from the plant canopy.

Plant response to low temperature can be detected by morphological information and spectral features, as shown in tomato plants [37]. TPCA and morphological profiles were obtained by a two-camera machine vision system. The reflectance of plant under-side canopy and average gray level were chosen as spectral features. Low temperature response can be detected within two weeks by TPCA and plant profile, while spectral information obtained from the under-side of the canopy can be used to detect plant response within a week.

Thermal images have also been used to detect canopy temperature. Meyer et al. [43] could detect a leaf temperature difference of +/– 0.5 °C in a poinsettia plant canopy. Dark areas showed cooler canopy temperature, while brighter areas represented dead or diseased leaves. Infra-red imaging has also been used to detect water stress a few hours before visible wilting of a cucumber crop [39].

Remote sensing of leaf temperature with infrared thermometers (IRTs) is a cost-effective alternative to thermal imaging. Like imaging, the sensors measure the leaf surface without contact, and provide an average surface temperature of one or more leaves, rather than just a single point on one leaf as with thermocouples and thermistors.

The accuracy of infrared thermometers is affected by the field of view and the angle with which the IRT is aimed at the surface to be measured [24]. If the field of view is too wide, then extraneous surfaces such as the floor or sky might be included. The IRT works best when positioned directly above or below the surface to be measured. Care must also be taken to ensure that the IRT does not shade the surface being measured.

In theory, water stress in plants may be detected based on the difference between the leaf temperature and the temperature of the air surrounding it (Fig. 2). Ben-Asher et al. [2] cautioned that the resolution of the IRT was insufficient to detect small differences between well-irrigated treatments, and it was unable to assess transpiration on a short time-scale. Similarly, Kacira et al. [34] reported that water stress was not detected until after three days of treatment. Errors may also result from stomatal closure during periods of peak solar radiation or high CO_2 concentration, and because of disease. Nevertheless, water stress can be determined by means of a "Crop Water Stress Index" [1], which is somewhat more complex than simply examining the leaf-air temperature differential.

Automated monitoring of leaf temperature would also improve climate management. For example, vapor pressure deficit (vpd) is currently estimated from ambient air temperature in the greenhouse, and is used to modulate crop transpiration. However, this value is only an approximation of the true driving force for water movement, which is in reality determined by the vapor pressure gradient between leaf (at saturated vapor pressure) and air (at some vpd). Measurement of canopy temperature would provide a more precise measure of this driving force, since the saturated vapor pressure within the leaf is temperature-dependent.

2.4. Current constraints

The advantages and constraints of using machine vision to monitor plant growth or to detect plant stress were reviewed by Morden et al. [46].

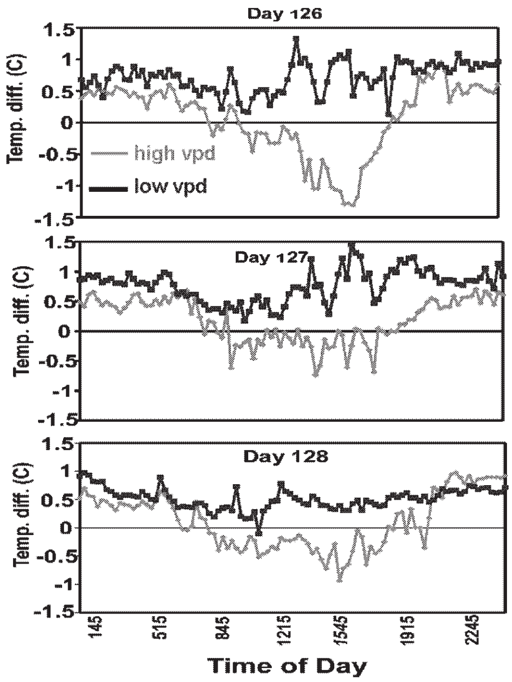

Figure 2. Plot of canopy temperature minus air temperature on three consecutive calendar dates, showing that leaf temperature can substantially differ from air temperature. High vapor pressure deficit (vpd) tends to produce cooler leaves than does a low vpd environment. Canopy temperature was measured with IR-thermometers (Ehret, unpublished).

The equipment is costly, and too complicated for use by non-experts. Because imaging techniques are solely based on reflectance, lighting conditions may affect the quality of the image, which is why studies are frequently conducted under very controlled lighting situations. The constant variation in sunlight poses a challenge for routine use of imaging as a monitoring device. Image processing can also affect the accuracy of the measurements [53]. Third, some method of recording system characteristics over time must be incorporated so that malfunctions of the equipment can be identified.

3. DIRECT MEASUREMENTS

Direct methods, as differentiated from remote, or non-contact methods of detection, involve some form of physical contact with the plant. This is the more traditional means of gathering information. Special care must be taken to prevent the monitoring equipment from influencing the measurements.

3.1. Lysimeters and load cells

Lysimeters can be used to monitor the flow of water in and out of the media and they are considered the most accurate and/or simplest means of determining the water usage of a crop. Lysimeters have also been widely used in the scientific community in the testing and calibration of other sensors and models [1]. Traditional lysimeters work by placing the growing media in large impermeable containers which allow the leachate or excess irrigation water to be collected. Modern weighing lysimeters in the form of electronic balances or scales can be used to measure the entire weight of the growing media. They can range in size from one or two plants on a single scale [68], up to entire trees [23], or rows of crops supported by multiple load cells. Boukchina et al. [3] measured weight changes relatively infrequently, from one to 24 hours. However, van Meurs and Stanghellini [68] have developed a method of monitoring the changes of the media weight every minute. With corrections for plant growth, it is possible to obtain a very accurate estimate of when and how much water a plant uses.

Weighing lysimeters have the advantage of relatively low maintenance. There is no calibration required for separate soils, and the accuracy can be easily verified with the simple addition of known weights. There are a few drawbacks associated with the use of lysimeters for irrigation control. Lysimeters do not necessarily give the absolute water content of the media. Though they can show the movement of water in and out of the system, they cannot determine exactly how much water is present in the media, nor where that water is located spatially. The growth of the plant itself can confound the estimation of water content, in that over the long term, it would show up as an increase in weight that would be thought to be due to irrigation. Without correction for growth, the plants would receive diminishing amounts of water over time. Furthermore, as lysimeters are supporting the entire growing media of the plant, and need to be free standing, they may interfere with crop production activities. Due to their size and typical greenhouse conditions, they may be susceptible to jarring, wind, traffic or handling which may cause incorrect readings.

At least one commercial computer control company now offers software to control irrigation frequency based on information obtained from lysimeters. De Graaf [11] reported techniques for automating the water supply of glasshouse crops by calculating transpiration as a function of greenhouse climate data and measuring the amount of water draining from the growing media. Drainage water was measured with level sensors in a reservoir in which EC and pH were also recorded, in order to determine if water supply was correct. It is also feasible to use load cells to measure drainage amounts, and to use such measurements as a means to estimate plant water use [59].

3.2. Sap flow meters

Sap flow meters provide a direct way of measuring the flow of water through a plant. The two most common techniques use heat to track the flow of the sap. In the first technique the stem is subjected to a constant heat source, and the temperature of the stem before and after the heater is measured. By examining the temperatures and performing a heat balance on the stem, the mass flow rate of sap can be deduced. The second technique records the time it takes a heat pulse generated by the heater to reach the temperature sensor located above it, and based on the cross-sectional area of the stem, a mass flow rate can be determined. The heat pulse technique is restricted to plants with woody stems [60]. Sap flow measurements can be easily automated as all of the sensors involved are electronic.

There are shortcomings associated with the sap flow measurements. Probably the greatest concern is the fact that they are rather plant intrusive. The sensor itself is attached to the stem, and may restrict growth, and/or diurnal stem diameter changes; it may cause wounds in the plant and create an entry point for infection. There are also the questions of whether long term use of the sensor might affect the health and performance of the plant being monitored, and the unknown effect of heating of the sap on the condition of the plant [59].

Successful use of sap flow sensors requires a good understanding of their theory, so that potential sources of error can be minimized [6, 7, 22, 60]. Most of the error arises from the violation of assumptions and simplifications that are necessary to make the heat-balance equations workable. For instance, when the temperature difference between the upstream and downstream temperature sensors is small at low flow rates, the mass flow rate becomes more uncertain. For this reason, Grime and Sinclair [22] suggested that variable power heaters be used to increase the temperature difference at both high and low flows.

3.3. Linear variable displacement transducers

Linear variable displacement transducers (also called linear variable differential transformers, or LVDTs) consist of a cylindrical case with a central bore in which is inserted a freely-moving iron core. A voltage is induced by electrical coils within the case which is proportional to the longitudinal position of the core. Hsiao et al. [29] were among the first to use LVDTs to measure growth of a plant organ. They measured the linear growth of maize leaves in relation to leaf water potential. Since then, LVDTs have been used to characterize growth in a host of physiological studies (for a list of examples, see [15]).

One of the most successful uses of LVDTs is the measurement of short-term changes in stem or trunk thickness as an indicator of plant water status. During the day, the stems of some plants contract due to a net loss of water caused by high evaporative demand. Recovery (expansion) occurs when evaporative demand is lessened in the evening and at night, and cell turgor increases. This technique has been applied primarily to fruit trees [20, 54] and could potentially be used as a tool in irrigation management. Woody or non-growing branches, stems or trunks should be selected in order to minimize the complications of changes due to growth. LVDTs have been used for similar purposes in greenhouse crops such as peppers [1, 7, 67].

LVDTs have also been used to monitor change in the dimensions of fruit as a measure of growth in both greenhouse [14, 21, 51, 52, 71] and outdoor [54, 70] environments. However, an accurate growth rate is difficult to measure because of simultaneous changes to fruit water status. For example, fruit shrinkage due to a net water loss from the fruit under a high evaporative demand has been documented [71]. In this study, the fruit were clearly not growing but rather dehydrating. However, when growth resumes, perhaps later in the day, it cannot be separated from the process of fruit rehydration as water balance is restored. Hence one must be careful in attributing short-term change in fruit diameter strictly to growth. In the greenhouse, an accurate measure of daily (24-hour) growth may be obtained by comparing diameters at a time of day, usually pre-dawn, when plant water status is at a maximum and does not vary significantly from day to day. Changes in fruit diameter can also offer more general information on how the plant is responding to changes in atmospheric parameters such as temperature, light, and humidity [21, 51, 52, 71] and edaphic factors such as nutrient solution EC [14] and irrigation frequency.

LVDTs may be extremely responsive to small changes in a linear dimension, with sensitivities of 0.1 µm being common. However, this high degree of sensitivity may sometimes require elaborate means of preventing movement of the organ being measured. The instrument must also be periodically adjusted as the fruit grows. This results in a period of up to several hours during which no data may be collected as the system stabilizes after an adjustment.

3.4. Suspended load cells

Monitoring changes in plant weight over time is the most direct method of determining overall growth. Ideally, part or all of the plant shoot would be weighed continuously. Using lysimeters or load cells to weigh the entire plant plus the growing medium would introduce the complication of accounting for changes in the water content of the growing medium while trying to measure growth. However, measurement of the aerial weight of vine crops such as tomatoes and cucumbers, which are suspended from overhead wires, may be readily achieved with load cells (Fig. 3) [12]. As in the case of LVDTs, measurements of growth are confounded by concurrent changes in plant water status, so daily measures of growth taken pre-dawn would be the most reliable. The raw data may be either collected on a data logger for subsequent analysis on a PC or downloaded directly to the PC. In either case, software would be used to extract data on growth and short-term changes in water status which may then be analyzed in relation to climate, irrigation and other cultural features of the crop.

3.5. Direct physiological measurements

Considerable research has been carried out on the relationship between physiological status of crops and their growth. Much of this research has focused on water relations parameters and gas diffusion (transpiration and photosynthesis). In addition, phytochemicals that accumulate during stress, especially water stress, have been identified. These chemicals include amino acids such as

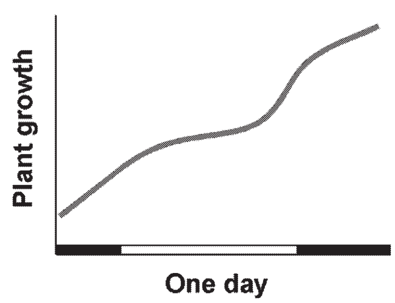

Figure 3. Stylized graph of the daily change in plant mass which can be measured with suspended load cells. The black portions of the x-axis represent dark, and the white portions represent light periods of the day. The changes in mass during the daylight hours are likely due to growth plus dehydration/rehydration events (Ehret, unpublished).

glycine and proline, and the plant growth regulator abscisic acid. The transport of abscisic acid from roots to leaves has been proposed as an indicator of water stress [10]. Most chemical indicators of water stress can be measured only with destructive sampling and are of little value in terms of practical crop monitoring. Similarly, measurement of plant water potential and its components usually require excision of a leaf or leaf plus stem for insertion into a pressure bomb, pressure plate, or into psychrometers and/or hygrometers.

Unfortunately, there are but a few instruments that can measure water status in plants non-destructively. Total water potential can be measured with the stem hygrometer, which is a psychrometer that is attached to the stems of herbaceous plants [13]. Like other psychrometers, it measures the humidity of the air in the small chamber that is in equilibrium with the total water potential of the stem. To reduce the effect of gradients in air temperature, a rather large heat sink is used and adjustment is made for ambient temperature. The instrument cannot be read continuously because the thermocouple junction first has to be cooled to condense atmospheric water vapor on the junction, then allowed to re-warm so that the rate of evaporation of the condensate, which is controlled by vapor pressure deficit, is measured. Each hygrometer needs to be calibrated against standards and they are very sensitive to mechanical damage and accumulation of dirt. Because of the exacting measurement accuracy required by this method, these instruments require great care and attention.

Water status in plants can also be detected acoustically [44]. Although most studies on acoustic emissions have been done on woody plants [65], there are a few studies on herbaceous plants such as *Plantago major* [45] and *Zea mays* [66]. Sound associated with water loss can be detected in the audible range, but there is less background interference at ultrasonic frequencies. The cause of the acoustic emissions is not well understood. Several researchers have suggested that each sound emission is produced by the cavitation of water in xylem vessels which may be subject to enormous suction (negative pressure). This hypothesis suggests that these emissions indicate the breakdown of the water conduction system in the plant as gas interrupts the continuous water columns. Vessels with greater diameter would be more prone to cavitation that those with smaller diameters, but smaller vessels conduct water less rapidly. Problems with the cavitation hypothesis are that the phenomenon is difficult to observe directly and that the number of emissions may exceed the number of vascular cells within range of the transducer (unpublished data). The mechanism whereby the cavitated vessels are re-supplied with water during a recovery period is not clear.

A direct physiological measurement of plant growth, or more precisely, increase in dry weight, is CO_2 flux resulting from net photosynthesis during the day and respiration at night. Instruments for measuring CO_2 are now relatively inexpensive, and continuous or repeated non-destructive measurements are possible. Typically, the tissue to be measured is enclosed in a chamber. For continuous measurements, environmental conditions within the chamber must be kept very close to ambient, especially with respect to CO_2, water vapor, light and temperature. The chamber should be removed or moved periodically. Short term measurements do not require as much environmental control within the chamber but these systems are typically not continuous. Alternatively, flux of CO_2 to or from the canopy can be measured with chamberless techniques.

Since CO_2 exchange is affected mostly by the aperture of stomata, a simpler method to infer photosynthetic activity is to measure leaf diffusion conductance (or resistance) with a diffusion porometer. These instruments are typically less expensive than CO_2 instruments, but also require chambers which must be moved frequently to avoid interference.

In addition to the problems already mentioned, there are two fundamental problems that limit the use of physiological monitoring for automating greenhouse controls at the present time. The first is that these measurements are generally confined to small portions of individual plants. To obtain meaningful measurements, several or even many sensors must be installed and tended to.

The second problem is that, despite numerous studies, measured parameters of water status and even gas exchange are very difficult to interpret and hence to apply to environmental controls. Water relations parameters have been widely used as sort of linear stress indices [4] but the relationships are not well understood. For example, the decline in total water potential (suction) indicates water deficit, but the suction pressure is required for drawing water and nutrient through plants. Is there an ideal plant water potential for maximum nutrient uptake and growth? Similarly, cell expansion and stomatal conductance are influenced by pressure (turgor) potential [30, 64]. However, the relationship between turgor and growth is variable, as is the relationship between leaf turgor and stomatal conductance, making optimum turgor difficult to predict [41].

Osmotic adjustments which help maintain tissue turgor during periods of water stress are caused by the accumulation of solutes (carbohydrates and inorganic ions) in cells [47]. The accumulated solutes also serve as a reservoir of substrate which supports accelerated growth during periods of recovery from stress, referred to as compensatory growth [16]. The ability of plants to compensate for periods of slow growth further complicates the interpretation of short-term measurements of physiological parameters.

Perhaps measurement of whole plant photosynthesis holds the greatest promise for physiological monitoring of plants for direct environmental control. Nevertheless, because photosynthetic activity is so dynamic, being influenced by a host of environmental and biological variables, we are years away from being able to use even this physiological parameter in a commercial setting.

4. ARTIFICIAL INTELLIGENCE

Advances in crop monitoring will be of most value to commercial growers when the sensor information is fully integrated with the greenhouse control computer. At that point, a true "speaking plant" environment will be created, whereby the crop becomes part of the control procedure. However, as described in Section 3.5, our understanding of key features of plant function which are important to commercial growers, such as water stress, growth and photosynthesis, is still woefully inadequate, and hence our ability to build suitable mechanistic models for plant-based environmental control is hampered. Furthermore, many of these models have not been validated, or are too difficult and costly to do so [69]. For this reason, new approaches which seek not to explain crop response, but only to develop control systems based on empirical relationships are being investigated. Development of these black box models is being helped by methods using artificial intelligence.

The use of in situ plant water measurements for greenhouse climate and irrigation control dates back to the early 1980s [28]. One of the pioneer computer systems (CBT Plant Guard System, Berlin, Germany) that adopted the speaking plant approach to greenhouse climate control based their control algorithm on plant transpiration [56]. Heissner [26] used the transpiration data for sweet pepper to develop a model for greenhouse climate control. Model parameters were estimated by means of nonlinear regression analysis with several thousand sets of measured transpiration rate, irradiance, air temperature, leaf temperature, humidity and leaf area.

To overcome the complexity and uncertainty of agricultural systems, a new intelligent control technique, which mimics empirical human thinking and actions by employing a fuzzy controller and two optimizers, is proposed by Morimoto et al. [48]. The control input can be, for instance, environment (relative humidity) and the control output can be fruit response (water loss and skin color) during product storage. The main controller is a fuzzy controller. Two optimizers, consisting of neural networks and genetic algorithms, search for optimal steps of setpoints of the environment and optimally tune a fuzzy controller through simulations of the corresponding neural-network models. The control technique was quite useful for the sophisticated control of agricultural systems such as agricultural robots.

Neural network predictive tools are similar to conventional predictive models in that they utilize commonly and easily measured climate data and estimate the resulting response (for example, transpiration) of the crop [9]. Murase et al. [50] identified non-linear relationships between plant water status and the textural features of pictorial information of the plant canopy by using a layered neural network. The mean value of leaf water potential measured at various parts of the plant was chosen as an output parameter of the network. The validated neural network model was used as a bio-response feedback control strategy for developing an intelligent water management system. Seginer et al. [57, 58] also studied artificial neural network applications in greenhouse environmental control. They concluded that proper neural network training required large multi-dimensional sets of data to reduce the risk of extrapolation, hence it was crucial to minimize the complexity of the problem in terms of both inputs and state vectors. In a study comparing a neural network model and a statistical regression model of lettuce canopy photosynthesis, the neural network model was found to be less accurate during the 11-day validation period [17]. Both models lost accuracy in long-term photosynthesis predictions.

As a result of developments in crop growth models, decision support systems, integrated crop management and intelligent supervisory control, there has recently been a growing demand to communicate and exchange data among greenhouse environmental control systems. Due to a lack of standardization in protocols for data exchange and a lack of software for integration and analysis, commercial greenhouse operators have to integrate and analyse this data manually. The BACnet^{TM} standard and communication software was developed to overcome this problem and to permit implementation of advanced integrated-management schemes in greenhouses [33].

5. CONCLUSIONS

Further improvements in the control of yield and quality of greenhouse crops will likely come from more precise control of the crop environment. A more carefully managed greenhouse environment will reduce wastage of inputs such as CO_2, water and fertilizer and should improve the environmental sustainability of the industry.

Table I. Uses, advantages and disadvantages of various sensors applied to automated crop monitoring.

Sensor	Used to detect	Advantages	Disadvantages
Imaging camera	Plant growth Canopy temperature Water stress Fruit quality Mineral status	No interference with the plants Monitors many plants simultaneously Fully automated	Complicated equipment Affected by lighting conditions Expensive
IR- thermometer	Canopy temperature Water stress Heat stress	No interference with the plants Monitors many plants simultaneously Fully automated Instant response	Field of view must be precisely aligned May not detect short time-scale changes
Sap flow meter	Transpiration Water stress	Measures whole plant transpiration (compared to porometers which do not)	Small sample size (one plant) May interfere with the plant if not moved periodically, hence only semi-automated Requires consistently good fit around the stem
Weighing lysimeter	Transpiration Water stress	May be configured to monitor several plants simultaneously No interference with the plants Fully automated Low maintenance requirements	Sensitive to perturbations Measurements should be corrected for plant growth or changes to the mass of the growing media over time
Lvdt	Growth Water stress	Measures small increments in organ growth or contraction over short time periods Instant response	Small sample size (one fruit, one stem or one plant) Sensitive to perturbations and may require stabilizing superstructure
Suspended load cells	Growth Water stress	May be configured to monitor many plants simultaneously No interference with the plants Fully automated	Restricted to use on suspended vine crops such as tomatoes Sensitive to perturbations Hourly measurements may be confounded by simultaneous changes in water status and growth
Photosynthesis meter or porometer	Photosynthesis Transpiration Water stress	Measures gas exchange at precise locations within the canopy Instant response	Small sample size (part of one leaf) May interfere with the plant if not moved periodically, hence only semi-automated Expensive
Stem hygrometer	Plant water status Water stress	Most direct measure of plant water potential Instant response	Small sample size (one plant) May interfere with the plant if not moved periodically, hence only semi-automated Sensitive to mechanical damage Difficult to use; requires careful calibration

The best way to improve that precision is to use information gathered from the crop itself. Here, the challenge is to employ the most appropriate, reliable and accurate sensors (Tab. I). Various aspects of plant growth and development have been monitored under carefully controlled laboratory or growth chamber conditions for decades, in some cases on a continuous or semi-automated basis. The rationale was always to gain a better understanding of plant function. Only recently have some of these sensors been applied to a greenhouse situation, with the aim of optimizing growth, yield and quality, and reducing unnecessary inputs. Part of the reason for this is the advent of ever-faster computer processing technology, which permits virtually instantaneous observation of the parameter of interest.

For now, monitoring systems can provide continuous data about specific aspects of crop growth and development, but do not allow automated control of either the greenhouse climate or crop characteristics such as growth and fruit quality. The data must be integrated with the intuitive and observational knowledge of commercial growers. Further development of suitable models using artificial intelligence methods such as neural networks and genetic algorithms promise a means of eventually integrating crop data signals on a real-time basis for environmental control. A blending of plant-based sensors and environment-based sensor technology, perhaps using models to improve predictions of micro-climate [72], will likely occur to maximize the full benefits of each.

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