NON-CONTACTING TECHNIQUES FOR DETECTING PLANT DROUGHT STRESS IN A CLOSED ENVIRONMENT

DISSERATION

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By
Yang Yang, M.S.

The Ohio State University
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Dissertation Committee:
Dr. Peter P. Ling, Adviser
Dr. Ted H. Short
Dr. Ross D. Brazee
Dr. Edward L. McCoy

Approved by

Adviser

Graduate Program in
Food, Agricultural, and
Biological Engineering
ABSTRACT

Plant drought stress refers to the condition in which plant cells and tissues are at less than full turgor. When drought stress occurs, almost all the processes associated with plant growth are affected. To insure high quality, high plant growth, drought stress detection is necessary for greenhouse.

The goal of this study was to examine non-contacting techniques in plant drought stress detection. Efforts were centered on confirming the previous findings using infrared-thermalcouples (IRT) and imaging techniques, and the development and evaluation of a model based multi-spectral technique in drought stress detection for New Guinea Impatiens plants grown in a controlled environment.

To validate previous study reports on using IRT and imaging techniques in drought stress detection, experiments were conducted in a growth chamber. Infrared thermometry was applied to measure the plant canopy temperatures during the experiments. The crop water stress index (CWSI) values of the plants were calculated from the measured plant canopy temperatures, the air temperature, the vapor pressure deficit (VPD) of the air, and other environmental conditions. Plants' top projected canopy area (TPCA) images were acquired using a machine vision system. The motion of the plants was extracted from
the TPCA images. The indicators used to describe the motion of the plants were the covariance of the TPCA (COVtpca) and the instant relative canopy motion (IRCM).

Plant canopy multispectral reflectance was measured using a spectroradiometer system. The average equivalent water thickness (EWT) of the plants was calculated from the measured canopy reflectance, using an established procedure based on model inversion techniques.

The canopy temperatures of the stress plants were found to be 1-2 °C higher than the air temperature, and to be consistently higher than the canopy temperature of the control plants. The threshold values of CWSI were established, using the CWSI values of the control plants. The performance of this indicator was evaluated by comparing the timing of detection of the threshold values against the timing of human visual detection. It was confirmed that the CWSI threshold values could detect the drought stress earlier than the human visual detection in most of the cases.

The threshold values of the COVtpca and IRCM were also determined. It was confirmed that the plant motion-based indicators could detect the plant drought stress no latter than human visual observation.

The studies on multispectral reflectance of the plants on both the leaf and canopy scales indicated that the multispectral technique was able to differentiate plants at different water status. The threshold values of the EWT determined were found effective
in detecting the plant drought stress. Most EWT based detections were earlier than visual
detection most of the times.

Comparison among performances of the above indicators showed that the CWSI
was the best indicator in early plant drought stress detection. The timing of the drought
stress detection from the earliest to the latest are CWSI, EWT, and the plant motion based
approaches.
DEDICATED

TO

MY WIFE

AND

MY PARENTS
ACKNOWLEDGMENTS

To come into a different culture and to study in a totally different education system is quite an experience. To me, the past six years have been quite an odyssey. I would like to thank The Department of Food, Agricultural, and Biological Engineering of the Ohio State University for providing me the chance and support to make it possible to study in such an excellent institution.

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VITA

May 4, 1969 ................................................. Born – Wuhan, China

July, 1991 ..................................................... B.S., Agricultural Engineering,
HuaZhong Agri. University

July, 1994 ..................................................... M.S., Agricultural Engineering,
HuaZhong Agri. University

1994 - 1997 ................................................... Post Graduation Education,
HuaZhong Agri. University

1997 - present ............................................ Graduate Research Associate,
The Ohio State University

PUBLICATIONS


FIELD OF STUDY

Major Field : Agricultural Engineering

Studies in :

- Application of remote sensing in agriculture;
- Plant modeling and monitoring;
- Electromagnetic and spectroscopy;
- Computer based data acquisition and control systems;
- Digital image processing and analysis;
- Plant health monitoring;
- Automation for controlled environment plant production.
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<th>DESCRIPTION</th>
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<tr>
<td>( C_p )</td>
<td>Specific heat of the air at constant pressure</td>
<td>( J^0C^{-1} kg^{-1} )</td>
</tr>
<tr>
<td>CWSI</td>
<td>Crop water stress index</td>
<td>--</td>
</tr>
<tr>
<td>CWSI_NPDT</td>
<td>Crop water stress index calculated with control plant canopy temperature that was lower than the air temperature</td>
<td>--</td>
</tr>
<tr>
<td>( ET_a )</td>
<td>Actual evapotranspiration rate</td>
<td>( kg m^{-2} s^{-1} )</td>
</tr>
<tr>
<td>( ET_p )</td>
<td>Potential evapotranspiration rate</td>
<td>( kg m^{-2} s^{-1} )</td>
</tr>
<tr>
<td>LAI</td>
<td>Leaf area index</td>
<td>--</td>
</tr>
<tr>
<td>( Q_{rad} )</td>
<td>Radiation</td>
<td>( W m^{-2} )</td>
</tr>
<tr>
<td>( k_H )</td>
<td>Molecular diffusion coefficient of heat transfer in air</td>
<td>( m^2 s^{-1} )</td>
</tr>
<tr>
<td>Nu</td>
<td>Nusselt number</td>
<td>--</td>
</tr>
<tr>
<td>( \alpha_{ah} )</td>
<td>Air resistance for heat diffusion</td>
<td>( s m^{-1} )</td>
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<tr>
<td>( \alpha_s )</td>
<td>Resistance to water vapor transfer at leaf level</td>
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<td>RH</td>
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<td>%</td>
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<tr>
<td>( T_a )</td>
<td>Air temperature</td>
<td>( ^0C )</td>
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<tr>
<td>( Tc )</td>
<td>Canopy temperature</td>
<td>( ^0C )</td>
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<tr>
<td>VPD</td>
<td>Vapor pressure deficit of air</td>
<td>Pa</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>Thermodynamic psychrometric constant</td>
<td>( Pa^0C^{-1} )</td>
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<tr>
<td>( \delta )</td>
<td>Slope of saturated vapor pressure-temperature curve</td>
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<td>( \rho )</td>
<td>Density of the air</td>
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<td>TPCA</td>
<td>Top projected plant canopy area</td>
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<td>COV(_{tpca})</td>
<td>Coefficient of variation of TPCA</td>
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<tr>
<td>( W_d )</td>
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<tr>
<td>( S_l )</td>
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</tr>
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<td>-------------</td>
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</tr>
<tr>
<td>N</td>
<td>Leaf internal structure index</td>
<td>--</td>
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<tr>
<td>SLA</td>
<td>Specific leaf area</td>
<td>cm² mg⁻¹</td>
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<td>ε</td>
<td>Sum of the square of errors</td>
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<tr>
<td>λ</td>
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<td>nm</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root mean square error</td>
<td>Unit varied</td>
</tr>
<tr>
<td>α</td>
<td>Maximum incidence angle</td>
<td>Degree</td>
</tr>
<tr>
<td>n</td>
<td>Refractive index</td>
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</tr>
<tr>
<td>tₘ中学(α, n)</td>
<td>Transmissivity of a dielectric plane surface</td>
<td>%</td>
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<tr>
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<td>Simulated reflectance of a leaf with N layers</td>
<td>%</td>
</tr>
<tr>
<td>TN,α</td>
<td>Simulated Transmittance of a leaf with N layers</td>
<td>%</td>
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<td>Cab</td>
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<td>Relative water content</td>
<td>%</td>
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<tr>
<td>NIR</td>
<td>Near-infrared</td>
<td>--</td>
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<tr>
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<tr>
<td>VIS</td>
<td>Visible band</td>
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</tr>
<tr>
<td>rᵢ</td>
<td>Leaf reflectance</td>
<td>%</td>
</tr>
<tr>
<td>tᵢ</td>
<td>Leaf transmittance</td>
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<td>θᵢ</td>
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<td>Degrees</td>
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<td>Eₛ</td>
<td>Solar flux</td>
<td>W</td>
</tr>
<tr>
<td>Eₒ</td>
<td>Radiance in the direction of observation</td>
<td>W sr⁻¹ m⁻²</td>
</tr>
<tr>
<td>Eₜ</td>
<td>Diffuse downward flux</td>
<td>W</td>
</tr>
<tr>
<td>E₊</td>
<td>Diffuse upward flux</td>
<td>W</td>
</tr>
<tr>
<td>κ</td>
<td>Extinction coefficient for the diffuse fluxes</td>
<td>--</td>
</tr>
<tr>
<td>K</td>
<td>Extinction coefficient for Eₒ</td>
<td>--</td>
</tr>
<tr>
<td>a</td>
<td>Attenuation coefficient</td>
<td>--</td>
</tr>
<tr>
<td>s’</td>
<td>Forward scattering coefficient for solar flux</td>
<td>--</td>
</tr>
<tr>
<td>s</td>
<td>Backward scattering coefficient for solar flux</td>
<td>--</td>
</tr>
<tr>
<td>μ</td>
<td>Forward scattering coefficient for diffuse flux</td>
<td>--</td>
</tr>
<tr>
<td>υ</td>
<td>Backward scattering coefficient for diffuse flux</td>
<td>--</td>
</tr>
<tr>
<td>ω</td>
<td>Bi-directional scattering coefficient</td>
<td>--</td>
</tr>
<tr>
<td>σ</td>
<td>Coefficient of backscattering of E₊</td>
<td>--</td>
</tr>
<tr>
<td>φᵢ</td>
<td>Azimuth angle of the leaf’s upward normal</td>
<td>Degree</td>
</tr>
<tr>
<td>g(θᵢ, φᵢ)</td>
<td>Leaf area orientation density function</td>
<td>--</td>
</tr>
<tr>
<td>k</td>
<td>Spectral absorption coefficient</td>
<td>--</td>
</tr>
<tr>
<td>Kₐb(λ)</td>
<td>Chlorophyll specific absorption coefficient</td>
<td>cm² μg⁻¹</td>
</tr>
<tr>
<td>Kₚ(λ)</td>
<td>Water specific absorption coefficient</td>
<td>cm⁻¹</td>
</tr>
</tbody>
</table>
1.1 What Is Drought Stress

Vegetation status is an indicator of the degree of stress experienced by plants in their environments (Larcher, 1995). The word “stress”, although difficult to define from a physiological point of view, is commonly used to signify any disturbance that adversely influences plant growth (Jackson et al., 1981). Plant drought stress refers to the condition in which plant cells and tissues are at less than full turgor. This occurs whenever the loss of water by transpiration exceeds the rate of water absorption (Kramer, 1969). It can happen when soil moisture availability is low, limiting the supply of water to the roots; it can also happen when environmental temperature or irradiance level is high, causing high evaporative load. Thus drought stress may occur seasonally as soil moisture reserves are depleted, or diurnally as transpiration exceeds the rate at which water is supplied to the leaves.
1.2 Why is Drought Stress Detection Important

Plants grow as a result of the influences of their genetics and their surrounding microenvironments. In order to obtain high-product and high-quality horticulture production, extensive efforts have been taken to optimize environmental factors such as temperature, humidity, radiation intensity, carbon dioxide concentration, which influence the growth and quality of plants, in greenhouses. Because the goal of such efforts is to control the plant growth and appearance, the environmental factors should thus be adjusted based on the plant status as relates to the current environment. As such, a crucial part in optimizing environmental factors is an understanding of how plants respond to their microenvironments.

With the occurrence of drought stress, almost all of the processes associated with plant growth are affected. The effects may vary with the degree and with the duration of drought and with the growth stage of the plant. In general, however, the leaf water potential decreases when drought stress occurs. The decreased leaf water potential closes stomata and decreases transpiration that in turn increases leaf surface temperature. The increased leaf temperature reduces the biochemical processes. The decreased transpiration rate also decreases carbon assimilation because of reduction in physical transfer of CO₂ molecules. It has also been observed that drought stress reduces uptake of nutrients. Severe drought stress thus affects the accumulation of biomass, limits plant productivity and yield by reducing photosynthesis and leaf growth, and can also affect
partition of biomass to the harvestable parts of the plant. (Hsiao, 1981; Boyer, 1982; Bradford and Hsiao, 1982; Saini and Lalonde, 1998).

Substantial increases in yield could be possible if irrigation water was applied at the most appropriate time to prevent excessive drought stress. With the increase in the cost of energy required to pump and move water to desired locations, coupled with the decrease of available water for irrigation, it is essential to attain the maximum benefit from each unit quantity of water used for irrigation. Plant drought stress detection is thus of great importance.

1.3 Traditional Way in Drought Stress Detection

An experienced grower can tell if a plant is under drought stress by monitoring the appearance of the leaves. However, visual assessment of crop stress is qualitative at best, with the terms “good” or “poor” frequently used to describe crop condition (Jackson et al., 1986). To improve the monitoring and irrigation process, automatic monitoring and quantitative describing of the plant water status are necessary.

Sensors for some plant drought stress response measurements are available commercially. For example, plant water status can be measured in terms of plant water potential by attaching a thermocouple psychrometric transducer directly to the underside of a leaf where the stomata mainly are located. Other examples include the pressure bomb (Scholander et al., 1965), the leaf diffusion porometer (Kanemasu et al., 1978), and petiole and leaf water content measurements (Longenecker and Lyerly, 1969), etc.
These methods can only take the measurement of a single point on a plant one plant at a time. Therefore to characterize a field using these methods requires numerous measurements and is a time-consuming process, and vast application of these methods is impractical. Furthermore, even a slight contact of foreign materials with plant tissues can disturb the physiological activity of the plant. While over a short period of time the disturbance may be negligible, it is impractical to obtain long-term observation with these approaches. Some non-destructive approaches have attempted to measure soil moisture. However, the degree of drought stress in a plant could not be predicted reliably from the measurement of soil drought stress (Hashimoto and Kramer, 1990). A non-contact, non-intrusive sensing technology based on the direct measurement of the condition of the plant is desirable for \textit{in situ} plant monitoring.

Efforts have thus been made to develop non-contacting, non-destructive plant monitoring methods that can be applied in plant drought stress detection. Thermal infrared, imaging-based technique and canopy reflectance have attracted scientists' interest in such efforts.

1.4 Non-contacting Methods in Monitoring and Quantifying Drought Stress

1.4.1 Techniques based on canopy temperature

The use of canopy temperatures to detect drought stress in plants is based upon the assumption that transpired water evaporates and cools the leaves to a level below the temperature of the surrounding air. As water becomes limited, transpiration is reduced,
and leaf surface temperature will gradually become warmer than the air temperature because of absorbed radiation.

Ehrler (1973) directly addressed the possibility of using leaf-air temperature difference as a guide to irrigation scheduling, and a significant result of this study was the demonstration of a linear relationship between the leaf-air temperature difference and the vapor pressure deficit (VPD) of the air, which is a measurement of the dryness of the air. To quantify the drought stress level of a plant, indices based on the canopy and the air temperature measurement, such as the stress degree day (Idso et al., 1981; Jackson et al., 1977; Jackson et al., 1981) and the temperature stress day (Clawson and Blad, 1982) have been developed.

Jackson et al. (1981) and Idso et al. (1981) developed the crop drought stress index (CWSI) from the measurement of the canopy temperature and the VPD of the air. They presented the theory behind the balance of energy that separates the total incoming energy into sensible heat, which heats up the plant, and latent heat, which is used for transpiration. The CWSI can be used to quantify the relative transpiration rate of a plant. When a plant is transpiring at its full potential rate, the leaf temperature is 1 to 4 °C below the air temperature, and the CWSI is 0. When plant is under drought stress, the transpiration rate decreases, the leaf surface temperature increases and the value of CWSI also increases. When the plant is no longer transpiring, the CWSI is 1.

CWSI has been widely applied to study the effect of drought stress on plant yield and quality (Braunworth and Mack, 1989; Hattendorf et al., 1988; Halim et al., 1990; Garrot et al., 1993; Irmak et al., 2000), to determine the water requirement of plants
(Samis and Jernigan, 1992), and to schedule the irrigation of plants (Garrot et al., 1997; Yazar et al., 1999).

1.4.2 Application of imaging techniques

Leaf motion is driven by variation in the turgor potential of the pulvinus (or pulvinule) organ at the base of the leaf blade. In addition to normal diurnal movement, plant leaves also move in response to biotic/abiotic stresses. Leaf movement has long been associated with drought stress (Dubetz, 1969; Berg and Heuchelin, 1990; Ling, et al., 1996; Kao and Tsai, 1998).

A machine vision system can be programmed to monitor plant health status using morphological information such as size, shape, growth, and motion of the plant. Leaf motion extracted from continuously acquired plant images has been used in plant nutrient stress and temperature stress detection (Ling, et al., 1996; Giacomelli et al., 1998; Li et al., 1998). Using image analysis techniques, Seginer et al. (1992) followed the vertical movement of the tips of fully expanded tomato leaves and reported that the movement could be used as an indicator of incipient drought stress before the appearance of visual wilt symptoms.

As the leaves move, the top projected canopy area (TPCA) of the plant changes. Nyakwende et al. (1996) correlated the boundary movement of plants with drought stress. Kacira et al. (2002) computed the TPCA and its coefficient of variation (COV) for well-watered and drought stressed New Guinea Impatiens plants and demonstrated that the
value of COV of TPCA (COVtpca) could indicate the occurrence of drought stress 5 to 29 hours before the onset of visual wilt symptoms.

1.4.3 Application of multispectral techniques

The reflectance of an object is defined as the percentage of the reflected radiance from the object to the incident radiance through a range of wavelengths. The assumption that the plant reflectance characteristics can be used to detect plant drought stress is based on the theory that the reflected light from the leaves actually consists of two parts. One is the regular reflectance from the initial surface. The part that is not reflected from the leaf surface will penetrate the leaf surface, entering the interior of the leaf. As the light travels through the tissues, it encounters different geometric configurations of internal surfaces and is scattered at each refractive discontinuity (Gausman and Allen 1973; Gausman 1974), and part of it will eventually be reflected back through the leaf surface. As a result of the absorption of the radiation by the chemical materials inside a leaf, the spectral distribution of radiant energy reflected from the interior of the leaf differs from that of the incident light. Thus the information of the materials inside the leaf can be induced from the reflectance spectrum. Infrared reflectance spectroscopy has been used successfully to predict chemical contents such as protein, lignin and fiber fractions in plant leaves (Goetz et al., 1994).

The plant reflectance has been characterized by many researchers (Gates et al., 1965; Knipling, 1970; Thomas and Gausman, 1977; Gausman, 1977). The chemical
constituents of leaves affect their spectral properties in the visible (VIS, 400-750 nm) and infrared (750-2500 nm) ranges. In the visible range, pigments, especially chlorophylls (chlorophyll a and b), absorb most of the incident light and the reflectance is low (Thomas and Gausman, 1977; Gausman, 1977). Reflectance in VIS has been applied in the estimation of the chlorophyll content/concentration of the leaf, the monitoring of the plant nutritional status, and the detection of different kinds of plant physiological stress (Thomas and Gausman, 1977; Woolley, 1971; Dat, 1998; Carter, 1991, 1992, 1993).

The infrared range is further divided into near-infrared (NIR, 750-1,300 nm) and middle-infrared (MIR, 1,300-2,500 nm). In the NIR range, the water absorption is known to be weak and no pigments absorbs strongly in this range. This is thus a region of high reflectance that is determined primarily by properties of the leaf internal structure (Gausman et al., 1972, 1978; Gausman 1974; Gates 1980; Gausman and Allen, 1973; Kumar and Silva, 1973; Sinclair et al., 1973; Grant, 1987).

The reflectance of plant in MIR is dominated by the optical properties of water in the plant tissues (Knipling, 1970). Woolley (1971) indicated that as the relative water content of maize leaves decreased from 97% to 77%, the leaf reflectance increased considerably in the MIR range. Because of the strong absorption of water, the reflectance of leaves in this region is low, especially at the strong water absorption bands 1,450 nm and 1,950 nm. The peaks were observed following these bands at 1,650 nm and 2,200 nm wavelengths, respectively, decreases as leaf tissue water content increases (Gausman, 1985). Carter (1991) found out that absorption of radiation by water in the leaf tended to decrease the reflectance in the MIR band. Ling (1996) also found that when water was
lost from a leaf, absorption decreased and reflectance tend to increase in the 1, 300-2, 500nm range. Since the absorption in the MIR range depended solely on the radioactive property of water, it was defined as the "primary" effect of water content on the reflectance.

Studies that try to detect the plant drought stress from the measured spectral reflectance studied the relationship between the leaf vitality and leaf reflectance first (Carter, 1993; Penuelas et al., 1994; Blackburn, 1999). The knowledge and relationship obtained from these studies were then applied or extended to the study of the relationship between whole plant physiological status and the canopy reflectance.

The studies on both the leaf and canopy scales have relied on three basic approaches. The first approach is to develop multi-spectral vegetation indices that are sensitive to the changes of plants chemical contents/concentrations. The second approach is to utilize the characteristics of the shape of the reflectance spectrum, rather than the magnitude of the reflectance. The third is an approach based on the application of physical models to predict the relationship of leaf/canopy reflectance to varying moisture levels.

1.4.3.1 Wavebands and indices in visible band

Because chlorophyll plays a vital role in the photochemical synthesis of carbohydrates in plants (Curran et al., 1991), the concentration of chlorophyll in plant leaves and canopies can thus be expected to be a key indicator of plant physiological
status. Leaf reflectance at 550 nm, 705 nm, 680 nm, 635 nm and 670 nm were found to be sensitive to the changes in leaf chlorophyll content (Gitelson, 1994a, 1994b; Blackburn, 1998). A number of indices developed from the reflectance in these wavebands have been used to measure chlorophyll content. Because these indices are sensitive to high and medium chlorophyll content, they all have the potential to be used to detect the early degradation of chlorophyll that is related to plant stress.

However, researchers have indicated that, while variations in chlorophyll content can be caused by drought stress, they also can be caused by other reasons such as the phenological status of the plant, atmospheric pollution, nutrient deficiency, plant diseases and radiation stress (Gond et al., 1999; Korner, 1999; Ceccato et al., 2001). The VIS indices developed may not be the best choices for the plant drought stress detection.

### 1.4.3.2 Wavebands and indices in infrared band

Reflectance in the infrared range (750-2,500 nm), on the other hand, have shown to be more promising in plant water status study (Thomas et al., 1971; Holben et al., 1983; Ripple 1986; Hunt et al., 1987). Allen et al. (1969, 1970) reported that the 1, 400 -2, 500 nm absorption spectra of plant leaves were not statistically different from that of the liquid water contained in the leaves. Tucker (1980) indicated that the reflectance measured between 1550 nm and 1750 nm was best suited for remotely measuring leaf water content.
A water-band index (WBI, R970/R902, Penuelas et al., 1993) and a water index (WI, R900/R970, Penuelas and Inoue, 1999) were developed using the reflectance around 970 nm. It was discovered that the water index was well-correlated with relative water content (RWC) of peanut and wheat leaves.

Wavelengths such as 1665 nm, 2212 nm are found to be sensitive to the changes in leaf RWC. Indices have been developed using the reflectance at these sensitive wavebands. Both linear relationship (Bowman, 1989) and non-linear relationship (Cibula et al., 1992) between the indices and RWC have been reported.

Hunt (1991) found that as the equivalent water thickness (EWT) of a single drying leaf became smaller, there was little change in NIR, but the reflectance in MIR increased. Hunt also found that for leaves of different morphologies, the reflectance ratio of the middle-infrared band (MIR, 1550 - 1750 nm) to the near infrared band (NIR, 760-900 nm) was linearly related to the log_{10} EWT for single leaves of different morphologies.

Sensitive wavelengths and indices also have been found and developed on the canopy scales (Wiegand and Richardson, 1990; Blackburn, 1998; Govaerts et al., 1999). Gao (1996) proposed a normalized water index (NDWI) using reflectance at 860 nm and 1,240 nm. The author indicated that NDWI was sensitive to the total amount of liquid water in the stacked leaves, thus it was possible to infer EWT from NDWI over areas fully covered by green vegetation.

Niemann et al. (2002) studied the potential of using high altitude airborne imaging spectrometer data to identify moisture variations in a conifer canopy. Their results
showed that variation in relative moisture content could be detected through the use of remotely sensed data. The reflectance in the water absorption wavelengths centered on 750nm, 970 nm, and 1165 nm were found to possess strong consistent variations as the relative moisture level changed.

1.4.3.3 Analysis based on the shape of the reflectance spectrum

Another method relies heavily on derivative analysis or the determination of the difference in the shape of the reflectance spectrum at the edges at specific absorption bands (Danson et al., 1992; Kupiec and Curran, 1995).

In remote sensing of green vegetation, derivative techniques have been used mostly to locate the "red edge", which is the point of maximum slope between 670 nm and 800 nm in vegetation reflectance spectrum (Gates et al., 1965). The red edge position in the derivative spectrum has been related mainly to the chlorophyll concentration in the plant leaf (Curran et al., 1990, 1991; Holer et al., 1983; Baret et al., 1992; Munden et al., 1994).

Drought stress also affects the shape and position of the red edge because drought stress affects leaf internal structure, causing change in the scattering of light inside leaves (Knipling, 1970). Horler et al. (1983) found that up to 17% of the loss of fresh weight in the leaves of peas caused a small shift of the red edge to longer wavelengths. Weight loss greater than 35% caused a movement of the red edge to shorter wavelengths. Filella and Penuelas (1994) also found out that when relative water content was smaller than 75%,
progressive drying of the plant would cause a significant change in the amplitude of the main peak in the first order derivative of the reflectance spectrum.

Danson et al. (1992) attempted to apply derivative reflectance spectroscopy to relate spectral measurement to leaf water content. Derivatives at eight wavelengths corresponding to the maximum slopes on the edges of the water absorption features were selected with the aid of the first derivative spectrum. Correlation analysis showed that the first derivatives of the reflectance spectra, at wavelengths corresponding to these slopes, were closely related to the water content of the leaves.

As indicated by Verstraete (1994), the advantages of the indices and red edge-based technique include that the indices can be easily computed and the fact that they are routinely available for very large areas and long periods of time. However, since they exploit only part of the information contained in the original data, at most one piece of information could be retrieved from any single vegetation index. Furthermore, the usefulness of these techniques derives exclusively from the empirical relations that may be found between them and other variables of interest. As Utsin et al. (1998), Kumar et al. (2001) and Verdebout et al. (1994) pointed out, while the semi-empirical or empirical methods such as multiple linear regression or ratio techniques could be used for the estimation of water content, they required data-specific calibrations and therefore have shown little potential for more automated applications. This has led to the advancement of new techniques for estimating foliar biochemical content from canopy reflectance spectra, such as radiative transfer modeling or spectral matching techniques (Gao and Goetz, 1995).
1.4.3.4 Model-based methods in spectrum analysis

According to Verdebout et al. (1994), although plant leaves present numerous anatomical structures, the basic elements of all leaves are the same and the variability of the leaf optical properties results only from their arrangement inside the leaf. Factors that affect leaf optical properties include composition, amount and distribution of pigments, internal leaf structure, and water content (Ross, 1981). Leaf reflectance may be simulated once knowledge on the above parameters is obtained.

Both descriptive and physically based models are used to describe leaf reflectance. Typical descriptive models include the ray tracing models and the stochastic models, etc. This modeling approach is mainly used to test assumptions about light interactions with other media within the leaf. Since the structure description of a leaf is too complex, it is not practical to invert the model so as to retrieve the information on the leaf constituents.

Allen and Richardson (1968) developed an “N-flux” model in which the leaf was considered as a slab of diffusing and absorbing material. The leaf’s internal radiant flow was assumed to be a flux in either the upward or downward direction, with the flow described by a pair of linear, first-order differential equations. Yamada and Fujimura (1988, 1991) later developed a more sophisticated N-flux model in which the leaf was described as composed of four layers. Each layer was modeled by the K-M theory with different parameters, and the solutions were coupled with boundary conditions to yield the leaf reflectance and transmittance. This model was used to perform non-destructive measurements of chlorophyll concentration.
Allen et al. (1969) introduced the first plate model. Plate models represent the leaf as one or several absorbing plates with rough surfaces giving rise to isotropic diffusion. The model was able to successfully reproduce the reflectance spectrum of corn leaves. The plate model was later (Allen et al., 1970; Gausman et al., 1970) extended to the case of noncompact leaves which were considered as a pile of N plates separated by N-1 air spaces, where N does not need to be an integer. In fact, the additional parameter N describes the internal structure of the leaf.

The PROSPECT model (Jacquemoud and Baret, 1990) is probably the latest development of plate model. In the PROSPECT model, variables such as water content, leaf chlorophyll concentration and leaf mesophyll structural parameter are used to simulate leaf optical properties in the 400 to 2,500 nm range. The main advantage of this model is that it can be easily inverted and thus can be used for extraction of parameters from remotely sensed data.

Jacquemoud et al. (1996) tried to estimate leaf biochemistry content by inverting the PROSPECT model. Their results showed that leaf water content in the fresh leaves was estimated with a coefficient of determination value of 95%. On dry leaves, the accuracy of the estimated water content was 54%. This result agreed with what Fourty et al. (1996) found when they attempted to estimate the leaf biochemical compounds’ specific absorption coefficients in order to use them to predict leaf biochemistry. The only characteristics that could be retrieved accurately turned out to be leaf water and dry matter contents per unit of leaf area. Aldakheel and Danson (1997) studied leaf spectral response resulting from changes in leaf water content and evaluated the possibility of
using the PROSPECT model in predicting the spectral behavior of the dehydrating leaf. The PROSPECT model was proven for its capability to simulate the leaf reflectance at different water statuses. However, as leaf water content decreased, the difference between measured and modeled reflectance increased. The authors hypothesized that the difference were caused by a changed leaf internal structure as the leaf lost water.

Allen and Richardson (1968) developed a so-called "two-flux" model to simulate the diffuse upward reflectance from the plant canopies with different number of layers. The model showed satisfactory results in simulating the canopy reflectance and the multiple scattering in the near-infrared region. The two-flux model was modified later (Allen et al., 1970) to include a third flux for the direct solar radiation. Suit (1972) proposed a modification to the three-flux model by including the effects of foliage orientations in the model. In the model, all leaves were assumed to be a mixture of either vertical or horizontal projections, and thus the angular response of the model was artificial. In an attempt to correct this problem, Verhoef (1984) proposed the SAIL (Scattering by Arbitrarily Inclined Leaves) model, in which the foliage could be of any inclination distribution.

In the SAIL model, the leaf reflectance and transmittance value at a specific wavelength is assumed to have been measured in advance. To be able to retrieve the information on the canopy biochemistry content, a model that can set up the relationship between the canopy reflectance and the canopy biochemistry content must be developed.

One approach in developing this kind of model is to couple the canopy models with leaf models that can simulate the reflectance of leaves with different chemical contents.
Jacquemoud (1993) developed a coupled leaf/canopy model called PROSPECT+SAIL to simulate the plant canopy reflectance as a function of leaf biochemistry, canopy architecture and observing geometries. The authors also studied the possibility of estimating canopy parameters using only a reflectance spectrum other than several reflectance measurements made at specific wavelengths from different angles. The coupled PROSPECT+SAIL model was proven to be numerically invertible, using the reflectance spectrum as input. The leaf water content and chlorophyll content which describe the leaf physiological status were retrieved with reasonable accuracies, but the model showed difficulties in the estimation of the canopy geometrical parameters.

Jacquemoud et al. (1995) inverted the PROSPECT+SAIL model using a set of 96 AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) equivalent spectra gathered in a field experiment on sugar beet plots. The structural parameters of the canopy were again poorly estimated, however, water content was evaluated reasonably well: the root mean square error (RMSE) was between 0.0128 to 0.0234 cm while the measured water depth was between 0.03 to 0.05 cm. Combal et al. (2002) attempted to apply prior information on the vegetation variables such as leaf area index (LAI), water content and chlorophyll content, etc., to the inversion of the PROSPECT+SAIL model so as to reduce the uncertainties associated with the estimation of canopy biophysical variables in the inversion process, and demonstrated that the use of a priori information significantly improved the estimation of canopy biophysical variables.

The advantage of the radiative transfer models is that they can be adapted to various experimental conditions because they account for the physical processes that explain the
influence of biochemical information on spectral measurement. These models can be used to define and to test predictive equations, or to determine surface biochemistry directly because they can be inverted.

1.5 Goal and Objectives of this Dissertation

The goal of this study was to examine non-contacting techniques for plant drought stress detection. Efforts were centered on confirming the previous findings using infrared-thermal-couples (IRT) and imaging techniques, and the development and evaluation of model based multi-spectral technique. The objectives of this study were:

1. To validate the effectiveness of using CWSI for the drought stress detection.
2. To validate the effectiveness of using digital imaging technique determined canopy motion for the drought stress detection.
3. To determine an appropriate model inversion method in retrieving plant water status from both leaf and canopy levels and to study the practicality of using the retrieved water status for the plant drought stress detection.

1.6 Structure of the Work

This dissertation consists of four compiled studies and documentations focused on two topics below. The first topic is detailed in Chapter 2 to validate the previous reported findings of using crop water stress index (CWSI) and top projected canopy area (TPCA)
deduced indicators in plant drought stress detection. Plant canopy temperature and environmental conditions were acquired and suitable data was used in the calculation of CWSI. Also acquired were the TPCA of plants. Plant motions were calculated from the TPCA data. The timing of the drought stress detection using the CWSI and the plant motion-based indicators were compared with the incipient drought stress defined by measured ET rate of the plant and visual detection so as to evaluate their performance in drought stress detection.

The second topic (Chapter 3 through Chapter 5) studied was the application of a model-based multispectral technique in drought stress detection. The study was conducted at both leaf and canopy scales. On the leaf scale (chapter 3), the leaf hemispherical reflectance was measured, fed into the inversion procedure of the leaf reflectance model PROSPECT to calculate the EWT of the leaf. The reflectance spectra of leaves at different water statuses were acquired to study the possibility of calculating the EWT of leaves with changing water status by inverting the PROSPECT model. Since relative water content is commonly used in horticultural field, as EWT in remote sensing field to express plant water status, the relationship between EWT and RWC was also studied so as to determine if EWT can also be used in the detection of plant drought stress.

On the canopy scale, the inversion procedure of the coupled PROSPECT+SAIL model is presented in Chapter 4. The measured plant canopy reflectance was fed into the inversion procedure of the PROSPECT+SAIL model to calculate the EWT of the plant
canopy. The accuracy of the inversion procedure was studied by comparing the retrieved EWT values with the physically measured values.

The evaluation of using the retrieved EWT in plant drought stress detection is presented in Chapter 5. Canopy reflectance spectra from plants at different water statuses were acquired, and the EWT values were retrieved from the measured spectra. The retrieved EWT values were compared with the measured ET rates to study how the retrieved EWT values could be used for the drought stress detection. The performance of EWT in drought stress detection was also compared with the performance of the other indicators discussed in Chapter 2.

1.7 Methodology

1.7.1 Growth chamber experiments

To evaluate the performance of the different techniques in plant drought stress detection, six experiments were conducted in a walk-in growth chamber in the Department of Food, Agricultural and Biological Engineering at The Ohio State University, Wooster, Ohio. The air temperature in the growth chamber was controlled by a Honeywell temperature controller (UDC 3300, Honeywell, Fort Washington, PA). The relative humidity level of the growth chamber air was set to a have a minimum level using a steam humidifier (AutoFlo, Model WSU-14, EWC Controls Inc., Englishtown, NJ), but not controlled. The chamber was set to a lighting scheme of 14 hours of lighting
and 10 hours of darkness every day. A detailed description of the dimensions and the lighting and air temperature control mechanisms of the growth chamber is available from Kacira et al. (2000). An automatic turn-table system in the growth chamber allowed continuous, automated monitoring of the plants and provided the plants an uniform environment (Kacira and Ling, 2001).

To determine the demand force of water transpiration in the growth chamber, the environmental variables, such as air dry bulb temperature was measured using a type-K thermocouple, ambient air velocity was measured using a hot-wire anemometer (TSI 8455-12, TSI Inc., St. Paul, MN), radiation level was measured using a LI-COR sensor (PY 8017, LI-COR Inc., Lincoln, NE), and the relative humidity was measured using a relative humidity sensor (H3V-200, Rotronic Instrument Corp., Huntington, NY). The Type-K thermocouple was placed 10 cm above the turntable center. RH, air velocity and radiation level were measured on a stationary platform raised 1.5 m above the ground, an elevation which was at approximately the height of the plant canopy level.

New Guinea Impatiens were used as model plants in the experiments. In each experiment, plants were transplanted into individual pots and separated into the control and the treatment groups. The ET rates of the plants were determined from measured pot weights using the lysimeters (Model 355, Tede-Huntleigh, CA). The ET rates of the control plants in each experiment were used to calculate the baseline that defined the occurrence of incipient drought stress. The volumetric soil moisture of the growing medium in each pot was measured using soil moisture sensors (Model ML2, Dynamx, Houston, TX) to determine the water supply condition in each pot.
Also measured were the canopy temperature, TPCA, and canopy reflectance, from which the CWSI, the canopy motion represented by covariance of TPCA (COVtpca) and instant relative canopy motion (IRCM), and the EWT of each plant were calculated. The performances of these indicators in the experiments were evaluated by comparing the drought stress detected by the ET-defined incipient drought stress and visual detection.

In depth descriptions on the characteristics of the plants, the sensors used in the measurement of plant ET, canopy temperature and canopy projected area, as well as the evaluation of the performance of CWSI and plant motion in drought stress detection are provided in Chapter 2. The plant canopy reflectance measurement and the performance evaluation of the EWT values in drought stress detection are described in Chapter 5.

As a reference, the duration of each experiment, the variety of plants used in the experiments, the environmental conditions in the growth chamber during the experiments are listed in table 1.1. Since some of the data in experiment 1 were contaminated due to operator’s error, only data from experiments 2 to 6 are reported in this work. The mean and standard deviation values of the control plants’ indicators, and the highest and lowest values of the indicators of each plant in the experiments are listed in table 1.2.
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<td>Paradise</td>
<td>Pure Beauty</td>
<td>Pure Beauty</td>
<td>Paradise</td>
<td>Paradise</td>
</tr>
<tr>
<td>Experiment duration (day)</td>
<td>8</td>
<td>8</td>
<td>10</td>
<td>16</td>
<td>10</td>
</tr>
<tr>
<td>Cycles of drought stress</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Time to stop experiment</td>
<td>3-4 days after visual detection</td>
<td>2-3 days after visual detection</td>
<td>In the second cycle, 2-3 days after visual detection, the experiment was terminated.</td>
<td>In the second cycle, 2-3 days after visual detection, the experiment was terminated.</td>
<td>On the day of visual detection</td>
</tr>
<tr>
<td>Air temperature (°C)</td>
<td>Average±Stdev</td>
<td>26.98 ± 0.20</td>
<td>28.63 ± 0.29</td>
<td>28.67 ± 0.23</td>
<td>27.28 ± 0.45</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>27.07</td>
<td>29.12</td>
<td>28.97</td>
<td>27.86</td>
</tr>
<tr>
<td>Relative Humidity (%)</td>
<td>Average±Stdev</td>
<td>34.58 ± 1.48</td>
<td>53.61 ± 5.57</td>
<td>46.83 ± 22.97</td>
<td>27.36 ± 8.43</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>38.39</td>
<td>59.30</td>
<td>60.79</td>
<td>51.31</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>33.41</td>
<td>44.10</td>
<td>33.86</td>
<td>18.94</td>
</tr>
<tr>
<td>VPD (Pa)</td>
<td>Average±Stdev</td>
<td>2335.18 ± 61.34</td>
<td>1851.17 ± 199.57</td>
<td>2990.34 ± 424.00</td>
<td>2600.63 ± 348.45</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>2374.04</td>
<td>2238.00</td>
<td>2576.07</td>
<td>3128.99</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>2196.29</td>
<td>1630.61</td>
<td>1543.14</td>
<td>1783.27</td>
</tr>
<tr>
<td>Radiation level (J/m²*s)</td>
<td>Average±Stdev</td>
<td>133.56 ± 2.64</td>
<td>131.18 ± 4.21</td>
<td>133.41 ± 2.27</td>
<td>116.65 ± 1.63</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>135.11</td>
<td>134.58</td>
<td>135.45</td>
<td>117.82</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>132.05</td>
<td>120.25</td>
<td>130.96</td>
<td>114.50</td>
</tr>
<tr>
<td>Wind velocity (m/s)</td>
<td>Average±Stdev</td>
<td>0.61 ± 0.14</td>
<td>0.57 ± 0.11</td>
<td>0.58 ± 0.13</td>
<td>0.69 ± 0.19</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>0.76</td>
<td>0.70</td>
<td>0.76</td>
<td>1.17</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
</tr>
<tr>
<td>Soil moisture (%)</td>
<td>Control average</td>
<td>33.5 ± 4.8</td>
<td>57.3 ± 1.7</td>
<td>62.4 ± 1.8</td>
<td>74.0 ± 1.9</td>
</tr>
<tr>
<td></td>
<td>Treatment Maximum</td>
<td>54.4</td>
<td>57.5</td>
<td>51.9</td>
<td>81.9</td>
</tr>
<tr>
<td></td>
<td>Treatment Minimum</td>
<td>14.3</td>
<td>12.2</td>
<td>20.3</td>
<td>18.9</td>
</tr>
</tbody>
</table>

Table 1.1 Plant cultivars used and environmental conditions in the experiments
<table>
<thead>
<tr>
<th></th>
<th>Exp 2</th>
<th>Exp 3</th>
<th>Exp 4</th>
<th>Exp 5</th>
<th>Exp 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. of Cntrs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ET (kg/hour m²)</td>
<td>0.159 ± 0.016</td>
<td>0.189 ± 0.062</td>
<td>0.239 ± 0.058</td>
<td>0.23 ± 0.047</td>
<td>0.279 ± 0.082</td>
</tr>
<tr>
<td>CWSI</td>
<td>0.175 ± 0.059</td>
<td>0.815 ± 0.184</td>
<td>0.506 ± 0.035</td>
<td>0.685 ± 0.220</td>
<td>0.141 ± 0.033</td>
</tr>
<tr>
<td>COVtpca (%)</td>
<td>0.48 ± 0.16</td>
<td>8.69 ± 0.38</td>
<td>7.68 ± 0.11</td>
<td>13.28 ± 0.16</td>
<td>3.69 ± 0.24</td>
</tr>
<tr>
<td>IRCM (%)</td>
<td>0.77 ± 0.79</td>
<td>5.19 ± 35.18</td>
<td>1.73 ± 26.18</td>
<td>1.68 ± 34.85</td>
<td>1.27 ± 0.89</td>
</tr>
<tr>
<td>EWT (cm)</td>
<td>0.0214 ± 0.001</td>
<td>0.0213 ± 0.0162</td>
<td>0.0208 ± 0.0177</td>
<td>0.0216 ± 0.0153</td>
<td>0.0359 ± 0.004</td>
</tr>
</tbody>
</table>

Table 1.2 Ranges of the indicators’ values of the experiments. The average and standard deviation values of the control plants, and the highest to lowest values of the treatment plants are listed in the table.
1.7.2 Models and algorithm description

1.7.2.1 The CWSI model

The CWSI values of each plant were calculated using the measured canopy temperature and environmental parameters. A theoretical methodology was adopted in the calculation of the CWSI. The CWSI model was described in detail by Kacira et al. (2002). It is a model based on the energy balance of the plants,

\[
CWSI = 1 - \frac{ET_a}{ET_p} = \frac{\gamma \left( 0.81 + \frac{r_s}{r_{ah}} \right) - \gamma^*}{\sigma + \gamma \left( 0.81 + \frac{r_s}{r_{ah}} \right)}
\]  

(1)

The ratio of \( r_s/r_{ah} \) was calculated using the following equation:

\[
\frac{r_s}{r_{ah}} = \frac{0.81 Q_{rad} r_{ah} \gamma}{2LAI \rho C_p} - \left[ (T_c - T_a) (0.81 \gamma + \delta) \right] - VPD \frac{1}{\gamma \left( T_c - T_a \right) - \frac{Q_{rad} r_{ah}}{2LAI \rho C_p}}
\]  

(2)

The \( \gamma^* \) is obtained by the following equation and was determined from the measurements collected from the control plants as:

\[
\gamma^* = \gamma \left[ 0.81 + \left( \frac{r_s}{r_{ah}} \right)_p \right]
\]  

(3)

\[
r_{ah} = \frac{L_d}{k_H \cdot Nu}
\]  

(4)
1.7.2.2 Reflectance model on the leaf scale

The PROSPECT model (Jacquemound and Baret, 1990) was adopted in Chapter 3 in the simulation of leaf reflectance. The PROSPECT model was a modified “plate model”, in which the reflectance $\rho_\alpha$ and transmittance $\tau_\alpha$ of a plate at a given wavelength are calculated using the following equations:

\[
\rho_\alpha = \left[1 - t_{av}(\alpha, n)\right] + \frac{t_{av}(90, n)t_{av}(\alpha, n)\theta^2}{n^4 - \theta^2\left[n^2 - t_{av}(90, n)\right]^2} \tag{5}
\]

\[
\tau_\alpha = \frac{t_{av}(90, n)t_{av}(\alpha, n)\theta^2}{n^4 - \theta^2\left[n^2 - t_{av}(90, n)\right]^2} \tag{6}
\]

where,

$\alpha$ is the maximum incidence angle defining the solid angle $\Omega$

$n$ is the refractive index

$\theta$ is the transmission coefficient

$t_{av}(\alpha, n)$ is the transmissivity of a dielectric plane surface, averaged over all directions of incidence and over all polarizations

In a generalized situation, a leaf is assumed to be composed of a pile of $N$ homogeneous layers, and the total reflectance $R_N, \alpha$ and transmittance $T_N, \alpha$ of a leaf consists of $N$ identical layers are,
\[ R_{N,\alpha} = xR_{N,90} + y \] 
\[ T_{N,\alpha} = xT_{N,90} \]

where
\[ x = \frac{t_{av}(\alpha , n)}{t_{av}(90 , n)} \]
\[ y = x(t_{av}(90 , n) - 1) + 1 - t_{av}(\alpha , n) \]

where \( N \) represents the number of the layers used in the leaf model.

This model has four input parameters: \( \alpha , n , \theta \), and \( N \). The value of \( \alpha \) has been set to 59° by the developer of the model, and the refractive index \( n \) is also provided by the authors as a tabulated function. According to the authors of the model, the value of \( N \) ranges between 1 and 1.5 corresponding to monocotyledons; and 1.5 to 2.5 corresponding to dicotyledons characterized by a spongy parenchyma with air cavities on the abaxial face. \( N \) values also changes with the changes in the physiological status of a leaf. For example, \( N \) values greater than 2.5 represent senescent leaves with a disorganized internal structure. Therefore, for leaves at different physiological status, \( N \) may have different values.

Allen et al. (1969) calculated the transmission coefficient \( \theta \) from the absorption coefficient \( k \) through the following equation:

\[ \theta - (1-k)e^{-k} - k^2 \int_{k}^{\infty} x^{-1}e^{-x}dx = 0 \]

where \( k \) is the spectral absorption coefficient and can be written in the form
\[ k(\lambda) = \sum K_i(\lambda)C_i \]  

(12)

where \( \lambda \) is the wavelength, \( K_i(\lambda) \) is the spectral specific absorption coefficient relative to the component \( i \), and \( C_i \) is the leaf component \( i \) content per unit leaf area.

In this study, the major components of the leaf were chlorophylls and water. Since the absorption features of chlorophylls and water are spectrally separated, the spectral absorption coefficient in the 400-800 nm domain and 800-2,500 nm domain can be written as:

\[ k(\lambda) = K_{ab}(\lambda)C_{ab} \]  

(13)

and

\[ k(\lambda) = K_{w}(\lambda)C_{w} \]  

(14)

where:

- \( K_{ab}(\lambda) \) is the chlorophyll specific absorption coefficient (cm\(^2\)µg\(^{-1}\))
- \( K_{w}(\lambda) \) is the water specific absorption coefficient (cm\(^{-1}\))
- \( C_{w} \) is the equivalent water thickness (cm)
- \( C_{ab} \) is the chlorophyll content (µg cm\(^{-2}\))

As such, the leaf reflectance in VIS or IR range can be simulated independent to each other.
1.7.2.3 Reflectance model on the canopy scale

The model used in this work to describe the canopy reflectance is the SAIL model (Verhoef, 1984). Following the Verhoef’s notation, the SAIL model consists of a system of four differential equations as follows

\[
\frac{dE_s}{dx} = \kappa E_s, \quad (15\ a)
\]
\[
\frac{dE_-}{dx} = -sE_s + aE_- - \sigma E_+ \quad (15\ b)
\]
\[
\frac{dE_+}{dx} = sE_s + \sigma E_- - aE_+ \quad (15\ c)
\]
\[
\frac{dE_o}{dx} = \omega E_s + \nu E_- + \mu E_+ - KE_o \quad (15\ d)
\]

where

\(dx\) is the thickness of an infinitesimal layer

\(E_s\) is the direct solar irradiance

\(E_o\) is the radiance in the direction of observation, multiplied by \(\pi\)

\(E\) is a diffuse downward irradiance

\(E_+\) is a diffuse upward irradiance

\(\kappa\) is the extinction coefficient for the diffuse fluxes

\(K\) is the extinction coefficient for \(E_o\)

\(a\) is the attenuation coefficient

\(s'\) and \(s\) are the forward and backward scattering coefficient for solar flux

\(\mu\) and \(\nu\) are the scattering coefficient for diffuse flux
\( \sigma \) is the coefficient of backscattering of \( E_+ \).

\( \omega \) is the bi-directional scattering coefficient.

The SAIL model assumes that the canopy is horizontal and infinitely extended, that the only canopy components are small and flat leaves and that the layer is homogeneous.

It is also assumed that the leaf’s azimuth is distributed at random. Thus, the leaf inclination density function \( f(\theta_i) \) is:

\[
 f(\theta_i) = 2 \pi g(\theta_i, \varphi_i) \sin \theta_i \quad (16)
\]

where \( \theta_i \) is the polar zenith angle of the leaf’s upward normal,

\( \varphi_i \) is the azimuth angle of the leaf’s upward normal,

\( g(\theta_i, \varphi_i) \) is the leaf area orientation density function.

The fraction of the leaf area index (LAI) oriented such that the leaf inclination is with the interval \( \theta_i \) to \( \theta_i + d\theta_i \) and the leaf’s azimuth is within the interval \( \varphi_i \) and \( \varphi_i + d\varphi_i \), can be expressed as a function of \( f(\theta_i) \):

\[
 d^2 LAI(\theta_i, \varphi_i) = LAI \frac{d \varphi_i}{2\pi} f(\theta_i) d\theta_i \quad (17)
\]

From equation (17), it can be seen that the LAI and leaf inclination angle \( \theta_i \) in fact is not independent to each other in the SAIL model. This interaction between the geometry parameters was noted in the inversion of the canopy model.
1.7.2.4 The model inversion algorithm

In Chapter 3 and 4, the inversion of the reflectance models at both the leaf and canopy scales are discussed. Because the complexity of the models, analytical inversion was prevented, instead numerical methods were used to approximate solutions. The algorithm used for the model inversions in this work was the Levenberg-Marquardt Method (Marquardt, 1963).

The Levenberg-Marquardt method uses a search direction that is a solution of a linear set of equations

\[
(J(x_k))^T J(x_k) + \lambda_k I \right) d_k = -J(x_k)F(x_k)
\]

(18)

Where \(J(x_k)\) is the Jacobian matrix, \(I\) is the identity matrix, \(d_k\) is the searching direction, and \(\lambda_k\) is a scalar that controls both the magnitude and the direction of \(d_k\).

When \(\lambda_k\) is zero, the direction \(d_k\) is identical to that of the Gauss-Newton method (Gill and Murray, 1972). As \(\lambda_k\) tends to infinity, \(d_k\) tends toward a vector of zeros and a steepest descent direction. Thus, this algorithm combines the stability of the steepest descent method and the fast convergence speed of the Gauss-Newton method.

1.8 Results and discussion

Data in table 1.1 and table 1.2 indicates that the ET rates and other parameters of the plants were affected by both the varieties of the plants and the environmental conditions. Plants used in the Exps 3 and 4 were of the Pure Beauty variety, and the ET
rate, CWSI, and EWT, etc. of the plants in these two experiments were similar in magnitudes, but different from the plants in the other three experiments. However, the averaged ET rate of the control plants in Exp 4 was higher than those in the Exp 3. The reason was that while the radiation level during these two experiments were close to each other, the VPD in the growth chamber during Exp 3 was lower that during the Exp 4, implying a lower environmental driving force for evapotranspiration. Plants in Exps 2, 5 and 6 were of the Paradise variety. The magnitude of ET, CWSI and EWT were of the similar magnitudes. The highest VPD value in Exp 5 resulted in the highest average ET rate of the control plants among these three experiments. On the other hand, the VPD, radiation level and wind velocity in Exp 6 were the lowest among the three experiments, thus the values of the indicators in this experiments were lower than those in the other two experiments. On the other hand, since the control plants in Exp 2 were under minor drought stress as discussed in Chapter 2, the averaged CWSI value of the control plants in this experiment was the highest among the experiments.

Data analysis in Chapter 2 also disclosed that the ET rate of the control plants were kept at relatively stable levels, whereas those of the treatment plants became lower than the original levels soon after irrigation events were withheld.

The measured canopy temperature of the plants showed that the canopy temperatures of the treatment plants became higher than the canopy temperature of the control plants and the air temperature as drought stress developed. This result agrees with the findings of Kacira et al. (2002). However, the data also indicated that the canopy temperatures of the control plants were not necessarily always lower than the air
temperature. In fact, during most of the time at the second half of each light period, the control plants’ temperatures were higher than the air temperature. However, when calculating the CWSI value using Kacira’s (2000) model, the “potential canopy temperature” measured from a control plant canopy was assumed to be always lower than the air temperature. If however, the canopy temperature of the control plant is higher than the air temperature, and yet it is still used as the “potential temperature” in the calculation, the resulted CWSI values of the treatment plants will be lower than they otherwise should be.

Thus in this study only the control canopy temperatures in the first half of the lighting period were used as the “potential” canopy temperature and were used in the calculation of the CWSI of the plants. The coefficient of determination between the modified CWSI values and the canopy-air temperature difference (Tc-Ta) were 0.78, 0.86, 0.80, 0.59 and 0.45, for Exps 2, 3, 4, 5 and 6. These values agreed with what Kacira (2000) reported under similar environmental conditions.

The CWSI values calculated in the Chapter 2 also displayed differences between the control and the treatment plants: the CWSI values of the control plants were stable, but those of the treatment plants became larger as the drought stress developed. It was also found that the threshold value of CWSI (shown in table 1.3) of the Paradise plants in Exps 5 and 6 (0.161 and 0.203, respectively) agreed with the threshold values set up by Kacira (2000) for the plants of the same varieties.

Studies on the motion of the plants found similar trend as that of the CWSI: the motion of the control plants described using either the co-variance of TPCA (COVtpca)
or the instant relative canopy motion (IRCM) maintained at consistent levels, while the motion of the treatment plants became larger as drought stress developed. The threshold values of COVtpca of the Paradise plants in Exps 5 and 6 (0.63 and 0.37, table 1.3) again showed very good agreement with what Kacira (2000) set up for the plants of the same varieties (0.70 and 0.36).

<table>
<thead>
<tr>
<th></th>
<th>Exp 2</th>
<th>Exp 3</th>
<th>Exp 4</th>
<th>Exp 5</th>
<th>Exp 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>ET (kg/hour*m²)</td>
<td>0.129</td>
<td>0.182</td>
<td>0.206</td>
<td>0.146</td>
<td>0.078</td>
</tr>
<tr>
<td>CWSI</td>
<td>0.307</td>
<td>0.277</td>
<td>0.282</td>
<td>0.161</td>
<td>0.203</td>
</tr>
<tr>
<td>COVtpca (%)</td>
<td>1.02</td>
<td>1.49</td>
<td>0.76</td>
<td>0.63</td>
<td>0.37</td>
</tr>
<tr>
<td>IRCM (%)</td>
<td>-1.94</td>
<td>-1.04</td>
<td>-0.89</td>
<td>-0.04</td>
<td>-0.7</td>
</tr>
<tr>
<td>EWT (cm)</td>
<td>0.0195</td>
<td>0.0353</td>
<td>0.0313</td>
<td>0.023</td>
<td>0.0213</td>
</tr>
</tbody>
</table>

Table 1.3 Threshold values of the indicators in the experiments

<table>
<thead>
<tr>
<th></th>
<th>Experiment 2</th>
<th>Experiment 3</th>
<th>Experiment 4</th>
<th>Experiment 5</th>
<th>Experiment 6</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>T1</td>
<td>T2</td>
<td>T3</td>
<td>T1</td>
<td>T2</td>
</tr>
<tr>
<td>ET</td>
<td>4</td>
<td>5</td>
<td>5</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>CWSI</td>
<td>4</td>
<td>5</td>
<td>5</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>COVtpca</td>
<td>5</td>
<td>7</td>
<td>6</td>
<td>6</td>
<td>8</td>
</tr>
<tr>
<td>IRCM</td>
<td>4</td>
<td>6</td>
<td>6</td>
<td>5</td>
<td>8</td>
</tr>
<tr>
<td>EWT</td>
<td>4</td>
<td>5</td>
<td>5</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Visual</td>
<td>5</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>7</td>
</tr>
</tbody>
</table>

Table 1.4 Timing of the drought stress detection using each of the indicators studied in this research. Individual timing of the stress detection is provided for each of the three treatment plants (designated as T1, T2 and T3) in each of the five experiments. The values in the table means how many days since the experiment started.
When comparing the timings of the drought stress detection using the techniques discussed above and the visual detection (Table 1.4), it turned out that the objective indicators evaluated were able to detect the drought stress symptom of the treatment plants no later than the visual detection for most cases. In fact, of the fifteen treatment plants in the experiments, the CWSI approach succeeded in detecting onset of drought stress in thirteen plants before visual detection, and in two plants later than visual detection. The COVtpca approach detected the occurrence of drought stress in five plants before visual detection, in seven plants at the same time of visual detection and in three plants after visual detection. Using IRCM as an indicator, one could detect the drought stress in ten plants before visual detection, in three plants at the same time as visual detection and in two plants after visual detection.

Table 1.4 also indicates that in most cases, the CWSI based technique was able to detect the stress at least one to two days prior to the time of visual detection of the stress. The COVtpca-based threshold values could detect the drought stress symptom mostly on the same day as visual detection. These results both confirmed what Kacira reported in 2000.

The discussions on the model inversion on the leaf scale in the Chapter 3 showed that when inverting the PROSPECT at the leaf scale, the effect of the change in the leaf internal structure caused by the dehydration has to be taken into consideration. In fact, data in Chapter 3 showed that the accuracy of the estimated EWT was higher when the changes in the leaf internal structure were considered in the inversion procedure. Also
shown was that by measuring the leaf reflectance and using the model inversion technique, it was possible to follow the progressive changes in leaf water status.

Discussion in Chapter 4 indicated that the local minima were the biggest concerns of the model inversion procedure of the PROSPECT+SAIL model. To deal with the problem caused by the local minima, a narrower search domain was defined by acquiring the parameters values from physical measurements. The interaction between two parameters in the model, the leaf area index (LAI) and the leaf inclination angle, was also restricted to reduce the dimensionality of independent variables. Model inversion was also performed using the reflectance from different spectral bands. The result indicated that it was possible to do the model inversion using only the reflectance in the MIR range as input to avoid problems caused by the HID lightings in the growth chamber.

After the model inversion procedure was established, Chapter 5 describes the procedure used to determine EWT from measured canopy reflectance for the drought stress detection evaluation. The EWT values were compared against the measured ET rate of the plants. It turned out that these two indicators were linearly correlated, implying that when the ET rate of a treatment plant decreases, the EWT value of the plant also decreases, and thus has the ability to detect the ET-defined drought stress. However, the ET rate change was found to be higher than the change of EWT values, implying that the EWT could not detect the drought stress as fast as ET. However, discussion in Chapter 5 also indicated that the EWT values of the control plants were different from those of the treatment plants, and that using the EWT values, the drought stress could be detected earlier than visual detection in most of the treatment plants. In fact, data in table 1.4
shows that the EWT-based threshold values could detect the drought stress in twelve plants before visual detection, in two plants in the same time as visual detection and only one plant after visual detection.

To evaluate the performance of EWT-based techniques against the other indicators, the timing of detection of EWT was compared with the others’ in table 1.5. It can be seen from the table that the EWT-based threshold values could detect the drought stress one time before CWSI, nine times after CWSI and five times at the same time as CWSI. Comparing with the indicators extracted from plant motions, it showed that the EWT could detect the drought stress eight times before, three times after, and four times at the same time as COVtpca. When it was compared against the IRCM, table 1.5 shows that the EWT could detect the drought stress four times before, six times and five times at the same time as the IRCM.

<table>
<thead>
<tr>
<th></th>
<th>Before</th>
<th>Same Time</th>
<th>After</th>
</tr>
</thead>
<tbody>
<tr>
<td>CWSI</td>
<td>1</td>
<td>5</td>
<td>14</td>
</tr>
<tr>
<td>COVtpca</td>
<td>8</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>IRCM</td>
<td>4</td>
<td>5</td>
<td>6</td>
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Table 1.5 Performance comparisons of EWT and other indicators. Number of days between the detection time of of EWT and other indicator are listed in the table

These comparisons indicate that the CWSI was the most reliable indicator among all the indicators that had been evaluated in this study. Among other potential indicators, the EWT values could detect the drought stress earlier than the plant motion-based
indicators and visual detection in most of the plants. The COVtpca on the other hand, had the lowest sensitivity to the drought stress, but it could still detect the drought stress in most of the plants at the same time of visual detection.

1.9 Conclusions

The general and main conclusions which can be drawn from the research work are listed below:

- It was confirmed that the CWSI-based technique was the most reliable non-contacting method in the detection of plant drought stress (Chapter 2).
- It was confirmed that the COVtpca of the plants was no worse at detecting drought stress than visual observation (Chapter 2).
- Further studies on IRCM of the plants could detect the drought stress slightly earlier than COVtpca (Chapter 2).
- The PROSPECT model was found to be able to follow the changes in the leaf water status and to detect early drought stress on the leaf scale (Chapter 3).
- An inversion procedure of the canopy reflectance model PROSPECT+SAIL was developed to determine water status of New Guinea Impatiens plants grown under artificial lights (Chapter 4).
- The performance of the water status assessment using only the MIR spectral information was found to be satisfactory (Chapter 4).
− The EWT value could be used to differentiate drought stressed plants from healthy plants (Chapter 5).
− The threshold values of EWT values could detect the ET-defined drought stress in the plants earlier than visual detection in most cases (Chapter 5).
− The EWT based drought stress detection approach performed no worse than the plant motion-based indicators, and in most cases, better than visual detection.

1.10 References


Gao, Bo-cai. 1996. NDWI-A normalized difference water index for remote sensing of vegetation liquid water from space. Remote sens. environ. 58: 257-266


2.1 Introduction

Plants with a sufficient water supply can obtain enough water to meet the evaporative demand for transpiration. When the transpiration demand is larger than the plant’s ability to extract water from the soil, the plant is under drought stress.

The use of canopy temperatures to detect water stress in plants is based upon the assumption that transpired water evaporates and cools the leaves below the temperature of the surrounding air. As water supply becomes limited, transpiration is reduced and leaf surface temperature will become warmer than the ambient air temperature because of absorbed radiation energy (Ehrler, 1973; Gardner et al., 1981).

With the potential use of infrared (IR) thermometers, several indices, such as Stress Degree Day (SDD) (Idso et al. 1977) and Temperature Stress Day (TSD, Clawson and Blad, 1982) etc. have been proposed for use in irrigation scheduling. Kacira et al. (2002) reported an effort to quantitatively measure plant drought stress using the theoretically
derived Crop Water Stress Index (CWSI). The authors’ results indicated that using CWSI, it was possible to detect drought stress in New Guinea Impatiens one to two days before visual detection in growth chamber environments.

Drooping leaves are generally associated with plants under drought stress. Thus machine vision techniques might also be applied to extract plant top project area (TPCA), which could provide information on the expansion and motion of the plants. Leaflet movements have been used to detect plant drought stress in soybean (Oosterhuis et al., 1985), tomato (Seginer et al., 1992) and ornamental plants (Revollon et al., 1998). Kacira and Ling (2002) pointed out that TPCA is mainly affected by the motions of fully developed leaves and that the motions of the leaves consisted of noise, diurnal motion, and stress induced motion on drought stressed plants. Efforts were made to extract the plant motion using acquired TPCA. Results showed that in low humidity conditions, the TPCA-induced plant motion could detect plant drought stress before visual detection, and that in high humidity conditions, plant drought stress could be detected at the same time as visual detection using the motion data.

The goal of this part of the study is to confirm the performance of using CWSI, and plant motion for drought stress detection. Specific objectives include: 1. Set up the baseline of plant drought stress using measured evapotranspiration (ET); 2. Evaluate the possibility of differentiate drought stress plants from healthy plants using measured canopy temperature and canopy motion; 3. Evaluate the performance of CWSI and plant motion-induced indicators in drought stress detection.
2.2 Materials and Methods

2.2.1 Data collection

Six experiments were conducted in a walk-in growth chamber in the Department of Food, Agricultural and Biological Engineering at the Ohio State University, Wooster, Ohio. The environmental conditions in the growth chamber during each experiment and the sensors used to measure the environmental conditions were described in Chapter 1.

An automatic turn-table system in the growth chamber system allowed continuous, automated monitoring of the plants and provided the plants a uniform environment (Kacira and Ling, 2001).

New Guinea Impatiens were used model plants in this study. The plants were obtained from Paul Ecke Ranch. New Guinea Impatiens is native to the Australian New Guinea subtropical highlands, and is known to be “low light” and “low transpiring” plants. The cultivar Paradise was used in Exps 1, 2, 5 and 6 and the cultivar Pure Beauty was used in Exps 3 and 4. Both cultivar had green foliage and pink flowering plant characteristics.

In each experiment, six New Guinea Impatiens plants with similar appearances and sizes were used. Three of these plants were designated as treatment plants and the other three as control plants. Prior to each experiment, all six plants were transplanted into 152 mm pots and were watered thoroughly. After the experiment started, the control group plants were kept well watered, while water was withheld from the treatment group plants.
In the first three experiments, the experiments continued until two to three days after the drought stress symptoms of the treatment plants could be visually observed. In Exps 4 and 5, the treatment plants were irrigated again after the drought stress symptoms were visually observed, and subjected to a second round of drought stress treatment. In the sixth experiment, a treatment plant was harvested once the drought stress symptoms were visually obvious in the plant.

To monitor the water supply conditions, soil moisture sensors (Model ML2, Dynamx, Houston, TX) were used to measure the volumetric soil moisture of the growing medium in each pot. The sensors were inserted into the pots from the side and were placed close to the root zone of the plants. These sensors used time domain reflectometry principle to measure the soil moisture, and the working mechanism of the sensor was described in details by Kacira and Ling (2001). The working range of the sensors was 0-1 m$^3$/m$^3$ and with accuracy of ± 0.02 m$^3$/m$^3$. The response time of the probe was less than 0.5 seconds.

To monitor the ET rate of the plants, the weight of each plant was measured. During each experiment, each pot was mounted on a custom-built lysimeter (Kacira, 2000) to monitor its weight change. The maximum weighing capacity and resolution of the lysimeter was 5000 grams and ± 1 gram, respectively. The weight measurement of each plant was read every minute and average data was recorded every five minutes.

Plant canopy temperatures were measured using infrared sensors IRTC-P Precision Model (Apogee Instruments, Logan, UT). The field of view (FOV) of the sensors was found to be at 3:1 ratio (0.01 m diameter area sensed at a stand-off distance of 0.03 m)
(Kacira and Ling, 2001). In the first four experiments, two sensors were mounted at a stationary position that was about 0.05 m to 0.08 m above the path of the plants to measure the plants’ canopy temperatures. The average of the two sensor readings was recorded as canopy temperature. In experiments five and six, since one of the sensors was found defective, only one sensor was used to measure the plant canopy temperature. The canopy temperatures of each plant were recorded every ten minutes.

The output of the infrared sensor was determined by the difference between the temperature of the target and the body temperature of the sensor. The fluctuation in the sensor temperature would result in error in the temperature measurement. To minimize this error, Bugbee et al. (1998) added thermal mass around the sensor in order to prevent rapid changes in sensor body temperature and to keep all parts of the sensor at the same temperature. The sensors used in this study also had thermal mass around their detectors to prevent the errors caused by rapid sensor body temperature change.

To capture the motion of the plants, the top view of the plants were obtained by an image acquisition system consisting of a monochrome CCD camera (Pulnix TM-200, Pulnix America Inc., Sunnyvale, CA) and a 640 × 480 × 8 resolution frame grabber board (Matrox Meteor II Standard, Matrox Electronic System Ltd., Quebec, Canada) installed in a personal computer.

The camera was mounted perpendicularly to the plant 1.0 m above the turntable. Images of each plant were captured approximately every 10 minutes. To reduce the noise caused by the chamber vibration, air movement-induced plant motion, and other random electronic noises, four consecutive images of the same plant were taken each time the
plant came into the FOV of the camera. The top projected canopy area (TPCA) in each image was calculated and the average TPCA values of the four images was deemed as the TPCA of the plant.

### 2.2.2 Stress indicator extraction

The plants’ evapotranspiration rates were calculated using the measured pot weights of the plants. The difference between two consecutive weight measurements of a plant was calculated and reckoned as the water loss of the plant due to ET during the time between the two measurements. The hourly ET rate is calculated by normalizing the day ET rate of a plant by the number of hours during the lighting period and the TPCA of the plant.

\[
\text{Instantaneous ET rate} = (\text{Weight (i)} - \text{Weight (i-1)}) \quad (1)
\]

\[
\text{Total ET rate in the lighting period} = \Sigma (\text{Instant ET}) \quad (2)
\]

\[
\text{Hourly ET rate} = \frac{\text{Total ET rate}}{(\text{Hours} \times \text{m}^2)} \quad (3)
\]

The hourly ET rate is presented as kg/(hr•m²) in the following discussions. The water status of the plants was defined by the ET rates. The ET rate threshold value to define the occurrence of incipient water stress was determined by using the mean minus two standard deviations of the ET rates of the well-watered plants. When the ET rate of a treatment plant fell below this threshold value, the plant was identified as a plant under drought stress.
The CWSI values of each plant were calculated using the measured canopy temperature and other environmental parameters. A theoretical methodology (Jackson et al., 1981) was adopted in the calculation of the CWSI. The CWSI model was described in details by Kacira et al. (2002) and the equations were listed in Chapter 1.

Images of plants’ TPCA were processed using a commercial image processing software (Visilog 5.1, Noesis S. A., Velizy, France). The flow chart of the image processing procedure was described in Kacira et al. (2002). In general, it consists of noise removal, thresholding of the images and blob analysis. Gray level images were first processed to remove noises from the original images.

Definitions of the plant TPCA as well as the COVtpca both follow those described in Kacira et al. (2002), but the time resolution of the calculations was changed to every lighting period instead of every five hours. After the initial noise removal and thresholding operations, binary images were used for blob analysis. In blob analysis, the TPCA in the image was determined by the number of pixels comprising the canopy:

\[ TPCA = \sum_{i,j} g(i, j) \]  

(4)

Where \( g(i, j) = 1 \) if pixels lies within the canopy

\( g(i, j) = 0 \) if not

The TPCA values were then further calibrated so as to obtain the values the form of \( m^2 \). Plant motion during the daily lighting period was described by calculating the
coefficient of variation of TPCA (COVtpca). The COVtpca describes how large the variation of TPCA was relative to the mean value of TPCA during the lighting period.

\[
\text{COV}_{\text{TPCA}} = \frac{\sigma_{\text{TPCA}}}{\mu_{\text{TPCA}}} \times 100\% \tag{5}
\]

Where \(\sigma_{\text{TPCA}}\) is the variation of the TPCA and \(\mu_{\text{TPCA}}\) is the mean value of TPCA.

Comparing the difference between the TPCA values at a certain time with the averaged TPCA value in the previous day might also reveal some information on the water status of the plant. Both the expansion and diurnal motion of leaves result in the change of TPCA value. The drought stress causes the leaves to droop, reducing the area of the canopy. The diurnal motion of the leaves of the canopy can result in either a larger or a smaller canopy area. As the drought stress develops, more leaf drooping is generally observed, while the diurnal motion of the leaves becomes less (Sharp and Davies, 1989). As the leaf drooping gradually becomes the dominant factor in the changing of TPCA, the TPCA value displays a consistently decreasing trend. For a well-watered plant, the increases in canopy area caused by diurnal motion is superimposed by the canopy expansion, and the decrease in the canopy area caused by diurnal motion is compensated by the canopy expansion to some extent. In general, the TPCA value of a well-watered shows display an increasing trend. Based on this assumption, the instant relative canopy motion (IRCM) of a canopy during the experiment was calculated. The IRCM of a canopy is defined as follows:

\[
\text{IRCM} = \frac{T_{\text{TPCA},i,j} - T_{\text{TPCA average}(i-1)}}{T_{\text{TPCA average}(i-1)}} \times 100 \tag{6}
\]
Where TPCA_{i,j} is the TPCA at moment j in day i;

TPCA_{\text{average}(i-1)} is the average TPCA in the previous day.

### 2.2.3 Threshold value determination

The threshold value of CWSI for drought stress detection was calculated. To set up this threshold value, the mean ($\mu$) and standard deviation ($\sigma$) of the CWSI values of the control plants were first calculated, and then the threshold value of the CWSI for drought stress detection was defined as $\mu + 2\sigma$.

The threshold value of COV_{tpca} for drought stress detection was determined using the values of the control plants. When a plant is experiencing drought stress, the leaves of the plant will droop, resulting in a larger variation in the observed TPCA values. Thus, the COV_{tpca} of a stressed plant is assumed to be larger when the stress symptoms develop. The threshold value of COV_{tpca} for drought stress detection was calculated as the sum of the $\mu$ of the COV_{tpca} value of the control plants and two times the $\sigma$ of the COV_{tpca} value of the control plants.

The threshold value of IRCM for drought stress detection was determined using the daily minimum IRCM values of the control plants. As drought stress develops, the decrease in the canopy area caused by leaf drooping becomes dominant. So the canopy area of a stressed plant is supposed to be decreasing, causing a reducing trend in the IRCM values of the canopy. The threshold value of IRCM for drought stress detection is calculated as the average of the daily minimum IRCM value of the control plants minus
two times the standard deviation of the values. When the daily minimum IRCM value of a treatment plant became lower than this threshold value, the plant was defined as under drought stress.

To facilitate discussion of plant specific observations, a specific plant in a specific experiment is represented as Plant (experiment number, plant number). For example, treatment group plant 1 in experiment 2 (Exp 2) is designated as Plant(2, t1); control group plant 3 in experiment 5 (Exp 5) is designated as Plant(5, c3). The experiments are represented as Exp experiment number. For example, the experiment 2 is represented as Exp 2.

The environmental conditions and the status of the control plants in the experiments are expressed as the $\mu \pm \sigma$, where $\mu$ is the mean value and $\sigma$ is the standard deviation. In the figures, the timing of drought stress defined by ET rate on each treatment plant is labeled by “¶”, and the timing of visual detection of drought stress on each treatment plant is labeled by “¶”.

Another observation worth noting is that during the last several days of Exp 3, it was noticed that the plants, especially the treatment plants were infected by insects.
2.3 Results and Discussion

2.3.1 Water supply and demand during the experiments

Figures 2.1 illustrates the history of the volumetric soil moisture change for control and treatment plants during each experiment. As described above, in every experiment there were six potted New Guinea Impatiens plants: three treatment plants and three control plants. After the experiment was started, water was withheld from the treatment plants. Meanwhile, water was added to each control plant every day before the lighting period ended. The amount of water was added to each pot so as to compensate for the ET water loss. The average soil moistures of the control plants were about 0.34, 0.57, 0.62, 0.74 and 0.58 m$^3$/m$^3$, for Exps 2, 3, 4, 5 and 6, respectively. During Exp 2, the amount of water added to the control plants was not able to compensate for the ET water loss. As a result, the soil moisture of the control plants decreased gradually during the experiment. During the Exp 4 and 5, water was added to the media of the treatment plants when the stress was observed, so the soil moisture level was brought back to well-watered conditions. It took the treatment plants approximately five to six and ten days to display stress symptoms in Exp 4 and Exp 5, respectively. The difference in the time required for the plants to show symptoms can be explained by the difference in the environmental conditions between these experiments. As can be seen from table 1.1, both the radiation level and the VPD values during Exp 5 were lower than those values during experiment Exp 4. Lower radiation level and lower VPD value provided less driving force in Exp 5. Besides, the cultivars of plants used in these two experiments were different. This
difference may also have contributed to the difference in the time it took for the plant to display the stress symptoms.

Figure 2.1 Daily average soil moisture in each pot during the experiments. Sub-figures a, b, c, d, e illustrate the information from Exp 2, 3, 4, 5, 6, respectively. (Continued)
Figure 2.1: Continued

(Continued)
Figure 2.1: Continued

![Graph of Soil Moisture vs. Duration for Exp 5 and Exp 6]
The VPD of the air in the growth chamber during each experiment was calculated to be 2335±61 Pa, 1851±200 Pa, 2090±424 Pa, 2600±348 Pa and 2036±195 Pa respectively in Exps 2, 3, 4, 5 and 6, respectively. From the values it is clear that the VPD was maintained most steadily in Exp 2. In Exps 4 and 5, the VPD experienced large changes during the experiment as demonstrated by the large standard deviation values.

The radiation level in the growth chamber during Exps 2, 3, 4, 5 and 6 was 133.56 ± 2.64, 131.18 ± 4.21, 133.41 ± 2.27, 116.65 ± 1.63 and 114.84 ± 2.24 J/(s•m²), respectively. The lower VPD and radiation level in Exp 6 resulted in the lowest ET rate among the experiments.

2.3.2 Plant ET rates determined from measured pot weights

The ET rates of the control group plants remained at relatively stable levels during the experiments, while those of the treatment group plants decreased. The data in Exp 2 and Exp 3 are shown in this chapter as examples.

The pot weight and ET rate of each plant during Exp 2 are shown in figures 2.2. Figure 2.2 (a) shows the average daily pot weight of the plants. At the beginning of the experiment, the pot weights of all the plants were very similar. As the experiment progressed, there was a divergence between the control and the treatment plants. Since the control plants were irrigated every day, the pot weights of these plants did not decrease as much as those of the treatment plants. The change in pot weight of each control plant was less than 10% during this experiment. In contrast, since no water was
added to the treatment plants after the experiment was started, the pot weight of these
plants continued to decrease during the experiment. At the end of the experiment the pot
weights of the treatment plants were 40% less than their initial weights.

ET rate also showed a diverging trend between the control and treatment plants. In
figure 2.2 (b), it is clear that at the beginning of the experiment, the hourly ET rates of
five of the plants were between 0.180 and 0.208 kg/(hr×m²). One of the treatment plants
even showed an ET rate close to 0.239 kg/(hr×m²). During the experiment, the ET rates
of the control plants decreased slightly, but were kept above 0.120 kg/(hr×m²). Since no
water was added to the treatment plants, as experiment progressed, the
evaportranspiration of the plants depleted the soil moisture content, as was evident in the
decreasing of the soil moisture and of the pot weight of the plants. As a result, the ET
rates of the treatment plants decreased continuously during the experiment. When the
experiment ended, the ET rates of the treatment plants were at less than 60% of their
original level.
Figure 2.2 Daily average pot weights, (a), and hourly ET rates, (b), of the Exp 2 plants
The daily average pot weights and ET rates of the plants during Exp 3 are shown in figure 2.3. In figure 2.3 (a), it can be seen that at the beginning of the experiment, the pot weights of Plant (3, c2) and Plant(3, c3) and all the treatment plants were similar: about 1.2 to 1.4 kg. The weight of Plant(3, c1) was larger than those of the others. It is also clear that the pot weights of the control plants were almost constant during the experiment, meaning that the water lost from daily ET was fully compensated by daily irrigation. On the other hand, the pot weight of the treatment plants continued to decrease.

In figure 2.3 (b), it can be seen that at the beginning of the experiment, the ET rates of all the plants were similar: around 0.193-0.318 kg/(hr×m²). The ET of all the plants increased in the first two days of the experiment, but then the treatment plants began to diverge from the control plants. The ET rates of the treatment plants decreased continuously during the rest of the experiment, while those of the control plants remained constant levels: the ET rates of Plant(3, c2) and Plant(3, c3) remained around 0.250 kg/(hr×m²), while the ET values of Plant(3, c1) remained around 0.350 kg/(hr×m²).

The increase in ET rate for all the plants during the first two days corresponds to the decrease of the relative humidity (RH) of the air in the chamber. Figure 2.4 shows that in the first two days of the experiment, the RH in the chamber decreased by 8%. While the other environment conditions, especially the air temperature, were kept at relatively constant levels, the decrease in RH meant higher VPD values as shown in figure 2.4. Higher VPD values meant high driving force for ET, and resulted in the increased ET rates.
The pot weights and the ET rates of the plants in Exp 4 are shown in figures 2.5. As shown in figure 2.5 (a), the pot weights of the control plants were very stable during the experiment. The weights of the treatment plants decreased steadily from the beginning to the end of the experiment. The treatment plants were irrigated after the visual detection. After the plants were re-irrigated, the pot weights recovered briefly. Afterwards, since no more water was added, the pot weights of the treatment plants decreased again until the end of the experiment.

In figure 2.5 (b), it can be seen that the ET rates of the all the plants were around 0.239-0.322 kg/(hr×m²) in the first two days of the experiment. After day two, the ET rates of the control plants decreased slightly, but the ET rates of the treatment plants decreased obviously until day five and day six of the experiment, when the ET rates were 50% lower than their original levels and the treatment plants were re-irrigated. The ET rate did recover slightly to 0.111-0.176 kg/(hr×m²) after the re-irrigation.
Figure 2.3 Daily average pot weights, (a), and hourly ET rates, (b), of the plants of Exp 3
Figure 2.4 History of RH and VPD in the growth chamber of Exp 3
Figure 2.5 Daily average pot weights (a) and daily average hourly ET rates (b) of the plants in Exp 4.
From figure 2.6 it can be seen that during Exp 4, the RH values in the growth chamber were higher in the last five days than that of the first five, so the VPD values during the last five days were lower (Figure 2.6). The lower VPD values meant lowered driving force for the transpiration, and thus the ET rate of the control plants during the last five days were slightly lower than the original levels. For the same reason, after the re-irrigation, the ET rates of the treatment plants did not recover to the original levels.

Another reason that can be used to explained the low recovery of the treatment plants in Exp 4 was that, by the time the treatment plants were re-irrigated, the drought
stress had become so severe that the plants could not recover completely, so after the re-irrigation the ET rates of the treatment plants could not return to their original levels.

The pot weights and the ET rates of the plants in Exp 5 are shown in figures 2.7. In figure 2.7 (a), it is clear that the pot weights of the control plants were very stable during the experiment, meaning that the water lost from the ET was compensated by irrigation every day during the experiment. On the other hand, the pot weights of the treatment plants decreased continuously until water was added. After the irrigation, the pot weight of the treatment plants recovered for one day, then the weights decreased again until the end of the experiment.

Figure 2.7 (b) shows that the ET rates of the control plants were stable. The ET rates of the treatment plants remained at about 0.175 kg/(hr×m²) in the first three days, then started to decrease after the third day of the experiment. Since the data in the second day were lost due to false operation, it was not shown in the figure. After re-irrigation on day two and day eleven, the ET rates of the treatment plants recovered a little and became steady until the end of the experiment.

The high values of the ET rates of Plant(5, t2) at the end of the experiment were caused by the partly recovered ET rate of the plant, and by the decrease in the projected plant canopy area. Because the ET rate of the plant was normalized by the TPCA of the plant, but the end of the experiment, the TPCA of the plant decreased because of the drooping and shrinking of the leaves. As a result, at the end of the experiment, the
calculated ET rate of this treatment plant seemed to have fully recovered, although the visually observation clearly indicated that the plant was under drought stress at that time.

The slightly lowered values of the control plants ET rates during day 7 and day 8 corresponded to the decrease of the VPD in those days. Shown in figure 2.8 is the history of the VPD values during the Exp 5. It is clear that on days 7 and 8, the VPD values were the lowest and caused the ET rates of the control plants to decrease slightly.
Figure 2.7 Daily average pot weights (a) and daily average hourly ET rates (b) of the plants in Exp5.
Figure 2.8 History of the VPD in Exp 5

The pots weights and ET rates of the plants in Exp 6 are shown in figures 2.9. It is again clear that the pot weights and ET rate of the control plants remained at stable levels during the experiment, while those of the treatment plants decreased continuously until the end of the experiment.
Figure 2.9 Daily average pot weights (a) and daily average hourly ET rates (b) of the plants in Exp 6
2.3.3 Temperature of the plants in each experiment

According to the law of energy conservation, the temperature of the surface of any object would respond to changes in the supply or in the dissipation of heat to that object. If the supply of income energy is increased while the outflow of the heat is restricted, the surface temperature of the object will rise accordingly. Under certain environments, if a plant is transpiring at its full capacity, the transpired water will consume a large amount of latent heat. In fact, according to Gates (1964), if a plant is transpiring at 102 g/(hr×m²), the latent heat cost of the transpiration is 60 Kcal/(hour×m²). The canopy temperature of such a plant is supposed to be 1-2 degrees lower than the air temperature. On the contrary, if the water supply is limited, the transpiration rate will decrease as is evident in the aforementioned measurement of plants’ ET rates. As a result, the latent heat consumed by the reduced transpiration will decrease. And the canopy temperature of a drought-stressed plant becomes higher than the air temperature.

The measured temperatures of the plants in all the experiments in this research showed that plant canopy temperature is a good indicator of plant water status. The temperature data showed that the canopy temperature of the treatment plants would become higher than the ambient air temperature as drought stress developed. It also showed that as drought stress developed, the canopy temperature of the treatment plants became higher than the canopy temperature of the control plants. The data also indicated, however, that it was not necessarily true that the canopy temperature of the well-watered plants would always be lower than the air temperature.
Figure 2.10 shows the difference between daily average canopy temperatures and the air temperature (Tc-Ta) in Exp 2. The Tc-Ta of the treatment plants decreased slightly in the first two days, and then the differences increased until day 6. After the day 6, the difference values decreased again. This decrease may have been caused by the background noise coming from the growth media and the surface of the turn-table. As the drought stress developed, the leaves of the plants drooped and the TPCA shrunk, leaving part of the pot uncovered. Some of the background (in this case, mostly growth media) thus may have been revealed in the FOV of the sensors. As a consequence, the recorded target temperature was lower, and so were the Tc-Ta values. The Tc-Ta values of the control plants showed that in the first four to five days of the experiment, the canopy temperatures of the control plants were very close to the air temperature, but not necessarily lower than the air temperatures. In fact, in the first five days, the Tc-Ta values of the control plants were between -0.5 °C to 0.5 °C. After day 5, the Tc-Ta values of the control plants increased continuously to 1 °C, then decreased only slightly. Considering that there was a minor decrease in both the soil moisture levels and in the ET rates of these plants during the experiment, the increases in Tc-Ta values suggested that the plants were experiencing some minor drought stress during the final two days of the experiment, although not intentionally. The intrusion of insects may also have affected the physiological status of the control plants and have caused an increase in the plants canopy temperatures.
Figure 2.10 Temperature differences between the plants and the air in Exp 2. The Tc-Ta values of the treatment plants kept increasing as the experiment progressed. The positive Tc-Ta values of the control plants, especially the increasing in the Tc-Ta values of the control plants were also observed in the experiment.

The Tc-Ta values of the plants in Exps 3 and 4 are shown in figure 2.11 (a) and (b), respectively. In these two experiments, the Tc-Ta values displayed very similar trend. The Tc-Ta values of the treatment plants were only slightly higher than zero during the earlier days of the experiments. After day three, the differences in the temperatures increased steadily. In Exp 3, the canopy temperature of one of the treatment plants increased to 2 °C above the air temperature on day three, then the canopy temperature decreased slightly and remained at 0.5 °C above the air temperature. The temperatures of
the other two treatment plants in Exp 3 continued to increase steadily. The largest value of Tc-Ta of these plants was around 2-2.5 °C. In Exp 4, the canopy temperature of one treatment plant increased to 2 °C above the air temperature until it was re-irrigated, and then the canopy temperature gradually decreased to 1 °C above the air temperature. The temperatures of the other two treatment plants in the experiment also increased steadily, but the highest temperature of these plants was only 1 °C above the air temperature. On the other hand, the canopy temperatures of the control plants in both Exp 3 and Exp 4 were very stable and remained close to the air temperature. In each experiment, the average daily canopy temperatures of two control plants were lower than the air temperature during most of the days in the experiments. The other one displayed a slightly higher temperature during several days, and also showed temperatures lower than the air temperature in the other days. The similarity between two control plants and the large difference of the third control plants resulted in large standard deviation of the Tc-Ta values of the control plants, and thus resulted in lower threshold values of CWSI.
Figure 2.11 Temperature difference between the plants and the air in Exp 3, (a), and Exp 4, (b). The Tc-Ta value of the treatment plants increased steadily as the experiment developed, and became consistently positive. Those of the control plants were only slightly negative and did not change much during the experiment.
Figure 2.12 display the Tc-Ta values of the plants in Exp 5. The Tc-Ta values of the treatment plants showed trends similar to those in the previously described experiments. After day five of the experiment, the canopy temperatures became higher than the air temperature. After the plants were re-irrigated, the canopy temperature decreased a little and increased again. However, in this figure, it can be seen that the canopy temperatures of the control plants were close to 1 °C over the air temperatures during day 6, 7, 8, 9 and the last several days of the experiment. The main reason for this increase in the Tc-Ta of the control plants was the abrupt decrease in the air temperature during these days. In fact, as shown in Table 1.1, the standard deviation of the air temperature in Exp 5 was ± 0.45 °C, while the standard deviations in the other four experiments were between ± 0.2 to ± 0.32 °C. As shown in figure 2.12, from day 5 to day 8, the air temperature decreased by as much as 2.5 °C. At the mean time, the Tc-Ta of the control plants increased about 1 °C. During days 9, 10, 11, the air temperature increased about 1 °C, and the Tc-Ta decreased about 1 °C. So, it was very obvious that the variation in the air temperature resulted in the positive difference between the canopy temperature of the control plants and the air temperature.
Figure 2.12 Temperature difference between the plants and the air in Exp 5. The 1 °C decrease in the air temperature from day 5 to day 8 resulted in a 0.5 °C increase in the Tc-Ta of the control plants.

Figure 2.13 show the Tc-Ta values of all the plants in experiment 6. It can be seen that the canopy temperatures of both the control and treatment plants were lower than air temperature at the beginning of the experiment. As the experiment developed, the canopy temperature of the treatment plants gradually increased and became higher than the air temperature. The canopy temperatures of the control plants were kept very close to the air temperature during the same time. In fact, most of the days the canopy temperatures were
lower than the air temperature. Since the air temperature was relatively stable during the experiment, the canopy temperature of the control plants did increase as observed in Exp 5.

Figure 2.13 Temperature difference between the plants and the air in Exp 6. Since the air temperature was relatively stable during the experiment, the canopy temperature of the control plants thus did not change as much as was observed in Exp 5.
2.3.4 CWSI of the plants in each experiment

The CWSI values of the plants in each experiment were first calculated using all the measured canopy temperatures of the control plants as the “potential” temperatures in the calculations. The results of these calculations are shown in figure 2.14. In these figures, it can be seen that the CWSI value is a good indicator in the quantification of the water status of the plants. At the beginning of the experiments, the CWSI values of both the control and the treatment plants were similar. However, as the experiments progressed, the CWSI values of the treatment plants increased and became larger than those of the control plants. In Exp 4 and Exp 5, after the treatment plants were re-irrigated, the CWSI values of these plants reduced briefly. Afterward, as the water stress developed, the CWSI values of the treatment plants also increased again. On the other hand, the CWSI values of the control plants were maintained at the consistent levels throughout the experiments.
Figure 2.14 CWSI values of the plants in Exps 2-6. Sub-figures 2(a), 2(b), 2(c), 2(d), and 2(e) depict daily CWSI values in Exp 2, 3, 4, 5 and 6. The ⦿ in 2(c) and 2(d) indicates visual detection and watering events of the treatment group plants. (Continued)
Figure 2.14: Continued

(Continued)
Figure 2.14 (a) also shows that during the final two days of Exp 2, the CWSI value of the treatment plants were very similar as those of the control plants. This is because the canopy temperatures of the control plants were fairly high during these two days. In fact, the average daily canopy temperatures of these plants were about 1.0°C to 1.28°C higher than the air temperature. This magnitude was the same as those of the treatment plants. By taking into account of ET (figure 2.2 (a), section 2.3.2, and soil moisture content (figure 2.1 (a), section 2.3.1) discussed previously, it was concluded that the control plants were under minor drought stress at the final two to three days of the experiment. The high canopy temperatures of the control plants (figure 2.10, section 2.33) further support this conclusion. Because the CWSI values were calculated using the
control plant temperature as reference, and in these case the temperatures of the control and treatment plants were the same, so the CWSI values of the treatment plants were underestimated and were as low as those of the control plants, even though the plants were under drought stress in these two days.

When the recorded hourly canopy temperatures during each lighting cycle were analyzed, it was observed that the canopy temperatures of the control plants were not always lower than the air temperature during the lighting period. In this situation, the CWSI values of the treatment plants may also have been underestimated during other experiments. Because all the data showed the similar trend, the data from Exp 4 was used as an example to illustrate (figure 2.15). The CWSI value of the treatment plant should increase when the plant canopy temperature increases. However, figure 2.15 shows that the CWSI values of the treatment plant sometimes became very small even though the canopy temperature was still higher than the air temperature. Other times, especially during the second half of the light period, the CWSI value decreased even when the canopy temperature increased. When the CWSI values are further compared with the average Tc-Ta of the control plants, it turns out that the canopy temperature of the control plants were not always lower than the air temperature. In fact, during the second half of each lighting period, the canopy temperature increased and gradually became higher than the air temperature. The figure also shows that the increase in the CWSI values of the treatment plant corresponded very well with the increase in the average Tc-Ta values of the control plants.
This un-characteristic decrease in the CWSI values of the treatment plant was mainly caused by the way the CWSI was calculated. Notice that in calculation of the CWSI values, the modified thermodynamic psychometric constant was calculated from the “potential” ratio of the resistance of water vapor transfer of the canopy and the air. This in turn was calculated using the average canopy temperature of the control plants in the equation. The assumption beneath this operation was that the control plants were well-watered during the experiment, so their canopy temperatures were the temperatures that the temperature of a plant can “potentially” reach. These “potential” temperatures should never be higher than the air temperature. However, in figure 2.15 it is clear that

Figure 2.15 Original CWSI values, Tc-Ta values of Plant(4, t2) and average Tc-Ta values of the control plants in Exp 4

This un-characteristic decrease in the CWSI values of the treatment plant was mainly caused by the way the CWSI was calculated. Notice that in calculation of the CWSI values, the modified thermodynamic psychometric constant was calculated from the “potential” ratio of the resistance of water vapor transfer of the canopy and the air. This in turn was calculated using the average canopy temperature of the control plants in the equation. The assumption beneath this operation was that the control plants were well-watered during the experiment, so their canopy temperatures were the temperatures that the temperature of a plant can “potentially” reach. These “potential” temperatures should never be higher than the air temperature. However, in figure 2.15 it is clear that
the average canopy temperature of the control plants became higher than the air temperature 5-6 hours before the lighting period ended. In figure 2.16, a set of ET values of the control plants was shown. It can also be seen that the ET rate of the control plants was lower in the second half during every lighting period, implying that the control plants were not transpiring at their “potential” rate during the second half of the light period. This decrease in the ET rates is the manifestation of the “low transpiring” characteristics of New Guinea Impatiens. For healthy plants with plenty of water, there was plenty of water reserved in the leaves’ cells, so the transpiration rate was able to catch up with the environmental demand after the light was turned on. Gradually, the “low transpiring” characteristics caught up with the plant: the water uptake from the soil could no longer keep up with the rate of transpiration, even though there was plenty of water in the soil. As a result, the rate of transpiration was reduced. One result of the reduced ET rate, of course, was the increase in the canopy temperature, and thus the increase in the Tc-Ta values.
Figure 2.16 Average hourly ET rates of the control group plants in Exp 4. 5-6 hours before the end of the lighting period, the ET rate became lower.

This phenomenon indicates that when using the Kacira et al. (2002) CWSI calculation model, only those canopy temperatures of the control plants which are lower than the air temperatures, or before the “jumping” in the canopy temperatures occurs, should be considered as the “potential” temperatures in the calculation. The CWSI values of all the plants during each experiment was then calculated again using the modified canopy temperatures of the control plants: those control canopy temperatures that were higher than the air temperature (generally these are the temperatures after hour 7 during the lighting period) were substituted by the values that were lower than the air
temperature. In the cases where the air temperature was lower than the canopy temperatures all day, the temperatures in the second half of the lighting period were substituted by those in the first half of the lighting period, before the canopy temperature increased drastically. Figure 2.17 shows that after the CWSI were calculated using only the control plant temperatures that were lower than the air temperature as reference “potential” value in the calculation, the values of CWSI could reflect the change in the treatment plant canopy temperature more properly: the CWSI value would increase when the canopy temperature became higher.

Figure 2.17 The CWSI values calculated using all the control temperatures, CWSI values calculated using only those control temperatures that were lower than the air temperature, and the Tc-Ta values of Plant(4, t2)
Figures 2.18 show the CWSI values of the treatment plants calculated using non-positive Tc-Ta values of the control plants as references (CWSI_NPTD). It can be seen that the developing divergence trend between the treatment plants and control plants were still displayed in the CWSI_NPTD values. However, the magnitudes of the CWSI_NPTD values were found to be higher. Furthermore, because only the low canopy temperatures of the control plants were used in the calculation of CWSI_NPTD, the differences between the control and the treatment plants were clearer at the end of each experiment: the CWSI_NPTD values of the treatment plants were consistently higher than those values of the control plants.

Figure 2.18  CWSI_NPTD values of the plants in the experiments. The CWSI values of the treatment plants were calculated using only the control plant temperatures that were lower than the air temperatures. (Continued)
Figure 2.18: Continued

(Continued)
Figure 2.18: Continued
Previous studies found that the leaf temperature of a drought stressed plant increased and were higher than the leaf temperatures of well-watered plants due to reductions in evaporative cooling through latent heat loss (Kacira, 2000). This study confirmed the above finding. It was also found that when using only those control temperatures which were lower than the air temperature as “potential canopy temperature” in the calculation of CWSI, the CWSI_NPTD values showed a higher linear correlation with Tc-Ta values. Table 2.1 shows that when the CWSI values were calculated using all the control canopy temperatures as “potential canopy temperatures”, the $R^2$ values of the linear correlation between CWSI and Tc-Ta were 0.42, 0.5, 0.32, 0.31 and 0.44, respectively, in Exps 2, 3, 4, 5 and 6. On the other hand, when the CWSI values were calculated using only those control canopy temperatures that were lower than the air temperature, the correlation between CWSI values and Tc-Ta values was improved. The $R^2$ values in the later case were 0.78, 0.86, 0.80, 0.59 and 0.45, respectively. In Kacira’s (2000) report, the canopy temperatures of the control plants were found to be always lower than the air temperature, and thus the $R^2$ values between CWSI and Tc-Ta were 0.72 — 0.87, which agreed with the $R^2$ values in Exps 2, 3 and 4 quite well. The $R^2$ values of 0.59 and 0.45 in Exps 5 and 6, respectively, were relatively low. The high canopy temperature of one or several of the control plants can explain these low $R^2$ values during the experiments. As reported in the canopy temperature measurement, in Exp 5, the decrease of the air temperature resulted in the control plants canopy temperatures that were higher than the air temperature in some days. In Exp 6, one control plant showed higher than the air temperature for some days. These high
control canopy temperatures resulted in a high potential temperature in the calculation of CWSI. So the CWSI value of the treatment plants could have been underestimated, and thus the $R^2$ values in these two experiments were not as high as in other experiments.

Table 2.2 shows the values of the slope and interceptions of the linear functions between $T_c$-$T_a$ and the CWSI values. It can be seen that the values of the slopes and the interceptions between $T_c$-$T_a$ and CWSI_NPTD were higher than those of the CWSI values between modifications. Also can be observed, interestingly, is that the different plant varieties show different relationship between $T_c$-$T_a$ and CWSI_NPTD. Plants in Exp 2, 5 and 6 were of the Paradise variety, and the slope and interception values were of the similar magnitudes. The plants in Exps 3 and 4 were of the Red on Pink variety, and the slope and interception values were similar to each other but different from the values in the other three experiments.

<table>
<thead>
<tr>
<th></th>
<th>Exp 2</th>
<th>Exp 3</th>
<th>Exp 4</th>
<th>Exp 5</th>
<th>Exp 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$ values when CWSI values were calculated using all the control plants temperatures</td>
<td>0.42</td>
<td>0.5</td>
<td>0.32</td>
<td>0.31</td>
<td>0.44</td>
</tr>
<tr>
<td>$R^2$ value when CWSI values were calculated using only those control canopy temperatures that were lower than the air temperature</td>
<td>0.78</td>
<td>0.86</td>
<td>0.80</td>
<td>0.59</td>
<td>0.45</td>
</tr>
</tbody>
</table>

Table 2.1 $R^2$ values of the linear correlation between CWSI and $T_c$-$T_a$ before and after the modification to the calculation of CWSI. The $R^2$ values between the CWSI values calculated using only those control plant temperatures there were lower than the air temperature and $T_c$-$T_a$ of the treatment plants were higher.
<table>
<thead>
<tr>
<th></th>
<th>Exp 2</th>
<th>Exp 3</th>
<th>Exp 4</th>
<th>Exp 5</th>
<th>Exp 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope of the linear function between Tc-Ta and CWSI</td>
<td>0.149</td>
<td>0.244</td>
<td>0.152</td>
<td>0.204</td>
<td>0.184</td>
</tr>
<tr>
<td>Interception of the linear function between Tc-Ta and CWSI</td>
<td>0.015</td>
<td>0.11</td>
<td>0.069</td>
<td>0.177</td>
<td>0.081</td>
</tr>
</tbody>
</table>

Table 2.2 Slope and interception of the linear function between Tc-Ta and CWSI values. The values of the slopes and interceptions of the functions between Tc-Ta and CWSI_NPTD were consistently higher.

### 2.3.5 Motion of the plants

The COV of TPCA is the ratio between the daily variance in TPCA versus the daily average TPCA of the same day. It in essence describes the magnitude of variation of the TPCA during a certain period (in this study, one day). As drought stress develops, the drooping of leaves occurs, the value of COVtpca is expected to increase. On the other hand, the instant relative canopy motion (IRCM) is affected by both expansion and diurnal motion of a canopy. The projected canopy area of a plant under drought stress should be shrinking. This shrinkage could somehow neutralize the diurnal motion of the leaves in the direction of increasing the canopy area, and magnify the diurnal motion of
the leaves in the direction that decrease the canopy area. The IRCM of a treatment plant should thus show a decreasing trend. Since the IRCM of a canopy contains the information on the difference between the present canopy area and the previous day’s canopy area, supposedly this index should be an earlier indicator than COVtpca for the drought stress detection, which only consider the variance of a canopy during one day. Since the performance of these two indicators would later be compared with the performance of CWSI and the multispectral-based indicators, and those two indicators were calculated in a “day” temporal resolution, thus these two motion indicators were also calculated in a day temporal resolution. Daily minimum value was used to set up the IRCM threshold values. Since as drought stress develops, it is certain that the daily minimum IRCM value of a treatment plant consists of both the negative canopy expansion and negative diurnal motion. This value will become smaller as drought stress becomes severe and the canopy shrinkage becomes obvious. On the other hand, the daily minimum IRCM of a control plant can be either positive or negative, depending on the magnitude of the expansion and diurnal motion, however, because of the expansion of the canopy, it will never become smaller. Figure 2.19 (a, b) through Figure 2.23 (a, b) display the covariance of TPCA (COVtpca) values and the daily minimum IRCM values of the plants in the experiments.

Figures 2.19-2.23 (a) show that, at the initial time period of the experiments, the COVtpca values of the treatment plants were similar to those of the control plants. As the experiments progressed, drought stress developed in the treatment plants, and the COVtpca values of these plants increased.
In Exps 4 and 5, water was added to the treatment plants after the stress symptom was visually observed. It is clear in figure 2.21 (a) and in figure 2.22 (a) that the COVtpca values of the treatment plants decreased after the re-irrigation for one or two days. Afterward, as drought stress further developed, the COVtpca values of the treatment plants increased again. On the other hand, the COVtpca values of the control plants were fairly stable during the experiments.

Figures 2.19-2.23 (b) show that during the first two to three days in the experiments, the IRCM values of the treatment plants were similar to those of the control plants, implying that both the growth and the motion of the treatment plants were similar to those of the control plants during this period. Afterward, the IRCM of the treatment plants started to decrease, becoming increasingly negative. In Exp 4 (Figure 2.21 b), the daily minimum IRCM of Plant(4, t2) and Plant(4, t3) became positive after the plants were re-irrigated. The increase in the IRCM values of these two plants indicated that the turgor of the plants leaves recovered, so the leaves were no longer drooping, resulting in larger TPCA values in the following days. Plant(4, t1) also recovered, as indicated by the increased IRCM value of the plant after the re-irrigation. However, the plant did not recovered completely, since the value of the IRCM was still negative. This means that the leaves of the plant were still drooping even after the re-irrigation, even though the drooping was not as severe as before the re-irrigation. In Exp 5 (Figure 2.22 b), only one treatment plant displayed positive IRCM values after the re-irrigation. The other two plants did show some extent of recoveries with higher IRCM values, but the values were still negative, meaning that the leaves of the plants were still drooping even after the re-
irrigation. This continuous leaf drooping after the irrigation implies that by the time the observer realized that the plants were under drought stress and re-irrigated the plants, the plants had been experiencing drought stress for a while, and therefore plant could not recover fully. And this may also explain where there was a long time gap between the ET-defined incipient stress and the visual detection.
Figure 2.19 Motion of the plants in Exp 2 characterized using COV\textsubscript{tpca} (a) and IRCM (b)
Figure 2.20 Motion of the plants in Exp 3 characterized using COV\textsubscript{tpca} (a) and IRCM (b)
Figure 2.21 Motion of the plants in Exp 4 characterized using $\text{COV}_{\text{tpca}}$ (a) and IRCM
Figure 2.22 Motion of the plants in Exp 5 characterized using COV_{tpca} (a) and IRCM (b)
Figure 2.23 Motion of the plants in Exp 4 characterized using COV_{tpca} (a) and IRCM (b)
2.3.6 Drought stress detection

The baseline for water stress detection was determined using measured ET rates. The ET threshold value to define the occurrence of incipient water stress was determined using the ET rates of the control plants. When the ET rate of a treatment plant fell below the threshold value, the plant was reckoned as a plant under drought stress. The timing visual detection of the drought stress on each treatment plant was also recorded as another reference baseline. Since the environmental condition in an experiment was relatively stable, so a single threshold value for every indicator was defined in each experiment.

2.3.6.1 Detection using CWSI

To determine the drought stress using the calculated CWSI values, a threshold value of CWSI was first calculated from the CWSI values of the control plants. The CWSI values used were those that were calculated using the canopy temperatures of the control plants that were lower than the air temperatures.

In Exp 2, the threshold value of ET was calculated to be 0.129 kg/hr×m². The ET-defined drought stress was first observed on day four on Plant(2, t1), on day five on Plant(2, t2) and Plant(2, t3) (Figure 2.24 a). The threshold value of CWSI was calculated to be 0.307. Comparing with this threshold value, the drought stress happened on day four for Plant(2, t1), and on day five for Plant(2, t2) and Plant(2, t3) (Figure 2.24 b).
Figure 2.24 The baseline of drought stress defined by ET, (a), and the threshold value of CWSI_NPTD, (b), for drought stress detection in Exp 2. ET defined drought stress occurred on days 4 and 5 of the experiment. The upward and downward arrows indicate timing of the ET defined and visually detected drought stress.
In Exp 3, the threshold value of ET rate was 0.185 kg/hr×m². The ET-defined drought stress occurred on day 4 for Plant(3, t1), day five on Plant(3, t2), and on day 3 on Plant(3, t3) (Figure 2.25 a). The threshold value of CWSI was 0.277. In comparison with this threshold value, all the treatment plants were determined as under drought stress on day three of the experiment (Figure 2.25 b). The earlier than the ET defined stress detection of CWSI on Plant(3, t1) and Plant(3, t2) was caused by the rapid increase in the canopy temperature of the plants as shown in figure 2.11(a). However, since the measured ET rates of the plant did not indicate that the plants were under drought stress on day 3, the increase in the canopy temperatures could have been caused by other abiotic stress such as insect intrusion.
Figure 25 The baseline of drought stress defined by ET, (a), and the threshold value of CWSI_NTPD for drought stress detection in Exp 3.
The threshold value of ET in Exp 4 was 0.206 kg/hr×m² (Figure 2.26 a). Using this defined baseline, the incipient drought stress occurred on day three on both Plant(4, t1) and Plant(4, t2), and on day four on Plant(4, t3). The threshold value of CWSI in Exp 4 was calculated as 0.282 (Figure 2.26 b). Using this threshold value, the drought stress on Plant(4, t1) and Plant(4, t2) could be detected on day 4 of the experiment. The drought stress on Plant(4, t3) could be detected on day 5 of the experiment. After being re-irrigated on day 5 of the experiment, the CWSI values of the treatment plants decreased during the following day. The CWSI value of Plant(4, t1) and Plant(4, t2) returned to levels very close to the threshold value and the CWSI value of Plant(4, t2) was lower than the threshold value for three days before it increased again. But the CWSI value of Plant(4, t3) did not decrease much after the re-irrigation. In fact, the measured ET rate also showed the same information: after re-irrigation, the ET rates of Plant(4, t1) and Plant(4, t2) were higher than that of Plant(4, t3) and the recovered ET of Plant(4, t2) was the closest to the ET threshold value for drought stress detection.
Figure 2.26 The baseline of drought stress defined by ET, (a), and the threshold value of CWSI NTPD, (b) for drought stress detection in Exp 4. The up arrows indicate visual detection of drought stress; the down arrows indicate ET defined drought stress.
The threshold value of ET in Exp 5 was 0.146 kg/hr×m² (Figure 2.27 a). Using this defined baseline, Plant(5, t1) was determined to be under drought stress from the fourth day of the experiment. Plant(5, t2) was under drought stress since day five of the experiment, and Plant(5, t2) was under drought stress on day six of the experiment.

The threshold value of CWSI in Exp 5 was calculated as 0.161 (Figure 2.27 b). Using this threshold value, the drought stress on Plant(5, t1) could be detected on day 5 of the experiment. The drought stress on Plant(5, t2) and Plant(5, t3) could be detected on day 7 of the experiment. The CWSI value of Plant(5, t2) decreased to a level very close to the threshold value on day 14, two days after been re-irrigated, indicating a time delay in the recovery of the plant. The CWSI values of the other two treatment plants did not decrease much after the re-irrigation. This indicates that the plants did not recovery much after re-irrigation, which was also evident in the measured ET rates of the plants shown in figure 2.27 (a). In the figure, the ET rates of Plant(5, t1) and Plant(5, t3) did not recover to levels near the defined baseline, while the ET rate of Plant(5, t2) recovered across the baseline.
Figure 2.27  The baseline of drought stress defined by ET, (a), and the threshold value of CWSI_NPTD, (b), for drought stress detection in Exp 5
The baseline of ET in Exp 6 was 0.078 kg/hr×m² (Figure 2.28 a). Using this baseline, Plant(6, t1), Plant(6, t2) and Plant(6, t3) were identified as drought stressed since day 7 of the experiment.

The threshold value of CWSI in Exp 6 was calculated as 0.203 (Figure 2.28 b). Using this threshold value, the drought stress on Plant(6, t1), Plant(6, t2) and plant(6, t3) were detected on day 10, 3 and 5, respectively of the experiment.

In Exps 2, 3 and 6, the ET-defined drought stress occurred relatively late compared to Exps 4 and 5. When studied closely, it was found that the relatively lower baseline of ET by the divergence in the ET rate of the control plant and by the way the ET baseline was defined. In fact, in Exp 2, control plants 1 and 3 showed very similar ET rates, but control plant 2 exhibited an ET rate that was lower than the ET rates of the other two plants. In Exp 3 and Exp 6, control plant 1 showed a larger ET rate, while the ET rates of the other two control plants were very similar. The large variations in the ET rates of the control plants gives rise to the large standard deviation of the data group. Since the baseline was defined as the difference between the mean value of the well-watered plants’ ET and the standard deviation of the well-watered plants’ ET rates, an increased standard deviation inevitably reduced the value of the baseline, thus delaying the timing of the defined drought stress.
Figure 2.28 The baseline of drought stress defined by the ET, (a), and the threshold value of CWSI_NPTD, (b), drought stress detection in Exp 6
Kacira et al. (2002 a) reported that the CWSI threshold values of Paradise variety were 0.20 and 0.10, respectively, in two different experiments. The plants used in Exp 2, 5 and 6 of this study were also of Paradise variety, and the threshold values were 0.307, 0.161 and 0.203. The ET and canopy temperature measurement have proven that the control plants in Exp 2 were experiencing minor drought stress, thus the threshold value was higher in this experiment. The values of 0.161 and 0.203 actually agreed quite well with the findings reported by Kacira et al. (2000). The variety of plants used in Exps 3 and 4 were of Pure Beauty. Thus the CWSI threshold values determined in these two experiments were close to each other (0.277 and 0.282, respectively), but different from the other three experiments.

In Exp 2, the CWSI threshold value could detect the drought stress in the treatment plants 1 day before visual detection. In Exp 5, the CWSI threshold value could detect the drought stress 4 days to 6 days before visual detection. In Exp 6, the CWSI detected the stress on the same day as visual detection or up to 6 days before visual detection. In Kacira’s (2000) report, CWSI threshold value could detect the drought stress in the Paradise plant 19-112 hours before visual detection, which equals to about 1 to 5 days before visual detection. The timing of detection in this two studies thus seem to agree with each other.
2.3.6.2 Detection using plant motion

To establish the baselines of COVtpca and IRCM for the drought stress detection, the threshold values of COVtpca and of daily IRCM were calculated using the values of the control plants. The values of COVtpca and the daily minimum IRCM of the treatment plants were then compared with the defined threshold values so as to study when these indicators detected the occurrence of the drought stress.

In Exp 2 (Figure 2.29 a), the threshold value of COVtpca was 1.02%. Using this threshold value, the drought stress of Plant(2, t1), Plant(2, t2) and Plant(2, t3) could be detected on day 5, day 7 and day 6 of the experiment, respectively. For Plant(2, t1) and Plant(2, t3) the timing of the detection was the same as the ET-defined drought stress and as human visual observation. For Plant(2, t2), COVtpca detected stress was one day after the ET-defined stress and human observation.

The threshold value of COVtpca in Exp 3 was 1.5% (Figure 2.29 b). This threshold value indicated that Plant(3, t1) was under drought stress on day 7, Plant(3, t2) was under drought stress on day 9, and Plant(3, t3) was under water stress on day 4 of the experiment. For Plant(3, t1), the COVtpca detected the drought stress on the same day as ET-defined drought stress and visual observation. For Plant(3, t2), COVtpca detection occurred one day after the ET-defined drought stress and human observation. For Plant(3, t3), COVtpca detection occurred one day earlier than the ET-defined drought stress and on the same day as the human observation.
The COVtpca values and the threshold value of the plants in Exp 4 are shown in Figure 2.29 (c). The threshold value was 0.76%. Using this threshold value, the drought stress could be detected in Plant(4, t1) and Plant(4, t2) on day 5, and in Plant(4, t3) on day 6 of the experiment. For Plant(4, t1) and Plant(4, t2), the timing of COVtpca detection was the same as that of visual detection and two days after the occurrence of ET-defined drought stress. For Plant(4, t3), the time of COVtpca detection was the same as visual observation and two days later than the occurrence of ET-defined drought stress.

The threshold value of COVtpca in Exp 5 (Figure 2.29 d) was 0.63%. Using this threshold value, one could detect the drought stress in Plant(5, t1) on day 10, in Plant(5, t2) on day 9 of the experiment, and detect the drought stress on Plant(5, t3) on day 15 of the experiment. For Plant(5, t1) and Plant(5, t2), this time of detection was one and two days earlier than visual detection. For Plant(5, t3), the timing of COVtpca detection was three days later than visual detection.

In Exp 6, the threshold value of COVtpca was 0.37%. According to this threshold value, Plant(6, t1) was under drought stress on day nine and Plant(6, t3) was under drought stress on day eight. In each case, the detection time of COVtpca occurred one and two days earlier than visual detection and ET defined drought stress. And, using this threshold value, it turned out that Plant(6, t2) was under drought stress during all days except for day 5 of the experiment.

The threshold values of COVtpca in Exps 5 and 6 were 0.63% and 0.37% respectively. These values were very close to those threshold values of Paradise variety reported by Kacira et al. (2002 b, 0.70% and 0.36%, respectively). The variety of the
plants used in Exp 2 was also Paradise, but the threshold value was a bit higher: 1.02%. It has been indicated before that the minor stress of the control plants in this experiment resulted in higher CWSI threshold values. The high threshold value of COVtpca must have been caused by the same reason.

In Kacira’s (2000) report, the COVtpca threshold values could detect the drought stress on the Paradise plants at the same time as visual detection or up to 24 hours before visual detection. In this study, the COVtpca threshold values could detect the drought stress of the Paradise plant on the same day or up to two days before visual detection. These timings of detection found in this research agreed well with that reported by Kacira et al. (2002 a, 2002 b).

The threshold values of daily minimum IRCM and the drought stress detection time of each treatment plant using these threshold values during the experiments are listed in table 2.3. While the timing of detection on 14 of the plants was reasonable, the detection timing on Plant(6, t2) was on day 1 of the experiment, which was doubtable. In the first day, the CWSI_NPTD value of Plant(6, t2) was similar to those of the control plants. However, because the variation of the CWSI_NPTD of the control plants was low, so the $\mu+2\sigma$ of the CWSI-NPTD of the control plants was still lower than the value of Plant(6,t2), thus resulting in the early (false) detection.
Figure 2.29 The COVtpca of the treatment plants and the threshold value of COVtpca in the research. Sub-figures 2.29 a – 2.29 e depict findings from Exp 2 – 6 (Continued)
Figure 2.29: Continued

(Continued)
Figure 2.29: Continued

![Graph showing COVtpca (%) over duration (Day) with data points for different experiments and treatment plants.]

Table 2.3 Threshold values of daily minimum IRCM and drought stress detection timing of each treatment plant of the experiments

<table>
<thead>
<tr>
<th>Experiment #</th>
<th>Exp 2</th>
<th>Exp 3</th>
<th>Exp 4</th>
<th>Exp 5</th>
<th>Exp 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Threshold value (%)</td>
<td>-1.94</td>
<td>-1.04</td>
<td>-0.89</td>
<td>-0.04</td>
<td>-0.7</td>
</tr>
<tr>
<td>Detection timing (days after water withholding)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment plant 1</td>
<td>4</td>
<td>6</td>
<td>4</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>Treatment plant 2</td>
<td>6</td>
<td>9</td>
<td>4</td>
<td>6</td>
<td>1*</td>
</tr>
<tr>
<td>Treatment plant 3</td>
<td>6</td>
<td>4</td>
<td>6</td>
<td>10</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 2.3 Threshold values of daily minimum IRCM and drought stress detection timing of each treatment plant of the experiments
2.3.6.3 Comparison of CWSI and plant motion based stress detection

When evaluate the performance of the indicators in drought stress detection, it is also of interests to see if and in how many times can the indicators detect the drought stress before visual detection. The comparison of the CWSI, COVtpca and IRCM versus visual detection is shown in table 2.4.

<table>
<thead>
<tr>
<th></th>
<th>Before visual detection</th>
<th>Same time as visual detection</th>
<th>After visual detection</th>
</tr>
</thead>
<tbody>
<tr>
<td>CWSI</td>
<td>13</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>COVtpca</td>
<td>5</td>
<td>7</td>
<td>3</td>
</tr>
<tr>
<td>IRCM</td>
<td>10</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 2.4 Timing of the drought stress detection using various indicators compared against visual detection

Table 2.4 shows that of the fifteen treatment plants, the CWSI could detect the drought stress in 13 of them before visual detection, and in 2 of them the same time as visual detection. The COVtpca could detect the drought stress in 5 plants before visual detection, in 7 of the plants the same time as visual detection and in 3 plants after visual detection. The IRCM could detect the drought stress in 10 plants before visual detection, in 3 plants at the same time as visual detection and in 2 plants after visual detection.

From this comparison, it is clear that both the CWSI and the plant motion-based indicators can be used in drought stress detection. It is also clear that in general the
performance of these indicators in drought stress detection is no worse than visual
detection. Also, it can be seen that the performance of the CWSI was the best among
these three indicators, and that the IRCM can do a better job than COVtpca in drought
stress detection.

2.4 Conclusions

The observation of this study confirmed the findings reported by Kacira (2000) in
using canopy temperature derived index: CWSI and plant motion: COVtpca, in drought
stress detection. It was confirmed that as drought stress developed, the canopy
temperature of the treatment plants became higher than the canopy temperature of the
control plants and the air temperature. The canopy temperatures of the control plants
were found to be fairly stable during the experiments. However, the canopy temperatures
of the control plants were found not to be lower than the air temperature all the times.

The calculation of CWSI was thus modified, using only those temperatures of the
control plants that were lower than the air temperature as the “potential temperature” in
the calculation. The CWSI values calculated this way showed similar coefficient of
determination values verses Tc-Ta as those reported by Karica (2000).

The measured ET rates, CWSI values and COVtpca values of the plants showed
that the behavior of the plants were affected by both the variety of the plants and the
environmental conditions. Plants of different varieties showed different magnitude in ET
rate, CWSI value and plant motion pattern. Different environmental conditions resulted
in different ET rates, CWSI values and motion patterns, even if the plants were of the same variety.

The threshold values of the Paradise variety plants in this study were found to be very close to the threshold values of the same variety reported by Karcia (2000). Thus, it was confirmed that the CWSI values can be used in plant drought stress detection, and that the CWSI value can detect the drought stress before visual detection. The threshold values of CWSI were 0.307, 0.277, 0.282, 0.161 and 0.203 in Exps 2 to 6, respectively. The established CWSI threshold values were able to detect the ET-defined plant drought stress in each of the six experiments. Of the fifteen treatment plants, the CWSI threshold values were able to detect the onset of drought stress in thirteen plants before visual detection, and in two plants later than visual detection.

The motion of the plants in the form of the COVtpca values and the IRCM were extracted from the acquired TPCA of the plants. The COVtpca of control plants were stable during the experiments, while those of the treatment plants became larger as the drought stress developed. The threshold values of the COVtpca in experiments 2 through 6 were 1.02%, 1.49%, 0.76%, 0.63% and 0.37%, respectively. The threshold values detected the occurrence of drought stress in five plants before visual detection, in seven plants at the same time of visual detection and in three plants after visual detection. The COVtpca threshold values of the Paradise were also found to be close of the same varieties reported by Kacira (2002).

The IRCM of the control plants were found to be stable during the experiments, while the IRCM of the treatment plants continued to decrease as drought stress
developed. The threshold values of IRCM in each experiment was –1.94%, -1.04%, -0.89%, -0.04%, and –0.7% respectively. The threshold values detected the drought stress in ten plants before visual detection, in three plants at the same time as visual detection and in one plant after visual detection.

These results confirmed that the plant motion-based indicators such as COVtpca and instant relative canopy motion (IRCM) could be used in plant drought stress detection, and that in most times, the performance indicators were no worse than visual observation in plant drought stress detection. The study also showed that the IRCM could detect the drought stress slightly earlier than COVtpca.

2.5 References


CHAPTER 3

PROGRESSIVE LEAF WATER CONTENT DETECTION USING THE PROSPECT MODEL

When studying the possibility of detecting plant water status using multispectral reflectance, one can obtain reflectance data from either a leaf or plant canopy. The next three chapters report the studies at both scales. As a starting point, the study on leaf scale is reported first in this chapter. The studies on canopy scales are reported in the following chapters.

3.1 Introduction

Leaves are the most important plant parts where transpiration and photosynthesis take place. Understanding the leaf properties as affected by biophysical characteristics of leaves is essential in non-contacting water stress detection.

Near infrared reflectance spectroscopy (700 to 2,500 nm) has been used to successfully predict chemical contents such as protein, lignin and fiber fractions in plant leaves (Wessman, 1994). It has been pointed out that the reflectance spectra of
green leaves have similar shapes, varying principally in magnitudes (Billings and Morris, 1951). In the visible wavelengths, pigments, especially chlorophyll, dominate the spectral responses of leaves. In the near infrared (NIR: 700-1,300 nm) region, the reflectance rises noticeably because the green leaves absorb very little energy. In the middle infrared (MIR: 1,300-2,500 nm) region, water absorbs energy strongly at particular wavelengths. Since green leaves have very high moisture contents, these water-absorption bands dominate the spectral response in this region.

Two different approaches have been applied to interpret leaf reflectance as related to leaf physiological status (Jacquemoud, 1993). The first approach relies on empirical correlations between the leaf reflectance (or transmittance) and biochemical content (Jacquemoud et al., 1995, 1996). The second approach develops physically based models of photon transport inside leaves.

Applying the first approach, regressional relationships between leaf reflectance and physiological status have been reported. While some of the resulting indices did succeed in detecting the change in leaf water status, application of these indices in plant water stress detection has been criticized because the sensitivity of the indices was not sufficient for plant water stress detection. A fully hydrated leaf must lose about 50% of its water before a significant difference in the indices caused by water stress can be sensed. On the other hand, drought stress is known to occur when relative water contents drops only 20-30% (Hunt, 1991). A better understanding of the relationship between spectral property of leaves and their water status is necessary to improve water stress detection sensitivity.
The efforts in modeling the leaf optical properties brought about two categories of model. Descriptive models (Tucker, 1980; Brakke and Smith, 1987; Yamada and Fujimura, 1988) applied either ray tracing or Markov approaches in describing the leaf optical property. While these models have been reported to work well in representing the optical phenomenon, the complex mechanisms involved in these models make the inversion very computationally demanding.

On the other hand, invertible models such as the “plate model” proposed by Allen et al. (1969), or the PROSPECT model (Jacquemoud and Baret, 1990) have parameters that can be inferred from remotely sensed measurements. In particular, the PROSPECT model has notable advantages. PROSPECT calculates the leaf hemispherical reflectance and transmittance from 400 nm to 2500 nm using only three parameters: equivalent water thickness (EWT), content of chlorophyll a and b (C_{ab}), and leaf internal structure index (N). EWT is the hypothetical thickness of a single layer of water averaged over the entire leaf and is recorded as the depth of water in the leaf (Hunt, 1991; Danson, et al., 1992). The leaf internal structure index (N) relates to the cellular arrangement within the leaf. Jacquemoud and Baret (1990) determined N using the following equation.

\[
N = \frac{0.9 \times \text{SLA} + 0.025}{\text{SLA} - 0.1} \quad (1)
\]

Where SLA (specific leaf area) is defined as the leaf area per unit of dry weight (cm²/mg).

The PROSPECT model has good potential in retrieving leaf water content from leaf reflectance measurement. In fact, several efforts have been made to apply this model in
the study of leaf water status. Burgan (1996) tested the capability of the PROSPECT model in describing a leaf water stress. The authors pointed out that for the application of the PROSPECT model on a single leaf, the leaf internal structure index N was very important because it might change from one leaf to another. The authors also concluded that N did not vary significantly between unstressed and stressed leaves. However, when Aldakhell and Danson (1997) tried to study leaf spectral response resulting from changes in leaf water content, and evaluated the use of the PROSPECT model in predicting the spectra of dehydrating leaves, they found out that the difference between measured and modeled reflectance increased as leaf water content decreased. The authors pointed out that this might have been caused by the changes in the leaf internal structure that were not accounted for by the model. Ceccato et al. (2001) echoed this assumption by pointing out that the EWT was not the only parameter responsible for significant reflectance variations within the infrared range and that additional information was required on the variations due to the parameter N. However, no effort has been reported on using PROSPECT for progressive water status study of the leaf. Furthermore, no effort has been made at using PROSPECT in drought stress detection in plants grown in a controlled environment.

The goal of this chapter is to evaluate the PROSPECT model for early drought stress detection in plants grown in a controlled environment. In PROSPECT, leaf water content is represented by EWT. However, plant drought stress status is mostly associated with Relative Water Content (RWC) in the field of horticulture. In order to relate the well-documented RWC drought stress threshold to EWT value, the relationship between RWC and EWT must first be established. The EWT threshold can then be used with
PROSPECT to detect drought stress. In addition, to improve the sensitivity of the model for early stress detection, the selection of leaf internal structure index should be evaluated. In the original development of PROSPECT, leaf internal structure index N was assumed to be a fixed value for a wide range of plant species. Previous researches on using PROSPECT in leaf water status study seems to have drawn controversial conclusions on the values of N. Considering that the leaf internal structure is associated with plant age, species and turgidity, which in turn are affected by drought stress, a closer examination of the change in reflectance caused by N is warranted to improve the accuracy of water content determination using this model.

The main objectives of this research were to: (1) determine the relationship between EWT and RWC and to determine if EWT is a good indicator for drought stress detection; (2) evaluate the effect of leaf internal structure (N) value variation, due to plant species and water content, in the leaf reflectance simulation; (3) evaluate the performance of the PROSPECT model in retrieving the EWT values of New Guinea Impatiens plants grown in a controlled environments; (4) evaluate the feasibility of using the PROSPECT model for drought stress detection.

3.2 Materials and Methods

To study the relationship between EWT and RWC, data from 40 detached New Guinea Impatiens “Equinox” leaves were used. The adaxial (upper) leaf area was first measured using a video imaging system(ΔT Area Meter, Delta-Devices Ltd, Cambridge,
UK). The measurements of leaf EWT and RWC followed the protocol described by Cibula et al. (1992). The detached leaves were immersed in fresh water in a low light environment for 24 hours to reach full turgor before they were wiped dry on both surfaces and left to air dry. The weight of individual leaf was measured three times after they were left to air dry. The first two measurements were conducted within 6 hours after the leaves were taken out of the water, with 3 hours between each measurement. The last measurement was conducted 24 hours after the leaves were left to air dry. The leaf dry weight was obtained after oven drying at 70 °C for 48 hours. The EWT and RWC values of the leaves were calculated using equations (2) and (3).

$$\text{EWT} = \frac{W_f - W_d}{S_l} \quad (2)$$

$$\text{RWC} = 100\left(\frac{W_f - W_d}{W_t - W_d}\right) \quad (3)$$

Where $W_f$ is the leaf fresh weight (g), $W_d$ is the leaf dry weight (g), $S_l$ is the leaf area (cm$^2$), and $W_t$ is the leaf full turgor weight (g).

To validate the established relationship between RWC and EWT, 162 water status data from 54 additional leaves were collected. RWC values were calculated using the obtained relationship between EWT and RWC, and the computed values were compared with the measured RWC values.
To study the leaf reflectance response to dehydration, the leaf reflectance spectra were measured using a spectroradiometer system (LabSpec® Pro, ASD, Boulder, CO) equipped with an integrating sphere. The resolution of the spectral measurement was 3 nm in the 350-1000 nm region and 10 nm in the 1000-2500 nm range. The reflectance spectrum of each leaf at different water status was acquired immediately after each weight determination of the leaf. Spectra of some of the leaves were not measured after 24 hours of drying because the leaves were too dry by then. A total of 142 spectra were obtained.

To evaluate the performance of the PROSPECT model in simulating leaf spectral characteristics at different water status, model simulated spectrum was evaluated against measured spectral data. To specify the required inputs in the PROSPECT model, the EWT value of the sample leaf water was determined using equation (2). The value of leaf internal structure index N was calculated using equation (1). Because the chlorophyll content of the leaves was not measured, and because the change in leaf water content and leaf internal structure mainly affects the reflectance in the infrared range, the comparison between simulation and measurement was conducted in the infrared range, namely from 755 nm to 2500 nm.

Finally, the performance of determining EWT by inverting the PROSPECT model was evaluated. The inversion of the PROSPECT model consists of determining the value of the parameters in the model, which minimizes the following merit function in the whole spectrum:
\[ \varepsilon = \sum_{\lambda} \left[ R_{\text{mes}}(\lambda) - R_{\text{sim}}(\lambda) \right]^2 \]  

(4)

Where \( \varepsilon \) is the sum of the square of errors between \( R_{\text{mes}}(\lambda) \), the measured leaf reflectance, and \( R_{\text{sim}}(\lambda) \), the simulated leaf reflectance at wavelength \( \lambda \). Because of the non-linearity of the model, this minimization was achieved numerically using the Levenberg-Marquardt algorithm. This method is an elegant compromise between the steepest descent and the Gauss-Newton algorithm. The algorithm in C code from Reich (1992) was modified to link the inversion algorithm with the model simulation.

Using the 142 acquired spectra, EWT values were retrieved under two scenarios of N values. In the first scenarios, a constant N value was used in the retrieval process, and only EWT was searched using the spectral information. The process used N value defined by equation 1. In the second scenario, both N and EWT were adjusted simultaneously in the retrieval process. To evaluate the performance of EWT retrieving from model inversion of PROSPECT, the retrieved EWT values were compared with the measured EWT values.

### 3.3 Results and Discussion

This section describes the relationship between the RWC and the EWT, the change in leaf reflectance due to dehydration, and compares the measured and modeled change in reflectance. The performance of the EWT determination from the reflectance spectra is also reported.
3.3.1 Relationship between EWT and RWC

The study on the relationship between RWC and EWT shows that these two parameters are linearly correlated with one another, with the $R^2 = 0.82$. As shown in Figure 3.1, RWC can be expressed by EWT as:

$$
RWC = 30.5 \times EWT(cm)
$$

(5)

The comparison between the measured RWC values and the RWC values calculated using equation (5) is shown in figure 3.2. It can be seen that the calculated RWC values fit closely with the measurements barring a few exceptions, in which the RWC values were pretty low. The Root Mean Square Error (RMSE) of the whole data set equals 0.058. When comparing the RWCs with values larger than 60%, the calculated RWC was found to be a slightly further from the measured values, with RMSE equals to 0.072. However, as can be seen from figure 3.2, the estimation at this range still agreed quite well with the measurement in this range.
Figure 3.1 Relationship between RWC and EWT. The linear relationship between these two variables shows that EWT can also be used as an indicator for leaf water stress.

Figure 3.2. Relationship between measured RWC values and RWC values determined by EWT.
Knowing that the RWC value when plant drought stress develops is approximately 0.8-0.7 (Hunt, 1991) and understanding the established relationship between RWC and EWT, one can easily find the drought stress region using EWT as indicated in Figure 3.1. Therefore, EWT values retrieved by the PROSPECT model using leaf reflectance measurement can also be conveniently used for the leaf drought stress evaluation of horticultural crops.

3.3.2 Spectral characteristics of dehydrating Leaf

The reflectance measurements of the 40 leaves showed that as dehydration developed, leaf reflectance increased in both the NIR and MIR regions. A typical group of spectra of one leaf at different water status was shown in Figure 3.3. In the MIR region, the spectral response to leaf water thickness change is directly related to the absorption of liquid water (Danson et al., 1992). Strong water absorption bands located at 1,450 nm and 1,950 nm along with two adjacent wavebands (1680 and 2210 nm) were found to be sensitive to the changes of EWT.

The reflectance increases in the NIR region can be explained by the critical reflection of radiation at the cell wall-air interface. When leaf water content is high, the air space between cells is filled with water, reducing the discontinuity in the light refraction index between cell wall and air. Thus, the reflectance in the near infrared range is low. As the leaf loses water, the air space inside the leaf increases and , the shrinkage
of leaf cells also results in more cell wall-air interface, which in turn provides more opportunity for multiple scattering of radiation.

In the VIS region, changes in leaf reflectance should be caused mainly by the degradation of the photosynthetic pigments. In this experiment, no obvious reflectance changes in this region were observed, which indicates that the dehydration process of New Guinea Impatiens leaves may occur so quickly that the effect of pigment degradation was not obvious. Thus, the changes in the NIR and MIR regions were more sensitive to the leaf dehydration than those in the VIS region.

Figure 3.3 Typical reflectance spectra of a New Guinea Impatiens leaf during dehydration. As EWT decreases, the reflectance in the NIR and MIR ranges increases.
3.3.3 Reflectance simulation

Since no obvious differences were observed in the VIS region during leaf dehydration, the evaluation of the model was focused on the NIR and MIR regions. Two model parameters that were responsible for the spectral changes were leaf internal structure index in the NIR region and leaf water status (EWT) in the MIR region.

Figure 3.4(a) shows the typical comparison between the measured reflectance and the model simulations using an N value determined by equation (1). The N value used for this group of simulations was 1.486. In this case, the PROSPECT model simulated the general characteristics of the reflectance of New Guinea Impatiens leaves quite well. The reflectance plateau in the NIR region and the absorption bands in the MIR region were all closely followed by the model. However, with an N value equal to 1.486, it was clear that the simulation overestimated the reflectance in most of the NIR and MIR regions when the leaf water content was high. As leaf dehydration developed, simulation consistently underestimated the reflectance in these two region, and the difference between the measurements and the simulations increased. The difference between the measured and simulated spectra are shown in figure 3.4(b). It is clear that large differences occurred in the NIR and MIR region. When the leaf water content was high, the simulation overestimated the reflectance by as much as 17% at 755 nm. When leaf EWT decreased to 0.0163 cm, the largest discrepancy was 14% at around 1000 nm.
Figure 3.4 Comparison between simulated reflectance with a fixed N value (1.485) and observed reflectance during dehydration. The simulation predicted the spectral distribution well, yet either underestimated or overestimated the actual reflectance; As EWT decreased, the difference between simulations and measured spectrum increased.
3.3.4 Water status retrieving from reflectance

The under- and over-estimation of the reflectance shown in figure 3.4 indicates that first, the N value specified by equation 1 overestimated the leaf internal structure of New Guinea Impatiens when the leaf water content was high. Secondly, the calculated N value could not follow the change in leaf internal structure when leaf dehydration developed. These findings suggest that using a dynamically changing value of N in the inversion of the PROSEPECT model could increase the accuracy of the retrieval procedure.

To evaluate the performance of the PROSPECT model in retrieving leaf water status, the EWT values of the 40 leaves were retrieved with both fixed and dynamically adjustable N values in the inversion procedure. First, a fixed N value was used in the retrieving process; the retrieving procedure adjusted only the EWT value in the PROSPECT model to minimize the merit function (equation (5)) in the NIR/MIR regions. N values were calculated as previously described in section 1. Second, EWT values were retrieved with both N and EWT values simultaneously adjusted in the retrieval procedure. Since the N value could not be physically measured, and since the primary goal of this study was to retrieve the water content from reflectance, the evaluation of the performance of these two scenarios concentrated on the comparison between the retrieved and the measured EWT values. The comparison between the measured EWT values and the retrieved EWT values for both methods are shown in figure 3.5. In the figure, the closer the data group is to the 45° diagonal, the better the retrieved result.
The effect of adjusting the N value can be seen clearly from the comparison between the measured and the retrieved EWT values. The RMSE between the retrieved and measured EWT was 0.0073 cm when a fixed N value, as given by equation 1, was used. When N values were dynamically adjusted corresponding to different EWT levels, the RMSE of the prediction was reduced to 0.0056 cm.

Figure 3.5 Evaluation of EWT retrieval using the PROSPECT model. The leaf internal structure index N was calculated in different ways: the global N values were determined using equation (1); N value was made adjustable in the EWT retrieving procedure.
Figure 3.6. Comparison between the retrieved and the measured EWT values that were larger than 0.015 cm. The EWT values retrieved with both N and EWT dynamically adjusted in the procedure possess an even larger advantage in the turns of accuracy.

To evaluate the performance of EWT retrieval at an EWT range that is physiologically significant, the comparison was further conducted for the EWT with values larger than 0.015 cm. This value, according to equation 5, corresponded to 60% of water content. The comparison is shown in figure 3.6. It can be seen that for EWT values larger than 0.015 cm, the RMSE of the EWT retrieved with fixed N values was increased to 0.0083 cm, whereas the RMSE of those retrieved with dynamic N values was still 0.0056 cm.
A closer look at figure 3.6 shows that when both N and EWT were set free in the model inversion procedure, the retrieved EWT fairly consistently underestimated the EWT with values larger than approximately 0.03 cm. These were most commonly the EWT values when the leaves were at full turgor. It seems that at high leaf water content, because of the strong absorption of water in the MIR range, the model was saturated so that it could not follow the leaf water content as accurately as it did when leaf dehydration developed. A clustering analysis was further performed to separate the saturated data group from the non-saturated data group. The results are shown in figure 3.7. It can be seen from figure 3.7 that the RMSE of retrieved EWT values larger than 0.0275 cm was 0.0073 and that the RMSE of retrieved EWT between 0.015 and 0.0275 cm was 0.0034 cm. This range, according to equation 5, corresponds to the RWC values that are within 60-80%, which are the critical values for leaf water stress detection.
Figure 3.7 Retrieved EWT values consistently underestimated the measured values when leaves were at full turgor. The saturated data group was separated from the non-saturated data group. Values of the non-saturated data group corresponded to critical values of leaf water stress.

3.4 Conclusions

This research showed that Equivalent Water Thickness (EWT) used in the PROSPECT model is a good indicator of leaf water status, relating closely to the RWC that is commonly used in horticulture as an indicator of plant water status. The linear relationship between RWC and EWT ($R^2 = 0.86$) shows that although PROSPECT determines leaf water content in terms of EWT, it can be used to assess leaf water stress for horticultural applications.
The leaf internal structure index N was affected by the leaf water status. When using the N values determined by the semi-empirical relationships as a function of specific leaf area (SLA), the PROSPECT model simulated spectrum overestimated the reflectance of New Guinea Impatiens leaves with high water content. When leaf dehydration developed, the model underestimated the reflectance of New Guinea Impatiens leaf by as much as 14%. To retrieve the leaf water content accurately, the change in leaf internal structure must be taken into consideration in an attempt to better assess water stress of New Guinea Impatiens leaves.

Using a dynamic iterative process to retrieve EWT, the prediction error (RMSE) was reduced from 0.0073 when the N value was fixed to 0.0056 when the designation of the N value was changed from a fixed value to an adjustable value in the retrieval procedure. When considering the EWTs with value larger than 0.015 cm, the EWT values retrieved with a dynamic N value appear to be even better in comparing with those values retrieved with a fixed N value in the inversion procedure.

The PROSPECT model can be used to detect early drought stress symptoms. The RMSE of the retrieved EWT with values between 0.015 cm and 0.0275 cm was only 0.0034. This range correspond to the critical range for leaf water stress detection determined by RWC values, which are 60-80%.
3.5 References


CHAPTER 4

MODEL INVERSION PROCEDURE FOR WATER STATUS ASSESSMENT ON THE CANOPY SCALE

The following two chapters will concentrate on using the plant canopy reflectance in plant drought stress detection. This chapter will try to set up the procedure for retrieving the average leaf water thickness from measured canopy reflectance. The next chapter will concentrate on the evaluation of the performance of the retrieved leaf water content in plant drought stress detection.

4.1 Introduction

Researchers have reported that plant water status can be detected by the measurement of plant near-infrared (NIR) and middle-infrared (MIR) reflectance (Hunt et al., 1987; Hunt and Rock, 1989; Miemann et al., 2002; Tian et al., 2001). Two approaches have been applied to utilize vegetation spectra to identify canopy characteristics: spectral indices and physical modeling.

In the semi-empirical approach, multi-spectral band indices such as the leaf water
content index (LWCI) (Hunt et al., 1987), the MIR/NIR ratio (Hunt, 1991) and the normalized difference water index (NDWI) (Gao, 1996) have been established to define relationships between plant leaf reflectance and plant physiological status.

The information on plant water status is extracted using the established relationships and the measured reflectance. The development of high-resolution spectral sensors provide information on relationships between the shapes of reflectance spectrum, such as Red-edge of green vegetations, to the plant physiological status. Because the indices and Red-edge are of an empirical nature, their robustness is limited without calibration for different crops in different environment.

Crop characteristics can also be determined through the inversion of physical models. This approach consists first in developing an analytical reflectance model to describe the interactions between the light and the canopy. Once the model is set up, the inversion procedure is performed to estimate biophysical and biochemical variables from measured reflectance. A schematic illustration of the model based multispectral water status assessment procedure is shown below:
Figure 4.1 The procedure that calculates EWT from measured reflectance by model inversion

In this approach, an accurate model and an appropriate inversion procedure are essential to assure reliable assessment of plant water status. The general goal of the following two chapters is to evaluate the performance of model inversion approach for drought stress detection in a controlled environment.
This chapter determines the procedure that reliably and accurately retrieves the water status of a plant from the canopy reflectance by inverting the PROSPECT+SAIL model.

### 4.1.1 Description of the models

The model chosen for this study is the PROSPECT+SAIL model (Jacquemoud, 1993; Jacquemoud et al., 1995). This model couples the leaf radiative transfer model PROSPECT (Jacquemoud and Baret, 1990) and the canopy radiative transfer model SAIL (Verhoef, 1984).

The PROSPECT model assumes that the spectral (400 – 2,500 nm) property of a leaf is a function of three variables: the leaf internal cell structure \( N \) (dimensionless), chlorophyll \( a+b \) concentration \( \text{Cab} \) (\( \mu \text{g/cm}^2 \)), and leaf water content \( \text{Cw} \) (cm). \( \text{Cw} \) was represented by equivalent water thickness (EWT). A lower \( N \) value represents a compact cellular arrangement within the leaf, and a higher \( N \) value represents a more spongy cellular arrangement with more air cavities. \( \text{Cab} \) and \( \text{Cw} \) affect the reflectance simulation in visible and near-infrared band, respectively, and they are assumed to have homogeneous distribution in a leaf. Since the model assumes that the leaf reflectance \( \rho_l \) and leaf transmittance \( \tau_l \) are mainly determined by chlorophylls and water content, \( \rho_l \) and \( \tau_l \) are thus independent of leaf type.

The PROSPECT model has been applied either in forward or inverse mode to simulate the reflectance of leaves with different EWT values (Aldakheel and Danson, 1994).
1997) or to detect vegetation leaf water content from measured reflectance (Ceccato et al., 2001). Yang and Ling (2001) reported the relationship between the EWT and relative water content (RWC), which is used more often in horticulture to describe plant water status, and concluded that the retrieved EWT by inverting the PROSPECT model could be used as an indicator for water status at the leaf level.

The canopy model SAIL was developed to describe the reflectance of plant canopies with different geometric structures. This model assumes that a vegetation canopy is a homogeneous semi-infinite medium with lambertian reflecting leaves. The azimuth angles of the leaves are assumed to be randomly distributed, and the zenith angles follow an ellipsoidal distribution characterized by a mean leaf inclination angle ($\theta_l$). Leaf area index (LAI) is used in the model to describe the plant canopy structure.

By coupling the PROSPECT and the SAIL models, the PROSPECT+SAIL model computes canopy reflectance spectra (400 nm – 2,500 nm) from the following parameters:

Canopy parameters: $\text{Cab}$, $\text{Cw}$, $N$, LAI, and $\theta_l$;

External parameters: zenith and azimuth viewing angles and zenith light source angle

To use the PROSPECT+SAIL model, leaf reflectance and transmittance is first simulated using the PROSPECT model and then fed into the SAIL model. The outputs of the PROSPECT+SAIL model are thus functions of both canopy geometry structure and of the physiological characteristics of the plant.
Inversion of the PROSPECT+SAIL model consists of determining simultaneously some of the above parameters (Cab, Cw, N, LAI, $\theta_l$) from measured reflectance. The external parameters are assigned the values of the measurement system configuration in the experiment. Because of the complexity of the model, analytical inversion of the model is prohibitive, so the model is inverted numerically. The inversion procedure selects parameter values such that the deviation ($\varepsilon$) between model prediction ($y_\lambda(p)$) and measurement ($v_\lambda$) is as small as is achievable, where subscribe $\lambda$ is given wavelength of reflectance spectra. Mathematically it consists of determining the parameter vector $p$ of the model by minimizing the merit function

$$
\varepsilon = \sum_\lambda \left[ y_\lambda(p) - v_\lambda \right]^2
$$

(1)

Using the spectral reflectance between 400 nm and 2, 500 nm, Jacquemoud (1993) and Jacquemoud et al. (1995) demonstrated the invertibility of the PROSPECT+SAIL model. Biophysical characteristics, including averaged canopy EWT, were retrieved from canopy reflectance. The retrieved EWT values, however, were not necessarily most accurate as multiple solutions were possible when numerical methods were used to approximate solutions of a non-linear system such as the PROSPECT+SAIL model.
4.1.2 Considerations of local minima

A major limitation of the inversion procedure was the existence of multiple solutions at local minima, which led to large inaccuracies in the estimation of biophysical parameters (Fang et al., 2003). In the inversion of the PROSPECT+SAIL model, the multiple local minima are caused by two main factors: the non-linearity of the model and the two correlated variables in the model.

4.1.2.1 Non-linearity of the model

Because of the non-linearity and the complexity of the PROSPECT+SAIL model, the merit function in equation (1) is a non-convex function. Because of this non-convex characteristic, many possible solutions, or multiple local minima exist. Traditional optimization algorithms search a so-called “best parameter value” in a direction that reduces the objective function value. The procedure is terminated when the algorithm cannot reduce the function value any more, even if the obtained point is a local minimum. For this reason, the final solution of the inversion procedure is often affected by the starting point of the optimization procedure. To make sure that the inversion procedure can find the best solution, the searching procedure has to be initiated from as many points as possible. In another words, one must perform an exhaustive search for the global minimum.
To improve the effectiveness of the exhaustive searching, the searching domain of the parameters must be restricted so as to avoid fruitless searching in physically improbable regions. Reasonable range of each of the parameters should be established.

4.1.2.2 Interaction between LAI and $\theta_i$

As indicated by Jacquemoud (1993) and Jacquemoud et al. (1995), the multiple local minima are also caused by the interactive natures of two geometric parameters in the model: LAI and $\theta_i$. For example, a small value of LAI combined with a low $\theta_i$ value can give a very similar spectrum as one that is simulated with a large LAI and a high $\theta_i$ value. As a result, the inversion procedure may converge on solutions far from true values of the parameters.

An illustration of the interaction between LAI and $\theta_i$ is shown in table 4.1 and in figure 4.1. Table 4.1 shows that, because of the interaction between LAI and $\theta_i$, when a measured canopy reflectance is used as input in the model inversion procedure, several different combinations of parameter values can be obtained. A simulation spectrum using the parameter values in table 4.1 were then obtained and compared against the original measured spectrum in figure 4.2. In the figure, it can be seen that all of the three simulations follow the measured spectrum quite well, even though the parameter values used in the simulations are very different. Without a prior knowledge of the appropriate ranges of some or all of the parameters, it is challenging to determine which group of parameter values is appropriate.
Table 4.1 Illustration of the situation of multiple solutions. Different combinations of the LAI and \( \theta_l \) values resulted in different values of both \( C_w \) and \( N \). Without any prior knowledge on the parameters, it is hard to tell which group of parameter values is appropriate.

<table>
<thead>
<tr>
<th>( N )</th>
<th>( C_w )</th>
<th>LAI</th>
<th>leaf angle</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.022</td>
<td>1.25</td>
<td>40</td>
</tr>
<tr>
<td>3</td>
<td>0.015</td>
<td>2</td>
<td>56</td>
</tr>
<tr>
<td>3.77</td>
<td>0.0065</td>
<td>5.15</td>
<td>75.8</td>
</tr>
</tbody>
</table>

Figure 4.2 Comparison between a measured spectrum and spectra simulated using the parameter values in table 4.1. All the three simulations follow the measured spectrum quite well.
To remove the interaction between two correlated parameters, one approach is to set one parameter to a known value and use it as a constant in the retrieval procedure (Jacquemoud et al., 1995). However, before either of the canopy geometry parameters can be assigned a fixed value in the calculation, the sensitivity of the inversion procedure to these parameters should first be studied to determine which parameter has lower sensitivity value in the inversion procedure.

4.1.3 Spiky characteristics of artificial light

Another major obstacle in the application of the PROSPECT+SAIL model in a controlled environment is attributed to the spectral characteristics of artificial light sources. Two types of lamps are commonly used in growth chambers: high-pressure sodium (HPS) vapor lamps, which emit predominantly orange light, and metal halide (MH) lamps, which produce a broad but noisy spectrum. Because of the non-continuity nature of the light source spectra, the canopy reflectance measured in the growth chamber was noisy in the visible (VIS) and near-infrared (NIR) region. This spiky nature of the spectrum, especially in the NIR range, made it difficult to perform model inversion to obtain reasonable solutions. Figure 4.3 shows the comparison between one spectrum acquired in a growth chamber and one simulated spectrum using the model. It is clear that while the measured spectrum follows the general trend of the green vegetation reflectance, the spikes in the near-infrared bands are uncharacteristic of the vegetation reflectance, and cannot be simulated using the PROSPECT+SAIL model. Meanwhile, it
is also clear from figure 4.3 that the model did a good job in describing spectral characteristics in the mid-infrared (1,300 – 2,500 nm) (MIR) region, in which major water absorption bands exist. Since the main goal of this study is to assess plant water status, it is of interests to ascertain whether or not the PROSPECT+SAIL model can be inverted using only the reflectance in the MIR range.

![Figure 4.3](image)

**Figure 4.3** A comparison between a reflectance spectrum measured in a growth chamber and one simulated using the PROSPECT+SAIL model. In the visible (VIS) and near-infrared (NIR) ranges, the model cannot follow the measured spectrum, because of spiky spectral nature of the artificial light sources. In the middle infrared range (MIR), where the major water absorption bands exist, strong agreement was found between the model simulated and measured spectra.
The general goal of this research was to reliably and accurately retrieve the values of the plant water content from the canopy reflectance by inverting the PROSPECT+SAIL model. The specific objectives were to: 1) determine the proper boundaries of the parameters using destructive measurement of canopy samples; 2) evaluate the geometrical parameters LAI and $\theta_l$ to determine which one is more sensitive to the inversion procedure, so that the less sensitive parameter can be assigned a measured value in the model inversion procedure; 3) study the invertibility of the model in the MIR range; 4) evaluate the accuracy of the retrieved plant canopy water status, represented by EWT, from measured canopy reflectance using the PROSPECT+SAIL model.

4.2 Materials and Method

4.2.1 Data collection

The canopy reflectance (400-2500 nm), the leaf area index (LAI), the canopy leaf inclination angle ($\theta_l$) and the fresh weight and dry leaf weights of 32 New Guinea Impatiens plants were collected individually for this study. A fiber optic probe was mounted at a position that was 20° from the nadir and 330-350 mm from the plant canopy. The fiber optic was connected to a spectroradiometer (PS-2, ASD, Inc., Boulder, Colorado) to collect reflectance. Spectral resolutions of the spectroradiometer were 1 nm in the visible band and 1.5 nm in the NIR and MIR bands. Each measurement was an average of 30 scans of the canopy.
The total leaf area of the plant canopy and top projected areas (TPCA) of each plant were collected to determine an LAI. The adaxial (upper) leaf area of each leaf were acquired using a video imaging system (ΔT Area Meter, Delta-Devices Ltd, Cambridge, UK). TPCA was defined as the area enclosed by the outline of a plant canopy when viewed from the top. The LAI of each plant was calculated using equation 2.

\[
\text{LAI} = \frac{\text{Total Leaf Surface Area}}{\text{TPCA}} \quad (2)
\]

The inclination angle of a plant canopy is an average of all the inclination angles of the individual leaves in a canopy, measured using protractors. Also measured was the fresh weight of each leaf. The leaves were then put into a drying oven at 75°C for 48 hours. The difference between the fresh weight and dry weight of the leaves was the water content of the leaves, and EWT of the leaves was calculated from the measured leaf surface areas and the water content, using equation (3).

\[
\text{EWT} = \frac{\text{Total Leaf Fresh Weight} - \text{Total Leaf Dry Weight}}{\text{Total Leaf Surface Area}} \quad (3)
\]

Using these destructive measurements, the boundaries of the parameters in the model, or the searching domains of the inversion procedure were determined.

### 4.2.2 Sensitivity analysis on LAI and leaf inclination angle

To determine the sensitivity of LAI on the Cw retrieval using the NIR and MIR ranges reflectance, simulated spectra were first generated. Since no chlorophyll-absorbing band exists in this range, Cab is not needed in the reflectance simulation. Thus
the spectra were generated using assigned N, Cw, θl, and LAI values. The spectra were then inverted to retrieve possible values of the parameters, i.e N, Cw, θl, and LAI, in the model. Cw values in the solution sets that have LAI values similar to those that were initially assigned were compared and used as an indication of how varied LAI values can affect the water status assessment. Constant parameter values used to generate spectra were N=1.5, Cw=0.0255 cm and θl = 45°. Nine LAI values were used including base values, ±15% and ±30% of the base values. Base LAI values used in this study were 1, 2 and 3.

A similar approach was used to study the effect of varied θl values on the Cw retrieval. The canopy reflectance were first simulated using the constant parameter values: N=1.5, Cw=0.0255 cm, LAI=3. θl had base values of 15°, 45°, 65°. Base values ±15% and ±30% were used to evaluate the sensitivity of θl in the model.

The algorithm used for the inversion was the Levenberg-Marquardt algorithm (Marquardt, 1963). This algorithm is a compromise between the steepest descent method and the Gauss-Newton method, thus combining the stability of the steepest descent method and the fast convergence speed of the Gauss-Newton method. Another advantage of this method is that it allows user defined search domains to define the boundaries of the dependent variables to be estimated. It also does not require the calculation of the second derivative of the function. The algorithm in C code from Reich (1992) was modified to link the inversion algorithm with the PROSPECT+SAIL model.
4.2.3 Model inversion using MIR reflectance

The determination of Cw using only MIR reflectance was studied using the PROSPECT+SAIL model simulated spectra. There is no absorption band of chlorophyll a+b in this waveband in MIR, therefore Cab was left out and only Cw, N, LAI, and θ₁ were considered in this study. Thirty-six canopy reflectance spectra from 1,320 nm to 2,500 nm were generated using the values listed in table 4.2.

<table>
<thead>
<tr>
<th>N</th>
<th>Cw (cm)</th>
<th>LAI</th>
<th>θ₁(°)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.5</td>
<td>0.0200</td>
<td>2.00</td>
<td>25.0</td>
</tr>
<tr>
<td>2.5</td>
<td>0.0300</td>
<td>3.00</td>
<td>45.0</td>
</tr>
<tr>
<td></td>
<td>0.0400</td>
<td></td>
<td>65.0</td>
</tr>
</tbody>
</table>

Table 4.2 Values of each parameter used in the simulations

To evaluate the performance of the inversion procedure in the MIR range, new sets of parameter values were retrieved from the simulated spectra with an initial guess: N=1.5, Cw=0.0255 cm, LAI=3 and θ₁=35°.

4.2.4 Evaluation of the Cw retrieval

The Cw in terms of EWT of each of the plants was retrieved from the measured canopy reflectance by inverting the PROSPECT+SAIL model. In the inversion calculation, the performances of three different strategies were evaluated. In the first
strategy, reflectance in both the NIR and the MIR bands were used as input in the inversion procedure. The spectral range was between 760 nm and 2,500 nm, containing reflectance at 88 different wavelengths. The values of all the four parameters in the model were searched by the inversion procedure. In the second strategy, the inputs were also the reflectance in the NIR and the MIR range. However, the geometric parameter that was determined to be less influential to the inversion calculation was individually assigned a predetermined value for each plant. Only three parameters, therefore, were searched in the inversion procedure. In the third strategy, the input of the model was restricted to MIR reflectance that ranged from 1320 nm to 2500 nm represented by 60 evenly distributed wavelengths. The values of three parameters were searched, with one geometric parameter assigned value that is measured from individual plants.

To ensure that the model inversion procedure found the global minimum instead of local minima an exhaustive searching approach was executed. The search was initiated from all possible points in the search domain that would result in multiple local convergent locations defined by sets of searched variable values. A comparison among the fitting criterion values of all convergent points defined by equation (1) was performed and the combination of parameter values that gave the lowest fitting error was chosen as the final inversion result or the global minimum.
4.3 Results and Discussion

The boundaries of the model parameters, the sensitivity of the geometric parameters in the model inversion and the invertibility of the model using only the MIR spectrum are reported below. Also reported is the evaluation on the accuracy of the retrieved plant canopy water status.

4.3.1 Boundaries of model parameters

The average, maximum and minimum values of leaf area index (LAI), canopy leaf inclination angle ($\theta_l$), and plant water status (Cw), represented by equivalent water status (EWT) that were obtained from the New Guinea Impatiens plants by destructive measurement, are shown in table 4.3.

The maximum and minimum values of LAI and EWT in the table were used to define the boundaries of the parameters. To ensure that the inversion procedure could cover a more realistic searching domain, the boundary values for the parameters were determined using the measured values as references. For LAI, the boundaries were set to be 4 and 1. The boundaries of $\theta_l$ were between $85^\circ$ and $15^\circ$ and the Cw value was between 0.05 cm and 0.01 cm. The value of the leaf internal structure (N) was difficult to measure physically. According to Jacquemoud and Baret (1990), however, N values ranging from 1 to 3 represent a significant change in leaf internal structure. Therefore, N is defined as having a value between 1 and 3.
<table>
<thead>
<tr>
<th></th>
<th>LAI</th>
<th>$\theta_l$ (°)</th>
<th>Cw (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>1.38</td>
<td>35.0</td>
<td>0.0365</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.78</td>
<td>66.0</td>
<td>0.0434</td>
</tr>
<tr>
<td>Minimum</td>
<td>1.08</td>
<td>12.5</td>
<td>0.0283</td>
</tr>
</tbody>
</table>

Table 4.3 Range of the parameters. The measured average, maximum, and minimum values of leaf area index (LAI), leaf zenith angle ($\theta_l$), and the water thickness (Cw) of the 32 New Guinea Impatiens plants.

**4.3.2 Sensitivity analysis**

Sensitivity analysis on LAI and $\theta_l$ indicated that the inversion procedure of the model was less sensitive to $\theta_l$ (table 4.4). The first four columns of the table 4.4 show that when LAI values were decreased by 30% from the original LAI values of 3, 2, and 1, the retrieved Cw values became 36% (LAI=2.10), 27% (LAI=1.40) and 8% (LAI=0.70) higher than the original values. On the other hand, when $\theta_l$ values were decreased 30% from 65°, 45°, and 15°, the retrieved Cw values became 24% ($\theta_l=45.5°$), 15% ($\theta_l=31.5°$), and 2% ($\theta_l=10.5°$) higher than that of using the original leaf inclination angles. The effects of changing $\theta_l$ are shown in last four columns in table 5.4. Other data in the table 5.4 also showed similar contrasts between LAI and $\theta_l$ when they were varied by -15%, +15%, and +30%. When $\theta_l$ was increased 15% from 65° to 84.5°, the inversion procedure could not converge, thus the NA in table 4.4.
As suggested by the data from the sensitivity study, water status assessment using the PROSPECT+SAIL model is more sensitive to the change in LAI value than the change in $\theta_l$. Therefore, it is better to assign a fixed value to $\theta_l$ for the model inversion procedure. This result is contrary to what was reported by Jacquemoud (1993) who performed similar analysis using simulated spectra. However, Jacquemoud et al. (1995) did point out that LAI was one of the most important variables for determining growth and yield of the plants, and thus did not assign any fixed value to LAI in an effort to extract the biophysical information of sugar beet from canopy reflectance data (Jacquemoud et al., 1995).
<table>
<thead>
<tr>
<th>LAI</th>
<th>change in LAI (%)</th>
<th>Cw (cm)</th>
<th>change in Cw (%)</th>
<th>$\theta_l$</th>
<th>Change in $\theta_l$ (%)</th>
<th>Cw (cm)</th>
<th>Change in Cw (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.10</td>
<td>-30</td>
<td>0.0348</td>
<td>36</td>
<td>45.5</td>
<td>-30</td>
<td>0.0317</td>
<td>24</td>
</tr>
<tr>
<td>2.55</td>
<td>-15</td>
<td>0.0297</td>
<td>16</td>
<td>55.3</td>
<td>-15</td>
<td>0.0277</td>
<td>9</td>
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<tr>
<td>3</td>
<td>0.0255</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>65</td>
<td>0.0255</td>
</tr>
<tr>
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<td>0.0221</td>
<td>-13</td>
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<td>-12</td>
</tr>
<tr>
<td>3.90</td>
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<td>30</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.40</td>
<td>-30</td>
<td>0.0324</td>
<td>27</td>
<td>31.5</td>
<td>-30</td>
<td>0.0293</td>
<td>15</td>
</tr>
<tr>
<td>1.70</td>
<td>-15</td>
<td>0.0287</td>
<td>13</td>
<td>38.3</td>
<td>-15</td>
<td>0.0281</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
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<td></td>
<td></td>
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<td>0.0255</td>
</tr>
<tr>
<td>2.30</td>
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<td>0.0227</td>
<td>-11</td>
<td>51.8</td>
<td>15</td>
<td>0.0226</td>
<td>-11</td>
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<td>30</td>
<td>0.0202</td>
<td>-21</td>
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<td>30</td>
<td>0.0211</td>
<td>-17</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>0.70</td>
<td>-30</td>
<td>0.0276</td>
<td>8</td>
<td>10.5</td>
<td>-30</td>
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<td>2</td>
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<tr>
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<td>0.0268</td>
<td>5</td>
<td>12.8</td>
<td>-15</td>
<td>0.0259</td>
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<td>1</td>
<td>0.0255</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>15</td>
<td>0.0255</td>
</tr>
<tr>
<td>1.15</td>
<td>15</td>
<td>0.0240</td>
<td>-6</td>
<td>17.3</td>
<td>15</td>
<td>0.0251</td>
<td>-2</td>
</tr>
<tr>
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<td>0.0225</td>
<td>-12</td>
<td>19.5</td>
<td>30</td>
<td>0.0249</td>
<td>-2</td>
</tr>
</tbody>
</table>

Table 4.4 Sensitivity analyses. Inversion results of simulated spectra defined by N=1.5, Cw=0.0255, LAI=1, 2, 3, and $\theta_l = 45^\circ$ (left half). In each case, LAI is kept fixed to a value near the values listed above. Inversion of synthetic spectra defined by N=1.5, Cw=0.0255, LAI=3, and $\theta_l = 15^\circ, 45^\circ,$ and $65^\circ$ (right half). In each case, $\theta_l$ is kept fixed to a value close to the values listed above.
4.3.3 Invertibility of the model using MIR reflectance

The performance of using MIR reflectance to retrieve Cw was evaluated using artificially generated spectra as described in Section 4.2.3. The inversion procedure converged using every simulated spectrum. The obtained parameter values were very close to the original values. The RMSE of the calculated EWT values was in fact zero. This result suggested that the PROSPECT+SAIL model is invertible using only reflectance in the MIR waveband.

4.3.4 Evaluation of Cw retrieval

The three searching strategies were evaluated for the Rw retrieval. To facilitate the discussion of various searching strategies, “Complete Search” is designated when both NIR and MIR information were used as the model input to search all of the four parameters. “Search w/ Fixed Angle” is similar to the previous strategy except \( \theta_l \) was assigned a value for each plant and only three other parameters were searched. Lastly, “MIR Search W/ Fixed Angle” strategy used only the MIR reflectance as the model input to search Cw, N, and LAI. A comparison between the retrieved EWT values using the three strategies and the measured EWT values of the 32 plants is shown in figure 4.4.

Of the 32 measured spectra, the inversion process converged on 31 of them. It can be seen that the Complete Search strategy had the lowest accuracy in retrieving EWT. The data series was labeled as “□” in the figure. This low accuracy was probably caused by the noise contamination in the NIR range and the interaction between LAI and \( \theta_l \) of
the model. Improved Cw value retrieval was gained when the Search w/ Fixed Angle strategy was implemented. The retrieved EWT values had a tighter distribution and better one-to-one correspondence with the measured EWT as indicated by the 45° line in figure 5 (data series labeled as “○” in the figure). However, the values retrieved this way mostly overestimated the EWT values. This overestimation may have been induced by the noise in the NIR range. The best performance was found with the MIR Search W/ Fixed Angle strategy that resulted in the smallest root mean square error (RMSE) of 0.0038 cm among the three groups of the data. The data were labeled as “▲” in the figure.
Figure 4.4 Comparison of the values of the retrieved EWT from the different strategies and the measured values. The values retrieved using only MIR reflectance, fixed $\theta_l$ to search $C_w$ show the highest accuracy. $C_w$ was measured in equivalent water thickness (EWT).
To further investigate if the inversion procedure could be simplified, the EWT values were retrieved again with one leaf angle, 35°, assigned to all the plants. The value was in fact the average leaf inclination angle of all the measured plants. The effects on the accuracy of the retrieved EWT values of using static leaf angle value and an adaptively assigned leaf angle was compared in figure 4.5. In this figure, it can be seen that as the EWT was retrieved when the leaf angle was assigned a static value of 35°, the RMSE equaled 0.0073 cm. When the leaf angle was assigned a specific measured value for each individual plant, the RMSE was decreased to 0.0038 cm. This result suggested that it was better to have the leaf inclination angle assigned at a specific value for each individual plant. Measuring the average leaf inclination angle of each individual plant is time consuming and impractical in real time application. However if needed, images of plant top project area can be acquired and the information on the average leaf inclination angle can be retrieved from the images.
In the introduction part, it has been pointed out that the efforts to extract canopy chemical content by translating leaf-level relationships to canopy scale were greatly affected by the canopy geometry. For this reason, the application of the empirical methods was rather approximate. On the other hand, from the above discussion, it can be seen that the PROSPECT+SAIL model could simulate the canopy reflectance with
different canopy geometry. The change in canopy geometry of a plant would not affect the calculation of chemical content as much, as long as a reasonable calculation range has been define. The property makes the model inversion method a more robust and more preferable method than the empirical/semi-empirical methods.

4.4 Conclusions

A searching procedure was developed to determine water status of New Guinea Impatiens plants grown under artificial lights. Major effort in establishing the procedure was taken to avoid improbable local minima while searching for the best combination of plant biochemical and biophysical parameters that would produce a spectral curve matching the measured canopy spectral reflectance. Steps taken to improve the accuracy of the equivalent water thickness (EWT) retrieval by inverting the PROSPECT+SAIL model were 1) to define the boundaries of dependable variables in the model, 2) to eliminate correlated dependable variables in the model by first conducting a sensitivity analysis, and 3) to evaluate the model’s performance using only spectral information in a range between 1300-2500 nm.

Reasonable ranges of LAI, leaf inclination angle ($\theta_l$) and EWT were established to better define the searching domain of the model inversion process. The measured ranges were 1.08-1.78, 12.5°-66°, and 0.0283 – 0.0434 mm for LAI, $\theta_l$ and EWT, respectively.

Leaf area index (LAI) and leaf inclination angle ($\theta_l$) in the model were found to be correlated that could cause ambiguity in the model inversion results. Sensitivity analyses
were performed and $\theta_l$ was identified as a parameter that should be fixed as a constant during the model inversion procedure.

The performance of the water status assessment using only the MIR spectral information was found to be satisfactory. Accurate EWT values were retrieved without spectral information in visible and near infrared ranges where artificial lights caused spiky reflectance distribution that could not be reproduced by the PROSPECT+SAIL model.

The most accurate water status assessment under artificial lighting was obtained using the following procedure. By adaptively assigning $\theta_l$ values for individual plants, searching solutions in the pre-defined domain, and using only MIR reflectance, the model was able to estimated EWT with an accuracy of the root mean square equal to 0.0038 cm. That is approximately 10% of average EWT of the New Guinea Impatiens plants.
4.5 References


CHAPTER 5

MODEL BASED MULTISPECTRAL DROUGHT STRESS DETECTION

5.1 Introduction

A procedure that can reliably and accurately retrieve the equivalent water thickness (EWT) of a plant from the canopy reflectance by inverting the PROSPECT+SAIL model was discussed in Chapter 4. The feasibility of using the retrieved EWT for the plant drought stress detection was studied further.

The goal of this chapter was to evaluate the model based multispectral approach for the drought stress detection. The objectives included: 1) to compare the EWT and the ET of the treatment plants; 2) to compare the EWT of the treatment and the control plants; 3) to establish EWT threshold value and evaluate its performance for drought stress detection.
5.2 Materials and Method

5.2.1 Data collection

In the growth chamber experiments described in chapter 1, the weight change of each plant was collected and the daily ET calculated. Also collected was the canopy reflectance of each plant. A fiber optic probe was mounted at a stationary position that was 20 degrees from the nadir and 330 mm – 350 mm from the plants’ canopy. The fiber optic probe was connected to a spectroradiometer (PS-2, ASD, Inc., Boulder, Colorado) to collect reflectance data in the spectral range of 400 – 2,500 nm. The resolution was 1 nm in the visible band and 1.5 nm in the near- and mid-infrared band. The measurement of a plant’s canopy reflectance was made when the plant was positioned underneath the fiber optic sensor. Each measurement was an average of 30 scans of the canopy. In most days, a total of seven reflectance spectra, collected every 2 hours, from each plant were collected in the lighting period. In some days, since the experiments were not started at exactly the same time as in other days, so six instead of seven spectra of each plant were collected.

5.2.2 Water status extraction

The model inversion approach was utilized to extract the plants’ water status value from the measured canopy reflectance. The model implemented was the PROSEPCt+SAIL model described in Chapter 4. The model inversion procedure
determined in Chapter 4 was applied in retrieving water status of the plants from the measured spectra.

5.2.3 **Drought stress detection**

This part discusses the difference between the EWT values of the drought stressed plants and the well-watered plants, and the relationship between the EWT values and the ET rate of the plants. Also discussed is the performance of extracting EWT threshold values for drought stress detection.

5.2.3.1 **Differences between well-watered and drought stressed plants**

The retrieved EWT values of the treatment plants were first compared with those of the control plants so as to determine whether or not there were differences in the EWT values of the treatment and the control plants. To further determine if the EWT values could be used in differentiating between the well watered and the drought stressed plants, a threshold value was determined for each experiment to separate treatment and control plants.
5.2.3.2 Comparison between EWT and ET of the treatment plants

When a plant experiences drought stress, the water supply from the soil cannot compensate for the transpirational demand driven by the environment, and thus the ET rate of the plant decreases. At the same time, the leaf water content may also decease because of the insufficient water supply to the leaf.

The relationship between the EWT and the ET of the drought stressed plant was studied. The Pearson’s coefficient of correlation between these two parameters was first calculated. Afterwards, the decreasing rate of all of the parameter during the experiment was compared against one another. The decreasing rate of EWT was calculated using the following equation:

\[
EWT\_Decreasing\_rate(i, j) = \frac{EWT(i, j) - EWT(1, j)}{EWT(1, j)} \times 100 \tag{1}
\]

Where \(EWT\_Decreasing\_rate(i, j)\) was the plant j’s decreasing rate of EWT on the ith day of the experiment, \(EWT(i, j)\) was the EWT of plant j on ith day, and \(EWT(1, j)\) was the EWT value of plant j on day one of the experiment.

\[
ET\_Decreasing\_rate(i, j) = \frac{ET(i, j) - ET(1, j)}{ET(1, j)} \times 100 \tag{2}
\]

Where \(ET\_Decreasing\_rate(i, j)\) was the decreasing rate of ET of plant j on the ith day of the experiment, \(ET(i, j)\) was the ET rate of plant j on ith day, and \(ET(1, j)\) was the ET value of plant j on day one of the experiment.
5.2.3.3 Water stress detection

The ET threshold value to define the occurrence of incipient water stress was determined using the mean minus two standard deviations of the ET rates of the control plants. When the ET rate of a treatment plant fell below this threshold value, the plant was identified as under drought stress.

To determine if and when EWT can detect the occurrence of water stress, an EWT threshold value for determining the occurrence of drought stress was calculated from the EWT of the control plants. It was defined as the average EWT values of the control plants minus two standard deviations of the EWT values. A treatment plant was identified as being drought stressed whenever the EWT value of the plant was lower than the threshold value. After the analysis, the detected occurrence time of drought stress was compared with that defined by ET to study how well EWT could be used to predict the plant drought stress.

5.3 Results and Discussion

5.3.1 Comparison between EWT of the dehydrating and the well-watered plants

The comparison between the EWT values of the treatment and the control plants in each experiment is shown in figures 5.1(a-e). The comparison indicates that, at the beginning of each experiment, the EWT values of the treatment plants and those of the control plants were at the same levels. As the experiment progressed, the treatment plants
started to lose water, and the EWT of the treatment plants became thinner. At the same time, the EWT of the control plants remained at consistent levels during the experiments.

In Exp 2 (figure 5.1 a), the EWT of the treatment plants became lower than 0.020 cm 4 days after the experiment started while the control plants had higher than 0.020 cm EWT throughout the experiment. The EWT values of all the three treatment plants became lower than 0.035 cm four days into Exp 3. Those of the control plants were higher than this value throughout the experiment (Figure 5.1 b).

In Exp 4 (Figure 5.1 c), water was added to Plant(4, t1) and Plant(4, t2) on day 5, and to Plant(4, t3) on day 6, when the stress symptoms were visually detected. After the re-irrigation, the EWT values of Plant(4, t1) and Plant(4, t2) increased slightly during the following day, but did not increased over 0.035 cm. Afterwards the EWT values of these two plants continued to decrease until the end of the experiment. The EWT value of Plant(4, t3) became higher than 0.035 cm two days after the re-irrigation and reached its highest level at 0.0414 cm the next day. Then the EWT value of Plant(4, t3) began to decrease again. In the last day of the experiment, the EWT of Plant(4, t3) became lower than 0.035 cm again.

In Exp 5 (Figure 5.1 d), drought stress was visually detected on Plant(5, t1), Plant(5, t2) and Plant(5, t3) on days 10, 11 and 12, respectively. At the time of visual detection, the EWT values of all three treatment plants was lower than 0.022 cm. Water was added to the treatment plants after the visual detection. After the re-irrigation, the EWT values of all the treatment plants did rebound but remained less than 0.022 cm.
After the brief recovery, the EWT values continued to decrease until the end of the experiment.

The EWT values of all the treatment plants in Exp 6 (Figure 5.1 e) were relatively low at the beginning of the experiment. In the first three days, the EWT values of all the plants increased continuously. During these three days, there was no obvious difference between the EWT values of the treatment and the control plants. After day 5, the EWT values of Plant(6, c1) and Plant(6, c3) maintained at a relatively stable level. However, EWT of Plant(6, c2) started decreasing, and became lower than the EWT values of the treatment plants. At the time of visual detection, the EWT value of 0.021 cm separated the well watered and the drought stressed plants.

It was observed that the EWT values of the plants could be used in the drought stress detection. The plants used in Exps 2, 5 and 6 were of the variety Paradise Red on Pink. According to the results presented in Chapter 3, an EWT value around 0.020 cm corresponds to an RWC value around 70%, which is the value that might indicate the occurrence of the plant drought stress (Hunt, 1991). This relationship indicates that the retrieved EWT value could be used as a quantitative indicator for the plant drought stress detection.

Also observed was that the EWT threshold values of different varieties were different. The plants used in Exp 3 and 4 were of the variety Pure Beauty Red on Pink. In these two experiments, the critical values that separated the well-watered and drought stressed plants were higher than the values in the other three experiments but similar to each other at around 0.035 cm. This indicated that the EWT values of the Pure Beauty
variety were thicker than those of the Paradise variety, and that the critical EWT values of different varieties should be different. Also, referring to Hunt’s (1991) reports, the EWT values of 0.035 cm in the plants of Pure Beauty Red on Pink should correspond to the RWC values below 70%.

Figure 5.1 Daily average EWT values of the plants in the experiments. Sub-figures a to e contains information of the EWT of the plants in Exps 2 to 6. As drought stress developed, the EWT values of the treatment plants became lower than those of the control plants. The lines in the figures indicate the critical EWT values that separate the treatment plants from the control plants. The arrows in the figure indicate the visual detection of drought stress on each treatment plant. (Continued)
Figure 5.1: Continued
Figure 5.1: Continued

Exp 5

Exp 6
5.3.2 Comparison between EWT and ET of the treatment plants

5.3.2.1 Relationship between EWT and ET

The values of Pearson’s correlation coefficient between EWT and ET in each experiment are shown in table 5.1. The table shows that the Pearson’s correlation coefficient between EWT and ET was positive in each experiment. This result implies that the two parameters were positively linearly correlated with one another, which in turn means that, in general, the EWT of a plant may decrease when ET of the plant decreases and *vice versa*. However, it can also be seen that the values of the correlation coefficients were not high, ranging from 0.538 in Exp 6 to 0.734 in Exp 3.

<table>
<thead>
<tr>
<th>Exp</th>
<th>Pearson’s coefficient of correlation between all EWT and ET values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exp2</td>
<td>0.551</td>
</tr>
<tr>
<td>Exp3</td>
<td>0.734</td>
</tr>
<tr>
<td>Exp4</td>
<td>0.631</td>
</tr>
<tr>
<td>Exp5</td>
<td>0.625</td>
</tr>
<tr>
<td>Exp6</td>
<td>0.538</td>
</tr>
</tbody>
</table>

Table 5.1 Pearson’s coefficient of correlation between EWT and ET calculated using all the EWT and ET values in the experiments.

When a plant was well-watered, the ET rate of the plant would increase when the environmental demand increased, or, it would decrease when the environmental demand decreased. Meanwhile, the EWT value of a well-watered plant would maintain relatively stable, because the water content of such a plant was relatively stable (Moonney and
Winner, 1991). On the other hand, as a plant was under drought stress, both the ET rate and the EWT value of the plant would gradually start to decrease, and thus the linear correlation between the two parameters should be stronger. So, it was of interests to study the relationship between the EWT values and ET rate when both of them were decreasing. The Pearson’s coefficient of correlation between these two parameters was thus calculated again, using only those decreasing values. The re-calculated values are listed in table 5.2. In the table, it can seen that the linear correlation is more pronounced between the decreasing EWT values and ET rates, with the Pearson’s coefficient value varying from 0.655 in Exp 4 to 0.781 in Exp 5.

<table>
<thead>
<tr>
<th></th>
<th>Exp2</th>
<th>Exp3</th>
<th>Exp4</th>
<th>Exp5</th>
<th>Exp6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pearson’s coefficient of correlation between all EWT and ET values</td>
<td>0.714</td>
<td>0.741</td>
<td>0.655</td>
<td>0.781</td>
<td>0.668</td>
</tr>
</tbody>
</table>

Table 5.2 Pearson’s coefficient of correlation between EWT and ET calculated using those decreasing EWT and ET values. The linear correlation is more pronounced between decreasing EWT and ET.

5.3.2.2 Changing rate of EWT and ET

To further study the relationship between EWT and ET, the rate change of EWT and ET were compared. The comparisons are shown in figures 5.2 (a-e), where, in general, EWT did not decrease as much as ET.
In Exp 2 (Figure 5.2 a), by the time the drought stress was visually detected in each plant, the EWT values of Plant(2, t1), Plant(2, t2) and Plant(2, t3) decreased by 22%, 6% and 7%, respectively. At same time span, the ET rates of the plants decreased by 62%, 68% and 69%, respectively. In Exp 3 (Figure 5.2 b), at the time of visual detection of the drought stress, the EWT values of Plant(3, t1), Plant(3, t2) and Plant(3, t3) decreased by 14%, 10% and 11%, respectively. At the same time, the ET rates of the plants were 54%, 55% and 48% lower than the original values.

In experiment 4 (Figure 5.2 c), at the time when drought stress was visually detected, the EWT values of Plant(4, t1), Plant(4, t2) and Plant(4, t3) were 25%, 58% and 21% lower than the original values, respectively. The EWT value of each treatment plant rebounded to different extents after the re-irrigation, and continued to decrease afterwards. At the end of the experiment, the EWT values of the treatment plants were 54%, 57% and 20% lower than the original values, respectively. The ET rates of the treatment plants decreased at a much faster rate than the EWT values did before the re-irrigation. One day before the visual detection of drought stress on Plant(4, t1) and Plant(4, t2), the ET rates of these two plants became 70% and 55% lower than their original values, respectively. On the day the drought stress was visually detected on Plant(4, t3), the ET rate of the plant was 68% lower than its original value. After re-irrigation, the ET values of the plants increased for one to two days, but never recovered to their original levels. After the brief recovery, the ET rates continued to decrease. At the end of the experiment, the ET rates of the plants were 58%, 43% and 51%, respectively, lower than the original values.
In Exp 5 (Figure 5.2 d), the EWT values of Plant(5, t1), Plant(5, t2) and Plant(5, t3) decreased by 6%, 19% and 18%, respectively, at the time of visual detection. The ET rate of Plant(5, t1) was 40% lower than the original value at the time of visual detection. The ET rates of Plant(5, t2) and Plant(5, t3) were 21% and 56% lower than the original values, respectively, at the time of visual detection. After the re-irrigation, the EWT values of the plant recovered briefly but continued to decrease afterward. On the other hand, the ET rates of the plants increased. At the end of the experiment, the ET rate of Plant(5, t2) was even 20% higher than the original value. Meanwhile, the ET rates of Plant(5, t1) and Plant(5, t3) increased to the levels that were still 27% and 45% lower than its original value.

In Exp 6 (Figure 5.2 e), when the drought stress on the plants was visually detected, the EWT value of Plant(6, t1) decreased by 22%, the EWT value of Plant(6, t2) decreased by 23% and the EWT value of Plant(6, t3) was 8% lower than the original value. The ET rates of the plants decreased more than the EWT values. When drought stress was visually detected, the ET rate of Plant(6, t1) was 53% lower than the original value, and the ET rates of Plant(6, t2) and Plant(6, t3) were 61% and 65% lower than the original values, respectively.

When the water supply from the soil to a plant cannot catch up with the environmental demand, the ET rate of the plant starts to decrease. At first, however, the plant may be able to partly compensate for the decreased supply by sacrificing part of the water reservoir in the cells, resulting in reduced leaf water content (Schulze, 1991), or in another word, lowered EWT values. With the development of drought stress, the
resistance to water vapor transfer from leaf into the air increases (Kacira, 2000), reducing the ET rate further. Since the decrease in EWT value occurs following the decrease in ET rate, and the change in the rate of decrease in ET affects the rate of decrease in EWT, so in general, the rate of decrease in EWT value of a drought stressed plant usually is slower and smaller than the decreasing rate of the ET of the plant.

Figure 5.2 Comparison between the change rate of ET rates and EWT values of the treatment plants in the experiments. Sub-figures a — e display the change rate of ET rates and EWT values of the treatment plants in Exps 2 – 6. As a general trend, the EWT value did not decrease as fast as ET rate did. (Continued)
Figure 5.2: Continued

Exp 3

Exp 4

(Continued)
Figure 5.2: Continued

![Graphs showing changes in ET and EWT for Exp 5 and Exp 6.](image)

- **Exp 5**: Graphs showing changes in ET and EWT for Experiment 5.
- **Exp 6**: Graphs showing changes in ET and EWT for Experiment 6.

Legend:
- ET_Plant(5, t1), ET_Plant(5, t2), ET_Plant(5, t3), ET_Plant(5, t4)
- EWT_Plant(5, t1), EWT_Plant(5, t2), EWT_Plant(5, t3), EWT_Plant(5, t4)

- **Change rate in ET (%)**
- **Change rate in EWT (%)**

X-axis: Duration (day)
Y-axis: Change in ET (%) and Change in EWT (%)

Note: The graphs illustrate the fluctuations in ET and EWT across different time points (t1 to t4) for Experiments 5 and 6.
5.3.2.3 Threshold value of EWT

The EWT threshold values and the EWT values of the treatment plants in each experiment were compared in figures 5.3. In the figures, the solid data points represent well-watered status defined by ET rates of the plants and those hollow points represent drought stressed status defined by ET rates. Using the EWT threshold values in drought stress detection, the type I error rate was 14.8% and the type II error rate was 26.1%, with well-watered status being the null hypothesis and the stressed status the alternative hypothesis.

The timing of drought stress on each treatment plant detected by EWT values was compared with the timing of ET defined incipient drought stress and the timing of visual detection. The comparison result is shown in table 5.3. From figure 5.3 and table 5.3, it can be seen that the EWT threshold values in each experiment were able to detect the drought stress defined by ET rate, though the timing of detection was later than that of the ET rate, which was reasonable, considering that EWT values decreased slower than ET rate did. On the other hand, of the 15 plants in the experiments, the EWT threshold values could detect the drought stress on 9 plants earlier than visual detection, on 5 plants at the same time as visual detection, and only on 1 plant later than visual detection.
<table>
<thead>
<tr>
<th>Experiments</th>
<th>Exp 2</th>
<th>Exp 3</th>
<th>Exp 4</th>
<th>Exp 5</th>
<th>Exp 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>EWT threshold value (cm)</td>
<td>0.020</td>
<td>0.035</td>
<td>0.031</td>
<td>0.023</td>
<td>0.021</td>
</tr>
<tr>
<td>Treatment plants</td>
<td>T1</td>
<td>T2</td>
<td>T3</td>
<td>T1</td>
<td>T2</td>
</tr>
<tr>
<td>Detection timing using EWT values (days after water withholding)</td>
<td>4</td>
<td>5</td>
<td>5</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>Timing of ET defined drought stress (days after water withholding)</td>
<td>4</td>
<td>5</td>
<td>5</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>Timing of visual detection (days after water withholding)</td>
<td>5</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>7</td>
</tr>
</tbody>
</table>

Table 5.3 Threshold values of EWT in the experiments and timing of drought stress detection by EWT values, ET rate and visual detection. The EWT threshold values were able to detect the drought stress defined by ET rate, and in most cases, were able to detect drought stress no later than visual detection.
Figure 5.3 EWT values of the treatment plants and the EWT threshold values in the experiments. Subfigure (a -- e) contain information in Exps 2 – 6. The solid data points in the figures represent the well-watered status defined by ET rate of the plants. The hollow data points represent the drought stressed status. The arrows in the figures indicate visual detection of drought stress on each treatment plant. (Continued)
Figure 5.3: Continued

![Graph showing data points for EWT (cm) over duration (day) for different plants under wellwatered and stressed conditions.]

(Continued)
Figure 5.3: Continued

![Graph showing water stress in plants over time.](image)

(Continued)
When comparing the threshold values in the experiments, it can be seen that the threshold values of the same varieties showed similarity. The Pure Beauty plants in experiments three and four had similar threshold values at 0.035 and 0.031 cm. The Paradise plants in Exp 2, 5 and 6 showed similar EWT threshold values of 0.020, 0.023 and 0.021 cm, respectively. Since the control plants were under minor stress during Exp 2, so the threshold value in Exp 2 was a little bit lower than the values in the other two experiments.

The results in this study indicate that the drought stress of New Guinea Impatiens plants generally occurs when the leaf relative water content (RWC) is lower than 70%.
Hunt (1991) once indicated the RWC range between 70-80% was critical. A plant could be defined as under drought stress if the RWC of the plant was lower than this range. According to equation (5) in chapter 3, the EWT threshold values in Exp 2, 5 and 6 corresponded to RWC values of 61%, 70.2% and 65%, respectively. These RWC values were just at the lower end of the critical RWC range defined by Hunt (1991). This agreement again suggested that the retrieved EWT values of the plants could be used to differentiate well-watered status and drought stressed status. The study on the ET-based classification and EWT-based classification, and the timing of EWT-based drought stress detection indicated that the EWT threshold values could detect the ET defined drought stress on the plants.

5.4 Conclusions

Data in this chapter demonstrated that the EWT values could be used to differentiate the drought stressed plants from the well-watered plants.

Comparison between the decreasing rate of the EWT values and ET rates of treatment plants showed that the EWT value decreased less than ET did as the drought stress developed.

The threshold values of the EWT were determined to be 0.020 to 0.023 cm for the New Guinea Impatiens variety Paradise Red on Pink, and 0.031 to 0.035 cm for the variety Pure Beauty.
The EWT threshold values determined in this study were consistent with the results found in the literatures, and the clustering analysis indicated that the threshold values could detect the ET-defined drought stress on the plants in the experiments. The relationship between the EWT and RWC values indicated that drought stress only occurred on the New Guinea Impatiens plants when the RWC value was low than 70%. It was also found out that the EWT-based method could detect the drought stress in most cases earlier than or at the same time as visual detection.

5.5 References


Bibliography


Appendix

Flow chart and Source Code for Water Retrieving Calculation
Start

Read in the measured reflectance

Initialize the value of LAI, Cw, Cab and N. Simulate the reflectance using the initial parameter values

Calculate the difference between the initial simulation and measured reflectance

Search for new parameter values. Simulate new spectrum. Calculate difference between new spectrum and measured reflectance

Yes

New simulation closer to measurement?

Yes

Calculation converges

End

No

Calculation converges

End
Figure A.1 Flow chart of water retrieval program

#include <stdio.h>
#include <stdlib.h>
#include "cbox1.h"  //math.h here not necessary

/*................................................................
int model; //model selector, useful in "predict"

//number of data and of parameters, resp. in C-language called from 0 to m-1, n-1
int m, n;

DATVEC x, response; //independent and measured data, m-vector

DATVEC refra, ke, kab, kw, km, rsoil; //for input of the absorption constants of leaf

/*start vector of parameters, of upper and lower permissible limits, n-vectors*/
PARVEC pstart, upper, lower;

/*optimal vector of parameters (if found), vector of standard deviations vector -d- of
scale factors vector -eig- of eigenvalues */
PARVEC popt, sdev, d, eig;

double sqsum; //final value of sum of squares

DATVEC fit; //predictions of measurements after fitting

BOOL fullresp, redundant, conver; //diagnostic indices of course of search

int it; //number of iterations as performed

MAT info, correl, bas, inv;

double angle;
void datinput(char aFileName[100]);
void frame(char inFileName[100]);
void finoutput(char ouFileName[100]);

void main(void)
{
    //a formal "main" calling the frame for the fitting procedure
int x, y, z;
char fileName[100];
FILE *inAngleFile;
inAngleFile = fopen("pilot_dpink_pwhite.txt", "r");

while ( ! feof(inAngleFile)) {
    fscanf(inAngleFile, "%s %lf", fileName, &angle); //reads data

    printf("filename is: %25s", fileName);
    printf("angle is: %lf", angle);
    datinput(fileName); //input of m, n, x, response, pstart, upper, lower

    for (x=1; x<=14; x++) {
        for (y = 1; y<=9; y++)
        {
            for(z = 1; z<=2; z++)
            {
                pstart[0]=1.0+x*0.1;
                pstart[1]=0.029+y*0.001;
                pstart[2]=1.0+z*0.1;
                frame(fileName);
            }
        }
    }
}
/*..........................................................................*/

void frame (char fileName[100])
{
    search();

    if (fullresp==TRUE || it > 1)
        finoutput(fileName);
    else //if not: no sense in calling output !
    {
        int i;
        printf("lack of response, check scale vector !");
        for (i=0; i<n; i++)
        {

    220
//Module Box 4: Input of Data (Routine Version)

#include <math.h>
#include <stdio.h>
#include "cbox1.h"

void datinput (char fileName[100])
{
    /* A simple way to transmit input data. Others are possible. */
    /* A predefined file "indata." is assumed, namely: int model, m, n, DATVEC
    x--response-pairs, PARVEC pstart-upper-lower triples */
    /* m is the number of data points, n is the dimension of parameter */
    extern int  m, n;
    extern DATVEC x, response;
    extern PARVEC pstart, upper, lower;

    //for input of the absorption constances of leaf
    extern DATVEC refra, ke, kab, kw, km, rsoil;

    int i, k;
    FILE *infile; // a file pointer

    printf("\nfullname is: %25s", fileName);
    infile = fopen(fileName, "r");
    fscanf(infile, "%i%i", &m, &n); //reads data

    for (k=0; k<m; k++)
        fscanf(infile, "%lf%lf", &x[k], &response[k]);

    for (k=0; k<m; k++)
        fscanf(infile, "%lf%lf%lf%lf%lf%lf", &refra[k], &ke[k],
               &kab[k], &kw[k], &km[k], &rsoil[k]);

    for (i=0; i<n; i++)
        fscanf(infile, "%lf%lf%lf", &pstart[i], &upper[i], &lower[i]);
} //end of "datinput" and of module box 4
void finoutput(char fileName[100])
{
 /* the final output and mathematical analysis of the final fit! */

 /* particular statistical quantities as calculated: */
 /* - optimal parameter set with standard error */
 /* - final value of fit criterion */
 /* - eigenvalues of correlation matrix */
 /* - optimal prediction versus measured response */
 /* - run test on residuals */
 /* - neighborhood correlation of residuals */
 /* - test on m/2 positive signs */
 /* - diagnostic booleans */

 /* the following globals are required for the final fit: */
 extern int it, m, n;
 extern double sqsum;
 extern PARVEC popt, sdev, eig, d;
 extern DATVEC response, fit;
 extern BOOL fullresp, conver, redundant;

 int i, k, pluses, runs;
 double rho, depot, store, ax1, ax2, ay1, ay2, ak;
 DATVEC dev;

 FILE *outfile;
 extern double angle;
 char outputFileName[150];
 sprintf(outputFileName, "c:\yangyang\results_canopy_4var\hb\%s", fileName);

 printf("noutcharf1ename is: %25s", outputFileName);
 outfile=fopen(outputFileName, "a+")get;
 if (eig[n-1]<CRITERION)
 printf("nAt least one redundant direction deleted!n");

 printf("nScole vector at final point:n");
 for (i=0; i<n; i++)
 {
  printf("%12f ",d[i]);
  if (i % 4 ==3) printf("n");
 }
depot=0.0;
    for (k=0; k<m; k++) depot += response[k];
if (depot > 0.0)
    depot = sqrt(sqsum/m) / depot*m*100;
if (depot > 0.0)
    depot = sqrt(sqsum/m) / depot*m*100;
fprintf(outfile, "%6.1f\n", depot);
/*
    for (k=0; k<m; k++)
        fit[k]=prosail(k,popt);

    for (k=0; k<m; k++)
        dev[k]=fit[k]-response[k];  /* residual vector */
ax1 = ay1 = ak = 0.0; runs=1;
if (dev[m-1]>0) pluses=1;
else pluses=0;
//the next lines are additions to get a succession of signs
if (dev[m-1]>0.0) printf("+\n"); else printf("-\n");

    for (k=0; k<m-1; k++)
    {
        if (dev[k]>0.0) pluses++;
        if (dev[k]>0.0) printf("+");
        else printf("-");
    //here end the added statements
    if (dev[k]*dev[k+1] <= 0) runs++;
    ax1 += dev[k];  /* sum of residual vectors */
    ay1 += dev[k+1];
    }
ax1 /= (m-1);
ay1 /= (m-1);  /* mean of residual vectors */
ax2=ay2=0.0;
for (k=0; k<m-1; k++)
    {
        ax2 += (dev[k]-ax1)*(dev[k]-ax1);
        ay2 += (dev[k+1]-ay1)*(dev[k+1]-ay1);
        ak  += (dev[k]-ax1)*(dev[k+1]-ay1);
    }
if (ax2*ay2 != 0.0) rho = ak/sqrt(ax2*ay2);
else rho=0.0;  /* neighborhood correlation coefficient */

if (fabs(rho) < 1.7/sqrt(m-1)) printf("not significant!\n");
else printf("significant! Indicates systematic deviations!\n");


printf("Number of plus deviations: %3i out of %3i: ", pluses, m);
if (m >= 6)
{
    if (fabs(2*pluses-m) < 1.645 * sqrt(m))
        printf("not significant!\n");
    else printf("significant! Outliers present?!\n");
}
else printf("not enough data for statistics!\n");
printf("Number of runs: %3i: ", runs);
depot=2.0 * pluses *(m-pluses) / m + 1.0;
if (pluses >= 4 && m-pluses >= 4)
{
    store=1.645*sqrt((depot-1)*(depot-2)/(m-1));
    if (runs<=depot+0.5+store && runs>=depot-0.5-store)
        printf("not significant!\n");
    else
        printf("significant! Indicates systematic trends!\n");
}
else printf("Not enough data for statistics!\n");

printf("Diagnostic indices: ");
if (conver==FALSE) printf("no ");
/*only if the convergence is obtained, will the starting parameter values, the final
parameter values, the fit criterium, the leaf angle, the iteration numbers be written into
the output file. */
else
{
    printf("convergence obtained.\n");
    fprintf(outfile, "convergence obtained. ");
    fprintf(outfile, "Starting parameter values: ");
    for (i=0; i<n; i++)
    {
        fprintf(outfile, "%16.4f", pstart[i]);
        if (i % 4==3) fprintf (outfile, "\n");
    }
    fprintf(outfile, "     Final parameter values:    ");
    for (i=0; i<n; i++)
    {
        fprintf(outfile, "%12f ", popt[i]);
    }
    fprintf(outfile, "     Fit criterion: %12f", sqsum);
    fprintf(outfile, "     The angle is now: %6.4f", angle);
    fprintf(outfile, "     Iterations: %i\n",it);
}
if (fullresp==FALSE)
    printf("Lack of response at final point!\n");
if (redundant==TRUE) printf("Parameter redundancy!\n");
else printf("No parameter redundancy!\n");
printf("Iterations until exit: %i\n",it);
fclose(outfile);
} /* end of "finoutput" and of module box 9 */

// Module box 5: Dumping input information

#include <math.h>
#include <stdio.h>
#include "cbox1.h"

void dumpdata (void)
{
//function echoes input data, for detection of format errors
    extern int model, m, n;
    extern DATVEC x, response;
    extern PARVEC pstart, upper, lower;

    extern DATVEC refra, ke, kab, kw, km, rsoil;
    int i, k;
    extern double angle;

    printf("\nNumber of observations: %3i", m);
    printf("\nNumber of parameters: %3i", n);
    printf("\n Leaf angle is: %6.4f", angle);

    printf("\nIndependent variable: \n");
    for (k=0; k<m; k++)
    {
        printf("%16.4f", x[k]);
        if (k % 4 == 3) printf("\n");
    }
    printf("\nResponse Vector\n");
    for (k=0; k<m; k++)
    {
        printf("%16.4f", response[k]);
        if (k % 4==3) printf ("\n");
    }
    printf("Absorption constances of leaf\n");

    {
for (k=0; k<m; k++)
{
    printf("%8.6lf %8.6lf %8.6lf %8.6lf %8.6lf %8.6lf\n", refra[k],
    ke[k], kab[k], kw[k], km[k], rsoil[k]);
}
printf("nStart vector, upper and lower limits: \n");

for (i=0; i<n; i++)
{
    printf("%16.4f", pstart[i]);
    if (i % 5==4) printf ("\n");
}
printf("n");

for (i=0; i<n; i++)
{
    printf("%16.4f", upper[i]);
    if (i % 5==4) printf ("\n");
}
printf("n");

for (i=0; i<n; i++)
{
    printf("%16.4f", lower[i]);
    if (i % 5==4) printf ("\n");
}
printf("n");

} //end of "dumpdata" and of module box 5

/*Module Box 6: checking input data */

#include <math.h>
#include <stdio.h>
#include "cbox1.h"

void checkinput (void)
{
    /* Calculation of initial fit criterion. Only if this is successful there can start
     a fitting cycle. User may add plausibility tests, e.g. limits of start-vector or
     others according to knowledge of data structure. */
    extern int m;
    extern DATVEC response;
    extern PARVEC pstart;
int k;
double fst, depot, acc;

depot=0.0;
for (k=0; k<m; k++)
{
    acc = prosail(k, pstart); //for debugging
    printf("%9.7lf %9.7lf %9.7lf\n", x[k], acc, response[k]);
    acc -= response[k];
    depot += acc*acc;
    acc=response[k];
    printf("response[%d]= ", k, response[k]);
}

fst = depot;

printf("Successful calculation, root of mean square %18.6f\n", sqrt(fst/m));

depot = 0.0;
for (k=0; k<m; k++)
    depot +=response[k];

if (depot>0.0) depot = sqrt(fst/m)/depot*m*100;

printf("\n in percent of average response: %8.1f\n", depot);

if (depot > 50.0) printf("\n High value ! Better start available ? ");
}

#include <math.h>
#include <stdio.h>
#include "cbox1.h"

void itoutput(void)
{
    extern double my,f;
    extern int it;

    /* during each iteration (counter it) the decadic exponent of    */
    /* my and f is displayed in one line. It is a short statement    */
    /* of what is going on during the iteration cycle              */

    /* Module Box 8: Output During Iteration                      */

    /* Module Box 8: Output During Iteration                      */

int expmy;
expmy = (int) (log10(my) + 0.5);
/* rounding the exponent of "my" */

if (my < 1) expmy--;
/* correcting in the case of a negative value */

} /* Module Box 10 : The Fitting Strategy "Search" */

#include <math.h>
#include <stdio.h>
#include "cbox1.h"

/* "Search" is the main routine that steers the curve fitting */
/* "Search" is called by "frame", requires globals from there */
/* "search" has a few own globals and constants. Definitions: */

double my,f,f1,fold;  /* my: damping factor; the f's fit criteria during iteration */

PARVEC dif,p,p1,pold,grad; /* dif: derivatives; p,p1 parameter values during iteration */

void search (void)
{
/* the following extern variables are defined and explained the head of "frame" */

extern int m,n;
extern DATVEC x, response;
extern PARVEC pstart, upper, lower;
extern PARVEC popt, sdev, d, eig;
extern double sqsum;
extern DATVEC fit;
extern BOOL fullresp, redundant, conver;
extern int it;
extern MAT info, correl, bas, inv;

BOOL success;
int i;
#if DBUG
   /* additional index for test output remove after debugging */
   int j;
#endif

my=0.01;            /* this starts step 1 */
it=0;
for (i=0; i<n; i++)
   p[i]=pstart[i];
f = squaresum (p);  /* initial sum of squares */
for (i=0; i<n; i++)
   pold[i]=p[i];
fold=f;

#if DBUG            /* test output, remove later */
   printf(" start parameters:\n");
   for (i=0; i<n; i++)
      printf("%18.6f",pstart[i]);
   printf("\n start sum of squares%18.6e",f);
#endif

do             /* main iteration loop, step 2 */
{
   success = FALSE;       /* step 3 */
   explore();           /* step 4 */

#if DBUG             /* test output, remove later */
   printf("\n\n iteration no.%2.1u",it);
   /* now special output after certain calls of explore */

   if (it<2)
   {
      /* info, grad and d as result from -fill- */

      printf("\n matrix info:\n");
      for (j=0; j<n; j++)
      {
         for (i=0; i<n; i++)
            printf("%18.6f",info[j][i]);
         printf("\n");
      }
      printf("\n gradient vector:\n");
   
#endif

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for (i=0; i<n; i++)
    printf("%18.6f",grad[i]);
printf("n scale vector d:\n");
for (i=0; i<n; i++)
    printf("%18.6f",d[i]);
printf("n BOOLEAN fullresp:%3.1u",fullresp);
printf("n correlation matrix after -scale\n");
    for (j=0; j<n; j++)
    {
        for (i=0; i<n; i++)
            printf("%18.6f",correl[j][i]);
        printf("n");
    }
/* now results from -decompse- */
printf(" eigenvector matrix\n");
for (j=0; j<n; j++)
    {
        for (i=0; i<n; i++)
            printf("%18.6f",bas[j][i]);
        printf("n");
    }
printf(" eigenvalues\n");
for (i=0; i<n; i++)
    printf("%18.6f",eig[i]);
printf("n");
}{ /* end output after -explore- */
#endif
it++;
/* step 5 */
if (fullresp==TRUE) /* step 6 */
while (my<=MYMAX && success==FALSE) /* step 7 */
    /* this starts the my-loop (damping loop) */
{
    find();
    /* step 8 */
#endif
/* output after certain calls of -find-, remove later */
#if DBUG
    /* output after certain calls of -find-, remove later */
    if (it==1 && my==0.01 || it==2)
    {
        printf("n matrix inv after call of find\n");
        for (j=0; j<n; j++)
            printf("%18.6f",bas[j][i]);
        for (j=0; j<n; j++)
            printf("%18.6f",eig[j][j]);
        printf("n");
    }
#endif
} /* end of function dot */


```c
    { 
      for (i=0; i<n; i++)
        printf("%18.6f",inv[j][i]);
      printf("n");
    }  /* end of if-loop */

    printf("n new p1-vector for my=%12.8f
",my);
    for (i=0; i<n; i++)
      printf("%18.6f",p1[i]);
    printf("n");

    if (inside(p1)==FALSE)
      printf(" new point is outside of permissible region, hence at once rejected\n");

    /* end of special output after "find" */

    #endif

    if (inside(p1)==TRUE)  /* step 9 */
    { 
      fl=squaresum(p1);  /* test of new parameter vector */

      #if DBUG
      /* output after new fit criterion, remove later */
      printf(" new fit criterion: %18.6e",f1);
      if (fl<f)
        printf("n accept new p1");
      else
        printf("n p1 not accepted");
      /* end of special output after fit criterion */
      #endif

      if (fl<f)  /* step 10 */
        /* better parameter vector */
      { 
        accept();  /* steps 11 and 12 */
        success=TRUE;  /* step 13 */
      }
    }  /* end of inside == TRUE */

    my *= 10.0;  /* step 14 */
    itoutput();  /* iteration output */
```
/* the "still progress" condition to continue the do-loop: */
while (it<ITMAX && success==TRUE &&
      significant(pold,p,fold,f)==TRUE); /* step 16 */

if (success==TRUE)
    explore(); /* step 17 */

if (fullresp==FALSE)
    conver=FALSE ;
else
    {
        redundant = FALSE;
        for ( i=0; i<n; i++)
            if (eig[i]<CRITERION)
                redundant = TRUE;
        find();
        if (m>n)
            for ( i=0; i<n; i++)
                sdev[i]= sqrt(inv[i][i]*f/(m-n));
        conver= significant(p,p1,f,f)==TRUE ? FALSE : TRUE ;
    }
for ( i=0; i<n; i++)
    popt[i]=p[i];
    sqsum=f;

/* end of search */
return;
} /* end of "search" and of module box 10 */

/* Module Box 11: Sum of Squares (Fit Criterion) */

#include <math.h>
#include <stdio.h>
#include "cbox1.h"

double squaresum (PARVEC p)
{
    /* calculates the sum of squared deviations (fit criterion) for the proposed parameter
     * vector p , without weighting */
/* requires global variables from "cbox1.h" int m, DATVEC response calls function "predict" */
extern int m;
extern DATVEC response;

double depot = 0.0;
double acc;
int k;

for (k=0; k<m; k++)
{
    acc = prosail(k,p) - response[k];
    depot += acc*acc;
}
return (depot);
} /* end of "squaresum" and of module box 11 */

/*-----------------------------------------------------------------------------*/

/* Module Box 12: Derivative of Functions */

#include <math.h>
#include <stdio.h>
#include "cbox1.h"

void derivative (int k)
{
    /* this function calculates, by a difference formula, the contribution of the k-th data
point to the derivative with respect to each one of the parameters, i.e. it fills the global
vector PARVEC dif. */
    /* "derivative" calls function "predict" */
    /* requires global variables from "cbox1.h" */
    /* int n, PARVEC p, and the constant INC (defined Box 10) */

    extern int n;
    extern PARVEC p, dif;

    PARVEC incp,decp; int j; double del,ps, finc, fdec;

    for (j=0; j<n; j++)
    {
        incp[j] = p[j];
        deep[j] = p[j];
    }
for (j=0; j<n; j++)
{
    ps = p[j];
    del = INC * ps;  /* "INC" is a global relative increment */
    if (ps==0.0)    /* defined in "cbox1.h" */
        del=INC;
    incp[j] = ps + del;  /* increased parameter value */
    deep[j] = ps - del;  /* decreased parameter value */
    finc = prosail(k,incp);  /* function value of incp */
    fdec = prosail(k,deep);  /* function value of deep */
    dif[j] = (finc-fdec)/2.0/del;  /* central difference formula */
    incp[j] = ps;  /* returning to original value */
    deep[j] = ps;
}

#if DEBUG
    /* test output, remove later! */
    printf("%4d%18.6f%18.6f%18.6f\n",k,dif[0],dif[1],dif[2]);
#endif

} /* end of "derivative" and of module box 12 */

/*---------------------------------------------------------------*/
/* Module Box 13 : Fill Information Matrix */
/*---------------------------------------------------------------*/

#include <math.h>
#include <stdio.h>
#include "cbox1.h"

void fill (void)
{
    /* this function fills the information matrix and the gradient by a difference procedure*/
    /*"fill" calls function "derivative" returning PARVEC dif */
    /* calls function "predict" */
    /* requires global variables from "cbox1.h" */

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extern int m,n;
extern DATVEC response;
extern PARVEC p, grad, d, dif;
extern MAT info;
extern BOOL fullresp;

int i,j,k;

fullresp=TRUE;
for (i=0; i<n; i++)
{
    for (j=i; j<n; j++)
        info[i][j]=0.0;
    grad[i]=0.0;
}
for (k=0; k<m; k++)
{
    derivative(k);
    for (i=0; i<n; i++)
    {
        for (j=i; j<n; j++)
            info[i][j] += dif[i] * dif[j];
        grad[i]    += dif[i]*(prosail(k,p)-response[k]);
    }
}
for (i=0; i<n; i++)
{
    d[i] =sqrt(info[i][i]);
    if (d[i]==0.0)
        fullresp=FALSE;
    for (j=0; j<i; j++)
        info[i][j]=info[j][i];
}
} /* end of "fill" and of module box 13 */

/*@ */
#include "cbox1.h"

void scale (void)
{
    /* this function reduces the global "info"-matrix to its scaled form "correl", using the
    scale vector "d" */
    /* requires global variables from "cbox1.h" */
    /* int n, PARVEC d, MAT info */
    /* returns global variable MAT correl */

    extern int n;
    extern PARVEC d;
    extern MAT info, correl;

    int i, j;

    for (i=0; i<n; i++)
        for (j=i; j<n; j++)
        {
            correl[i][j] = info[i][j]/d[i]/d[j];
            correl[j][i] = correl[i][j];
        }
}

/*---------------------------------------------------------------*/
/* Module Box 15: Eigenvalue Decomposition of Correlation Matrix */
/*---------------------------------------------------------------*/

#include <math.h>
#include <stdio.h>
#include "cbox1.h"

void decompose(void)
{
    /* symmetric n*n "bas", a correlation matrix, is transformed to its eigensystem by an
    iterative procedure due to H.F. Kaiser (Comp. J. 15 (1972) 271-273) */
    /* "bas" is overwritten; result is eigenvector matrix */
    /* n-vector "eig" receives eigenvalues decreasingly ordered */

    /* requires global int n */
    /* requires and changes global MAT bas */
    /* fills PARVEC eig */

    extern int n;
extern MAT bas;
extern PARVEC eig;

#define EPSANGLE 1.0E-8
#define ITBOUND 10

double scalprod,ww,wij,wih,jlong,hlong;
int i,j,h,ki,ni,itcount;
double teta,cteta,steta,flip,ac,le;

#if DEBUG     /* testoutput 1, remove later */
    /* some counters declared: */
    int absww, abscal, wwcount, scal2, g;
    absww = abscal = wwcount = scal2 = 0;
#endif

itcount=0;
ni = n * (n-1)/2;
ki=ni;
do
{    ++itcount;
    for (j=0; j<n-1; j++)
    {
        for (h=j+1; h<n; h++)
        {
            scalprod = jlong = hlong = 0.0;
            for (i=0; i<n; i++)
            {
                wij = bas [i][j];
                wih = bas [i][h];
                scalprod += wij*wih;
                jlong += wij*wij;
                hlong += wih*wih;
            }
            le=sqrt(jlong*hlong);
            if (le > 0.0)
                ac = fabs(scalprod/le);
            else
                ac = 0.0;
            scalprod += scalprod;
            ww = jlong-hlong;
        }
    }
#endif     /* test output 2, remove later */
printf("iteration: %2i  ac and ww: %8.3f %8.3f\n",
      itcount, ac, ww);
#endif
if ((ac>(EPSANGLE)||(ww<0.0))
{
    if((fabs(ww)>=fabs(scalprod)))
    {
        teta =fabs(scalprod/ww);
        cteta=1.0/sqrt(1.0+teta*teta);
        steta=teta*cteta;
    } else
    {
        teta =fabs(ww/scalprod);
        steta=1.0/sqrt(1.0+teta*teta);
        cteta=steta*teta;
        #if DEBUG        /* test output 4, remove later */
        abscal++;
        if (abscal==1)
        {
            printf("1st passage fabs(ww)<fabs(scalprod)\n");
            printf("cteta: %8.3f\n",cteta);
        }#endif
    }
} else
{
    teta =fabs(ww/scalprod);
    steta=1.0/sqrt(1.0+teta*teta);
    cteta=steta*teta;
    #if DEBUG        /* test output 4, remove later */
    abscal++;
    if (abscal==1)
    {
        printf("1st passage fabs(scalprod)<fabs(ww)\n");
        printf("cteta: %8.3f\n",cteta);
    }#endif
}
cteta =sqrt((1.0+cteta)/2.0);
steta /= 2.0*cteta;
if (ww<0.0)
{
flip = cteta;
cteta = steta;
steta = flip;

#if DEBUG /* test output 5, remove later */

wwcount++;
if (wwcount==1)
{
    printf("1st passage of ww<0\n");
    printf("new cteta, steta: %8.3f %8.3f\n", cteta, steta);
}
#endif
}

if (scalprod<0.0)
{
    steta = -steta;

#if DEBUG /* test output 6, remove later */

scal2++;
if (scal2==1)
printf("1st passage scalprod<0, new steta:%8.3f\n", steta);
#endif
}

for (i=0; i<n; i++)
{
    flip = bas[i][j];
    bas[i][j] = bas[i][h]*steta + flip * cteta;
    bas[i][h] = bas[i][h]*cteta - flip * steta;
} ;

ki = ni;

#if DEBUG /* test output 7, remove later */

if(itcount==1)
{
    printf("rotation nr. %3d\n", j+h);
    printf("new matrix: \n");
    for (i=0; i<n; i++)
    { 
        printf(\"%8.3f\n", bas[i][j]);
    } 
}
for (g=0; g<n; g++)
    printf("%8.3f ",bas[i][g]);
printf("\n");

#endif

} /* of if ac>EPSANGLE etc. */
else
    ki--;

} /* of h-loop */

} /* of j-loop */
} /* of do-loop */

while ((ki>0)&&(itcount<ITBOUND));

/* now calculation of eigenvalues */

#if DEBUG /* test output 8, remove later */

printf ("outcome after iteration %3i last matrix:\n",itcount);
for (i=0; i<n; i++)
    {
        for (g=0; g<n; g++) printf("%8.3f",bas[i][g]);
        printf("\n");
    }
#endif

for (j=0; j<n; j++)
    {
        eig[j]=0.0;
        for (i=0; i<n; i++)
            eig[j] += bas[i][j]*bas[i][j];
        eig[j]=sqrt(eig[j]);
        /* now calculation of eigenvectors */
    }

for (j=0; j<n; j++)
    {
        if (eig[j]!=0.0)
            for (i=0; i<n; i++)
bas[i][j] /= eig[j];
}

#if DEBUG     /* test output 9, remove later */
printf("scaled matrix\n");
for(i=0; i<n; i++)
{
    for(g=0; g<n; g++)
        printf("%8.3f ",bas[i][g]);
    printf("\n");
}
printf("eigenvalues\n");
for (i=0; i<n; i++)
    printf(" %8.3f ",eig[i]);
printf("\n");
#endif
return;
}
/* end of "decompose" and of module box 15 */

/*---------------------------------------------------------------*/
/* Module Box 16: Exploration at a Parameter Point */
/*---------------------------------------------------------------*/
#include <math.h>
#include <stdio.h>
#include "cbox1.h"

void explore (void)
{
    /* this function fills gradient and information matrix, scales it, and finds eigensystem decomposition */
    /* module requires global variables from "cbox1.h" */
    /* int n, BOOL fullresp, MAT correl */
    /* returns global variable MAT bas */
    /* calls functions "fill" and "decompose" */
    
    extern n;
    extern BOOL fullresp;
    extern MAT correl, bas;
    
    int i,j;

    fill ();     /* fills vector grad and matrix info */
if (fullresp==TRUE)
{
  scale();           /* scales "info" to "correl", scale vector "d" */

  for (j=0; j<n; j++)
    for (i=0; i<n; i++)
      bas[i][j] = correl[i][j];
  decompose();       /* decomposition of "correl"-matrix */
}
}        /* end of if */

} /* end of "explore" and of module box 16 */

/*---------------------------------------------------------------*/
/* Module Box 17: Finding New Parameter Vector */
/*---------------------------------------------------------------*/

#include <math.h>
#include <stdio.h>
#include "cbox1.h"

void find (void)
{
  /* this module calculates, for a given my-value and for principal axes and eigenvalues, 
  a new trial parameter */
  /* requires global variables as defined in "cbox1.h" */
  /* int n, double my, PARVEC eig, d, p, grad, MAT bas */
  /* fills MAT inv, PARVEC p1 */

  extern int n;
  extern double my;
  extern PARVEC eig, d, p, grad, p1;
  extern MAT bas, inv;

  int h,i,j;
  double depot;

  for (i=0; i<n; i++)
    for (j=0; j<n; j++)
      
        depot=0.0;        /* for accumulation of inverse */

        for (h=0; h<n; h++)
if (my>0.0 || my==0.0 && eig[h]>1.0e-6)

depot += bas[i][h] * bas[j][h] / d[i] / d[j] / (eig[h]+my);

inv[i][j] = inv[j][i] = depot;
}

for (i=0; i<n; i++)
{
    depot=0.0; /* for accumulation of step */
    for (j=0; j<n; j++)
        depot -= inv[i][j] * grad[j];
    p1[i] = p[i] + depot;
} /* end of i-loop */

} /* end of "find" and of module box 17 */

/*================================================================*/

/* Module Box 18: Testing if Parameter Vector is permissible */

#include <math.h>
#include <stdio.h>
#include "cbox1.h"

BOOL inside (PARVEC p)
{
    /* this module has the only task to prevent too large a further attempts with higher
damping factor will follow inside == TRUE means that the step remains within limits */
    /* requires global variables from "cbox1.h" */
    /* int n, PARVEC p, upper, lower */

    extern int n;
    extern PARVEC upper, lower;

    int i;
    BOOL outside;

    outside = FALSE;
    for (i=0; i<n; i++)
        if (p[i]>=upper[i] || p[i]<=lower[i])
            outside = TRUE;
    return (outside==TRUE ? FALSE : TRUE );
} /* end of "inside" and of module box 18 */

/*================================================================*/

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/* Module box 19: Accepting a Successful Step */

#include <math.h>
#include <stdio.h>
#include "cbox1.h"

void accept (void)
{
    /* this function performs restoring of old and current parameter vectors and of pertinent fit criteria after accepting */
    /* requires global variables from "cbox1.h" */
    /* int n, double f1, PARVEC p1 */
    /* requires and changes PARVEC p, double f */
    /* fills new PARVEC pold, double fold, my */

    extern int n;
    extern double f, f1, fold, my;
    extern PARVEC p, p1, pold;

    int i;

    for (i=0; i<n; i++)
    {
        pold[i] = p[i] ;
        p[i] = p1[i];
    }
    fold = f1;
    f    = f1;
    my /= 100.0;
} /* end of "accept" and of module box 19 */

/* Module Box 20: Testing Significance of a Parameter Step */

#include <math.h>
#include <stdio.h>
#include "cbox1.h"

BOOL significant (PARVEC q1, PARVEC q2, double fq1, double fq2)
{

extern int n;

BOOL ac;
int i;

ac = FALSE;

for (i=0; i<n; i++)
    if (fabs(1.0 - q2[i]/q1[i]) > EPSCONVER )
        ac = TRUE;
    if (fabs(1.0-fq2/fq1) > EPSCONVER)
        ac = TRUE;
return(ac);
} /* end of "significant" and of module box 20 */