Estimation of leaf water potential by thermal imagery and spatial analysis*

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Abstract

Canopy temperature has long been recognized as an indicator of plant water status and as a potential tool for irrigation scheduling. In the present study, the potential of using thermal images for an in-field estimation of the water status of cotton under a range of irrigation regimes was investigated. Thermal images were taken with a radiometric infrared video camera. Specific leaves that appeared in the camera field of view were sampled, their LWP was measured and their temperature was calculated from the images. Regression models were built in order to predict LWP according to the crop canopy temperature and to the empirical formulation of the crop water stress index (CWSI). Statistical analysis revealed that the relationship between CWSI and LWP was more stable and had slightly higher correlation coefficients than that between canopy temperature and LWP. The regression models of LWP against CWSI and against leaf temperatures were used to create LWP maps. The classified LWP maps showed that there was spatial variability in each treatment, some of which may be attributed to the difference between sunlit and shaded leaves. The distribution of LWP in the maps showed that irrigation treatments were better distinguished from each other when the maps were calculated from CWSI than from leaf temperature alone. Furthermore, the inclusion of the spatial pattern in the classification enhanced the differences between the treatments and was better matched to irrigation amounts. Optimal determination of the water status from thermal images should be based on an overall view of the physical status as well as on the analysis of the spatial structure. Future study will involve investigating the robustness of the models and the potential of using water status maps, derived from aerial thermal images, for irrigation scheduling and variable management in commercial fields.

Key words: Canopy temperature, cotton, CWSI, irrigation management, leaf water potential, thermal images.

Introduction

Site-specific irrigation may be defined as an irrigation regime that is matched (in timing and amount) to the actual crop need at the smallest manageable scale, to achieve the desired crop responses. Enhancing productivity (in terms of yield and quality) per unit of applied water will depend on the ability to map the variability of the crop water status, and on the development of site-specific water application technology to reduce site-specific water deficits. Site-specific irrigation application could improve irrigation efficiency and so resolve part of the water-shortage crises in agricultural production. The spatial variability of crop water status results from variability of soil, crop canopy, topography, irrigation level (either inherent in the application method or caused by malfunctions), or from other factors such as salinity, which typically is spatially variable.

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Abbreviations: LWP, leaf water potential; CWSI, crop water stress index; VPD, vapour pressure deficit; ARS, artificial reference surface; Oir, over-irrigated; WW, well-watered; LWS, low water stress; MWS, medium water stress; SWS, severe water stress; Tl, leaf temperature.

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Irrigation is normally carried out according to recommendations based on potential evapotranspiration and crop coefficients, with adjustments according to crop water status assessments such as leaf water potential (LWP) measurements. Characterization of the water status in the whole field and adjustments to irrigation management are usually determined by point measurements. In the case of LWP, only a few leaves in a representative area of the field are sampled. Therefore, it is not practicable to take the spatial variability of the water status into consideration, because of workload and cost constraints, as many leaves spread over the whole field would have to be measured.

Plant temperature has long been recognized as an indicator of plant water availability (Gates, 1964). Crop temperature measurements by infrared thermometers are reliable and non-invasive, yet they are commonly based on only a few point measurements, therefore the operator must assume uniformity of soil water content and of plant canopy for large areas. In order to map crop water status variability at an adequate resolution, the distribution of many infrared thermometers is required (Evans et al., 2000). Recent technological advances in remote thermal images offer the potential to acquire spatial information on surface temperature, and thus facilitate the mapping of canopy temperature variability over large areas. Thermal imagery is a viable alternative to point measurements, since the canopy temperature of the whole field can be measured at once and a map of the plant water status distribution in the field can be produced.

A temperature-based crop water stress index (CWSI) was developed by Idso et al. (1981). The CWSI is defined as (Idso et al., 1981; Jackson et al., 1981):

\[
CWSI = \frac{T_l - T_{\text{wet}}}{T_{\text{dry}} - T_{\text{wet}}}
\]

where \(T_l\) is the leaf temperature; \(T_{\text{wet}}\) is the lower boundary for canopy temperature, corresponding to a well-watered leaf with stomata fully open; and \(T_{\text{dry}}\) is the upper boundary for canopy temperature which equates to the temperature of a non-transpiring leaf, i.e. one with stomata completely closed. The CWSI approach has not been adopted for practical use, for two reasons: (i) when measured by handheld or high-altitude air-borne radiometers, temperatures of the relevant crop canopy, of the general leaf population, and of the soil background are mixed (Clarke, 1997); and (ii) normalization of CWSI is much more complicated under changing atmospheric conditions than using vapour pressure deficit (VPD) alone (Jackson et al., 1988; Jones, 1999a). Recent work has shown that the CWSI approach can be expanded in order to determine a soil water status index (Colaizzi et al., 2003) and the depth of root-zone water depletion, and this may improve the ability to determine irrigation amounts. This new approach relies on better temperature separation by means of novel imaging equipment and the use of a wet artificial reference surface (ARS) for CWSI calculation (Meron et al., 2003). The use of natural reference surfaces, such as well-watered crop sections, for CWSI normalization has been proposed by Clawson et al. (1989), and they were used by Jones (1999b, 2002) and Casa and Jones (2004); however, they are difficult to maintain. Meron, Tsimpis and Fuchs (unpublished report to the Ministry of Science, Israel, 1994) used dry and wet ARSs with known reflectance and aerodynamic attributes, and calculated CWSI by reformulation of the energy balance equation. From a practical standpoint, the ARS method seems the most suited for large-scale aerial application, as it provides flexible deployment and reproducible surfaces.

In the context of water status estimation, thermal images have recently been used without considering the potential value of incorporating spatial analysis into the process. Spatial patterns derived from thermal images may be combined to improve the delineation of homogeneous zones in the field and to improve the determination of their water status.

In the present study, the potential of using thermal images for an in-field estimation of the water status of cotton under a range of irrigation regimes was investigated. The long-term objective of this study is to establish a scientific and technological basis for evaluating the water status of cotton fields by thermal images, in order to optimize irrigation scheduling and to enable variable rate irrigation. The specific aims of the present study are (i) to develop a model for estimating LWP based on thermal images; and (ii) to develop a procedure for water status mapping that combines this model with spatial structure analysis.

**Materials and methods**

**Field plots**

Field measurements were conducted in the summer of 2003 on a clay loam soil at Kibbutz Shamir, Israel, where there is a Mediterranean climate. Plots planted with cotton (Gossypium barbadense L. cv. PF-15) were drip-irrigated with one lateral between every two rows. Each treatment was 6 m wide (six rows spaced 1 m apart) by 20 m long. The crop was grown in accordance with normal practices, with a daily water application of 1.0 × the daytime potential evapotranspiration. One treatment, designated as Tr-D, served as a non-stressed reference and was over-irrigated by using two drip laterals per row pair (instead of one). A second treatment, designated as Tr-0, represented the common practice of daily irrigation of 1.0 × potential evapotranspiration. Nearer the time of field measurements, three levels of stress were induced by suppressing irrigation for 2, 4, and 6 d and were designated as Tr-2, Tr-4, and Tr-6.

The treatments were in contiguous areas containing 10 plots arranged in end-to-end pairs in the row direction, with five such pairs side-by-side and perpendicular to the row direction. All plots received the same amount of nitrogen fertilizer through the irrigation system.

**Thermal image acquisition**

Thermal images of the plots were taken with an uncooled infrared thermal camera. The camera (ThermaCAM model PM545, FLIR...
systems) had a 320×240 pixels microbolometer sensor, sensitive in the spectral range of 7.5–13 nm, and a lens with an angular field of view of 24°. The camera was mounted at a height of 5 m above the ground, pointing downwards. The canopy height was about 1 m, so that the linear field of view at the canopy level was 2×(5–1)×tan(24°/2)=1.7 m (i.e. 0.5 cm per pixel). This resolution enabled a distinction to be made between leaves and soil and to select pixels that contained only leaves for further analysis.

Leaf samples
Five leaves from each treatment were sampled and their LWP was measured directly with a pressure chamber (model ARIMAD 1, Mevo Hama Instruments, Israel), as described by Meron et al. (1987). The youngest fully expanded leaf below the main stem terminal was chosen. Before each leaf was cut for the LWP measurement a thermal image was acquired, after the leaf petiole had been marked with a piece of aluminium foil in order to identify it in the image. The measurements were conducted around the time of solar zenith (11.00–15.00 h local time, GMT±2 h)

Crop water status was classified into five pre-determined categories according to LWP: (i) LWP > −1.4 MPa represents over-irrigated plants (Oir); (ii) −1.4 MPa > LWP > −1.7 MPa well-watered plants (WW); (iii) −1.7 MPa > LWP > −2.0 MPa low water stress (LWS); (iv) −2.0 MPa > LWP > −2.3 MPa medium water stress (MWS); (v) −2.3 MPa > LWP severe water stress (SWS).

Meteorological conditions and CWSI
Air temperature, relative humidity, and wind speed were measured by a meteorological station located within the experimental plot. Wind speed was measured at the crop canopy level. Meteorological data were acquired every 10 s and average values over 1 min intervals were stored.

CWSI was calculated using Equation 1. An artificial wet reference surface was placed in the camera field of view when thermal images were acquired. Its temperature was obtained from the thermal images and was used as \( T_{\text{wil}} \) in Equation 1. According to reports in the literature (Ehlerl et al., 1978; Irmak et al., 2000), the upper base line \( (T_{\text{a}}-T_{\text{wil}}) \) when transpiration has ceased, was found to be relatively constant, in the range of +4.6 °C to +5.0 °C. In this work, as in Meron et al. (2003), \( T_{\text{cry}} \) was estimated by adding 5.0 °C to the dry bulb temperature of air: \( T_{\text{cry}}=T_{\text{a}}+5 \) °C. The measurements were carried out on two dates, 15 July and 6 August 2003.

Processing of thermal images
Thermal images were processed with digital image processing tools. The raw thermal images were obtained in FLIR Systems’ proprietary format and converted to grey-scale images in which each grey level represented 0.1°, i.e. the span of the grey scale was 25.5°C for the 255-level grey scale that was used. This conversion was performed by (i) setting the temperature span of the images and saving them as bitmap images (BMP format) by means of ThermaCamExplorer software (FLIR Systems) and (ii) converting the bitmap images to 8-bit uncompressed TIFF format by means of Adobe Photoshop 7.0 software (Adobe Inc.) The images were then processed in two ways: (i) global image features were extracted with the Matlab R13 software (Mathworks Inc.); and (ii) spatial image analysis was performed with IMAGINE 8.7 software (Leica Inc.). In both cases, the temperature of each pixel was first calculated from the 8-bit grey level image, by using the following equation:

\[
T_{(x,y)} = T_{\text{span}} + \frac{T_{\text{span}} \cdot GL_{(x,y)}}{255}
\]

where \( T_{(x,y)} \) is the calculated temperature at pixel \( (x,y) \); \( GL_{(x,y)} \) is the grey level of pixel \( (x,y) \) in the 8-bit TIFF image; \( T_{\text{span}} \) is the temperature span in the image, as set in ThermaCamExplorer. This was always set to 25.5 °C; \( T_{\text{min}} \) is the temperature that corresponds to the grey level 0; 255 is the maximum number of grey levels in a 8-bit grey level image.

LWP regression models
The temperature of individual leaves in the images was then extracted in order to establish the relationship between measured and estimated LWP. The leaves that were marked with aluminium foil were manually segmented in the digital images and their mean temperature, along with additional descriptive statistics (variance, minimum, maximum, etc.) were calculated. These values were used to calculate the crop water stress index (CWSI) and to formulate regression models for LWP prediction.

LWP mapping and spatial analysis
Spatial and global information related to the temperature in each image was extracted after applying image preprocessing: in each image, leaves were initially separated from soil and from mixed pixels (a mixed pixel is one that contains information from more than one source, i.e. soil and leaf – usually pixels at the edge of the leaf) by using empirical maximum temperature thresholds: pixels with a temperature higher than 37.5 °C were initially grouped and marked as soil and mixed pixels. Then, these groups were refined by a spatial proximity analysis: the SEARCH and RECODE modules (Imagine 8.7) were used to detect the neighbouring pixels of these groups and reclassify them into a single united group of soil and mixed pixels. This united group was then excluded from further analysis. In addition, other objects that were mistakenly included in the image (e.g. hands) were manually excluded from the images.

Synthetic maps were constructed by concatenating images, one from each treatment, to create a map that contained artificial variability which covered the whole range of water status created by all five irrigation regimes. The extent of each synthetic map was 10×2 m. The maps depicted the estimated LWP of each pixel, according to two types of regression model: (i) LWP predicted from temperature measurement only; and (ii) LWP predicted from the CWSI index. Both sets of calculations were applied to each pixel separately. Water status maps were obtained by applying classification procedures, and the spatial patterns were subjected to object analysis.

The regression models and the mean values were subjected to analysis of variance and Duncan’s Multiple Grouping Test by means of the Proc GLM software (SAS Inc.), to determine their statistical significance at a level of \( P=0.05 \).

Results
Resolution of LWP in plant water status recognition
Direct measurements of the LWP of the sampled leaves were used in order to evaluate the resolution of LWP in plant water status recognition. The column ‘LWP measured’ in Table 1 summarizes the average LWP values of the five leaves that were sampled from each irrigation treatment. According to the definition of plant water status (see Materials and methods) and to the average LWP values of the five leaves that were sampled from each irrigation treatment, the five irrigation treatments were classified according to two water-status levels: Tr-D, Tr-0, and Tr-2 were classed as over-irrigated (Oir) in August and well-watered (WW) in July; and Tr-4 and Tr-6 were classed as medium water stress (MWS).
Table 1. Mean values of leaf water potential, leaf temperature, and calculated CWSI for five irrigation treatments

<table>
<thead>
<tr>
<th>Irrigation treatment</th>
<th>LWP measured (MPa)</th>
<th>Temperature (°C)</th>
<th>CWSI (ARS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>15 July 2003</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tr-6</td>
<td>-2.26 a</td>
<td>33.4 a</td>
<td>0.52 a</td>
</tr>
<tr>
<td>Tr-4</td>
<td>-2.20 a</td>
<td>32.3 a</td>
<td>0.43 a</td>
</tr>
<tr>
<td>Tr-2</td>
<td>-1.59 bc</td>
<td>30.6 b</td>
<td>0.20 b</td>
</tr>
<tr>
<td>Tr-0</td>
<td>-1.62 b</td>
<td>28.8 c</td>
<td>0.10 b</td>
</tr>
<tr>
<td>Tr-D</td>
<td>-1.40 c</td>
<td>29.0 c</td>
<td>0.10 b</td>
</tr>
<tr>
<td>6 August 2003</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tr-6</td>
<td>-2.29 a</td>
<td>33.9 a</td>
<td>0.58 a</td>
</tr>
<tr>
<td>Tr-4</td>
<td>-2.08 a</td>
<td>33.0 a</td>
<td>0.50 a</td>
</tr>
<tr>
<td>Tr-2</td>
<td>-1.34 b</td>
<td>30.2 b</td>
<td>0.12 b</td>
</tr>
<tr>
<td>Tr-0</td>
<td>-1.33 b</td>
<td>30.7 b</td>
<td>0.18 b</td>
</tr>
<tr>
<td>Tr-D</td>
<td>-0.83 c</td>
<td>28.5 c</td>
<td>-0.23 c</td>
</tr>
</tbody>
</table>

Tr-0 and Tr-2, whereas temperature groups Tr-D and Tr-0 together, with Tr-2 indicated as a separate group. The distribution of CWSI values is similar to that of temperatures. However, despite the lower average values of CWSI found for leaves from Tr-D and Tr-0 (0.1) as compared with those from Tr-2 (0.2), this criterion failed to differentiate between Tr-D and Tr-0, so that only two groups were obtained. August: The temperature- and the CWSI-based calculations yielded the same separation as the measured LWP.

Prediction of LWP values from temperature and CWSI

In addition to the relative separation between water status levels, the authors wanted to study the ability to predict absolute LWP value from temperature and CWSI values. Regression models were built that linked leaf temperature ($T_l$) and CWSI, separately, to the measured LWP of each leaf. Figures 1–4 present the respective regression lines between leaf temperature and CWSI, and the measured LWP in July and in August. Generally, good correlations with LWP were found on both dates, both for leaf temperature and for CWSI. Temperature and CWSI had higher correlations with LWP in August than in July, and in both months the correlation of CWSI with LWP was only slightly higher than that of temperature.

The combination of data from both months revealed a good correlation between direct measurements of LWP and CWSI (Fig. 5). In order to validate the regression, the August data were used for building the model and the July data for validation. Prediction revealed good correlation ($R^2 = 0.79$) (Fig. 6).

Mapping leaf water potential by thermal imaging

One objective of the present study is to assess the possibility of mapping LWP on the basis of thermal images and to examine to what extent this would add to being able to determine the water status of cotton fields or of predesignated irrigation zones. Figure 7a and b are raw thermal images of Tr-D and Tr-6, respectively, in August. The white arrow points to two adjacent wet ARSs. The cooler surface (darker in the thermal image) was used as...
Twet for CWSI calculations. The image of Tr-D is darker than that of Tr-6, i.e. the leaf temperatures (LTs) in Tr-D were lower than those in Tr-6. All the raw thermal images (25 images) were converted to LWP maps either directly from $T_l$ (termed hereafter as $T_l$-based LWP) or by conversion to CWSI (Equation 1) and then to LWP (termed hereafter as CWSI-based LWP), both based on the August regression equations (Figs 3 and 4, respectively). For each treatment, a representative LWP image was chosen and their pixel distributions are presented in Fig. 8a–d. Visual analysis shows that the distributions of LWP based on $T_l$ (Fig. 8a, c) are wider than those based on CWSI (Fig. 8b, d): i.e. the distinctions among the treatments according to the former are less marked than those based on the latter. In both months, the distribution of $T_l$-based LWP values in Tr-0 was similar to that in Tr-D. In contrast to that, the distribution of CWSI-based LWP for Tr-0 was shifted relative to that of the $T_l$-based LWP, and was located between those for Tr-D and Tr-2, which facilitated a better separation between the water status of Tr-D and that of Tr-0.

In order to test quantitatively whether the various irrigation treatments could be distinguished on the basis of the images, a mean LWP value was calculated for each image and Duncan’s test was performed for each date. The column ‘LWP calculated’ in Table 2 presents the results of Duncan’s test. On the basis of the mean values of the images, three groups were distinguished in July, with the mean value of LWP in Tr-0 not being significantly different from that of either Tr-D or Tr-2. This grouping provides a separation capability similar to that of the direct measurements of LWP (Table 1, column ‘LWP measured’). In August, it was possible to separate the estimated values of LWP into four groups (only Tr-4 and Tr-6 could not be significantly separated), whereas the directly measured values could only be separated into three groups.

Spatial structure analysis
An essential step towards precision irrigation is the ability to map the variability of water status and to use it as a basis for delineating irrigation management zones. In the present
study, each experimental plot was under controlled irrigation conditions and it was assumed that within-plot variability of water status is very limited. The water status variability within a field was simulated by artificially combining the five LWP maps from August into a single map (10×2 m). In this stage of the research, these synthetic small maps were used in order to design and evaluate a water status mapping procedure whose conceptual principles can be applied for aerial thermal images. Two synthetic maps were created: a map of the distribution of the LWP based on CWSI; and a map of the estimated LWP values derived from the raw thermal images. The first step involved detecting soil and mixed pixels and excluding them from further analysis (this procedure is explained in detail in the Materials and methods). Following that, water status maps were created by classifying each pixel of the LWP maps according to the five categories of water status defined above: over-irrigated (Oir), well-watered (WW), low water stress (LWS), moderate water stress (MWS), and severe water stress (SWS).

Fig. 7. Raw thermal images from August 2003: (a) Tr-D; (b) Tr-6. The white arrows point to two adjacent wet ARSs.

Fig. 8. Distribution of predicted values of LWP in images of different irrigation treatments: (a) Prediction of LWP based of $T_s$, July 2003. (b) Prediction of LWP based of CWSI, July 2003. (c) Prediction of LWP based of $T_s$, August 2003. (d) Prediction of LWP based of CWSI, August 2003.
Figure 9a and b show the artificially combined water status maps derived from LWP distribution maps based on CWSI and \( T_l \), respectively. Visual comparison between the treatments (Fig. 9a), together with reference to the subjectively perceived dominant level of water status, enables four different groups to be observed: (i) Tr-D, which is dominated by the Oir class; (ii) Tr-0 and Tr-2, which present a mixture of Oir and WW; (iii) Tr-4, which is dominated by LWS but also contains mixture of MWS and SWS; and (iv) Tr-6, which is dominated by SWS. In Fig. 9b similar groups of water status are apparent, except that, unlike Fig. 9a, there is no clear distinction between plots D, 0 and 2. In general, these groups and their LWP averages are in accordance with the grouping based on Duncan’s test and the LWP values of the measured leaves (Tables 1, 2). Nevertheless, the difference between Tr-4 and Tr-6 is more conspicuous on the map.

Beyond the visual analysis, the water status of each treatment was determined quantitatively for the LWP maps based on CWSI. Measures of a central tendency (such as the mean value), calculated for all the pixels in the image of each treatment, may not be representative in spatially fragmented areas. Spatially fragmented areas may contain local irregularities, i.e. scattered small clumps of specific water status which differ from the average water status of their surroundings. Therefore, spatial structure analysis was applied in order to identify and eliminate such small groups of pixels (clumps) in the classified LWP maps. The CLUMP and ELIMINATE modules (Imagine 8.7) were used for deleting clumps smaller than a predefined threshold. The threshold was set according to prior knowledge and spatial resolution. In this case, the threshold was set to the average size of a typical single leaf (150 pixels): a single leaf represents the smallest homogeneous object that can be recognized in the thermal images used here. The resulting maps were used for calculating the mean LWP of each treatment. Table 3 shows the water status classification of irrigation treatments, as calculated by using all pixels and by using clumps larger than 150 pixels. Indeed, use of the mean LWP value of large clumps led to water status values in Tr-s 0, 2, and 6 that differed from those obtained by using the mean LWP value of all pixels. The inclusion of the spatial pattern in the classification enhanced the differences between the treatments and led to a classification that corresponded to the irrigation amounts: the daily-irrigated treatments were classified as Oir, and those with 2, 4, and 6 d of no irrigation were classified as showing low, moderate, and severe water stress, respectively.

Spatial structure analysis can be also used to examine the fragmentation level of the LWP spatial distribution. A high level of fragmentation could prevent the delineation of irrigation zones. Figure 10 shows, for each treatment, the number of clumps in the LWP maps based on CWSI and \( T_l \).

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**Table 2. Comparison between leaf water potential values from direct measurements and those calculated from entire thermal images**

<table>
<thead>
<tr>
<th>Irrigation treatment</th>
<th>LWP calculated from entire images (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>15 July 2003</td>
<td></td>
</tr>
<tr>
<td>Tr-6 (MWS)</td>
<td>−2.26 a</td>
</tr>
<tr>
<td>Tr-4 (MWS)</td>
<td>−2.18 a</td>
</tr>
<tr>
<td>Tr-2 (WW)</td>
<td>−1.67 b</td>
</tr>
<tr>
<td>Tr-0 (WW)</td>
<td>−1.58 bc</td>
</tr>
<tr>
<td>Tr-D (WW)</td>
<td>−1.50 c</td>
</tr>
<tr>
<td>Tr-6 (MWS)</td>
<td>−2.10 a</td>
</tr>
<tr>
<td>Tr-4 (MWS)</td>
<td>−2.08 a</td>
</tr>
<tr>
<td>Tr-2 (WW)</td>
<td>−1.46 b</td>
</tr>
<tr>
<td>Tr-0 (Oir)</td>
<td>−1.37 c</td>
</tr>
<tr>
<td>Tr-D (Oir)</td>
<td>−1.08 d</td>
</tr>
<tr>
<td>6 August 2003</td>
<td></td>
</tr>
</tbody>
</table>

*Values from the same date and in the same column followed by a common letter are not significantly different at the \( P=0.05 \), according to Duncan’s Multiple Range Test.*

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Fig. 9. Artificially combined water status map derived from LWP maps calculated for images from August 2003: (a) based on CWSI, (b) based on \( T_l \).
of the limiting factors for robust characterization of the crop today is based on a limited number of leaves, which is one variability within each plant. Sampling of a large number of plants is needed since the variability between plants is added to the inherent variability of a single plant, and the problem becomes even more complicated when the water status of a crop in a field must be evaluated, measuring leaf water potential or stomatal conductivity. The water status of a single plant can be evaluated by addressing stomatal conductance and crop water stress (Idso et al., 1981; Jackson et al., 1981; Jackson, 1982; Jones, 1999a, b). Thermal imaging has the potential to replace direct leaf measurements and to provide a more robust measure of the crop water status and its spatial pattern, through mapping of extended areas of the crop. In the present study, it has been demonstrated that thermal images can be used as an alternative to direct LWP measurements. Furthermore, spatial mapping of LWP has the potential to represent the crop water status of a field more adequately than mapping based on direct measurements. First, it was shown that temperature measured from thermal images can be used to predict LWP; then the added value of spatial analysis techniques in evaluating crop water status was shown.

Temperature-based indices calculated from data extracted from thermal images and wet ARS measurements led to similar results to those obtained from direct LWP measurements on sampled cotton leaves (Table 1), in distinguishing between irrigation treatments. These indices enabled two main groups to be distinguished on both dates: one comprising Tr-D, Tr-0, and Tr-2 which were well watered; and the other comprising Tr-4 and Tr-6 which showed water stress.

The CWSI also exhibited good correlation with direct LWP measurements, and its regression lines had similar parameters (slope and intercept) for different sets of leaves. In the light of these results, it is suggested that CWSI can not only distinguish between different levels of water status of cotton leaves, but could also serve as a predicting index of absolute LWP of cotton leaves. Nevertheless, the slope and the intercept of the regression between CWSI and LWP were similar on both dates whereas, in the regression between leaf temperature and LWP, these regression parameters had different values. This indicates that if leaf temperature alone is to be used as a measure of plant water status then a more sophisticated index must be formulated, for example, daily time under stress (Wanjura and Upchurch, 2002). On the other hand, CWSI, which includes compensation for varying meteorological conditions (Idso et al., 1981), can be used as an alternative. With additional distinction between sunlit and shaded leaves, similar results have been published (Leinonen and Jones, 2004) that address stomatal conductance and crop water status.

The robustness of the LWP regression models was tested by evaluating their accuracy on a validation set. The regression model was built by using data from August 2003 and was applied to data from July 2003. The prediction of LWP in the validation set exhibited larger errors than in the calibration set, as expected. Nevertheless, the distinction between the two prominent groups of water status levels, as observed through the direct measurements of LWP, can still be observed in the two clusters formed in Fig. 6.
When the LWP histograms of the whole image were used for evaluating the water status (without referring to the spatial pattern of LWP within the image) large overlaps were found (Fig. 8a–d). Two main groups were easily distinguished: one group comprised Tr-D, Tr-0, and Tr-2 and the other comprised Tr-4 and Tr-6. This finding is consistent with the direct LWP measurements.

The observed overlap between the treatments may be the result of treating the temperatures of sunlit and shaded leaves together. Leinonen and Jones (2004) reported that making a distinction between sunlit and shaded leaves improved the ability to predict stomatal conductance and the CWSI from the thermal images. Nevertheless, selection of sunlit and shaded leaves cannot be achieved by using thermal images alone. Leinonen and Jones (2004) used multispectral images in the visible and NIR spectral ranges to distinguish between sunlit and shaded leaves. The co-registration of these images is essential for accurate distinction between the areas of sunlit and shaded leaves. Although the process of detecting sunlit and shaded leaves in the multispectral image was performed automatically, the registration and scale adaptation of the thermal and multispectral images were performed manually. Incorporation of this procedure in future work is expected to increase the capability to resolve the finer differences of crop water status.

An essential step towards precision irrigation is the mapping of water status variability. The water status variability within a single field was simulated by artificially combining the LWP distribution maps of the different irrigation treatments into a single map, which was then divided according to five water status classes. After mapping, the water status of predefined irrigation zones was determined. The currently available variable rate technology sets a lower limit to the size of an irrigation zone. In the present study, irrigation conditions were controlled which were assumed to serve as predefined irrigation zones. The optimal determination of the water status from thermal images should be based on an overall view of the physical status as well as its spatial pattern. Measures of a central tendency (such as a mean value), calculated for all the pixels in the image of each treatment may not be representative, therefore calculating the mean LWP of each treatment by using the mean LWP value of clumps larger than the smallest homogeneous object in the image is suggested. The inclusion of the spatial pattern in the determination of water status not only enhanced the differences between the treatments (to provide four groups instead of three groups; Table 3) but also provided a better match between water status and the irrigation amounts in the various treatments.

A complementary piece of information obtained from the spatial analysis of the map is the relative area of bare soil in a predefined irrigation zone. Since the irrigation regime affects the development of the canopy, the relative soil cover may serve as an additional spatial indicator of water status. In the present study it was found that relative area of soil detected using the thermal images increased as the amount of irrigation decreased.

The present study shows that leaf water potential can be well estimated by combining temperature values derived from thermal images with spatial analysis. The difficulties in relating temperature to plant water status may be overcome by combining spatial analysis due to the consideration of the local spatial variability and the surrounding conditions. This lays the basis for creating reliable water status maps for better irrigation scheduling and for variable irrigation management.

Future study will involve the following: (i) investigating the robustness of the models in different phenological, meteorological, and geographical conditions; (ii) implementation on commercial fields of cotton by aerial thermal images; and (iii) investigating the potential of using water status maps derived from aerial thermal images for irrigation scheduling and variable management in commercial fields.

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References


Cohen et al. 1852.