Estimating evapotranspiration and drought stress with ground-based thermal remote sensing in agriculture: a review

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Abstract

As evaporation of water is an energy-demanding process, increasing evapotranspiration rates decrease the surface temperature \( T_s \) of leaves and plants. Based on this principle, ground-based thermal remote sensing has become one of the most important methods for estimating evapotranspiration and drought stress and for irrigation. This paper reviews its application in agriculture. The review consists of four parts. First, the basics of thermal remote sensing are briefly reviewed. Second, the theoretical relation between \( T_s \) and the sensible and latent heat flux is elaborated. A modelling approach was used to evaluate the effect of weather conditions and leaf or vegetation properties on leaf and canopy temperature. \( T_s \) increases with increasing air temperature and incoming radiation and with decreasing wind speed and relative humidity. At the leaf level, the leaf angle and leaf dimension have a large influence on \( T_s \); at the vegetation level, \( T_s \) is strongly impacted by the roughness length; hence, by canopy height and structure. In the third part, an overview of the different ground-based thermal remote sensing techniques and approaches used to estimate drought stress or evapotranspiration in agriculture is provided. Among other methods, stress time, stress degree day, crop water stress index (CWSI), and stomatal conductance index are discussed. The theoretical models are used to evaluate the performance and sensitivity of the most important methods, corroborating the literature data. In the fourth and final part, a critical view on the future and remaining challenges of ground-based thermal remote sensing is presented.

Key words: Canopy temperature, corn, grapevine, infrared thermography, leaf temperature, non-contact thermocouple, thermal camera, wheat.

1 Introduction

Evapotranspiration is the process in which water stored in the soil or vegetation is converted from the liquid into the vapour phase and is transferred to the atmosphere. Because the energy required to break the hydrogen bonds in this phase transition is withdrawn from the soil or vegetation, evapotranspiration decreases the ecosystem’s surface temperature \( T_s \) (Jones, 1992, 1999b).

Therefore, since the 1960s, researchers tried to apply canopy surface temperature for assessing plant-water and plant-health status (see Fuchs and Tanner, 1966, for an early overview). This pioneering research revealed the extreme difficulties in using surface temperature measurements, caused by the large influence of meteorological conditions and crop characteristics on \( T_s \) (Idso, 1982). It wasn’t until measurement instruments became cheaper and new methods were developed to correct \( T_s \) for meteorological conditions that thermal remote sensing techniques could be applied in irrigation management and planning. The availability of thermal cameras led to a new boom in methods and applications of thermal remote sensing in the 2000s, an evolution that is still ongoing.

In this article, the application of ground-based thermal remote sensing in agriculture is reviewed. First, the basic principles and measurement techniques are introduced (section 2). Next, the theoretical relation between surface temperature and the evapotranspiration/
energy balance is elaborated at leaf and crop scale (section 3), after which the most important application methods are discussed (section 4). Finally, remaining knowledge gaps and future challenges for ground-based thermal remote sensing in agriculture are briefly discussed in section 5. A list of all abbreviations is given in Table 1.

This review focuses on ground-based thermal remote sensing and does not consider satellite or (high-altitude) airborne remote sensing techniques, as these are covered by several recent review papers (e.g. Gowda et al., 2008; Kalma et al., 2008; Li et al., 2009).

**Table 1. Abbreviation list**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Meaning</th>
<th>Unity</th>
</tr>
</thead>
<tbody>
<tr>
<td>α</td>
<td>Albedo</td>
<td>[-]</td>
</tr>
<tr>
<td>α_aer</td>
<td>Aerodynamic adjustment parameter</td>
<td>[-]</td>
</tr>
<tr>
<td>α_l</td>
<td>Albedo of lower leaf side</td>
<td>[-]</td>
</tr>
<tr>
<td>α_PT</td>
<td>Priestley-Taylor coefficient</td>
<td>[-]</td>
</tr>
<tr>
<td>α_u</td>
<td>Albedo of upper leaf side</td>
<td>[-]</td>
</tr>
<tr>
<td>a</td>
<td>Parameter in equation 34</td>
<td>[-]</td>
</tr>
<tr>
<td>a_0</td>
<td>Parameter (intercept) of non-water stressed baseline (equations 45, 47)</td>
<td>[-]</td>
</tr>
<tr>
<td>a_aero</td>
<td>Aerodynamic adjustment parameter (equation 38)</td>
<td>[-]</td>
</tr>
<tr>
<td>B</td>
<td>Sublayer-Stanton number (equation 35)</td>
<td>[-]</td>
</tr>
<tr>
<td>B iotic</td>
<td>Biologically Identified Optimal Temperature Interactive Console (ST)</td>
<td>[min or hours]</td>
</tr>
<tr>
<td>b_0</td>
<td>Parameter (slope) of non-water stressed baseline (equations 45, 48)</td>
<td>[-]</td>
</tr>
<tr>
<td>B_s</td>
<td>Sublayer-Stanton number adjusted for radiometric roughness length (equation 37)</td>
<td>[-]</td>
</tr>
<tr>
<td>c_p</td>
<td>The heat or thermal capacity of the air</td>
<td>[J kg⁻¹ K⁻¹]</td>
</tr>
<tr>
<td>CTD</td>
<td>Canopy Temperature Depression (T_c – T_a)</td>
<td>[K or °C]</td>
</tr>
<tr>
<td>CTV</td>
<td>Critical Temperature Variability (T_c,max – T_c,min)</td>
<td>[K or °C]</td>
</tr>
<tr>
<td>CWSI</td>
<td>Crop Water Stress Index (equation 41)</td>
<td>[-]</td>
</tr>
<tr>
<td>CWSI_a</td>
<td>CWSI obtained with analytical approach</td>
<td>[-]</td>
</tr>
<tr>
<td>CWSI_d</td>
<td>CWSI obtained with direct approach (equation 49)</td>
<td>[-]</td>
</tr>
<tr>
<td>CWSI_d,high</td>
<td>CWSI_d estimated from T_l, T_dry,high, and T_wet,high</td>
<td>[-]</td>
</tr>
<tr>
<td>CWSI_d,low</td>
<td>CWSI_d estimated from T_l, T_dry,low, and T_wet,low</td>
<td>[-]</td>
</tr>
<tr>
<td>CWSI_e</td>
<td>CWSI obtained with empirical approach</td>
<td>[-]</td>
</tr>
<tr>
<td>ε_e</td>
<td>Vapour pressure deficit</td>
<td>[Pa or kPa]</td>
</tr>
<tr>
<td>ΔT</td>
<td>Difference between canopy and air temperature (T_c – T_a)</td>
<td>[K or °C]</td>
</tr>
<tr>
<td>ΔT_dry</td>
<td>ΔT of a non-transpiring crop</td>
<td>[K or °C]</td>
</tr>
<tr>
<td>ΔT_pot</td>
<td>ΔT of a potential crop (crop not experiencing drought stress)</td>
<td>[K or °C]</td>
</tr>
<tr>
<td>d</td>
<td>Zero displacement height</td>
<td>[m]</td>
</tr>
<tr>
<td>D</td>
<td>Characteristic leaf dimension</td>
<td>[m]</td>
</tr>
<tr>
<td>D_i</td>
<td>Proportion of diffuse light</td>
<td>[-]</td>
</tr>
<tr>
<td>ε</td>
<td>Overall emissivity</td>
<td>[-]</td>
</tr>
<tr>
<td>ε_app</td>
<td>Apparent emissivity (equation 8)</td>
<td>[-]</td>
</tr>
<tr>
<td>ε_c</td>
<td>Canopy (or crop) emissivity</td>
<td>[-]</td>
</tr>
<tr>
<td>ε_clr</td>
<td>Clear-sky emissivity (equation 6)</td>
<td>[-]</td>
</tr>
<tr>
<td>ε_eff</td>
<td>Effective emissivity of the sky (equation 6)</td>
<td>[-]</td>
</tr>
<tr>
<td>n_l</td>
<td>Leaf emissivity</td>
<td>[-]</td>
</tr>
<tr>
<td>e_soil</td>
<td>Soil emissivity</td>
<td>[-]</td>
</tr>
<tr>
<td>e_a</td>
<td>Vapour pressure in the air</td>
<td>[Pa or kPa]</td>
</tr>
<tr>
<td>ε_s(T_0)</td>
<td>Saturated vapour pressure at temperature T_0</td>
<td>[Pa or kPa]</td>
</tr>
<tr>
<td>F</td>
<td>Factor (≥1) accounting for sky cloudiness (equation 6)</td>
<td>[-]</td>
</tr>
<tr>
<td>f_d(ϕ)</td>
<td>Fractional vegetation cover (equation 9)</td>
<td>[-]</td>
</tr>
<tr>
<td>γ</td>
<td>Psychrometric constant</td>
<td>[kPa K⁻¹]</td>
</tr>
<tr>
<td>Γ</td>
<td>G / R_n⁻¹ (equation 31)</td>
<td>[-]</td>
</tr>
<tr>
<td>G</td>
<td>Factor relating g_c and f_d (equation 58)</td>
<td>[mmol s⁻¹ m⁻² or mm s⁻¹]</td>
</tr>
<tr>
<td>g_h</td>
<td>Soil heat flux</td>
<td>[W m⁻²]</td>
</tr>
<tr>
<td>g_s</td>
<td>Crop stomatal conductance</td>
<td>[mmol s⁻¹ m⁻² or mm s⁻¹]</td>
</tr>
<tr>
<td>g_s,l</td>
<td>Leaf stomatal conductance</td>
<td>[mmol s⁻¹ m⁻² or mm s⁻¹]</td>
</tr>
<tr>
<td>g_s,u</td>
<td>Stomatal conductance on lower leaf side</td>
<td>[mmol s⁻¹ m⁻² or mm s⁻¹]</td>
</tr>
<tr>
<td>g_u,u</td>
<td>Stomatal conductance on upper leaf side</td>
<td>[mmol s⁻¹ m⁻² or mm s⁻¹]</td>
</tr>
<tr>
<td>H</td>
<td>Sensible heat flux (equation 14)</td>
<td>[W m⁻²]</td>
</tr>
<tr>
<td>h</td>
<td>Indicator of drought stress derived from 3T method (equation 62)</td>
<td>[-]</td>
</tr>
<tr>
<td>h_c</td>
<td>Vegetation (canopy) height</td>
<td>[m]</td>
</tr>
</tbody>
</table>
### Table 1. continued

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Meaning</th>
<th>Unity</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_{dry}$</td>
<td>H of a completely dry leaf</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$H_r$</td>
<td>Relative humidity</td>
<td>[%]</td>
</tr>
<tr>
<td>$H_{soil}$</td>
<td>H of soil layer in TSM</td>
<td></td>
</tr>
<tr>
<td>$I_g$</td>
<td>Stomatal conductance index (equation 57)</td>
<td>[-]</td>
</tr>
<tr>
<td>IRT</td>
<td>Infrared Thermometer: general name for non-imaging thermal infrared devices (temperature guns or stand-alone sensors)</td>
<td></td>
</tr>
<tr>
<td>$K_n$</td>
<td>Incoming shortwave radiance</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$K_{ni}$</td>
<td>$K_n$ at lower leaf side</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$K_{nu}$</td>
<td>$K_n$ at upper leaf side</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$K_{out}$</td>
<td>Outgoing shortwave radiance</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$k$</td>
<td>von Karman constant for momentum (0.41)</td>
<td>[-]</td>
</tr>
<tr>
<td>$\lambda E$</td>
<td>Latent heat flux (evapotranspiration flux density)</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$\lambda E_c$</td>
<td>$\lambda E$ of canopy layer in TSM</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$\lambda E_{pot}$</td>
<td>$\lambda E$ of potential crop (crop not experiencing drought stress)</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$\lambda E_{soil}$</td>
<td>$\lambda E$ of soil layer in TSM</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>L</td>
<td>Leaf length</td>
<td>[m]</td>
</tr>
<tr>
<td>$L_{emitted}$</td>
<td>Longwave radiation emitted by a system</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$L_n$</td>
<td>Incoming longwave radiance</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$L_{reflected}$</td>
<td>Reflected longwave radiation</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$L_{out}$</td>
<td>Outgoing longwave radiance (equation 3)</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>LAI</td>
<td>Leaf area index</td>
<td>[m$^2$ m$^{-1}$]</td>
</tr>
<tr>
<td>LAI$_{shade}$</td>
<td>LAI of shaded canopy</td>
<td>[m$^2$ m$^{-1}$]</td>
</tr>
<tr>
<td>LAI$_{sun}$</td>
<td>LAI of sunlit canopy</td>
<td>[m$^2$ m$^{-1}$]</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized difference vegetation index</td>
<td>[-]</td>
</tr>
<tr>
<td>OSM</td>
<td>One-source model</td>
<td></td>
</tr>
<tr>
<td>$\psi_H$</td>
<td>Morin-Obukhov stability function for heat flux</td>
<td>[-]</td>
</tr>
<tr>
<td>$\psi_M$</td>
<td>Morin-Obukhov stability function for momentum</td>
<td>[-]</td>
</tr>
<tr>
<td>$\rho_a$</td>
<td>Air density</td>
<td>[kg m$^{-3}$]</td>
</tr>
<tr>
<td>$r_{ae}$</td>
<td>Effective aerodynamic resistance (equation 38)</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$r_{HT}$</td>
<td>Leaf or canopy resistance to sensible heat transport</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$r_{HTL}$</td>
<td>Resistance to sensible heat transport on lower leaf side</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$r_{HTU}$</td>
<td>Resistance to sensible heat transport on upper leaf side</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$r_{HTU}(free)$</td>
<td>Leaf resistance to free convection of $H$ on upper leaf side</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$r_{HTU}(forced)$</td>
<td>Leaf resistance to forced convection of $H$ on upper leaf side</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$r_{st}$</td>
<td>Canopy resistance to momentum exchange</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$r_{stv}$</td>
<td>Resistance to vapour transport in the boundary layer/air</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$r_c$</td>
<td>Crop stomatal resistance</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$r_{c,po}$</td>
<td>$r_c$ of potential crop (crop not experiencing drought stress)</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$r_{HT}$</td>
<td>Leaf resistance to sensible heat transport and radiative heat loss</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$r_l$</td>
<td>Total resistance of leaves to vapour losses</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$r_{ld}$</td>
<td>(Virtual) leaf resistance to radiative transfer (equation 53)</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$r_s$</td>
<td>Leaf stomatal resistance</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$r_{soil}$</td>
<td>Resistance to heat flow between the soil layer and the canopy layer in TSM</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$r_T$</td>
<td>Total resistance to vapour transport</td>
<td>[s m$^{-1}$ or s mm$^{-1}$]</td>
</tr>
<tr>
<td>$R_n$</td>
<td>Net radiation</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$R_{ni}$</td>
<td>Isothermal net radiation</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$R_{nc}$</td>
<td>$R_n$ of the canopy layer</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$R_{ndry}$</td>
<td>$R_n$ of a completely dry leaf</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$R_{soil}$</td>
<td>$R_n$ of the soil layer</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Stefan-Boltzmann constant (5.675 $10^{-8}$ W m$^{-2}$ K$^{-4}$)</td>
<td>[W m$^{-2}$ K$^{-4}$]</td>
</tr>
<tr>
<td>$\sigma(e)$</td>
<td>Standard deviation of $e$ between leaves</td>
<td>[-]</td>
</tr>
<tr>
<td>$\sigma(T_c)$</td>
<td>Canopy temperature variability</td>
<td>[K or °C]</td>
</tr>
<tr>
<td>$\sigma(T)$</td>
<td>Standard deviation on $T_c$ measurement</td>
<td>[K or °C]</td>
</tr>
<tr>
<td>$s$</td>
<td>Slope of the curve relating $T$ with $e$, ($s$) (equation 17)</td>
<td>[Pa K$^{-1}$]</td>
</tr>
<tr>
<td>S</td>
<td>Total aboveground energy storage</td>
<td>[W m$^{-2}$]</td>
</tr>
<tr>
<td>SAVI</td>
<td>Soil-adjusted vegetation index</td>
<td>[-]</td>
</tr>
<tr>
<td>SDD</td>
<td>Stress degree day (equation 40)</td>
<td>[K or °C]</td>
</tr>
<tr>
<td>ST</td>
<td>Stress time index</td>
<td>[min or hours]</td>
</tr>
</tbody>
</table>
2 Basics of thermal remote sensing

2.1 Basic principles and terminology of thermal remote sensing

According to Planck’s Fundamental Radiation law and Wien’s Displacement law, every system with a temperature above 0 K emits radiation, of which the intensity and the spectral distribution are determined by the temperature of the system (Fuchs, 1990). The energy flux density of all ecosystems peaks at ~10 µm and can be detected optimally in the thermal infrared optical window between 7 and 14 µm (Fuchs and Tanner, 1966; Fuchs, 1990).

The total amount of radiation energy flux density emitted by a system \( L_{\text{emitted}} \) (W m\(^{-2}\)) is a function of its temperature (in K), according to the Stefan-Boltzmann law:

\[
L_{\text{emitted}} = \sigma T_{\text{bb}}^4 = \varepsilon \sigma T_s^4
\]  

(1)

with \( T_{\text{bb}} \) the blackbody temperature (K), \( T_s \) the surface radiometric temperature (K), \( \sigma \) the Stefan-Boltzmann constant (5.67 \( \times \) 10\(^{-8}\) W m\(^{-2}\) K\(^{-4}\)), and \( \varepsilon \) the overall emissivity (–) of the system.

A blackbody is an idealized object that is a perfect absorber of all incoming radiative energy and a perfect emitter of radiation. The blackbody temperature corresponds with the temperature that a blackbody would have if it emits the same radiation energy flux density as the system (Norman and Becker, 1995). In reality, however, systems are not perfect emitters or absorbers of radiation. The overall emissivity \( \varepsilon \) is a dimensionless variable between 0 and 1 that indicates how well a system resembles a blackbody in emitting radiation. Although \( \varepsilon \) is wavelength specific and depends on the viewing angle (Fuchs, 1990; Norman and Becker, 1995; Jones et al., 2003), a constant overall emissivity can be assumed in agricultural research (Fuchs, 1990) with negligible error (see Norman and Becker, 1995, for a discussion).

(Eco)systems are not perfect absorbers of radiation (i.e. they are not blackbodies), which implies that they reflect some of the incoming longwave radiation \( L_{\text{in}} \) (W m\(^{-2}\)). According to Kirchhoff’s law of thermal radiation, the absorption in the thermal wavelengths is equal to the emissivity and the reflected longwave radiation \( L_{\text{reflected}} \) is:

\[
L_{\text{reflected}} = (1 - \varepsilon) L_{\text{in}}
\]  

(2)
The total outgoing longwave radiation (L_{out}, \text{W} \cdot \text{m}^{-2}) from a system, i.e. the radiation measured by the thermal sensor, is:

\[ L_{\text{out}} = L_{\text{emitted}} + L_{\text{reflected}} = \varepsilon \sigma T_s^4 + (1 - \varepsilon) L_{\text{in}} \] (3)

Equation 3 can be rewritten in terms of temperature by analogy with the Stefan-Boltzmann law (L = \varepsilon \sigma T^4, see equation 1):

\[ T_{br}^4 = \varepsilon T_s^4 + (1 - \varepsilon) T_{bg}^4 \] (4)

In equation 4, T_{bg} is the background temperature, defined as

\[ T_{bg} = \frac{L_{\text{in}}}{\varepsilon \sigma}, \] and T_{br} the brightness temperature (both in K). T_{br} is not the same as T_{bb}; T_{bb} is the temperature of a blackbody that emits the same amount of radiation as the actual system emits; T_{br} is the temperature of a blackbody emitting the same amount of radiation as what the actual system emits and reflects (Norman and Becker, 1995; Jones et al., 2003), or, from equations 1 and 4,

\[ T_{br}^4 = (1 - \varepsilon) T_{bg}^4 + T_{bg}^4. \] T_{se} is the ‘temperature’ actually measured by the infrared radiometer. T_{br}, on the other hand, is a purely theoretical concept that is not measured directly.

In thermal remote sensing, one is not interested in the brightness temperature but in the surface radiometric temperature or surface temperature T_s, because it is T_s that reflects the internal energy status of the system. From equation 4, it follows that:

\[ T_s^4 = \frac{T_{br}^4 - (1 - \varepsilon) T_{bg}^4}{\varepsilon} \] (5)

2.2 Measuring surface temperature

T_s can be measured with non-imaging and with imaging devices. Non-imaging devices or infrared thermometers (IRTs) make use of non-contact thermocouples and can be either portable, hand-held ‘temperature guns’, or continuously monitoring cylindrical stand-alone sensors, which have to be connected to a data logger. They measure the average T_{br} within the field of view of the sensor. They are fast, cheap, do not require an external power resource, and can be installed permanently in the field. On the other hand, the measured T_{br} is often a composite of vegetation and background (soil/sky) temperatures, which makes the interpretation difficult and can cause large estimation errors (Jackson et al., 1981; Gardner et al., 1992b; Moran et al., 1994).

Imaging devices or thermal cameras predominantly use microbolometer sensors. They are more delicate, can often not be installed permanently on the field (because of price considerations, and because they are often not waterproof) and are much more expensive than IRTs, although prices have decreased in recent years. On the other hand, they provide images, are very precise and often give T_{br} rather than T_{se} as direct output (although T_{bg} and \varepsilon must still be supplied by the user).

Indeed, equation 5 shows that background temperature T_{bg} and \varepsilon are required to calculate T_s. T_{bg} can be assessed in several ways:

Directly: by measurement of T_{br} of overhead sky, without including the sun in the field of view (Loheide and Gorenlick, 2005), with an infrared thermometer, sensitive in the same wavelengths as the thermometer used to measure T_s (Blonquist et al., 2009).

Indirectly: measurement of T_{br} of blotted aluminum foil: as aluminum foil has an emissivity of 0.03, close to 0, T_{br} will be almost equal to T_{bg} (see equation 4) (Jones et al., 2002, 2003). By estimation: T_{bg} can be estimated from the air temperature T_a (K) as (Flerchinger et al., 2009; Sedlar and Hock, 2009):

\[ T_{bg}^4 = \varepsilon_{\text{eff}} TS^4 = \varepsilon_{\text{eff}} F TS^4 \] (6)

with \varepsilon_{\text{eff}} the effective sky emissivity, \varepsilon_{\text{sky}} the sky emissivity at clear sky, and F a unitless factor (21) accounting for the cloudiness of the sky. Methods to estimate \varepsilon_{\text{sky}} and F are reviewed and evaluated by Flerchinger et al. (2009) and Sedlar and Hock (2009). As a rule of thumb, \varepsilon_{\text{sky}} is close to 0.7. Hence, at T_a = 20 °C and for clear skies (F = 1), T_{bg} will be around 268 K or –5 °C. T_{bg} is close to T_s in greenhouses and with fully overcast skies and is lowest with clear skies.

2.2.1 Measuring leaf emissivity and leaf surface temperature

Values of leaf emissivity (\varepsilon_l) are available for a large number of plant species (see Gates et al., 1965 and Salisbury and D’Aria, 1992, for an overview) and are generally 0.95 or higher (Fuchs, 1990); 0.97 is a good approximation (Kustas et al., 2004).

Leaf emissivity can be estimated if T_{br}, T_{bg}, and T_{bg} are known:

\[ \varepsilon_l = \left( \frac{T_{br}^4 - T_{bg}^4}{T_s^4 - T_{bg}^4} \right) \] (7)

For the most precise measurements, leaves can best be put in well-stirred water baths with controlled temperatures; T_s can then be assumed to be equal to the temperature of the water, and T_{br} and T_{bg} can be measured.

Very often, T_{bg} is not measured or known and T_1 is calculated as T_1 = T_{br} or \varepsilon_l = \varepsilon_1 T_{br}^4 with \varepsilon_l taken from literature. However, both methods introduce significant error, as shown in Fig. 1a. When T_{br} is assumed equal to T_{se}, T_{se} is underestimated by 0.6–0.8 °C in clear-sky conditions; in cloudy conditions or inside greenhouses, errors are negligible. Applying \varepsilon_l without incorporating T_{bg} leads to a significant overestimation of T_s, which will be larger in cloudy conditions or inside greenhouses (Fig. 1a).

An alternative method in case T_{bg} cannot be measured uses an apparent emissivity (\varepsilon_{\text{app}}). \varepsilon_{\text{app}} is estimated from T_s (measured in a stirred bath or directly with contact thermocouples) and T_{br} only, as \varepsilon_{\text{app}} = T_{br}^4 - T_1^4 (Jones et al., 2003; Blonquist et al., 2009). Combining equation 4 with T_{br}^4 = \varepsilon_{\text{app}} T_1^4 gives:

\[ \varepsilon_{\text{app}} = \varepsilon_1 + \left( 1 - \varepsilon_1 \right) \frac{T_{bg}^4}{T_1^4} \] (8)

Hence, \varepsilon_{\text{app}} is higher than \varepsilon_1 and (\varepsilon_{\text{app}} - \varepsilon_1) is larger when T_{bg} is high and when \varepsilon_1 and T_1 are low. T_1 estimated with \varepsilon_{\text{app}} gives only an unbiased estimate of T_s when T_1 and T_{bg} are the same as they were when \varepsilon_{\text{app}} was estimated. The error for deviating T_1
temperatures, (ii) by using a literature value of \( \varepsilon \) for \( \varepsilon \) from literature, and (iii) by using \( \varepsilon \) for details. In both parts, \( T_a = 25 \, ^\circ C \) and \( T_{bg} = (0.7 \, T_a) \varepsilon = 0.97 \), \( T_a = 25 \, ^\circ C \), and \( T_l = 28 \, ^\circ C \); from equation 8, \( \varepsilon \) is more difficult than in the case of \( \varepsilon \) and requires night measurements; see Fuchs and Tanner (1966) or Huband and Monteith (1986) for a description of the methodology. Fortunately, because \( \varepsilon \) of dense canopies is very high (0.88–0.99; Huband and Monteith, 1986; Sobrino et al., 2001, 2002), measurement of \( T_{br} \) or precise knowledge of \( \varepsilon \) are of lesser importance; estimating \( T_l \) by either assuming \( T_s = T_{br} \) or by assuming \( \varepsilon_{app} = 0.99 \) will normally cause negligible error, in particular in cloudy conditions.

A second difference with leaf temperature measurements is the fact that the measured signal is a composite of surface temperatures of several objects, including leaves and branches, radiation (see section 3.2.2). It is therefore often preferable to measure the canopy surface temperature (\( T_c \)) as an aggregate of all leaf temperatures (Jones et al., 2009). Measurements of \( T_c \) differ in several ways from those of single leaves. First, canopy emissivity (\( \varepsilon_c \)) is larger than \( \varepsilon \), because of the partial cavities in the foliage, entrapping the radiation (Fuchs, 1990; Jones et al., 2003). Estimating \( \varepsilon_c \) is more difficult than in the case of \( \varepsilon \) and requires night measurements; see Fuchs and Tanner (1966) or Huband and Monteith (1986) for a description of the methodology. Fortunately, because \( \varepsilon_c \) of dense canopies is very high (0.88–0.99; Huband and Monteith, 1986; Sobrino et al., 2001, 2002), measurement of \( T_{br} \) or precise knowledge of \( \varepsilon_c \) are of lesser importance; estimating \( T_l \) by either assuming \( T_s = T_{br} \) or by assuming \( \varepsilon_{app} = 0.99 \) will normally cause negligible error, in particular in cloudy conditions.

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### Table 2. Correlation \( (R^2) \) between the measurement error in \( T_l \) and \( \varepsilon \), \( T_{bg} \) and \( T_{br} \), and the increase in \( \varepsilon \), \( T_{bg} \), and \( T_{br} \) that causes an increase in \( T_l \) of 0.1 °C, in open sky and cloudy conditions.

<table>
<thead>
<tr>
<th></th>
<th>Open sky</th>
<th>Cloudy</th>
<th></th>
<th>Open sky</th>
<th>Cloudy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( R^2 )</td>
<td>( \Delta x ) causing a ( \Delta T_l ) of 0.1 °C</td>
<td></td>
<td>( R^2 )</td>
<td>( \Delta x ) causing a ( \Delta T_l ) of 0.1 °C</td>
</tr>
<tr>
<td>( \varepsilon )</td>
<td>0.66</td>
<td>-0.0035</td>
<td></td>
<td>0.032</td>
<td>-0.0191</td>
</tr>
<tr>
<td>( T_{bg} )</td>
<td>2.10(^{-4})</td>
<td>5.6</td>
<td></td>
<td>4.10(^{-4})</td>
<td>-9.8</td>
</tr>
<tr>
<td>( T_{br} )</td>
<td>0.32</td>
<td>0.1</td>
<td></td>
<td>0.96</td>
<td>0.1</td>
</tr>
</tbody>
</table>
which make up the canopy, and soil (Kustas and Daughtry, 1990; Sánchez et al., 2008):

\[
\varepsilon T^4_s = f_s(\phi) \varepsilon T^4_c + (1 - f_s(\phi)) \varepsilon \text{soil} T^4_{\text{soil}} \tag{9}
\]

with \(\varepsilon\) and \(\varepsilon_{\text{soil}}\) the overall and soil emissivity, \(T_s\) the soil surface temperature, and \(f_s(\phi)\) the portion of the field of view occupied by the vegetation as influenced by viewing angle \(\phi\). In general, \(T_{\text{soil}}\) is higher than \(T_c\) (Kustas and Daughtry, 1990); the difference can be up to 30 °C in very sunny conditions and for dry, bare soils (Jackson, 1985). Hence, \(T_c\) is usually higher than \(T_s\). Particularly in orchards or in croplands at the beginning of the growing season, when the canopy cover is low, this can make \(T_s\) measurements unreliable.

Several ways exist to estimate \(T_s\) instead of \(T_c\). The first way is to simply delay the measurements until the canopy is fully closed and \(f_s(\phi)\) is (close to) 1. Obviously, delaying the measurements is not always an option.

Second, the viewing angle \(\phi\) can be adjusted to increase \(f_s(\phi)\). \(f_s(\phi)\) is in general smallest for nadir measurements (when the sensor is looking straight down) (Jones et al., 2003; Luquet et al., 2004) and highest for oblique views (Chehbouni et al., 2001; Koksal, 2008). However, increasing \(\phi\) is often not feasible and holds the risk of including air.

A third approach uses the angle-dependence of \(f_s(\phi)\) to estimate \(T_{\text{soil}}\) and \(T_c\) separately. Under the assumption \(\varepsilon_{\text{soil}} = \varepsilon = \varepsilon_c\), \(T_{\text{soil}}\) and \(T_c\) can be estimated separately from two simultaneous \(T_s\) measurements made under different viewing angles (Sánchez et al., 2008).

A fourth way to reduce the influence of \(T_{\text{soil}}\) is by using a thermal camera and by separating canopy from soil pixels combining visual and thermal images (e.g. Leinonen and Jones, 2004; Möller et al., 2007; Wang et al., 2010a).

3 Relation between surface temperature and sensible and latent heat flux

3.1 General relations between surface temperature and sensible and latent heat flux

The energy balance of a leaf or vegetation is given by:

\[
R_n = H + \lambda E + G_i + S \tag{10}
\]

with \(R_n\) the net radiation, \(\lambda E\) the latent heat flux, \(G_i\) the soil heat flux, and \(S\) the total aboveground energy storage (all in W m\(^{-2}\)).

The net radiation \(R_n\) is the sum of incoming (positive) and outgoing (negative) shortwave (0.3–3 \(\mu\)m) and longwave (3–50 \(\mu\)m) radiation, or:

\[
R_n = K_{in} - K_{out} + L_{in} - L_{out} \tag{11}
\]

with \(K_{in}\) the incoming and \(K_{out}\) the outgoing shortwave radiation. For vegetation, \(R_n\) is given by:

\[
R_n = K_{in} (1 - \alpha) + \varepsilon L_{in} - \varepsilon \sigma T^4_s \tag{12}
\]

where \(\alpha\) is the albedo (the fraction of incoming radiation that is reflected or reradiated). For leaves, \(R_n\) is still expressed per unit area (i.e. the leaf area on one side of the leaf), but the two leaf sides must be taken into account (Guilioni et al., 2008); in addition, \(R_n\) is influenced by the transmittance (the fraction of incoming radiation that passes through the leaves) of the leaf:

\[
R_n = K_{in,u} (1 - \alpha_u - \tau) + K_{in,l} (1 - \alpha_l - \tau) + \varepsilon_u L_{in,u} - \varepsilon_u \sigma T^4_l + \varepsilon_l L_{in,l} - \varepsilon_l \sigma T^4_l \tag{13}
\]

where the subscript \(u\) refers to the upper side and the subscript \(l\) to the lower side of the leaf.

The sensible heat flux \(H\) (W m\(^{-2}\)) from the surface to the air is given by (see derivation in Supplementary Data S1.1, available in JXB online):

\[
H = \rho\varepsilon c_p \frac{(T_0 - T_a)}{r_{al}} \tag{14}
\]

with \(\rho\varepsilon\) the air density (kg m\(^{-3}\)), \(c_p\) the specific heat of the air (J kg\(^{-1}\) K\(^{-1}\)), \(T_0\) the aerodynamic temperature, \(T_a\) the air temperature, and \(r_{al}\) the resistance of diffusive heat transfer to air (s m\(^{-1}\)). \(\rho\) and \(c_p\) can be considered constants. \(T_0\), the aerodynamic temperature, is defined by equation 14. For leaves, \(T_0 = T_1\) (Huband and Monteith, 1986). In vegetation, \(T_0\) is not a directly measurable variable. Although \(T_s\) is also commonly used as a surrogate for \(T_0\) in vegetation (Colaizzi et al., 2004), the relationship between \(T_0\) and \(T_s\) is a complex function of viewing angle, atmospheric stability and vegetation structure. This will be discussed in section 3.3.4.

The latent heat flux \(\lambda E\) (W m\(^{-2}\)) describes the energy transfer related to transpiration/evapo transpiration of water from a leaf/vegetation to the air. It is given by (see Supplementary Data S1.2 for derivation):

\[
\lambda E = \frac{\rho\varepsilon c_p (e^*_s(T_0) - e^*_0)}{\gamma} \tag{15}
\]

where \(\gamma\) is the psychrometric constant (kPa K\(^{-1}\)), which is a function of \(T_0\), \(e^*_s\) the vapour pressure in the air (kPa), \(r_i\) the total resistance to vapour transport (s m\(^{-1}\)), and \(e^*_0(T_0)\) the saturated vapour pressure (indicated by *) at the surface (indicated by subscript s) (kPa).
$T_0$ can be expressed as a function of the energy flux terms by combining equations 10 and 14:

$$T_0 = \frac{r_{alH}}{\rho_c c_p} (R_n - \lambda E - G_1 - S) + T_a$$

(16)

It follows that $T_0$ decreases linearly with increasing evapotranspiration. The relation between $T_0$ and $\lambda E$ is not as straightforward as it appears from equation 16. First of all, from equation 12, it follows that $T_s$ and $R_n$ (thus, also $T_0$ and $R_n$) are interrelated. Second, the resistance of the air to heat transfer, $r_{aH}$, is a complex function of leaf/vegetation characteristics and meteorological conditions. This issue will be discussed in more detail in sections 3.2 and 3.3.

It is often more convenient to express $T_0$ as a function of $r_V$ rather than $\lambda E$. This can be done by applying the Penman transformation:

$$e_s^*(T_0) - e_s = s(T_0 - T_a) + \delta e$$

(17)

in which $s$ is the slope of the curve relating $T$ with the saturated vapour pressure $e^*(T)$. $\delta e$ is the vapour pressure deficit (Pa or kPa) or the difference between the maximal possible amount and the actual amount of water vapour in an air volume at temperature $T_a$. $\delta e$ can be calculated from relative humidity ($H_r; \%$) and $T_a$ as:

$$\delta e = \frac{1 - H_r}{100} \exp \left( \frac{b T_a}{c + T_a} \right)$$

(18)

with $T_a$ in °C and $e^*(T_a)$ in Pa and, under normal atmospheric pressure, $a = 613.75$, $b = 17.502$, and $c = 240.97$.

Combining equations 10, 14, 15 and 17 gives:

$$(T_0 - T_a) = \frac{r_{alH} \gamma (R_n - G_1 - S) - r_{alH} \rho_c c_p \delta e}{\rho_c c_p (\gamma T_a + s r_{alH})}$$

(19)

It follows that if $(R_n - G_1 - S)$ increases or $\delta e$ decreases, $(T_0 - T_a)$ increases linearly. The relation between $(T_0 - T_a)$ and $r_{alH}$ and $r_V$ is less straightforward.

3.2 The relations between $T_s$, stomatal conductance, and weather at leaf scale

3.2.1 Resistances associated with energy processes at leaf scale

The resistance terms $r_{alH}$ and $r_V$ can be estimated by applying the electric circuit theory to transfer processes in leaves (Jones, 1992). The resistance terms are schematized in Fig. 2. $r_{alH}$ is the parallel sum of $r_{alH,u}$ and $r_{alH,l}$. As $r_{alH,u} = r_{alH,l}$ (Guilioni et al., 2008), $r_{alH}$ is:

$$r_{alH} = \left( r_{alH,u}^{-1} + r_{alH,l}^{-1} \right)^{-1} = 0.5 \ r_{alH,u}$$

(20)

Sensible heat exchange can occur either through free or through forced convection, which are also parallel processes. Forced air convection, with resistance $r_{alH,u}(\text{forced})$, is caused by wind flowing over the leaves altering the boundary layer; free air convection, giving rise to $r_{alH,u}(\text{free})$, occurs when air above a heated surface expands and rises. $r_{alH}$ is then given by:

$$r_{alH,u} = \left( r_{alH,u}(\text{forced})^{-1} + r_{alH,u}(\text{free})^{-1} \right)^{-1}$$

(21)

The stomatal resistance at each leaf side ($r_{s,u}$ and $r_{s,l}$) expresses the degree of stomatal closing (Jones, 1992); the reciprocal of the stomatal resistance is stomatal conductance ($g_{s,u}$ and $g_{s,l}$). It can be assumed that the resistance of the leaf to water vapour losses on each side is equal to its stomatal resistance (Jones, 1992). However, after the water has left the leaf, it still has to pass through the boundary layer of the air before it reaches the free-flowing air. This boundary layer is characterized by a resistance to vapour transport ($r_{aV,u}$ and $r_{aV,l}$; subscript a stands for air). It can also be assumed that $r_{aV,u} = r_{aV,l}$. Consequently, the total roughness length for water vapour transport of leaves, $r_V$, is a parallel sum of two serial sums (Fig. 2), or (Guilioni et al., 2008):

$$r_V = \left( \frac{1}{r_{aV,u} + r_{aV,l}} + \frac{1}{r_{s,u} + r_{s,l} + r_{aV,u}} \right)^{-1} \left( r_{s,u} + r_{aV,u} \right)$$

(22)

For isolateral leaves (leaves with $r_{s,l} = r_{s,u}$), equation 22 becomes:

$$r_V = \frac{r_{s,u} + r_{aV,l}}{2}$$

(23)

In hypostomatous leaves (leaves with stomata only on the lower leaf side), $r_{s,u} = \infty$ and $r_V$ is:

$$r_V = r_{s,l} + r_{aV,l}$$

(24)

Fig. 2. Schematic overview of the resistances associated with sensible and latent heat transfer and radiation at leaf scale (this figure is available in colour at JXB online).
3.2.2 Modelling the influence of leaf characteristics and weather on T_l

Model description T_l was estimated from equation 19, with T_l = T_0, G_l = 0, and S = 0. Equations from Jones (1992) were used to calculate r_u, r_v, and r_s as a function of T_u, r_sH_u (free) and r_sH_u (forced) were calculated from empirical relations of Monteith (1973) and Jones (1999a).

Conductances in mmol m^{-2} s^{-1} were converted to resistances in s m^{-1} as a function of Ta with equations from Jones (1992).

\[ r_{sH_u}^{\text{(free)}} = \frac{400}{|T_1 - T_2|^0.33} \] (25)
\[ r_{sH_u}^{\text{(forced)}} = 100 \left( \frac{D}{u} \right)^0.5 \] (26)

In equation 26, D is the characteristic leaf dimension (m) and u the wind speed (m s^{-1}). The model assumes ellipsoid shape with leaf length L and width W. Based on \( D = \sqrt{L^2 + W^2} \) (Dauzat et al., 2001), D was calculated from leaf size (A_l) and W/L as:

\[ D = \sqrt{\frac{A_l}{\pi} \left( \frac{1}{W/L} + \frac{W}{L} \right)} \] (27)

r_{sH_u} was calculated from equations 22, 25, and 26, r_{uv} from equation 20. The model assumes hypostomatous leaves; r_{uv} and g_{st} will further be denoted simply as r_u and g_s. r_v was calculated from equation 24, with r_{uv} = 0.92 r_{sH_u} (Jones, 1992). Conductances in mmol m^{-2} s^{-1} were converted to resistances in s m^{-1} as a function of T_u with equations from Jones (1992).

R_n was calculated from equation 13, with the following assumptions:

\[ K_{in} = K_{in,hor} ((1 - Di) \cos \theta + Di) \] (28)

Di was estimated as 0.15, typical for open-sky conditions (Gates, 2003; Jones et al., 2009).

K_{in} was modelled as \( K_{in} = \alpha K_{in,hor} \). This equation is obtained by assuming that the modelled leaf is a top leaf: hence, K_{in} is the reflected radiation by the lower canopy. This reflected radiation is assumed to be perfectly diffuse (hence, not a function of \( \theta \)).

\[ \alpha_u = \alpha_l = \alpha. \]

\( \alpha \) and \( \tau \) are not influenced by \( \theta \). Standard values for \( \alpha \) and \( \tau \) were 0.25 and 0.28, respectively, derived from the LOPEX93 library as the average \( \alpha \) and \( \tau \) of 10 crop species (Hosgood et al., 1994).

\[ \epsilon_u = \epsilon_l = \epsilon = 0.97 \] (Kustas et al., 2004).

\[ L_{in,u} = 0.7 \sigma T_s^4 \] (equation 6), also corresponding to open sky.

It was assumed that \( L_{in,l} \) is the radiation coming from the canopy below, which had the same T_l as the actual leaf, or \( L_{in,l} = \epsilon \sigma T_l^4 \). Note that in this (common) case, \( L_{in,l} = L_{out,l} \).

R_n was estimated as:

\[ R_n = K_{in,hor} \left( 1 - \alpha - \tau \right) (\theta) (1 - Di) \cos \theta \]
\[ + Di + \alpha) + 0.7 \sigma T_s^4 - \epsilon \sigma T_l^4 \] (29)

The mutual dependency of T_l and R_n (equations 19 and 29) required an iterative procedure, in which R_n, r_{uH}, r_{vH}, and r_{sH} were calculated, after a first assumption of \( (T_l - T_a) = 2 \), until the difference in subsequent estimates of \( (T_l - T_a) \) was less than 0.001 °C.

The influence of Ta on \( (T_l - T_a) \) was modelled for different levels of g_s by calculating \( (T_l - T_a) \) for varying Ta, while assuming constant standard values for all other factors. The influence on \( (T_l - T_a) \) of K_{in}, u, and \( \delta \) on and of the leaf properties \( \theta, A_l, W/L, \) and \( \alpha \) was simulated similarly. The 95% confidence intervals for measurement of \( (T_l - T_a) \) are indicated by the colour bars, with a width of 2 \( \sigma(T_l - T_a) \) on each side. \( \sigma(T_l - T_a) \) was 0.206 °C, obtained from \( \sigma^2(T_l - T_a) = \sigma^2(T_l) + \sigma^2(T_a) = 0.18^2 + 0.12^2 \) (see section 2.2.1).

Results

The influence of weather conditions on \( (T_l - T_a) \) is shown in Fig. 3. \( (T_l - T_a) \) decreases non-linearly with increasing g_s; the rate of decrease depends on the weather conditions.

T_a and \( \delta \alpha \) influence \( (T_l - T_a) \) in an analogous way (Fig. 3a, 3g); at low g_s, \( (T_l - T_a) \) does not depend on T_a or \( \delta \). The relationship between \( (T_l - T_a) \) and \( \delta \alpha \) when g_s is not zero, is linear (see also equation 19), an important characteristic first described by Ehrler (1973) and used as a basis for the calculation of the empirical crop water stress index (CWSI; see section 4.3.3). \( (T_l - T_a) \) rises linearly with increasing K_{in} with larger slopes for leaves with low g_s (Fig. 3c).

At high T_a, K_{in}, and \( \delta \alpha \) and low u, differences in \( (T_l - T_a) \) between leaves with different g_s are large; hence these are ideal conditions for thermal remote sensing. Overall, even modest changes in K_{in}, T_a, u, and \( \delta \alpha \) can have a profound impact on \( (T_l - T_a) \).

With the exception of \( \theta \), leaf characteristics have a much smaller impact on \( (T_l - T_a) \) than weather conditions (Fig. 4). There is little difference in \( (T_l - T_a) \) between ‘horizontal’ leaves (with \( \theta = 0 \)) and leaves with angles up to 30%. At higher \( \theta \), however, \( (T_l - T_a) \) can decrease with several degrees and the influence of g_s on \( (T_l - T_a) \) becomes less explicit (Fig. 4a, 4b).

\( (T_l - T_a) \) increases slightly with increasing leaf size. \( (T_l - T_a) \) of very small leaves tends to zero, regardless g_s (Fig. 4c, 4d). Similarly, for a constant A_l, leaf shape (W/L) has a rather limited influence on \( (T_l - T_a) \), except for very thin, needle-like leaves. \( (T_l - T_a) \) decreases slightly and steady with increasing \( \alpha \) (Fig. 4g, 4h). \epsilon, finally, has very limited impact on \( (T_l - T_a) \) (not shown).

Even if all leaves within the canopy have the same g_s (T_l - T_a) can be very heterogeneous because \( \theta \) and A_l tend to vary within the canopy and because shaded leaves, which receive lower K_{in} and experience lower T_a and \( \delta \alpha \), have a lower \( (T_l - T_a) \). As a consequence, it is often preferred to measure the temperature of (parts of) the entire canopy, rather than that of single leaves.

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Fig. 3. Influence on the mean and 95% confidence interval of \((T_l - T_a)\) of weather conditions air temperature \((T_a)\), incoming shortwave radiation \((K_{in})\), wind speed \((u)\), and vapour pressure deficit \((\delta e)\) for a low, medium, and high level of \(g_s\) (left column) and of \(g_s\) for a low, medium, and high level of \(T_a\), \(K_{in}\), \(u\), and \(\delta e\) (right column). See section 3.2.2 for model description. Standard conditions included \(T_a = 25 \, ^\circ\text{C}, K_{in} = 700 \, \text{W m}^{-2}, u = 2 \, \text{m s}^{-1},\) and \(\delta e = 1590 \, \text{Pa}\) (Hr = 50%). Standard leaf characteristics were \(\theta = 0 \, ^\circ, \varepsilon = 0.97; \tau = 28\%,\) \(\alpha = 25\%, A_I = 39.3 \, \text{cm}^2 \) (L = 10 cm), and W/L = 50%.
Fig. 4. Influence on the mean and 95% confidence interval of \((T_1 - T_a)\) of leaf characteristics (leaf angle, size, shape, and albedo) for a low, medium, and high level of \(g_s\) (left column) and of \(g_s\) on for a low, medium, and high level of leaf angle, size, shape, and albedo (right column). See Fig. 3 for model descriptions and standard conditions. Leaf shape = 100 leaf width/leaf length.
3.3 Relation between $T_a$ and evapotranspiration at canopy level

Equation 19 can be applied to estimate $T_0$ at field scale. In that case, the canopy (and soil) are represented as one single layer with one side (the ‘upper’ side), so $r_{al} = r_{aL}$ and $r_v = r_c + r_{av} = r_c + r_{al}$, with $r_c$ the canopy stomatal resistance:

$$T_0 - T_a = \frac{r_{al}(r_c + r_{al})}{\rho_a c_p} \left[ (R_n - G_i - S) - r_{al} \rho_a c_p \delta e \right] \frac{\gamma((r_c + r_{al}) + s r_{al})}{1} \tag{30}$$

3.3.1 Soil heat flux ($G_i$) and aboveground energy storage ($S$)

The soil heat flux ($G_i$) follows a daily trend that lags several hours behind $R_n$ (Jarvis et al., 1976; Samson and Lemeur, 2001). $G_i$ is most often calculated as a fraction of $R_n$ and is then denoted as $\Gamma_i$:

$$\Gamma_i = G_i / R_n$$

Whereas $\Gamma_i$ is usually small (~0.05) and is in practice often ignored in ecosystems with dense canopies (Clothier et al., 1986), it is significantly larger in ecosystems with sparse canopies (Norman et al., 1995; Su, 2002) or with very wet or permafrost soils (Chapin et al., 2002). Often, a value of 0.1 is often used for $\Gamma_i$ (Choudhury et al., 1986; Jackson et al., 1988).

When thermal measurements are performed around and short after solar noon, the aboveground energy storage term $S$ can be ignored (Meesters and Vugts, 1996; Samson and Lemeur, 2001), except in very dense woody vegetation (McCaughhey, 1985; Samson and Lemeur, 2001; Lindroth et al., 2010).

3.3.2 Canopy stomatal resistance $r_c$ and conductance $g_c$

The canopy stomatal conductance ($g_c$) can be interpreted as the stomatal conductance of the ‘big leaf’ that represents the canopy and is composed of the stomatal conductances of all individual leaves. The most practical way to calculate $g_c$ is by discerning a sunlit and a shaded layer (Blonquist et al., 2009):

$$g_c = g_{c,sun} LAI_{sun} + g_{c,shade} LAI_{shade} \tag{32}$$

where $LAI_{sun}$ and $LAI_{shade}$ are the leaf area index of the sunlit and the shaded canopy, respectively ($LAI_{sun} + LAI_{shade} = LAI$). $LAI_{sun}$ can be calculated, provided data of the solar zenith angle and canopy structure are available (Lemeur, 1973); else, $g_c$ can be roughly estimated for crops as (Allen et al., 1998):

$$g_c = 0.5 g_a LAI $$

with $g_c$ measured on sunlit leaves.

3.3.3 Resistance to sensible and latent heat transport in air $(r_{al}$ and $r_{av}$)

Based on the calculation of momentum flux and the observed logarithmic profile of wind speed close to surfaces, $r_{al}$ of ecosystems is given by (see Supplementary Data S2.3, equation S34):

$$r_{al} = \left[ \ln \left( \frac{z_u - d}{z_{0M}} \right) - \psi_{M} \right] \right] \cdot \left[ \ln \left( \frac{z_t - d}{z_{0H}} \right) - \psi_{H} \right] \tag{34}$$

where $z_u$ and $z_t$ are the heights at which $u$ and $T_a$ were measured, $d$ is the zero displacement height, $z_{0M}$ the roughness length of momentum, $z_{0H}$ the roughness length of sensible heat exchange, $k$ the dimensionless von Karman constant ($k = 0.41$), $\psi_{M}$ and $\psi_{H}$ the Monin-Obukhov stability functions for momentum and latent heat exchange, and $a_{al}$ a parameter.

The displacement height $d$ and roughness length $z_{0M}$ are complex functions of the vegetation height and architecture. They can be estimated precisely with drag partition models, taking canopy height ($h_c; m$), width, and element spacing into account (Raupach, 1992, 1994). Other methods estimate $d$ and $z_{0M}$ as a function of $h_c$ and leaf area index (LAI) (e.g. Pereira et al., 1999; Colaizzi et al., 2004) or of $h_c$ alone. Estimates of $d/h_c$ and $z_{0M}/h_c$ can be found for a wide variety of vegetation (e.g. Stanhill, 1969; Jarvis et al., 1976; Dolman, 1986). For dense crops, the values $d = 0.64 h_c$ and $z_{0M} = 0.13 h_c$ (Stanhill, 1969) are universally used.

The roughness length for sensible heat $z_{0al}$ is usually expressed as a function of $z_{0al}$ as (Owen and Thomson, 1963; Chamberlain, 1968; Colaizzi et al., 2004):

$$\ln(z_{0al}) = k B^{-1} \tag{35}$$

with $B$ the dimensionless sublayer-Stanton number. Although $k B^{-1}$ is a complex function of the time of day, weather, and the vegetation type (Garrath and Hicks, 1973; Mölder and Lindroth, 2001), constant values for $z_{0al}/z_{0M}$ of 0.0907 or 0.1 for dense crops and 0.2 for sparse crops are often used (Monteith, 1973; Campbell, 1977; Allen et al., 1989; Mölder and Lindroth, 2001).

$\psi_{M}$ and $\psi_{H}$, the Monin-Obukhov stability functions for momentum and latent heat exchange, can be estimated as a function of one of two variables, the Richardson number or the Monin-Obukhov length (see Supplementary Data S2.3, equations S35 and S36). This requires detailed meteorological measurements at several heights. Hence, it is often not feasible to estimate $\psi_{M}$ or $\psi_{H}$ in agricultural applications. Omitting $\psi_{M}$ and $\psi_{H}$ from equation 34 gives unrealistic results at low wind speeds (at $u = 0$, $r_{al}$ would become $\infty$, and so would $(T_0 - T_a)$ (see equation 34 below; also Jackson et al., 1988). This can be overcome by using $r_{ae}$ instead of $r_{al}$. $r_{ae}$ is the effective aerodynamic resistance. This semi-empirical equation includes the influence of buoyancy on aerodynamic resistance (Thom and Oliver, 1977):

$$r_{ae} = 4.72 \left[ \ln \left( \frac{z_u - d}{z_{0M}} \right) \right]^{-2} \tag{36}$$
Fig. 5. Influence on the mean and 95% confidence interval of \((T_i - T_a)\) of weather conditions air temperature \((T_a)\), incoming shortwave radiation \((K_m)\), wind speed \((u)\), and vapour pressure deficit \((\delta e)\) for a low, medium, and high level of \(g_s\) (left column) and of \(g_s\) (middle column) and \(\lambda E\) (right column) for a low, medium, and high level of \(T_a\), \(K_m\), \(u\) and \(\delta e\). See section 3.3.5 for a model description. Standard meteorological conditions were \(T_a = 25\) °C, \(K_m = 700\) W m\(^{-2}\), \(z_u = 3\) m, \(u = 2\) m s\(^{-1}\), and \(\delta e = 1590\) Pa (Hr = 50%). Standard crop properties were \(\alpha = 0.20\), \(h_c = 1\) m, \(LAI = 2\) m\(^2\) m\(^{-2}\), \(\varepsilon = 0.98\), \(z_0 = 0.13\) \(h_c\), and \(d = 0.64\) \(h_c\).
3.3.4 Surface temperature versus aerodynamic temperature

As mentioned, \( T_0 \) is not equal to \( T_s \) at canopy level. \( T_0 \) is not a directly measurable variable but is defined by equation 14 and represents the temperature of the apparent source/sink of sensible heat flux (Blonquist et al., 2009). From independent measurements of \( H \) and of \( T_0 \), it is known that \( T_s \) is usually 2-3 °C higher than \( T_0 \) for uniform canopy covers and up to 10 or 15 °C higher for incomplete canopy covers (Chavez et al., 2010), due to the influence of the high \( T_{soil} \) on \( T_s \).

\( T_0 \) is not always equal to \( T_s \) either. First, \( T_c - T_0 \) tends to be larger in stable than in unstable conditions (see Supplementary Data S2.3 for a discussion on atmospheric stability) (Choudhury et al., 1986; Colaizzi et al., 2004). Second, \( T_s \) is influenced by the viewing angle \( \phi \). The place of the virtual ‘big leaf’ of \( T_0 \) does not coincide with the canopy viewed when taking (near-)nadir \( T_0 \) measurements. Because all canopy layers in which transpiration occurs contribute to \( T_0 \), the virtual big leaf is located somewhere in the middle of the actual canopy (Blonquist et al., 2009). If \( T_s \) is measured from a (near-)nadir position, it is the temperature of the outer canopy layer, which tends to be larger than \( T_0 \) because of the direct sunlight received (Chehbouni et al., 2001; Jones et al., 2003; Colaizzi et al., 2004; Matsushima, 2005). At larger \( \phi \), the measured \( T_s \) incorporates the temperature of deeper canopy layers and is closer to \( T_{soil} \). In theory, an optimum \( \phi \), usually between 50 and 70 ° from nadir, exists at which \( T_s \) coincides with \( T_0 \) (Huband and Monteith, 1986; Matsushima and Kondo, 1997). Unfortunately, defining the optimum \( \phi \) is difficult, for it is influenced by canopy structure, sensor characteristics, and measurement conditions (Hall et al., 1992; Matsushima, 2005).

Several other approaches have therefore been developed for acquiring correct \( T_0 \) estimates. A first approach consists in replacing \( z_{0M} \) in equation 34 with \( z_{0HL} \), the so-called radiometric roughness length, usually expressed as a function of \( z_{0M} \), similar to equation 35 (Colaizzi et al., 2004; Mahrt and Vickers, 2004):

\[
\ln(z_{0M} z_{0HL}^{-1}) = k B_r^{-1}
\]

in which \( B_r \) is the sublayer-Stanton number, modified to radiometric roughness length. The determination of \( B_r \) and \( z_{0HL} \) has been the subject of intense research, which showed that \( B_r \) is a complex function of weather conditions, vegetation characteristics, and viewing angle (Blyth and Dolman, 1995; Matsushima and Kondo, 1997; Kustas et al., 2007). The application of \( z_{0HL} \) proved particularly difficult for partial canopies and has been largely abandoned (Kustas et al., 2007) in favour of approaches in which \( T_0 \) is estimated as a function of \( T_s \) and weather and canopy variables (e.g. Su et al., 2001; Mahrt and Vickers, 2004; Chavez et al., 2010).

One such approach, introduced by Chehbouni et al. (1997), uses an adjustment parameter \( \beta_{aero} \):

\[
\beta_{aero} = \frac{(T_0 - T_s)}{(T_s - T_a)}
\]

As \( (T_0 - T_s) = \frac{(T_0 - T_a)}{(T_s - T_a)}(T_s - T_a) = \beta_{aero}(T_s - T_a) \), equation 14 becomes:

\[
H = \rho \varepsilon \beta_{aero} \frac{(T_s - T_a)}{r_{sh}}
\]

Matsushima (2005) proposed the adjustment parameter \( \alpha_{aero} \) defined as \( \alpha_{aero} = \frac{(T_s - T_0)}{(T_s - T_a)} \); this is essentially the same approach. These adjustment parameters were estimated from independent measurements of \( T_s \), \( H \) and \( T_0 \) and were found to be closely related to LAI and hardly influenced by the viewing angle (Chehbouni et al., 1997; Matsushima, 2005). This approach is more reliable and robust than the \( z_{0HL} \) approach but has its limitations when \( T_s - T_0 \) is very large, due to more extreme weather conditions or vegetation characteristics (Kustas et al., 2007; Kustas and Anderson, 2009).

Finally, two-source models estimate the aerodynamic temperature of the soil and the canopy compartment separately (Kustas and Anderson, 2009). They will be discussed in section 4.6.

3.3.5 Modelling the influence of weather conditions and vegetation characteristics on \( (T_c - T_s) \)

Model description \( T_c \) will be simulated in order to illustrate the effect of ecosystem/canopy properties and weather conditions. The model is based on equation 19 and assumes that \( r_{sh} = r_{sH} \), \( S = 0 \), \( G = 0 \) (simulation of \( T_c \), not \( T_s \)), and \( T_c = T_0 \). \( g_c \) was calculated with equation 33, \( r_{sh} \) with equation 36, and \( L_m \) with equation 6, with \( \varepsilon_{eff} = 0.7 \). A value of 0.98 was used for emissivity. For all vegetations, it was assumed that \( d = 0.64 h_s \) and \( z_{0M} = 0.13 h_s \) (Stanhill, 1969). \( \lambda E \) (Fig. 5f) was calculated from the estimated \( T_s \) and from equation 10. Like for the \( (T_c - T_s) \) measurements, the 95% confidence intervals have a width of 0.206 °C and are indicated.

Results

The simulations show that the influence of weather conditions on \( (T_c - T_s) \) (Fig. 5) is similar to the influence on \( (T_s - T_c) \) (Fig. 3). \( (T_c - T_s) \) decreases non-linearly with increasing \( T_s \) and \( u \) and linearly with increasing \( \delta e \); this decrease is largest when stomata are wide open in the case of \( T_s \) and \( u \) and opposite in the case of increasing \( u \); \( (T_c - T_s) \) increases linearly with increasing \( K_{in} \), with the largest increase observed in drought-stressed vegetation. \( (T_c - T_s) \) also decreases non-linearly with increasing \( g_c \); all weather conditions have an impact on the relation between \( g_c \) and \( (T_s - T_c) \) (Fig. 5, middle column). \( (T_c - T_s) \) decreases linearly with increasing \( \lambda E \). The validity of this linear relationship has been confirmed in several studies (Vidal and Perrier, 1989; Loheide and Gorelick, 2005; Jones and Vaughan, 2010) and forms the basis of several thermal remote sensing applications (e.g. water deficit index, WDI, section 4.3.5). \( T_s \) and \( \delta e \) hardly influence this linear relation, whereas \( K_{in} \) influences the intercept and \( u \) the slope and intercept (Fig. 5, right column).

\( (T_c - T_s) \) decreases with increasing canopy height, leaf area index, and albedo, but the relations are very different (Fig. 6,
Canopy height has a particularly large influence on \((T_c - T_a)\), with \((T_c - T_a)\) becoming very high in drought-stressed very low vegetations. However, in taller vegetations, differences in \(g_s\) are much more difficult to detect with \((T_c - T_a)\) (Fig. 6a). The influence of LAI on \((T_c - T_a)\) is largest for fully transpiring vegetations; the crop albedo has little effect on the potential to detect differences in \((T_c - T_a)\) between vegetations of different \(g_s\). The three vegetation characteristics also influence the relation between \(g_s\) and \((T_c - T_a)\), although the impact of albedo is limited. Differences in LAI do not influence the relation between \(\lambda E\) and \((T_c - T_a)\); differences in albedo influence the intercept of this relation, whereas differences in \(h_c\) have a severe impact on both slope and intercept (Fig. 6, right column).

### 3.3.6 Thermal remote sensing in croplands versus orchards

The large difference in vegetation characteristics between croplands and orchards has a large influence on the...
applicability of thermal remote sensing. In croplands, during most of the growing season, the vegetation is homogeneous and the canopy very dense, ideal characteristics for thermal remote sensing. The characteristics of orchards, on the other hand, are more challenging for thermal remote sensing: the structure is heterogeneous, often with tall vegetation (trees) planted in rows with zones of bare soil or very low vegetation in between.

This heterogeneous canopy structure in orchards makes it difficult to estimate $G_c$, which is a function of the net radiation of the soil compartment $R_{a\text{-soil}}$ (Norman et al., 1995), in its turn a complex function of solar zenith angle and vegetation structure (e.g. Gijzen and Goudriaan, 1989; Kustas and Norman, 1999a). The uneven leaf distribution makes up scaling from $g_s$ to $g_c$ more difficult (equation 33 is no longer valid).

In this heterogeneous canopy structure, $d$ and $z_{OM}$ can often not be expressed as a simple function of $h_c$ (section 3.3.3).

Furthermore, it is challenging to acquire reliable thermal measurements in orchards:

Due to the sparse canopy, $T_s$ obtained from (near-)nadir viewing is much higher than $T_c$ and $T_0$, because of the large influence of the higher $T_{soil}$ (section 3.3.4). Hence, sensors must be installed at appropriate viewing angles. Tall trees can make thermal measurements with IRTs particularly challenging, because of the large noise when open sky is within in the sensor field of view. Thus, handheld measurements must be performed with great care; fixed IRT measurements are preferably installed on high poles. Moreover, the tree canopy usually has a vertical rather than a horizontal structure. As a consequence, there is a very large difference in $T_c$ between the shaded and the sunlit sides, making it much more difficult to obtain a reliable $T_c$ estimate.

Finally, due to the larger $h_c$ (taller canopies), $z_{OM}$, $d$, and $z_{OM}$ are relatively high. As a consequence, differences in $g_c$ (and $\lambda E$) are less reflected in $T_c$ than for lower cropland canopies (Fig. 5a). This, in combination with the higher variability in $T_c$, makes drought stress detection in orchard trees more difficult than for croplands.

It is therefore not surprising that ground-based thermal remote sensing methods were predominantly developed for application in homogeneous cropland. However, in recent years, the number of ground-based thermal remote sensing studies in orchards has increased significantly and includes applications in grapevine, olive, peach, nectarine, citrus, almond, and pistachio tree orchards. There are two reasons for this increased interest. First, the application of thermal cameras allows more precise assessment of $T_c$ and the removal of noise from the soil and background. Second, two-source models (section 4.6) were developed specifically for sparse canopies such as orchards. However, this does not mean that the classic one-source methods are of no use for orchards: in fact, most of these methods have recently been successfully applied in orchard vegetation as well, although the applications in cropland-like vegetations still outnumber those in orchards.

This heterogeneous canopy structure in orchards makes it difficult to estimate $G_c$, which is a function of the net radiation of the soil compartment ($R_{a\text{-soil}}$) (Norman et al., 1995), in its turn a complex function of solar zenith angle and vegetation structure (e.g. Gijzen and Goudriaan, 1989; Kustas and Norman, 1999a).

The uneven leaf distribution makes up scaling from $g_s$ to $g_c$ more difficult (equation 33 is no longer valid).

In this heterogeneous canopy structure, $d$ and $z_{OM}$ can often not be expressed as a simple function of $h_c$ (section 3.3.3).

4 Application of ground-based thermal remote sensing in agriculture

In this section, an overview is given of the most important applications of ground-based thermal remote sensing in agriculture, with a focus on applications related to the assessment of plant-water status, drought stress, or irrigation scheduling.

4.1 Direct use of brightness or surface temperature

4.1.1 Brightness and surface temperature

As discussed in section 3, under the assumption that $T_c = T_0$, $T_c$ is linearly related with $\lambda E$ and can be used as a proxy measure of $\lambda E$ or $g_c$. Canopy temperature has therefore been widely used in plant breeding studies of (winter) wheat (e.g. Araus et al., 2003; Nautiyal et al., 2008; Reynolds et al., 2009; Gutierrez et al., 2010) and other dense crops (Sanchez et al., 2001; Hamidou et al., 2007; Khan et al., 2007). In most of these studies, $T_{br}$ rather than $T_s$ or $T_c$ is used as the indicator. In general, varieties with a lower brightness temperature are preferred, as it is assumed that these are more successful in avoiding drought stress (Araus et al., 2003).

Similarly, $T_s$, $T_b$, or $T_{br}$ have been used as a drought stress index for the evaluation of different irrigation treatments of one (e.g. Singandhupe et al., 2003; Pettigrew, 2004; Yuan et al., 2004; Qiu et al., 2008) or several (e.g. Rashid et al., 1999; Siddique et al., 2000; Ko and Piccinni, 2009) crop varieties and for monitoring the effect of heat stress (Ayeneh et al., 2002; Sadas and Soar, 2009) and CO2 increases (Yoshimoto et al., 2005) on plant health.

Because of the large influence of meteorological conditions on $T_s$ (Figs. 4 and 6), repeated measurements will give very different $T_s$, unless meteorological conditions are extremely constant and vegetation structure does not change.

4.1.2 Temperature variability

At very low $g_s$ (i.e. in stressed conditions), the total range in $T_s$ between leaves of different inclinations is larger than in unstressed conditions (Fig. 3f). Several authors proposed canopy temperature variability as an index of drought stress (Aston and Vanbavel, 1972; Clasen and Blad, 1982; Fuchs, 1980). By either looking at the difference between the minimal and maximal $T_c$ (Critical Temperature Variability, CTV (Clasen and Blad, 1982) or at the standard deviation of $T_c$ ($\sigma_{T_c}$) within the canopy. Gonzalez-Dugo et al. found that $\sigma_{T_c}$ first increased with mild stress and then decreased again under more severely stressed vegetation, in airborne images of cotton (Gonzalez-Dugo et al., 2006) and of almond trees (Gonzalez-Dugo et al., 2012). However, in studies at plant and leaf scale, $\sigma_{T_c}$ was not correlated with $g_s$ or drought stress level (Grant et al., 2007; Maes et al., 2011).

Infrared thermography can also be used for disease detection. Because local infections within a leaf show up as either warm or cold spots, CTV and (to a lesser extent) $\sigma_{T_c}$ within the leaf are useful in disease detection (e.g. Vanderstraeten et al., 1995; Chaerle et al., 1999; Lindenthal et al., 2005; Oerke et al., 2006, 2011; Stoll and Jones, 2007).
4.1.3 Stress time (ST)

The stress time (ST) concept is the only concept that does not depart from the relation between \( g_s \) and \( \Delta E \) and \( T_c \). Instead, it is based on the relation between plant temperature and metabolic activity (Upchurch and Mahan, 1988) and is inspired by the positive correlation between plant performance and the period in which plant temperatures remain within a narrow optimal crop temperature window (Burke et al., 1988). Irrigation is started as soon as \( T_c \) exceeds a certain crop-specific threshold for a certain length of time.

The simplicity of the algorithm makes it very well suited for automated irrigation (O’Shaughnessy and Evett, 2010) of crops as cotton (Wanjura et al., 1990, 1992, 2002, 2006; Wanjura and Upchurch, 2000), corn (Evett et al., 2000), groundnut (Mahan et al., 2005), and soybean (Peters and Evett, 2007, 2008). ST can also be used to detect and to respond to spatial patterns of drought stress when measured with a large number of IRT sensors mounted on a centre pivot (Peters and Evett, 2007, 2008). Furthermore, ST outperformed the more commonly applied crop water stress index (CWSI, section 4.3) in estimating drought stress and yield (Wanjura et al., 2006; Bajwa and Vories, 2007).

However, ST has only been successfully applied in the semi-arid climates of Texas and, recently, Australia (Conaty, 2010). Other limitations are the requirement of continuous measurements, the crop specificity of the temperature thresholds and the sensitivity to \( T_{soil} \) measurements (see equation 9), limiting the application to full cover conditions only. ST is also known as the Temperature-Time Threshold (TTT) method (Wanjura et al., 1995) or the BIOTIC protocol (biologically identified optimal temperature interactive console) (Mahan et al., 2005; Wanjura et al., 2006).

4.2 Difference between canopy and air or reference crop temperature

\( T_c - T_a \), sometimes referred to as canopy temperature depression (CTD), is the most straightforward normalization of \( T_c \) and is used widely as an indicator of plant health, heat stress tolerance or drought stress in crops (e.g. Ehler, 1973; Sadler et al., 2000; 2002; Patel et al., 2001; Baker et al., 2007), often for studying crops experiencing different irrigation regimes (e.g. Olufayo et al., 1996; Singandhupe et al., 2003; Pettigrew, 2004; Qiu et al., 2008; Garcia-Tejero et al., 2011). \( (T_c - T_a) \) has also been used extensively for wheat cultivar selection (Amani et al., 1996; Olufayo et al., 1996; Rashid et al., 1999; Balota et al., 2007, 2008; Kumari et al., 2007). \( (T_c - T_a) \) is widely applied for woody crops as apple (Andrews et al., 1992), olive (Sepulcre-Canto et al., 2006), cherry (Stoimenov et al., 2007), grapevine (Serrano et al., 2010), peach (Massai et al., 2000; Wang and Gartung, 2010), and citrus (Garcia-Tejero et al., 2011; Zarco-Tejada et al., 2012), often showing to be closely related with irrigation treatment, leaf water potential, or \( g_s \).

Irrigation scheduling based on \( (T_c - T_a) \) has mostly occurred in the form of the stress degree day (SDD; °C or K) method, originally proposed by Idso et al. (1977) and Jackson et al. (1977):

\[
SDD = \sum_{i=1}^{n} (T_c - T_{a,i})
\]

4.3 Crop water stress index

4.3.1 Background and theory

The crop water stress index (CWSI) is a drought stress index that uses the \( T_c \) of a potential and dry crop. The potential crop is identical to the actual crop but is transpiring at maximal rate \( \lambda E_{pot} \) and temperature \( T_{pot} \). The dry crop, with associated \( \lambda E_{dry} \) and \( T_{dry} \), is a crop with identical properties as the actual crop that is not transpiring at all. CWSI is calculated as (see Supplementary Data S3):

\[
CWSI = 1 - \frac{\lambda E}{\lambda E_{pot}} = \frac{\frac{T_c - T_{c, pot}}{T_{a, pot}}}{\frac{T_{c, pot}}{T_{a, pot}}} = \frac{\Delta T_{pot} - \Delta T}{T_{pot} - T_{dry}}
\]

where \( \Delta T_{pot} \), \( \Delta T_{dry} \), and \( \Delta T_a \) are defined as \( (T_{pot} - T_c) \), \( (T_{dry} - T_c) \), and \( (T_c - T_a) \), respectively. The introduction of CWSI by Jackson et al. (1981) and Idso et al. (1981a) was an important breakthrough in ground-based thermal remote sensing. Its innovative aspect was the normalization by \( T_a \) and, more importantly, by \( \Delta T_{pot} \) and \( \Delta T_{dry} \), undepinned by a solid theoretical base. This approach of using an upper and lower boundary \( \Delta T \) or \( T_a \), was later used in the large majority of ground-based and airborne and satellite thermal remote sensing methods.

Different approaches to calculate CWSI were developed: the analytical (CWSIa), empirical (CWSIe), direct approach (CWSId),...
and the WDI will be discussed in the following sections. As they are all based on equation 41, it is important to know the underlying assumptions of this equation:

It is a one-source model.

\[ r_{ai} = r_{ai} = r_{ai} \]

with \( \text{raM} \) the roughness lengths for momentum exchange. This corresponds with assuming that the Reynolds analogy holds (see Supplementary Data S2.3 for a discussion).

\[ r_{ai,dry} = r_{ai, pot} = r_{ai} \]

Differences in \( R_n \) between \( T_{dry}, T_{pot} \) and \( T_c \), caused by the differences in outgoing longwave radiation (equation 12) can be ignored.

\[ S = 0 \]

\[ G_i = 0 \]

Jackson et al. (1988) proposed to replace \( R_n \) with 0.9 \( R_n \) (i.e. assuming \( \Gamma = 0.1 \); section 3.3.1) to compensate for this in the analytical approach.

\[ T_i = T_c \]

In partially vegetated fields, this assumption is problematic (Moran et al., 1994) and the use of the water deficit index (WDI; section 4.3.5) is recommended.

\[ T_0 = T_c \]

(Boulet et al., 2007, see section 3.3.4 for a discussion). In fact, most studies assume that \( T_{br} = T_c \).

4.3.2 Analytical approach (CWSIa)

In the analytical approach, \( T_c \) measurements are combined with meteorological data to compute CWSI. Originally, Jackson et al. (1981) proposed to calculate CWSIa from

\[
\text{CWSI} = \frac{s + s}{s + s + s} \left( \frac{r_c - r_{pot}}{r_{ai}} \right).
\]

This requires an estimate of \( r_{ai}, r_{pot} \), and \( r_c / r_{ai} \), estimated as (see Supplementary Data S3, equation S40):

\[
\frac{r_c}{r_{ai}} = \frac{\Delta T}{s + \gamma \left( \frac{r_c - r_{pot}}{r_{ai}} \right)}
\]

(42)

where \( s \) is calculated from the average of the air and surface temperature. Hence, \( \Delta T \) is used to calculate \( r_{ai} \). Although this method is still occasionally applied (e.g. da Silva and Rao, 2005; Berni et al., 2009a), most studies using CWSIa calculate \( \Delta T_{pot} \) and \( \Delta T_{dry} \) directly (e.g. Feldhake et al., 1997; Yuan et al., 2004; Gonzalez-Dugo et al., 2006; Gontia and Tiwari, 2008; Ben Gal et al., 2009; Alchanatis et al., 2010; Li et al., 2010) as (see Supplementary Data S3, equations S41 and S43):

\[
\Delta T_{pot} = \frac{r_{ai}}{s + \gamma \left( \frac{r_c - r_{pot}}{r_{ai}} \right)} \left( \frac{R_n - 1}{\Delta T} \right)
\]

(43)

\[
\Delta T_{dry} = \frac{r_{ai}}{s + \gamma \left( \frac{r_c - r_{pot}}{r_{ai}} \right)} \left( \frac{R_n - 1}{\Delta T} \right)
\]

Both methods are essentially the same and require, apart from standard meteorological data (\( T_a, \delta e, R_n \)), estimates of \( u, z_{0M}, d, h_c \) and possibly \( z_{0i} \) to estimate \( r_{ai} \) (equations 34 or 36). Furthermore, \( r_{pot} \) must be estimated (equation 43) from literature or derived from the observed \( \Delta T_{min} \) (the minimal observed \( \Delta T \)) during the growth period, as suggested by Jackson et al. (1981) and later elaborated by O’Toole and Real (1986).

CWSIa was developed for and has mostly been applied in dense crops, although it was also successfully applied for orchard trees as apple (Andrews et al., 1992), olive (Ben Gal et al., 2009; Berni et al., 2009a), and peach (Wang and Gartung, 2010).

Still, the large input requirements have hampered a routine use of the analytical approach (Gardner et al., 1992a; Payero et al., 2005). The most important sources of error are incorrect measurements of \( u, R_n, T_a, \) and \( T_c \) (Jackson et al., 1981). \( \Delta T_{dry} \) (equation 44) only requires \( R_n \) and \( r_{ai} \) for its estimation and is often assumed constant (see further; see also Fig. 5j). The estimation of \( \Delta T_{pot} \) bears more uncertainty (equation 43). Alves and Pereira (2000) suggested replacing \( T_{pot} \) by the wet bulb temperature, which can be measured directly without the requirement of wind speed or of crop data. This method is appealing but has the disadvantage that it sets \( r_{pot} = 0 \) (Yuan et al., 2004), making CWSI no longer equal to \( 1 - \frac{\Delta T}{\Delta T_{pot}} \).

4.3.3 Empirical or baseline approach (CWSIb)

Definition and baseline calculation of empirical approach

In the empirical or baseline approach, the data input is limited to \( T_a, \delta e, \) and \( T_c \). The approach was introduced by Idso et al. (1981a) and was inspired by the observation that \( \Delta T \) decreases linearly with \( \delta e \) (Ehler, 1973, see also Figs. 3d and 5d). This allows expressing \( \Delta T_{pot} \) as:

\[
\Delta T_{pot} = a_{pot} + b_{pot} \delta e
\]

(45)

Equation 45 is the mathematical expression of the lower or non-water stressed baseline (NWSB). The basic assumption of the method is that \( a_{pot} \) and \( b_{pot} \) are constant and crop specific, at least for a given location and for a certain growth stage.

These parameters can be derived in two ways. In the diurnal method, \( \Delta T \) of a fully watered crop is collected from different measurements during one or several days and plotted against \( \delta e \). As \( R_n \) is not constant during the sampling, this usually does not yield reliable estimates of \( a_{pot} \) and \( b_{pot} \). In the seasonal method, one \( \Delta T \) measurement of a fully watered crop is taken every day around solar noon during the entire growing season. Although more demanding, this gives more robust estimates (Gardner et al., 1992a). In Table S1 of Supplementary Data S4, an overview is presented of available non-water-stressed baselines, with data of 39 different crops.

\[
\Delta T_{dry} = \frac{a_{pot} + b_{pot} \left[ e^*(T_a) - e^*(T_c + a_{pot}) \right]}{e^*(T_c + a_{pot})}
\]

(46)
CWSI_e is unreliable when the canopy is not fully closed (Moran et al., 1994). This can only be partially overcome by adjusting the viewing angle. However, this does not guarantee reliable results (Koksal, 2008), in particular when the baselines were established for other viewing angles. The most important limitation, however, is related to the fact that $a_{pot}$ and $b_{pot}$ are not entirely crop specific or weather independent. Theoretically, they are estimated as (equation 43):

$$a_{pot} = \frac{r_{AH}}{\rho_s c_p} \left( 1 + \frac{r_{pot}}{r_{AH}} \right) R_n$$

$$b_{pot} = \frac{-1}{s + \gamma \left( 1 + \frac{r_{pot}}{r_{AH}} \right)}$$

$a_{pot}$ and $b_{pot}$ change with different $T_e$ and particularly $u$ (e.g. Jensen et al., 1990; Payero and Irmak, 2006; Testi et al., 2008) and $K_u$ (e.g. Gardner et al., 1992b; Olufayo et al., 1996; Al-Faraj et al., 2001; Ajayi and Olufayo, 2004). Hence, CWSI_e requires stable weather conditions (preferably hot and dry, with open skies) (Gardner et al., 1992b). Measurements should also be taken only around solar noon (Idso et al., 1981a; Jackson et al., 1981; Testi et al., 2008).

These requirements form an important drawback in humid or temperate regions (Payero et al., 2005; Payero and Irmak, 2006), where CWSI_e is only reliable when the weather is as described above (Keener and Kircher, 1983; Anda, 2009; Lebourgeois et al., 2010). Therefore, rather than as a stand-alone technique for irrigation monitoring, CWSI_e is often complemented with soil moisture measurements or used to assist decision making for irrigation scheduling (e.g. Steele et al., 1997; Yazar et al., 1999; Al-Faraj et al., 2001; Chen et al., 2010).

Another major drawback is the fact that $a_{pot}$ and $b_{pot}$ are not crop specific, but are influenced by crop characteristics as crop height and leaf area (Alves and Pereira, 2000; Payero and Irmak, 2006), so that the NWSB changes within the season and between seasons (e.g. Kirkham et al., 1983; Yuan et al., 2004; Simsek et al., 2005; Payero and Irmak, 2006; Erdem et al., 2010).

Adaptations and improvements of the empirical approach

Two methods were proposed to correct CWSI_e for non-constant meteorological conditions. In a first method, different classes of $R_h$ and/or $u$ are considered and a separate NWSB is built for each class (e.g. Jensen et al., 1990; Olufayo et al., 1996). In the second method, $u$, $R_h$ or $T_e$ are included in the regression model of the NWSB. Although more robust (e.g. Keener and Kircher, 1983; Jalalifarahani et al., 1993; Payero and Irmak, 2006), these methods require more input data and can be interpreted as intermediate between the empirical and analytical methods. A common adaptation to correct for crop growth is the definition of different NWSBs per growth stage, such as the pre-heading and post-heading phase in

with $e^*(T_e)$ and $e^*(T_e + a_{pot})$ the saturated vapour pressure at temperature $T_e$ and $(T_e + a_{pot})$, respectively.

The concept is illustrated in Fig. 7. CWSI_e is calculated as BC/AC. Note that if $\delta e$ changes while $r_c$ remains constant, the ratio of BC/AC, hence CWSI_e, will not change. This is illustrated by the thin grey line, which represents $\Delta T$ for $g_s = 50 \text{mmol m}^{-2} \text{s}^{-1}$.

**Application**

CWSI_e was closely correlated with leaf water potential (e.g. Idso et al., 1981bc; Wang et al., 2005; Testi et al., 2008), soil moisture level (Colaizzi et al., 2003a; Chen et al., 2010), and evapotranspiration (Nielsen and Anderson, 1989; Yazar et al., 1999; Lebourgeois et al., 2010) of a variety of crops. The average seasonal CWSI_e was closely related with water use efficiency (Garrot et al., 1993; Yazar et al., 1999; Wang et al., 2005; da Silva et al., 2007; Kirmak and Dogan, 2009) and can be used as precise indicators of crop yield (e.g. Garrot et al., 1994; Orta et al., 2003; Simsek et al., 2005; Emekli et al., 2007; Erdem et al., 2010). Although also developed for dense crops, CWSI_e has also been applied for orchard trees as pistachio trees, citrus, nectarine, and cherry trees (Table 2).

Soon after its introduction, CWSI_e became the most commonly used thermal drought stress index (Jackson et al., 1988; Gardner et al., 1992a), which it has remained ever since. It is one of the common irrigation scheduling methods in regions with stable sunny summer conditions (Gardner et al., 1992a,b, see also Table S1) and proved as reliable in terms of yield and water savings as more expensive soil water-based irrigation techniques (Stegman, 1986; Steele et al., 1994, 2000; Shae et al., 1999).

The main reasons for its success are the limited data requirements and straightforward calculation, which makes CWSI_e easy to apply for non-scientists. In addition, its introduction went hand in hand with a drop in price of portable IRTs, making CWSI_e relatively cheap to measure.

**Disadvantages and limitations of the empirical approach**

However, CWSI_e has its limitations:

In general, it is less reliable than CWSI_a (e.g. Stockle and Dugas, 1992; Jalalifarahani et al., 1993; Yuan et al., 2004).
wheat crops (e.g. Idso, 1982; Howell et al., 1986; Gontia and Tiwari, 2008).

4.3.4 Direct approach (CWSI_d)

In the direct approach, T_pot and/or T_dry are measured directly along with T_r. The original method, in which T_pot was measured as T_r of a fully transpiring crop, was applied in a limited number of studies (e.g. Katerji et al., 1988; Olufayo et al., 1996; Wanjura and Upchurch, 2000; Bajwa and Vorjes, 2007). A more practical method uses the temperature of dry or wet artificial reference surfaces.

At single plant level, dry reference surfaces, with corresponding temperature (T_dry) are created by covering leaves with a layer of petroleum jelly, blocking all transpiration flows. Wet leaves, with temperature Twet, are leaves sprayed with a thin layer of water on one or both leaf sides.

CWSI_d is then calculated as:

\[
CWSI_d = \frac{T_{\text{wet}} - T_r}{T_{\text{wet}} - T_{\text{dry}}} \tag{49}
\]

When thermal cameras are used, the reference leaves can be physically embedded in the scene and T_r, T_wet, and T_dry are measured within the same image. As such, no additional meteorological measurements are required. This makes the method very appealing, all the more because it allows for fully automated image analysis and CWSI_d assessment (Wang et al., 2010a). In addition, measurement errors of ε_1 or L_in are reduced because they will cause similar errors for T_wet, T_dry, and T_r. This makes CWSI_d a very appealing method. Its reliability and sensitivity for weather conditions and leaf characteristics are modelled in the next section.

Obtaining the sensitivity of CWSI_d at leaf level to weather conditions and leaf characteristics

Model description  T_r, T_dry, and T_wet were calculated with the model described in section 3.2 for the same range of weather conditions and leaf characteristics as in Figs. 3 and 4.

T_dry is calculated as (equation 19 and assuming r = ∞):

\[
T_{\text{dry}} = T_a + \frac{r_{\text{st}} R_n}{\rho_a c_p} \tag{50}
\]

T_wet of leaves sprayed on one side (r_V = r_{stV}, see equation 24) is:

\[
T_{\text{wet}} = T_a + \frac{r_{\text{st}} Y r_{\text{stV}} R_n - r_{\text{stH}} P_e c_p \delta e}{\rho_a c_p (Y t_{\text{stV}} + s r_{\text{stH}})} \tag{51}
\]

Two sets of confidence bands for CWSI_d were calculated. For the first set, it was assumed that the estimation error from each of the three temperature measurements (T_r, T_dry, and T_wet) is the only source of error. The average and standard deviation of CWSI_d (CWSI_d; σ(CWSI_d)) were calculated from 5000 random samples of T_r, T_dry, and T_wet, generated assuming a normal distribution with as average the T_r, T_dry, and T_wet value from the leaf model and 0.18 °C as standard deviation. Confidence bands were calculated as CWSI_d ± 2 σ(CWSI_d).

In the second set, a small difference in leaf characteristics or weather conditions between the measured and reference leaves was additionally taken into account. Because, in practice, dry and reference leaves are normally selected right next to each other and of two very similar leaves, it was assumed that the two reference leaves experienced identical weather conditions and leaf characteristics. T_dry and T_wet were estimated when (for instance) u is 10% higher (T_dry,high and T_wet,high) or 10% lower (T_dry,low and T_wet,low) than the wind speed experienced by the measured leaves. CWSI_d was calculated for 5000 randomly generated values of T_r, T_dry,high and T_wet,high (CWSI_d,high) or T_r, T_dry,low, and T_wet,low (CWSI_d,low) and the average and standard deviation of CWSI_d,high and CWSI_d,low calculated; the confidence bands were calculated as {minimum(CWSI_d,low) – 2 σ(CWSI_d,low), CWSI_d,high – 2 σ(CWSI_d,high)}; maximum (CWSI_d,low + 2 σ(CWSI_d,low), CWSI_d,high + 2 σ(CWSI_d,high)).

The relation between each variable and CWSI_d is calculated for three levels of g_s (20, 200, and 600 mmol m^{-2} s^{-1}) (Figs. 8 and 9, left column); additionally, the relation between g_s and CWSI_d is given for three levels of each variable (Figs. 8 and 9, right column). To further investigate the discriminative power, the CWSI_d values of the confidence bands were reconverted to g_s values using a splining algorithm. For each of the three g_s levels, this gives the lower and higher level of g_s that can be statistically distinguished from this level; the narrower the bands, the higher the discriminative power (Figs. 8 and 9, middle column).

Modelling results

Leaves with lower g_s have higher CWSI_d; however, CWSI_d is not linearly related with g_s (Fig. 8). The expected value of CWSI_d is not influenced by K_in, δe, θ, or α. Higher T_r and A_l and lower u lead to lower CWSI_d values.

If only measurement errors are considered, the discriminative power (dark confidence band width of graphs in middle column of Fig. 8) increases with increasing T_r, K_in, and δe and decreasing u (except for high g_s at very low u, Fig. 8d). The discriminative power is very low when δe is low. Differing conditions between the reference and measured leaves (a 10% difference was assumed, except for T_r where the difference was fixed at 0.2 °C) further decrease the discriminative power; the discriminative power is even rather constant over K_in. The lower discriminative power at g_s = 600 mmol m^{-2} s^{-1} is caused by the non-linear relationship between g_s and T_r; at higher g_s, a further increment in g_s has a lower impact on T_r (or ΔT_r/Δg_s decreases with increasing g_s, Figs. 3 and 4).

As long as the reference and the measured leaves have identical leaf characteristics, the discriminative power of CWSI_d is relatively independent of the leaf characteristics (Fig. 9, middle column). For measured leaves with high θ and (to a much lesser extent) α, deviations in α and θ between the measured and reference leaves reduce the discriminative power significantly (Fig. 9b, 9k).
Fig. 8. Influence of weather conditions on CWStL at leaf level. In the left column, the influence of the weather conditions air temperature ($T_a$), incoming shortwave radiation ($K_{in}$), wind speed ($u$), and vapour pressure deficit ($\delta e$) on the mean and 95% confidence intervals.
Application and evaluation of CWSId

Overall, the simulations showed that CWSId can be estimated with relatively low error, even in non-ideal measurement conditions. This has been confirmed experimentally: CWSId was measured in several studies and showed good correlations with \( g_c \) (Jones, 1999b; Leinonen and Jones, 2004; Grant et al., 2006, 2012; Maes et al., 2011), leaf (Grant et al., 2007) and stem water potential (Wang et al., 2010a).

Unfortunately, the method has a number of drawbacks as well. First of all, CWSId is analogous to but not the same as CWSIe or CWSL. Even at very high \( g_c \), CWSId does not tend to zero (Figs. 8 and 9), because \( T_{	ext{wet}} \) used to calculate CWSId, is much lower than \( T_{	ext{pot}} \). Furthermore, the lower boundary level of CWSId (e.g. at \( g_c = 1000 \text{ mmol m}^{-2} \text{s}^{-1} \)) depends on \( T_a \), \( u \), \( A_o \), and leaf shape (Figs. 8 and 9), which complicates the interpretation of CWSId. This is not the case when the same data are used to calculate \( I_e \) as will be discussed in section 4.4.

Another clear disadvantage of the method is related to the scale level, as working with single leaves is not feasible at field scale. To apply CWSId to the field, the wet reference leaves are replaced by wet artificial reference surfaces or WARS (Meron et al., 2003). This WARS consists of a plastic tray, filled with water and covered by a polystyrene foam, covered by a water-absorbent cloth (Möller et al., 2007). With the application of WARS, CWSId was highly correlated with the leaf water potential of cotton and soybean (e.g. Cohen et al., 2005; Meron et al., 2010; O’Shaughnessy et al., 2011), even higher than CWSId (Alchanatis et al., 2010). CWSId performs equally well for orchard trees as olive (Ben Gal et al., 2009) and grapevine (Möller et al., 2007). Given the ease of measurement, this currently seems the most promising CWSI technique for field application and is particularly suited for assessing the spatial variability of the crop water status.

However, some issues must be solved before the method can shift from purely scientific studies to application for irrigation steering. It is not clear how the WARS relates to \( T_{	ext{pot}} \) or \( T_{	ext{wet}} \), how its temperature is influenced by weather conditions, or whether it should be placed at a particular height above the ground. Moreover, the fact that the WARS needs to be visible or whether it should be placed at a particular height above the ground. Additionally, the WARS needs to be visible or whether it should be placed at a particular height above the ground.

In Fig. 10, WDI of a crop with \( f_c(\phi) \) and \( \Delta T \) of point B is calculated as WDI = \( \frac{\Delta \phi}{\Delta \phi_{	ext{pot}}} \). In practice, a vegetation index, calculated from the near infrared and red wavelengths of a pixel, is used instead of \( f_c(\phi) \). Moran et al. (1994) originally proposed to use the soil-adjusted vegetation index (SAVI), but as the normalized difference vegetation index (NDVI) gives more reliable results (Koksal, 2008), it is more commonly used. However, the underlying assumption that \( f_c(\phi) \) is linearly related with NDVI or SAVI is not correct (Jones and Vaughan, 2010).

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In Fig. 10, WDI of a crop with \( f_c(\phi) \) and \( \Delta T \) of point B is calculated as WDI = \( \frac{\Delta \phi}{\Delta \phi_{	ext{pot}}} \). In practice, a vegetation index, calculated from the near infrared and red wavelengths of a pixel, is used instead of \( f_c(\phi) \). Moran et al. (1994) originally proposed to use the soil-adjusted vegetation index (SAVI), but as the normalized difference vegetation index (NDVI) gives more reliable results (Koksal, 2008), it is more commonly used. However, the underlying assumption that \( f_c(\phi) \) is linearly related with NDVI or SAVI is not correct (Jones and Vaughan, 2010).
Fig. 9. Influence of leaf characteristics on CWSI at leaf level. In the left column, the influence of the leaf angle, size, shape, and albedo on the mean and 95% confidence intervals of CWSI is given for three levels of $g_s$; in the middle column, the discriminative power is.
4.4 Stomatal conductance index

4.4.1 Calculation and modelling

The stomatal conductance index \((I_g)\) uses the same input data as CWSI\(_d\) at leaf scale, but has the advantage over CWSI\(_d\) that it is linearly related with \(g_s\) (except for anisolateral leaves (amphistomatous leaves with \(r_{aH} \neq r_{aV}\)) (Guilioni et al., 2008)).

For its derivation, Jones (1999a,b) made use of the isothermal net radiation \(R_{ni}\), instead of \(R_n\). \(R_{ni}\) is defined as the net radiation of a leaf that would be received by an identical leaf if it were at air temperature (Jones, 1992). \(R_n\) can be substituted with \(R_{ni}\) in equations 19, 50, and 51 if \(r_{aH}\) is replaced by a new resistance term \(r_{HR}\). This is the parallel sum of \(r_{aV}\) and \(r_{HR}\) \((r_{HR} = (r_{aH} + r_{HR}))\), with \(r_{HR}\) the virtual leaf resistance to radiative transfer:

\[
I_g = \frac{r_{HR}c_p\gamma}{4\varepsilon\sigma T_{aH}^4} \tag{53}
\]

The derivation of \(R_{ni}\), \(r_{HR}\), and \(r_{HR}\) is given in Supplementary Data S5. Equations 19, 50, and 51 then become:

\[
T_1 = T_w + \frac{r_{HR}\gamma r_{aV}R_{ni} - r_{HR} \rho_s c_p \delta e}{\rho_s c_p (\gamma r_{aV} + s r_{HR})} \tag{54}
\]

\[
T_{dry} = T_a + \frac{r_{HR}R_{ni}}{\rho_s c_p (\gamma r_{aV} + s r_{HR})} \tag{55}
\]

\[
T_{wet} = T_a + \frac{r_{HR}\gamma r_{aV}R_{ni} - r_{HR} \rho_s c_p \delta e}{\rho_s c_p (\gamma r_{aV} + s r_{HR})} \tag{56}
\]

Note that \(T_{wet}\) in equation 56 is the \(T_1\) of a reference leaf wetted on one side; \(T_{wet}\) of leaves wetted on both sides is obtained by replacing \(r_{aV}\) with 0.5 \(r_{aV}\).

\(R_{ni}\) has the advantage that is independent of \(T_1\); hence, in contrast with \(R_n\) in equations 19, 50, and 51, \(R_{ni}\) has the same value in equations 54–56, which allows calculating the stomatal conductance index \(I_g\) as \((T_{dry} - T_1)/(T_1 - T_{wet})\). For hypostomatous leaves, combining equations 24 and 54–56 gives:

\[
I_g = \frac{(T_{dry} - T_1)}{(T_1 - T_{wet})} = \frac{\gamma r_{aV} + s r_{HR}}{\gamma r_s} \tag{57}
\]
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4.4.2 Application of \( I_g \) and its sensitivity to weather conditions and deviations in leaf characteristics

\( I_g \) is indeed linearly related with \( g_s \) (Figs. 12 and 13, but see also Fig. 12i). This agrees with observations in grapevine (Jones et al., 2002; Leinonen and Jones, 2004; Fuentes et al., 2005; Grant et al., 2006, 2007; Leinonen et al., 2006; Loveys et al., 2008), in several varieties of bean (Jones, 1999a,b; Leinonen and Jones, 2004; Grant et al., 2006), in cucumber (Kaukoranta et al., 2005), and in the biodiesel plant \textit{Jatropha curcas} L. (Maes et al., 2011).

A thermal and visual image of this last study is given in Fig. 14. The seedling on the left (drought plant) was not irrigated for about 2 months; the seedling on the right (control plant) was fully irrigated. \( T_{dry} \) was 27.3 for both plants and \( T_{wet} \) 19.4 and 18.4 for the drought and control plant, respectively. Average \( T_l \) of the control plant was 24.8 °C, resulting in \( I_g = 0.39 \) and CWSI\(_d\) = 0.72; and average \( T_l \) of the drought plant was 26.7, resulting in \( I_g = 0.09 \) and CWSI\(_d\) = 0.92.

Similar to CWSI\(_d\), the expected value of \( I_g \) is not influenced by \( K_{in} \), \( \delta e \), \( \theta \), or \( \alpha \) (Fig. 12), but increases with increasing \( T_a \) and \( A_l \), and with decreasing \( u \). Optimal conditions for application of \( I_g \) (i.e. higher difference between the lines in left column; lower confidence bandwidths in middle column of Fig. 12) include high \( T_a \), \( K_{in} \), and \( \delta e \) and relatively low \( u \) (Fig. 12), which are also the conditions in which most studies were performed; however, \( I_g \) has also been successfully applied at low or highly variable incoming radiation (Maes et al., 2011; Grant et al., 2012).

\[
g_s = I_g \frac{\gamma}{\gamma T_{AV} + s f_{IR}} = I_g G
\]

(58)

with \( G = \frac{\gamma}{\gamma T_{AV} + 2s f_{IR}} \). In other cases, the relation between \( I_g \) and \( g_s \) becomes more complex (see Guilioni et al. (2008) for an overview). In the case of anisolateral leaves, \( I_g \) is a linear function of \( r_V \) (equation 22), not of \( g_s \). For hypostomatous and isolateral leaves, \( I_g \) is linearly related with \( g_s \) as long as \( G \) remains constant (equation 58). The influence of \( g_s \) and meteorological conditions on \( G \) is given in Fig. 11. \( G \) hardly changes with \( g_s \), \( K_{in} \), or \( \delta e \), but is very much influenced by \( u \) and \( T_a \).

Although \( g_s \) can be calculated from \( I_g \), \( I_g \) is most often used as a stress indicator itself, because of the linear relation with \( g_s \) and the fact that no additional microclimatic measurements are needed. The reliability and sensitivity for weather conditions and leaf characteristics was modelled, using the same leaf model and techniques as for CWSI\(_d\) (hence, hypostomatous leaves with wet reference leaves wetted on one side, section 4.3.4).

Fig. 11. Influence of weather conditions: (a) air temperature (\( T_a \)), (b) incoming shortwave radiation (\( K_{in} \)), (c) wind speed (\( u \)), and (d) vapour pressure deficit (\( \delta e \)) on \( G \) (\( G = I_g g_s^{-1} \)), calculated for hypostomatous leaves, and for three levels of \( g_s \); 20 (green), 200 (blue), and 600 (red) mmol m\(^{-2}\) s\(^{-1}\). Based on equation 58 and derived from the leaf model described in section 3.2.2. See Fig. 3 for standard weather conditions and leaf characteristics.
Fig. 12. Influence of weather conditions air temperature ($T_a$), incoming shortwave radiation ($K_{in}$), wind speed ($u$), and vapour pressure deficit ($\delta e$) on $I_g$. See Fig. 8 for a detailed description.
Fig. 13. Influence of leaf characteristics (leaf angle, size, shape, and albedo) on $I_g$. See Fig. 9 for a detailed description.
Indeed, if differences between measured and reference leaves are taken into account, the discriminative power roughly does not change with $K_\text{in}$ (Fig. 12e).

As for CWSI$_d$, leaf characteristics have relatively little influence on the discriminative power, with the exception of $\theta$ at more vertical leaf angles. Note that $\theta$, defined as the angle between the leaves and the plane perpendicular to the incoming sunlight, is also influenced by the position of the sun; hence, measurements in early morning and later afternoon or in early spring or late autumn, are prone to significantly larger error.

In field conditions, the large variation in $T_l$ within the canopy, mainly as a consequence of leaf orientation and shading, complicates the use of $I_g$. Grant et al. (2006, 2012) suggested placing leaves in a horizontal grid, but it is not certain that this will not disturb leaf functioning — furthermore, this is often unfeasible. More robust $I_g$ estimates can be obtained by taking the average temperature of several leaves as input for $T_l$ in equation 57 (Maes et al., 2011). In addition, separating canopy from background pixels, based on visual or near-infrared images (e.g. Leinonen and Jones, 2004; Möller et al., 2007; Wang et al., 2010a; see section 5.3.1), makes the estimates more robust.

The large variability of leaf canopy temperature also complicates the assessment of a reliable reference leaf temperature estimate. If different dry reference leaves are spread over the canopy, their $T_{\text{dry}}$ can differ with several degrees, due to the impact of $\theta$ and $K_\text{in}$ on $T_{\text{dry}}$ (Figs. 3c, d and 4a, b). Grant et al. (2006) suggested taking the maximum observed $T_{\text{dry}}$, rather than average $T_{\text{dry}}$; Maes et al. (2011) pinpointed the need to measure and use a separate $T_{\text{dry}}$ per plant, if possible.

$T_{\text{wet}}$ is slightly less influenced by $K_\text{in}$ or $\theta$ (Figs. 3d and 4b), but there are practical limitations to its use (Jones et al., 2009). Moreover, different times between wetting and image capture can cause inconsistent $T_{\text{wet}}$ estimates and wetting the reference leaves can influence $T_l$ of other leaves, both directly (dripping of the water on other leaves) and indirectly (through changes in microclimate) (Jones et al., 2002; Grant et al., 2007).

This calls for alternatives for the single reference leaves for application of $I_g$ at canopy or field scale. The wet reference leaves could be replaced by the WARS, used in CWSI$_d$ (section 4.3.4); as mentioned, no larger-scale alternative exists at the moment for the dry reference surfaces; as for CWSI$_d$, $T_{\text{dry}}$ might be taken as a constant level or can be estimated from equation 44 or 55.

### 4.4.3 CWSI$_d$ or $I_g$?

As discussed, the same data are used for the calculation of CWSI$_d$ or $I_g$; in fact, CWSI$_d = (1 + I_g)^{-1}$ (equations 51 and 57). So, which indicator is to be preferred? Interestingly, the modelling shows that the discriminative power of both methods is very similar (compare middle columns of Figs. 8 and 12 and of Figs. 9 and 13). So far, most scientists have preferred CWSI$_d$ because the CWSI concept is well known. However, CWSI$_d$ is not linearly related with $g$, and, due to the use of $T_{\text{wet}}$ instead of $T_{\text{pot}}$, there is no firm theoretical relation between CWSI$_d$ and $1 - \frac{\Delta E}{\Delta F_{\text{pot}}}$. The use of $I_g$ can therefore be recommended, at least at leaf level.
4.4.4 Alternative indices
$(T_{dry} - T_l)/(T_{dry} - T_i)$ is a simplified index that avoids the measurement problems related to the wet reference leaf. $(T_{dry} - T_l)$ was closely related with $g_s$ in grapevine and *Jatropha* (Grant *et al.*, 2006; Maes *et al.*, 2011) Model simulations (Supplementary Figs. S1 and S2 in Supplementary Data S6) show that $(T_{dry} - T_l)$ is almost linearly related with $g_s$, and that the influence of weather conditions and leaf characteristics is similar to that of $I_q$, although the discriminative power is lower, particularly when there is a difference in $\theta$ between measured and dry reference leaves at large $\theta$.

Estimating $g_s$ without reference leaves or with only dry reference leaves
As discussed, one of the great advantages of $I_q$ (and CWSI$_d$) is the fact that it can be assessed without requiring additional microclimatic measurements. However, if the aim is to estimate $g_s$ or $r_s$, precise microclimatic measurements (particularly of $T_a$ and $u$) are required to estimate $r_{HR}$ and $r_{SV}$ (equations 20, 21, 25, 26, and 53) and to calculate $G$.

In that case, it would be more practical if the wet and/or dry reference leaves are not needed. For hypostomatous leaves, $r_s$ can be estimated directly as (equation 54):

$$r_s = -\frac{r_{HR} \rho_a c_p}{\gamma} \frac{s(T_l - T_a) + \delta e}{(T_{dry} - T_l) - \alpha R_n} - r_{SV}$$

(59)

However, due to its sensitivity to measurement errors (Leinonen *et al.*, 2006), $r_s$ calculated with equation 59 correlated rather poorly with the measured $r_s$ (Leinonen *et al.*, 2006; Grant *et al.*, 2012). A similar approach was used by Blonquist *et al.* (2009) to estimate $g_s$ at canopy scale. A sensitivity analysis showed that errors in $g_s$ were particularly large in cloudy conditions, and that very precise measurements of $T_a$ and $T_l$ are required.

If $T_{dry}$ is additionally measured, $r_s$ can be estimated as (again for hypostomatous leaves, and combining equations 54 and 55) (Leinonen *et al.*, 2006):

$$r_s = \frac{r_{HR} \rho_a c_p}{\gamma} \frac{s(T_l - T_a) + \delta e}{(T_{dry} - T_l) - \alpha R_n} - r_{SV}$$

(60)

Note that no radiation data are required, but that $\delta e$, $r_{HR}$, and $r_{SV}$ have to be determined precisely. Results show that estimations of $g_s$ are comparable or even better than those obtained with $I_q$ (Leinonen *et al.*, 2006; Grant *et al.*, 2011).

4.5 The three-temperature model (3T model)
The three-temperature model (3T model) was developed and tested by Qiu *et al.* (2000, 2002, 2003, 2009). It makes use of a dry reference leaf, with assumed $AE = S = G_i = 0$. From equations 10 and 14, it follows that $R_{n,dry} = H_{dry} = \rho_a c_p \frac{(T_{dry} - T_a)}{r_{SH}}$. For normal leaves, this sensible heat is given by $H = \rho_a c_p \frac{(T_l - T_a)}{r_{SH}} = R_n - \lambda E$.

Assuming an identical $r_{al}$ for normal and dry reference leaves gives:

$$\lambda E = R_n - R_{n,dry} \frac{(T_l - T_a)}{(T_{dry} - T_a)}$$

(61)

Equation 61 is the basic formula used in the three-temperature model, which owes its name to the three temperatures ($T_l$, $T_a$, and $T_{dry}$) needed for its calculation. In addition, $R_n$ and $R_{n,dry}$ must be known; $R_n$ is either measured or can be derived from measurements of $K_{se}$ and $T_l$, if estimates of $\alpha$, $\tau$, and $\epsilon$ are available for both leaf sides (equation 13); $R_{n,dry}$ can be calculated from $R_n$ replacing $T_l$ with $T_{dry}$ and assuming that $\alpha$ and $\epsilon$ of the reference leaf are the same as those of the actual leaves.

The ratio of the right-hand side of equation 61, called $h_{al}$, was proposed as an indicator of drought stress and stomatal conductance (Qiu *et al.*, 2003, 2009):

$$h_{al} = \frac{(T_l - T_a)}{(T_{dry} - T_a)}$$

(62)

The authors claimed that $h_{al} \leq 1$, with lower values indicating higher $AE$.

The method has been mainly tested for sorghum, but also for melon (Qiu *et al.*, 2000, 2003), tomato (Qiu *et al.*, 2003), and lettuce (Qiu *et al.*, 2009). High correlations were observed between $h_{al}$ obtained from equation 61 and measured $AE$ (Qiu *et al.*, 2000, 2002). In addition, $h_{al}$ was highly correlated ($R^2 = 0.97$) with CWSI$_d$ of sorghum (but with $T_{dry}$ obtained from the dry reference leaf) and was capable of distinguishing between different drought and temperature treatments of melon and tomato (Qiu *et al.*, 2009).

The method seems very appealing: $h_{al}$ can easily be measured, is linearly related with $AE$, and can be used to calculate $AE$ without requiring estimates of $r_{al}$ or $r_{SV}$ (hence, of $\delta e$ or $u$). Still, the method has not been picked up by other researchers, so there is still very little experience with this method. We therefore modelled the sensitivity of $h_{al}$ to weather conditions and leaf characteristics, using the same approach as explained in section 4.3.4 for CWSI$_d$. For the $T_l$ measurements, a standard deviation of 0.1 °C was assumed. The results are given in Figs. 15 and 16. $h_{al}$ decreases non-linearly with increasing $g_s$. Unlike $I_q$ and CWSI$_d$, the expected $h_{al}$ value is influenced by all weather variables and leaf characteristics. The influence of most variables on the discriminative power of $h_{al}$ is comparable with that of CWSI$_d$ and $I_q$, although the differences in $\delta e$ between the reference and the measured leaves furthermore do not influence $h_{al}$. However, $h_{al}$ responds strangely to decreasing $K_{se}$ and increasing $\theta$. At low irradiance, due to either low $K_{se}$ or high $\theta$, $(T_l - T_a)$ becomes negative, resulting in negative $h_{al}$ values. When the irradiance decreases further, $(T_{dry} - T_a)$ first tends to 0, resulting in very negative $h_{al}$ values; with an even further drop in irradiance, $(T_{dry} - T_a)$ can become negative (e.g. Figs. 3d and 4b), in which case $h_{al}$ actually attains very high positive values (e.g. Fig. 15f).
Fig. 15. Influence of weather conditions air temperature ($T_a$), incoming shortwave radiation ($K_{in}$), wind speed ($u$), and vapour pressure deficit ($\delta e$) on $h_{at}$. See Fig. 8 for a detailed description.
Fig. 16. Influence of leaf characteristics (leaf angle, size, shape, and albedo) on $h_{at}$. See Fig. 9 for a detailed description.
The unsuitability of \( h_u \) at low radiation levels was confirmed in a re-analysis of data from Maes et al. (2011) on \( \textit{Jatropha} \). Measurements were performed in relatively low-light conditions (max. 130 W m\(^{-2}\)) in six measurement runs. In all measurements runs, significant differences between the drought treatments could be distinguished using CWSId, \( I_g \) or \( (T_{\text{dry}} - T) \). However, when \( h_u \) was used, significant differences between the treatments were not found for any measurement run; in addition, in only two of the six measurement runs, \( h_u \) was significantly correlated with \( g_c \).

All in all, the use of the 3T model or \( h_u \) can be appealing for its simplicity and its limited data and labour requirements, but is highly restricted due to its sensitivity to low-irradiation conditions.

4.6 Direct estimation of canopy evapotranspiration: one- and two-source models

The methods discussed so far calculated indices from \( T_s \), \( T_c \), or \( T_l \) to express drought stress or as an indirect indicator of \( g_c \), \( g_c \) or \( \lambda E \). Although these methods are at least theoretically related with \( \lambda E \), treatments could be distinguished using CWSId, \( I_g \), or \( (T_{\text{dry}} - T) \). However, when \( h_u \) was used, significant differences between the treatments were not found for any measurement run; in addition, in only two of the six measurement runs, \( h_u \) was significantly correlated with \( g_c \).

In all, the use of the 3T model or \( h_u \) can be appealing for its simplicity and its limited data and labour requirements, but is highly restricted due to its sensitivity to low-irradiation conditions.

The total sensible heat flux \( H \) is:

\[
H = H_c + H_{\text{soil}} = \rho_s c_p \left( \frac{(T_c - T_h)}{r_{\text{al}} + r_{\text{soil}}} \right)
\]

where \( r_{\text{soil}} \) is calculated from the empirical function:

\[
r_{\text{soil}} = \frac{1}{0.004 + 0.012u_{\text{soil}}} \tag{65}
\]

with \( u_{\text{soil}} \) the wind speed just above the soil surface, estimated as:

\[
u_{\text{soil}} = u_c \exp \left( -a \left( 1 - \frac{0.05}{h_c} \right) \right) \tag{66}
\]

with \( u_c \) the wind speed at the top of the canopy (derived from the logarithmic wind speed profile) and \( a \) the extinction coefficient, which is a function of LAI, \( h_c \), vegetation width, and a clumping factor that takes vegetation density into account (see equation 8 of Kustas and Norman, 2000).

The total sensible heat flux \( H \) is:

\[
H = H_c + H_{\text{soil}} = \rho_s c_p \left( \frac{(T_c - T_h)}{r_{\text{al}} + r_{\text{soil}}} \right)
\]

The Priestley-Taylor equation is used to calculate \( \lambda E_c \) [see Supplementary Data S1.3, equation S18; setting \( G_\gamma = 0 \) (canopy layer)]:

\[
\lambda E_c = \alpha_{\text{PT}} f_g \frac{s}{s + \gamma} R_{n,c} \tag{68}
\]

with \( \alpha_{\text{PT}} \) the Priestley-Taylor coefficient and \( f_g \) the proportion of leaf area that is green. \( R_{n,c} \), the net radiation of the canopy layer, is the sum of shortwave and longwave radiation, calculated as a function of \( K_{\text{in}}, \alpha, \) LAI, and the clumping factor, corrected for solar angle. \( R_{n,\text{soil}} \) is calculated with a similar procedure, and \( G_i \) is calculated from \( R_{n,\text{soil}} \) using equation 31 with \( \Gamma_i = 0.3 \).

The iterative procedure to calculate \( \lambda E_c \) and \( \lambda E_{\text{soil}} \) goes as follows:

(a) A first estimate of \( \lambda E_c \) is obtained with equation 68 and assuming \( \alpha_{\text{PT}} = 1.3 \)

(b) From equation 10 (ignoring \( S \)), \( R_{n,c} - \lambda E_c = H_c = \frac{(T_c - T_h)}{r_{\text{al}}} \)

(c) \( T_{\text{soil}} \) is estimated from \( T_c \) and equation 63.

(d) \( H_{\text{soil}} \) is estimated from \( T_{\text{soil}} \) and equation 64.

(e) \( \lambda E_{\text{soil}} \) is calculated from \( \lambda E_{\text{soil}} = R_{n,\text{soil}} - G_i - H_{\text{soil}} \)

(f) If \( \lambda E_{\text{soil}} \geq 0 \), a solution for soil and canopy energy fluxes is reached. Else, \( \lambda E_{\text{soil}} \) is set to 0 allowing calculating a new estimate \( H_{\text{soil}} = R_{n,\text{soil}} - G_i \). Going through steps a–e backand forth gives estimates of \( T_{\text{soil}}, T_c, H_c, \) and \( \alpha_{\text{PT}} \). Steps a–e are repeated until a solution is found for \( \lambda E_{\text{soil}} \geq 0 \).

Note that with this approach, \( T_c \) and \( T_{\text{soil}} \) are derived from \( H_c \) and \( H_{\text{soil}} \); hence, they can be considered the aerodynamic temperature of the canopy and the soil layers.
This TSM generally outperformed OSMs for extreme conditions and in sparse vegetations or orchard-like ecosystems (Kustas et al., 2007; Kustas and Anderson, 2009); moreover, it offers the advantage over OSMs that separate energy balances are developed for the soil and canopy compartment. However, it is clear that this TSM relies on a highly detailed knowledge of the vegetation structure; this is also the case for the more advanced OSMs. As such, in contrast with airborne and satellite thermal remote sensing, the direct estimation of λE through ground-based thermal remote sensing is in general restricted to scientific studies.

5 The future and challenges of ground-based thermal remote sensing

5.1 From scientific methods to agricultural practice

Most methods discussed in section 4 are still only used for scientific purposes. The few methods that are applied in agricultural practice (e.g. stress time, CWSI) for drought stress detection and irrigation steering use IRT sensors rather than cameras. These methods have clear limitations. Most importantly, they can only be applied in regions with very constant (semi-)arid weather conditions during the growth season and are largely limited to low, homogeneous crops.

Still, there is a strong interest for new drought stress detection or irrigation steering methods. With the increasing pressure on blue water resources, there is a growing demand for efficient irrigation methods that maximize water productivity and minimize costs and wastes. This calls for new precision irrigation techniques (Fereres and Evans, 2006; Steppe et al., 2008; Fernández and Cuevas, 2010), preferably based on plant-water status measurements (Jones, 2004; Naor, 2008; Steppe et al., 2008; Fernández and Cuevas, 2010). With the currently available methods to measure plant-water status (e.g. sap flow and/or diameter measurements), it is impossible to assess the spatial variability. If plant-to-plant variability in plant-water status is high, this variability must be assessed for precision irrigation (Naor and Cohen, 2003; Arno et al., 2009). This is particularly the case for horticultural (i.e. orchard-like) cash crops such as grapevine (Acevedo Opazo et al., 2008).

Infrared thermography is particularly suited for these applications, because it allows the spatially explicit assessment of the water use in plants. However, several basic problems need to be overcome before thermal cameras can be used for commercial application in agriculture at this moment: (i) images of sufficiently high pixel resolution must be generated of the entire field; (ii) the acquired images must be processed automatically; and (iii) an adequate method must be developed to estimate drought stress or irrigation need at this scale.

5.2 Covering the entire field

Several methods have so far been used to increase the field area viewed by the camera. Thermal cameras are often positioned on fixed poles (e.g. Cohen et al., 2005; Alchanatis et al., 2010) or cranes (e.g. Möller et al., 2007; Ben Gal et al., 2009), but this does normally not allow viewing the entire field.

In fields equipped with a pivot irrigation system, IRT sensors (Sadler et al., 2002; Peters and Evett, 2007, 2008) or thermal cameras (Colaizzi et al., 2003b; El-Shikha et al., 2007) can be fixed on the pivot to assess the spatial variability. Else, the entire field can be viewed with thermal cameras installed on robotic cars (Luquet et al., 2003), which can be particularly suited in orchards. These truly ground-based methods allow viewing at off-nadir viewing angles but have the disadvantage that it takes considerable amount of time to cover the entire field, so that temperature correction of the images is needed sensors (Peters and Evett, 2007, 2008).

An alternative is to apply low-altitude airborne thermography. Although this is not strictly ground-based, the same methods are applied as for ground-based measurements. Application of unmanned flights will in most cases not be economic for agricultural practice, but in recent years, miniature unmanned aerial vehicles (UA Vs), small helicopters or airplanes that are able to fly autonomously, have been developed. With relatively low capital and very low operational costs, these UA Vs have the potential to become an affordable measurement tool. Moreover, they can be applied at virtually any desired moment and location, while covering areas of several hectares and providing very high resolution maps (5–25 cm, depending on flight altitude and sensor type). Their potential for assessing drought stress or estimating λE of agricultural fields has already been shown in a number of studies (e.g. Sullivan et al., 2007; Berni et al., 2009a,b; Gonzalez-Dugo et al., 2012; Zarco-Tejada et al., 2012). As such, miniature UA Vs currently seem to be the most promising method for the acquisition of high-resolution drought stress maps.

5.3 Automated image processing

Image processing is still a very time-consuming step that requires expert knowledge in both software and thermography. This must be largely automated before infrared thermography can be applied as a common tool in agricultural practice. The processing is different for ground-based or low-altitude airborne measurements.

5.3.1 Ground-based measurements

Although Tl or Tc can be derived directly from the thermal images, using temperature thresholds based on T₀ (e.g. Jones et al., 2002), the acquisition of precise estimates of Tl or Tc requires the use of visual images (e.g. Leinonen and Jones, 2004; Möller et al., 2007; Wang et al., 2010a).

First, the visual and thermal images have to be overlaid. As the images are not taken from the exact same position and as they have a different resolution, this is often a time-consuming step that involves warping and resampling of the visual images, based on ground control points that are recognizable on visual and thermal images (Leinonen and Jones, 2004). Wang et al. (2010b) recently proposed an advanced method in which the image registration is performed automatically based on automatic cross-correlation algorithm of edge images generated from the visual and thermal images.
Next, pixels must be classified as canopy/leaf (preferentially separating shaded and sunlit leaves) in order to extract $T_c$ or $T_v$. This is mostly done using the visual image only, through supervised classification (Leinonen and Jones, 2004; Jiménez-Bello et al., 2011) or, fully automatic, through colour identification (Wang et al., 2010a). As small errors in image overlap can generate significant errors in the average $T_{br}$ estimate, it is preferable to filter out very hot or very cold pixels, as proposed by Wang et al. (2010a). Finally, $T_{br}$ must be converted into $T_r$ or $T_c$, through the procedure explained in section 2.2. Note that this is not strictly required if reference temperatures of leaves/surfaces with very similar emissivity are used. If CWSI$_d$ or $I_g$ are to be calculated, the temperatures of the reference leaves must additionally be extracted. Wang et al. (2010a) proposed an automatic procedure to do so. Finally, CWSI$_d$, $I_g$ or another index can be calculated.

5.3.2 Low-altitude airborne measurements

In low-flight airborne remote sensing, a large number of images, taken within a short time span, must be mosaicked. Software is available that creates a mosaicked and geo-referenced image relatively automatically, often using the GPS location of the UAV or airplane (e.g. Berni et al., 2009b). If a large amount of images is taken with great overlap, digital terrain models can be calculated, visualizing the canopy structure. More precise georeferencing can be done using ground control points. Techniques to separate soil and canopy layers are similar to those for ground-based measurements, possibly extended with information of the digital terrain model.

5.4 Adaptation of methods to field scale

It is clear that the current ground-based methods need to be adapted before they can be applied in an automated procedure at field scale. As discussed, the most promising and straightforward ground-based thermal methods for estimating drought stress are those that use $T_{dry}$ and $T_{wet}$ to correct $T_s$ (e.g. CWI or $I_g$). $T_{wet}$ can be derived directly from the WARS, although the issues formulated in section 4.3.4 deserve further attention. Moreover, the required amount of reference surfaces is not clear. In theory, a reference surface should be present within each image, but this seems not feasible and even not necessary in the case of imaging with UAV systems, as all images are taken at virtually the same moment. $T_{dry}$ can be calculated from weather data (equation 50), although it seems preferable to derive $T_{dry}$ directly from a reference surface, which still has to be developed. Another option is to estimate $T_{dry}$ and $T_{pot}$ from the $T_c$ or the vegetation index–$T_c$ space, as is commonly performed for high-altitude remote sensing in, for example, the S-SEBI algorithm (Roerink et al., 2000) or the empirical version of WDI (Clarke, 1997). However, this does require the presence of a sufficient amount of extreme pixels (i.e. dry and wet pixels) in the image.

A possible future alternative would be to estimate $\lambda\varepsilon$ with OSMs or (particularly for orchards) TSMs. They could be automated provided that the information of the visual image and, if possible, the detailed digital terrain model, is used to automatically extract all required information of canopy structure.

Supplementary material

Supplementary data are available at JXB online.

Supplementary Data S1. Derivation of general relations between surface temperature and sensible and latent heat flux

Supplementary Data S2. Calculation of resistance to sensible and latent heat transport in air

Supplementary Data S3. Derivation of CWSI

Supplementary Data S4. Overview Table of non-water stressed baseline equations

Supplementary Data S5. Calculation of $R_{ni}$

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